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Essays on demand-side management policies and measures: renewables accommodation, energy poverty and pricing strategies

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CHAVE MÓVEL

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Dedicatória/Dedication

Para os meus pais, irmã, cunhado, sobrinhas, e futura esposa.

To my parents, sister, brother-in-law, nieces, and future wife.

Ponte Sobre Águas Turbulentas	**Bridge Over Troubled Water**
Quando estiver cansada	When you're weary
Sentindo-se pequena	Feeling small
Quando as lágrimas estiverem nos seus olhos	When tears are in your eyes
Eu as secarei todas	I will dry them all
Estou ao seu lado	I'm on your side
Quando os tempos ficarem difíceis	When times get rough
E os amigos desaparecerem	And friends just can't be found
Como uma ponte sobre águas turbulentas	Like a bridge over troubled water
Eu me estenderei	I will lay me down
Como uma ponte sobre águas turbulentas	Like a bridge over troubled water
Eu me estenderei	I will lay me down
Estarei ao seu lado	I'll take your part
Quando a escuridão chegar	When darkness comes
E o sofrimento te rondar	And pain is all around
Como uma ponte sobre águas turbulentas	Like a bridge over troubled water
Eu me estenderei	I will lay me down
Como uma ponte sobre águas turbulentas	Like a bridge over troubled water
Eu me estenderei	I will lay me down
Continue, garota	Sail on, silver girl
Siga em frente	Sail on by
Chegou a sua hora de brilhar	Your time has come to shine
Todos os seus sonhos estão a caminho	All your dreams are on their way
Veja como brilham	See how they shine
Se você precisar de um amigo	If you need a friend
Estarei vindo logo atrás	I'm sailing right behind
Como uma ponte sobre águas turbulentas	Like a bridge over troubled water
Eu acalmarei a sua mente	I will ease your mind
Como uma ponte sobre águas turbulentas	Like a bridge over troubled water
Eu acalmarei a sua mente	I will ease your mind
Composição: Paul Simon	*Composition: Paul Simon*
Interpretação: Simon & Garfunkel	*Interpretation: Simon & Garfunkel*

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Se eu vi mais longe, foi por estar sobre os ombros de gigantes. (Isaac Newton)

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“*If I have seen further, it is by standing on the shoulders of giants.*” (Isaac Newton)

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"A transition to clean energy is about making an investment in our future."

(Gloria Reuben)

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Resumo

As alterações climáticas têm sido causadas, principalmente, pelo aumento das emissões de dióxido de carbono e outros gases com efeito de estufa para a atmosfera. Uma parte substancial dessas emissões poluentes tem sido provocada pela combustão de combustíveis fósseis para gerar eletricidade. A geração de eletricidade a partir de recursos verdes e endógenos, tem sido apontada como a solução mais promissora para combater as alterações climáticas. Embora as fontes de energia renováveis tenham sido profusamente implementadas e utilizadas, os seus benefícios podem estar a ser restringidos pelas suas características, nomeadamente a sua intermitência. Espera-se que, a integração de fontes de energia renováveis intermitentes (eólica e solar fotovoltaica) com baixos custos marginais, reduza os preços da eletricidade, efeito também conhecido como merit-order effect. Contudo, o efeito contrário ocorre frequentemente, i.e., os preços de eletricidade mostraram uma tendência crescente com a implementação das fontes de energia renovável. Este efeito adversativo sugere que, a implementação das fontes de energia renováveis pode ainda agravar a vulnerabilidade das famílias, nomeadamente através dos problemas relacionados com a pobreza energética. Este raciocínio é, na verdade, a principal motivação para o primeiro ensaio desta tese que, pretende perceber qual o impacto da integração de fontes de energia renováveis no risco de pobreza e exclusão social das famílias europeias. Um painel de dados de países europeus foi analisado recorrendo a um teste de cointegração (Kao's residual cointegration test) e a um estimador autorregressivo (Panel autoregressive Distributed Lag). Os resultados deste ensaio indicaram que, um aumento da capacidade instalada de fontes de energia renováveis intermitentes acentua o risco de pobreza e exclusão social das famílias europeias. No entanto, foi verificado que, a geração de eletricidade a partir de energia eólica e hidroelétrica reduz o risco de pobreza e exclusão social, diminuindo a desigualdade de rendimentos das famílias. Esta divergência entre o impacto da capacidade instalada e a sua geração efetiva realça as consequências da intermitência das fontes de energia renováveis que, são mais percetíveis na energia eólica.

O potencial do lado da procura de eletricidade na acomodação de fontes de energia renováveis intermitentes nos sistemas electroprodutores é uma área que necessita de mais investigação. Esta tese apresenta uma linha de estudo inovadora para fornecer evidências empíricas sobre esse tópico. No segundo ensaio desta tese, foi conduzida uma análise empírica com dados diários para verificar as interações entre as fontes de energia

elétrica e os períodos de consumo diferenciado (períodos de consumo em pico e fora de pico). A análise do segundo ensaio indicou que, as flutuações do consumo de eletricidade constituem a principal barreira à integração das fontes de energia renováveis. Este resultado motivou os dois ensaios seguintes, o terceiro e o quarto ensaio que, propõe métodos inovadores para classificar a procura de eletricidade por níveis de consumo e períodos de tempo, através de dados históricos de elevada frequência (dados de 15 em 15 minutos e de 30 em 30 minutos). Os métodos propostos para classificar a procura/consumo de eletricidade forneceram novos conhecimentos sobre a ocorrência dos diversos níveis de procura de eletricidade (nomeadamente, o nível de pico, de vale e intermédio), que se demonstraram úteis para formular novas estratégias de preço da eletricidade que permitam fomentar a acomodação das fontes de energia renováveis no sistema electroprodutor. Os níveis de procura de eletricidade do sistema elétrico alemão e francês foram estudados, devido à elevada contribuição de fontes de energia renováveis intermitentes e, à contribuição elevada e rígida da fonte nuclear, respetivamente. No caso alemão (terceiro ensaio) e no caso francês (quarto ensaio) o potencial das tarifas Time-of-Use (bi-horárias e tri-horárias) foi evidenciado, para fornecer a flexibilidade necessária do lado da procura, para acomodar produção de eletricidade intermitente provida pelas fontes de energia renováveis. Por outras palavras, ambos os ensaios comprovaram o potencial das tarifas Time-of-Use para envolver os consumidores como atores ativos no mercado de eletricidade, alavancando a integração das fontes de energia renováveis.

É fundamental compreender se os potenciais benefícios das fontes de energia renováveis efetivamente ocorrem, especificamente para os agregados familiares em situação de pobreza energética. Ou se, pelo contrário, as fontes de energia renováveis irão contribuir para acentuar as desigualdades económicas e sociais existentes, aumentando o número de agregados familiares vulneráveis devido à pobreza energética. O quinto ensaio desta tese, seguindo o raciocínio da pobreza energética, dedicou-se a fornecer evidências empíricas sobre o impacto das formas de consumo de energia na pobreza energética. Este ensaio focou-se na avaliação da pobreza energética dos países europeus por grau de urbanização, nomeadamente nas cidades, vilas e subúrbios (áreas metropolitanas) e áreas rurais. Neste ensaio concluiu-se que, a transição de fontes de energia poluentes para eletricidade deve ser cuidadosamente planeada e estimulada nos diferentes graus de urbanização, de modo a não agravar a pobreza energética. No entanto, nas cidades, as famílias estão preparadas para satisfazer totalmente as suas necessidades de energia através do consumo de eletricidade, o que reduz a vulnerabilidade dessas famílias perante a eletrificação necessária para a transição energética.

Por fim, o último ensaio desta tese, avaliou o impacto das estratégias de preços de eletricidade (tarifas de eletricidade) no aumento dos custos de energia para os agregados familiares. O sexto ensaio foi o primeiro estudo que analisou os impactos sociais e económicos das estratégias de preços de eletricidade. Neste sentido, o sexto ensaio foi relevante para fornecer novos conhecimentos e orientações para o planeamento de políticas de energia, especialmente, para o planeamento de políticas focadas na transição energética e no empoderamento dos consumidores. Em suma, os diversos ensaios que compõem esta tese fornecem evidências empíricas e, propõem estratégias de preços e medidas de gestão ativa da procura de eletricidade, com o objetivo de aumentar a predisposição dos consumidores a ajustar a sua procura/consumo de eletricidade à disponibilidade das fontes de energia renováveis.

Palavras-chave

Fontes de Energia Renováveis; Procura Líquida; Classificação da Procura; Níveis de Procura de Eletricidade; Transição energética; Formas de consumo de energia; Estratégias de Preços; Risco de pobreza e exclusão social; Pobreza Energética; Gestão Ativa da Procura de Eletricidade

Resumo Alargado

Desde o início dos anos 2000, a preocupação com o aquecimento global e as suas consequências, tais como as alterações climáticas e o degelo (derretimento dos glaciares), provocadas pela poluição do ar e da água, tem sido reforçada. O crescimento acelerado das emissões de dióxido de carbono e de outros gases com efeito de estufa tem intensificado o aquecimento global. Esta situação instigou uma preocupação emergente em todo o mundo, conduzindo investigadores e formuladores de política a analisarem soluções para os problemas ambientais. A energia tem sido um ponto fulcral nessa análise, devido às suas externalidades ambientais negativas. Pois, é praticamente impossível extrair, produzir/refinar, transportar e consumir energia sem provocar danos ambientais. No entanto, a energia tem sido um dos principais impulsionadores do crescimento e do desenvolvimento económico e social. Os sistemas electroprodutores, são o principal objeto de estudo desta tese, uma vez que são cruciais no combate as alterações climáticas. Por um lado, a produção de eletricidade tem sido uma das principais causas das emissões nocivas para a atmosfera, devido ao uso de combustíveis fósseis (como o carvão, o gás natural e o petróleo) para gerar eletricidade. Por outro lado, os sistemas electroprodutores são apontados como a solução mais promissora para descarbonizar as economias, e mitigar a poluição ambiental.

A transição de fontes tradicionais (poluentes) para fontes de energia renováveis (FER) tem sido um fenómeno transversal em todo o mundo. Paralelamente, a eletrificação tem-se alargado até as regiões mais remotas (como as rurais ou montanhosas), e a todos os sectores, nomeadamente residencial, industrial, público, dos serviços e dos transportes. Espera-se que, a produção de eletricidade através de fontes verdes e limpas seja a principal fonte de energia para o consumo, tendo como objetivo cumprir os compromissos estabelecidos no Acordo de Paris, e noutros acordos internacionais para a proteção ambiental. As fontes de energia verde foram introduzidas no mix de eletricidade através de um portfolio de fontes de energia renováveis controláveis (FER-C) e intermitentes (FER-I). A produção de eletricidade através de FER-C, como a geotérmica, biomassa, hidroelétrica, pode ser controlada. Inversamente, a produção de eletricidade através de FER-I, como a eólica e solar fotovoltaica, é dependente da disponibilidade dos recursos naturais, logo a sua produção é intermitente e incontrolável.

A implementação de FER tem sido suportada por políticas públicas que desencadearam um aumento da sua capacidade instalada, intensificando a sua contribuição para o fornecimento de energia. Por outro lado, o aumento da procura de eletricidade causado pela eletrificação das economias, tem trazido novos desafios para a transição energética e para a segurança do sistema electroprodutor. Esta situação paradoxal é, na verdade, a principal motivação para o desenvolvimento desta tese. Esta tese tem como objetivo explorar medidas para fomentar a predisposição dos consumidores para alterar as suas necessidades de consumo para períodos em que haja uma elevada disponibilidade de recursos verdes e endógenos. Os consumidores podem beneficiar de poupanças efetivas através da alteração dos seus padrões de consumo. Assim, é possível aumentar o bem-estar dos consumidores e, até mesmo reduzir o número de agregados familiares afetados pela pobreza energética. Uma ferramenta-chave para promover as mudanças desejadas na procura de eletricidade é a gestão ativa da procura de eletricidade que, é o tema principal desta tese.

As quatro dimensões avaliadas nesta tese são: (i) a acomodação de FER; (ii) o consumo de eletricidade; (iii) a pobreza energética; e (iv) a formulação de estratégias de preço da eletricidade. Os seis ensaios desta tese mostram a proeminência da gestão ativa da procura de eletricidade para conectar as quatro dimensões em análise, fomentando medidas para superar os desafios que o sistema electroprodutor e a sociedade enfrentam. Em suma, esta tese pretende contribuir com sugestões de políticas e medidas concretas, principalmente ao nível da procura de eletricidade, para que a diversificação do mix de eletricidade seja possível sem agravar a pobreza energética. No primeiro ensaio, o impacto da implementação de FER na economia e na sociedade em geral é analisado, através de um painel de países europeus de 2005 a 2015. Os resultados do Kao residual cointegration test (um teste de cointegração) e do estimador Panel Autoregressive Distributed Lag, evidenciaram que existe uma relação de longo-prazo entre a implementação de FER e as condições de vida dos agregados familiares europeus, nomeadamente a desigualdade de rendimentos e o risco de pobreza e exclusão social.

As flutuações intra-diárias do consumo de eletricidade representam um desafio para os sistemas electroprodutores, dado que essa procura oscilante tem de ser satisfeita. Ademais, a geração de eletricidade através das FER-I variam também ao longo do dia, e os dados anuais não são capazes de fornecer evidências sobre o fenómeno da intermitência. O segundo ensaio apresenta uma linha de estudo inovadora, analisando as interações entre as fontes de eletricidade e os períodos com diferentes procuras de eletricidade, utilizando dados de 30 em 30 minutos do sistema elétrico francês, de 1 de Janeiro de 2012 até 31 de Dezembro de 2018. Este ensaio destacou as consequências da implementação e da utilização simultânea de FER e combustíveis fósseis, e da dinâmica da procura/consumo de eletricidade nos períodos de pico e fora de pico. Assim, o segundo ensaio fornece evidências empíricas sobre a diversificação do mix de eletricidade e o seu impacto nas emissões de dióxido de carbono. O estimador Vector Autoregressive foi utilizado, e mostrou que, o aumento da pressão da procura de eletricidade em períodos de pico, e o baixo consumo em períodos de fora de pico exacerbaram a ineficiência da exploração da fonte nuclear francesa. O segundo ensaio provou também que, a transferência de consumo dos períodos fora de pico para os períodos de pico, intensificou a necessidade de combustíveis fósseis mais flexíveis (gás natural).

O terceiro ensaio reavaliou a noção de consumo com mais detalhe, estudando a elevada contribuição das FER-I para o mix de eletricidade alemão, desde 1 de Janeiro de 2015 a 20 de Novembro de 2019. Este ensaio propôs um método inovador para classificar a procura de eletricidade em níveis, aplicando os conceitos de procura tradicional e procura líquida. O conceito de procura líquida considera a produção de FER-I como garantida, deste modo, a procura líquida refere-se ao consumo que as fontes controláveis devem satisfazer, ou, por outras palavras, a procura onde as políticas de gestão ativa da procura de eletricidade devem intervir. No terceiro ensaio provou-se que, a procura líquida e os níveis de procura líquida têm uma maior capacidade para explicar o preço da eletricidade no mercado grossista do que o conceito de procura tradicional, isto é, o consumo. Para além disso, quando os níveis de procura de pico e de vale da procura líquida e da procura tradicional são comparados, a diferença entre eles é claramente notória. Este ensaio evidenciou que, o conceito de procura líquida deve ser a referência para classificar os níveis de procura em pico, fora de pico, e vale, especialmente em sistemas elétricos com uma elevada capacidade instalada de FER-I. Os resultados obtidos neste ensaio demostraram também que, as tarifas Time-of-use (bi-horária, tri-horária) podem promover as mudanças na procura de eletricidade necessárias para alavancar a integração e acomodação das FER-I, adicionando flexibilidade ao sistema através do lado da procura de eletricidade.

O método de classificação da procura de eletricidade proposto no terceiro ensaio foi desenvolvido no quarto ensaio. Nesse quarto ensaio, os níveis diários de consumo de eletricidade foram subclassificados em períodos de tempo, endogenamente, recorrendo a gráficos de dispersão e histogramas. Neste ensaio, foram utilizados dados intra-diários da procura de eletricidade em França, desde 1 de Janeiro de 2013 a 31 de Outubro de 2020. Os perfis de carga franceses foram examinados, como o objetivo de delinear e quantificar os desafios e oportunidades para intervenções do lado da procura. Constatouse que, este método de classificação é capaz de fornecer estatísticas detalhadas sobre o comportamento da procura/consumo de eletricidade. As interações diárias entre os vários níveis de procura de eletricidade e períodos de tempo foram avaliadas empiricamente, como objetivo de fornecer evidências sobre os desafios e oportunidades para alcançar uma curva da procura diária suavizada, mas flexível. Os resultados do quarto ensaio demonstraram que, as principais barreiras à suavização da procura de eletricidade são provocadas por dois picos de consumo durante o dia, dado que estes não permitem uma eficiente utilização da energia nuclear. Esses picos ocorrem predominantemente durante o horário de trabalho e à noite (este último é especialmente acentuado nos meses de inverno). Ademais, a procura de vale (valley demand) da manhã também não deve ser desconsiderada, pois nesse período nem mesmo a oferta de energia nuclear é absorvida pela procura. Apesar das barreiras da procura de eletricidade nos dois picos e no vale, e a incapacidade de armazenar eletricidade em larga escala para diferir a produção de eletricidade no tempo, os resultados evidenciaram que uma tarifa time-of-use pode fornecer a flexibilidade necessária, para alcançar uma curva da procura de eletricidade suavizada.

As áreas urbanas têm necessidades de energia diferentes das áreas rurais e acesso a fontes de energia é também diferente, o que gera preferências distintivas nas suas formas de consumo de energia. É sabido que as áreas urbanas preferem o consumo de eletricidade, enquanto as áreas rurais preferem e têm ao seu dispor fontes de energia primária, como por exemplo biomassa/lenha e gás. A preferência pela biomassa/lenha advém, na generalidade, da disponibilidade abundante desses recursos nas áreas rurais, mas também é provocada pela carência de acesso à rede elétrica. Esta divergência no consumo de energia entre zonas urbanas e rurais motivou o quinto ensaio desta tese. Nele pretende-se averiguar como a preferência pela forma de consumo de energia influencia a pobreza energética, em três graus de urbanização. Este ensaio, analisou a pobreza energética em 12 países europeus com um conjunto de 3 painéis de dados, um para as cidades, outro para as vilas e subúrbios (áreas metropolitanas), e o último para as áreas rurais. A análise foi conduzida com dados anuais de 2005 a 2018, recorrendo ao estimador Feasible Generalized Least Squares. Os indicadores de pobreza energética e pobreza tradicional (pobreza provocada pelo baixo rendimento das famílias, ou bem-estar reduzido), foram explicadas através das formas de consumo de energia (petróleo, biomassa/lenha, gás natural, e eletricidade) no sector residencial. Neste ensaio também se estudou o impacto do consumo de eletricidade por atividade final (para aquecimento de águas, aquecimento do ambiente, cozinha, eletrodomésticos e iluminação) na pobreza energética e pobreza tradicional. O quinto ensaio acrescenta conhecimento à literatura, fornecendo informações para desenvolver e implementar políticas eficazes para aliviar a pobreza energética. Este ensaio também destacou que, as políticas de incentivo à transição energética devem evoluir para proteger as famílias mais vulneráveis, devendo ser planeadas a um nível mais desagregado (por exemplo por região ou grau de urbanização).

O sexto ensaio analisou o impacto das estratégias de preços de eletricidade na diminuição dos custos de energia para as famílias, e na redução da pobreza energética. Para isso, foram estudados os 51 estados dos Estados Unidos América, e 5 estratégias de preços de eletricidade, desde 2013 a 2019. Este ensaio concentrou-se nos Estados Unidos da América porque é o país mais desenvolvido em termos de disponibilidade de estratégias de preço da eletricidade, o que pode ser comprovado pelo elevado investimento na implementação da mais abrangente rede inteligente (smart grid) do mundo. Um estimador de painel dinâmico (Arellano & Bond consistent generalized method of moments) foi utilizado par avaliar o impacto das estratégias de preço no número de agregados familiares que são afetados pela pobreza energética. Os resultados do sexto ensaio enfatizam que, as estratégias de preço mais estáticas (Time-of-use ou Critical Peak Pricing) têm potencial para diminuir o número de agregados familiares afetados pela pobreza energética. No entanto, as estratégias de preço mais dinâmicas revelaram ter o efeito contrário, aumentando o número de famílias em situação de pobreza energética. Em suma, o resultado mais revelante ao longo de toda esta tese foi o potencial das estratégias de preço de tempo de uso (Time-of-use tariffs) para aliviar as problemáticas identificadas no lado da procura e no lado da oferta de eletricidade. De facto, estas estratégias de preço podem fornecer a flexibilidade necessária para acomodar as FER-I, alavancando a sua integração. Além disso, estas estratégias de preço podem também contribuir para aliviar a pobreza energética.

Essays on demand-side management policies and measures: renewables accommodation, energy poverty and pricing strategies

Abstract

Climate change is a phenomenon primarily caused by an increase in the percentage of carbon dioxide and other greenhouse gases in the atmosphere. A large proportion of these polluting emissions come from burning fossil fuels to generate electricity. Researchers and policymakers point to the generation of electricity from endogenous and green resources as the most promising solution to fight global climate change. While the deployment of renewable energy resources has been widely applied, their intermittent features largely mask their advantages over polluting fossil fuels. It is expected that the integration of intermittent renewable energy sources with low marginal costs would reduce electricity prices, also known as the merit-order effect. However, the opposite frequently occurs, i.e., electricity prices show a tendency to increase with the implementation of these energy sources. This could indicate that the deployment of renewable energy sources could deepen the problems related to energy poverty. This fact has been the motivation for the first essay of this thesis; the observation of the impact of renewable energy sources integration on the risk of poverty and social exclusion. A panel data of European countries was analyzed using Kao's residual cointegration test with a Panel Autoregressive Distributed Lag approach. The main findings suggest that an increase in the capacity of intermittent renewable energy as a whole accentuates the risk of poverty and social exclusion for European households. In contrast, it is found that electricity generation from wind power and hydropower reduces households' risk of poverty and social exclusion. These divergent effects highlight the consequences of the intermittency phenomenon of renewable energy, more noticeable with wind power.

The potential role of the demand-side in accommodating intermittent renewable energy sources in electricity systems is an area that needs further investigation. This thesis introduces an innovative line of study to provide enhanced empirical evidence about this topic. In the second essay, an empirical analysis of daily data was used to verify the interactions between electricity sources and the periods of differing consumption. The findings indicate that fluctuations in electricity demand are the main barrier to the integration of renewable energy sources. This outcome motivated the following two essays to go further and to break new ground by proposing demand classification methods by levels and time periods, obtained through the assessment of high-frequency historical data. The demand classification methods have provided new knowledge about the occurrence of electricity demand levels (namely, peak, valley, and intermediate), which is highly useful and valuable for designing new pricing strategies. These demand levels were studied in German and French electricity systems due to their high contribution of intermittent renewables and their largest rigid nuclear baseload sources, respectively. The most revealing finding in these two essays was the potential of a Time-of-Use tariff to provide the required demand-side flexibility to accurately accommodate renewables' intermittence. In other words, involving consumers as an active player in the electricity market, leveraging renewables integration, can be achieved through a time-of-use pricing strategy.

It is crucial to understand whether the benefits promised by renewables effectively occur, specifically for households already suffering from energy poverty, or whether they will contribute to accentuating inequalities, increasing the number of households threatened by energy poverty. Once again, following the energy poverty reasoning, the sixth essay is dedicated to providing evidence on the impact of residential energy consumption forms on energy poverty. This essay assessed the energy poverty of European countries by degrees of urbanization, namely in cities, towns and suburbs, and rural areas. It emerges that energy transition to electricity should be carefully planned and stimulated in towns and suburbs, and rural areas so as not to threaten families with energy poverty. Conversely, in cities, households are prepared to totally satisfy their energy consumption through electricity.

The last essay of this thesis assessed the impact of pricing strategies on households' energy cost burden. It is the first research that has extensively analyzed the social and economic impacts of electricity pricing strategies. In this sense, it was able to provide new knowledge and guidance on the design of energy policies, especially those focused on energy transition and on consumer empowerment. To sum up, this thesis proposes pricing strategies and demand-side management measures focused on increasing consumers' willingness to adjust their demand to the availability of renewable energy sources.

Keywords

Renewable Energy Sources; Net demand; Demand-Side Management; Demand classification; Electricity demand levels; Daily demand curve; Energy transition; Residential energy consumption forms; Pricing strategies; Energy poverty; Risk of poverty and social exclusion.

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Acronyms List

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AMI	Advanced Metering Infrastructure
AMI-HAN	Ami Within Customers' Home Area Network
AppLeBill	Appliance Level Billing
ARDL	Autoregressive Distributed Lag
ARP	At-Risk-Of-Poverty Rate
CPP	Critical-Peak-Pricing
CPR	Critical Peak Rebate
DR	Demand Response
DSM	Demand-Side Management
ECM	Error Correction Mechanism
EDLs	Electricity Demand Levels
EE	Energy Efficiency
EEG	Energy Sources Act
EPAH	Energy Poverty Advisory Hub
EIA	US Energy Information Administration
ELM	Energy Load Management
EU	European
EU-SILC	European Union Statistics On Income And Living Conditions
FER	Fontes De Energia Renováveis
FER-C	Fontes De Energia Renováveis Controláveis
FER-I	Fontes De Energia Renováveis Intermitentes
FERC	Federal Energy Regulatory Commission
FGLS	Feasible Generalised Least Squares
FiTs	Feed-In-Tariffs
FMOLS	Fully Modified Ordinary Least Squares
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GW	Gigawatts
GWh	Gigawatts/hour
HCO	Housing-Costs Overburden
HEGY	Hylleberg-Engle-Granger-Yoo
HQ	Hannan-Quinn
IAEE	International Association Of Energy Economics
ICT	U.S. Information And Communication Technology
IEDL	Intermediate Electricity Demand Level
IEDLs	Intermediate Demand Levels
IoT	Internet Of Things
IQR	Interquartile range
IRF	Impulse Response Functions
JSE	Joint Significance Tests
KPSS	Kwiatkowski Schmidt Shin

kWh	Kilowatt-Hour
LIHEAP	Low-Income Home Energy Assistance Program
LTECV	Loi Relative À La Transition Énergétique Pour La Croissance Verte
MOE	Merit-Order Effect
MW	Megawatts
MWh	Megawatt-Hour
NDemand	Net Demand
NEDLS	Net Electricity Demand Levels
NIEDL	Net Intermediate Electricity Demand Level
NPEDL	Net Peak Electricity Demand Level
NRES	Non-Renewable Energy Sources
NVEDL	Net Valley Electricity Demand Level
OECD	Organization For Economic Co-Operation And Development
OGHG	Other Greenhouse Gases
PACF	Partial Autocorrelation Function
PARDL	Panel Autoregressive Distributed Lag
PARPSE	People At Risk Of Poverty Or Social Exclusion
PCSE	Panel Corrected Standard Error
PEDL	Peak Electricity Demand Level
PP	Phillips And Perron
PV	Photovoltaic
RECS	Residential Energy Consumption Survey
RES	Renewable Energy Sources
RES-C	Controllable Renewable Energy Sources
RES-I	Intermittent Renewable Energy Sources
RPS	Renewable Portfolio Standard
RTE	Réseau De Transport D'Électricité
RTP	Real-Time Pricing
SARMA	Seasonal Autoregressive Moving Average
SARMAX	Seasonal Autoregressive Moving Average With Exogenous Regressors
SDGs	Sustainable Development Goals
SIC	Schwarz Information Criterion
SPToU	Super Peak Time-Of-Use
STEPLS	Stepwise Least Squares
TBTs	Time-Based Tariffs
TDemand	Traditional Demand
TEDLs	Traditional Electricity Demand Levels
TIEDL	Traditional Intermediate Electricity Demand Level
ToU	Time-Of-Use
TPEDL	Traditional Peak Electricity Demand Level
TSO	Transmission System Operator
TWh	Terawatt-Hours
UK	United Kingdom
US	United States
VAR	Vector Autoregressive
VDC	Variance Decomposition
VEDL	Valley Electricity Demand Level
VIF	Variance Inflation Factors
VPP	Variable Peak Pricing

WAP	Weatherization Assistance Program
WP	Watt-Peak

Chapter 1

Introduction

Since the early 2000s, air, water, and thermal pollution, as well as climate change and melting glaciers have been major concerns around the world. The accelerated growth of carbon dioxide (CO2) emissions and other greenhouse gases (OGHG) emissions around the world have intensified global warming day by day. This has incited an emergent concern for both researchers and policymakers worldwide striving for solutions to climate change issues. Energy is a pivotal point for climate change due to its negative externalities. It is virtually impossible to extract, produce/refine, transport, and consume energy without environmental damage. Without a doubt, the production of electricity by burning fossil fuels, such as coal, oil, and natural gas, has been the major mechanism responsible for the increase in CO2 and OGHG emissions, air and water pollution (Tiba & Omri, 2017)[1]. However, it is impossible for present and future generations to live and subsist without energy. Energy moves the world, powers societal activities, and is a major driver of economic growth and development (Ahmad, Aghdam, Butt, & Naveed, 2020; Le, Boubaker, & Nguyen, 2021). On the other hand, society cannot live in a polluted environment. So, what are the choices open to us?

The answer to this question is not an easy one. Notwithstanding, economic theory has a more pertinent/spot-on question. How can society employ green energy resources to satisfy its energy needs? Researchers and policymakers highlight electrification and endogenous green resources as the most promising solution to mitigate CO2 and OGHG emissions arising from energy production. Over the last two decades, an extension of electrification in different regions (namely in rural and remote areas) and persistent electrification of the residential, industrial, services, heating, and even transport sectors has been pursued. Meanwhile, technologies have been developed and deployed through financial aid to exploit endogenous and renewable energy resources, such as wind and sun. This coming era of energy transition proposes a shift from conventional (and pollutant energy sources) towards Renewable Energy Sources (RES), along with increasing electrification of economies. Therefore, it is expected that cleaner and greener electricity production will take over as the primary energy source for consumption,

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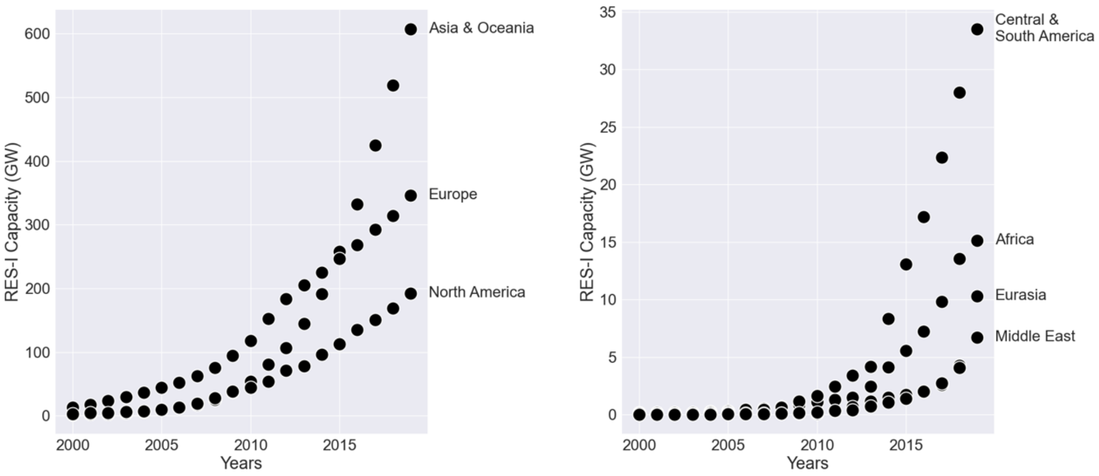
[1] The citation style APA 7th edition (American Psychological Association, 2010) was used throughout this thesis.

aiming to accomplish the Paris Agreement pledges, Millennium Development Goals, and Sustainable Development Goals.

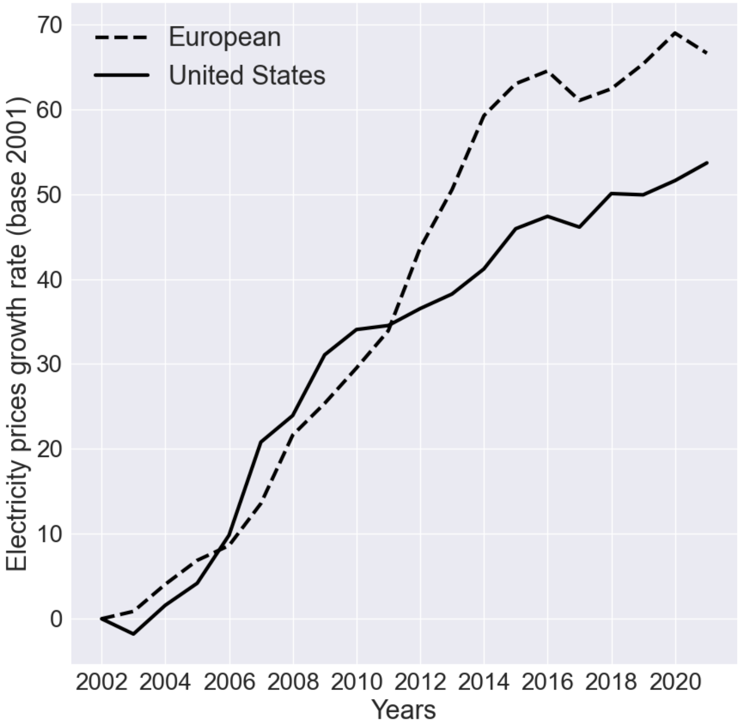
Green electricity sources have been introduced into the electricity generation mix (a combination of energy sources to produce electricity) through a portfolio of both Controllable Renewable Energy Sources (RES-C), and intermittent ones (RES-I). Electricity production from RES-C, such as geothermal, biomass, and hydropower, can be managed. Conversely, electricity production from RES-I, like wind and solar photovoltaic (PV) power, is dependent on the availability of natural resources. Therefore, their production is intermittent and unmanageable. Around the world, countries have designed and implemented public policies to support the deployment of RES (Marques, Fuinhas, & Pereira, 2019). Two particular policies schemes have received a good deal of attention and are the most frequently employed (Marques et al., 2019). Firstly, Feed-in-Tariffs (FiTs), a policy-driven approach, is seen as highly attractive to investors, as it guarantees the priority dispatch order and a fixed price for electricity generated through RES-I. Nevertheless secondly, the Renewable Portfolio Standard (RPS), a regulatory instrument, imposes a minimum share of RES in the electricity investor portfolio, providing also dispatch priority of these sources to the grid. This market-driven approach has steadily increased the minimum share of RES production over time and is not subject to sudden or uncertain changes. Despite their differences, these two RES support policies have triggered an escalation in the installed capacity of RES-I around the world, intensifying their contribution to the energy supply (Marques et al., 2019).



Notes: Own elaboration. Data source: EIA

Figure 1.1. RES capacity deployment

In Europe, there was an abrupt and early market diffusion of RES-I (as shown in Figure 1.1). In contrast, in North America, Asia and Oceania, there was a slow initial market integration of RES-I technologies (see Figure 1.1). Despite these countries having differences in their early adoption of RES-I, they now have a significant installed capacity of wind and solar PV power, providing them with a high share of RES-I in the electricity mix. One would expect that due to the low marginal costs of RES-I, electricity prices would decrease, leading to further RES-I implementation. However, as can be seen in Figure 1.2, a reduction in electricity prices has not been discernible. The rise in residential electricity prices over the last two decades is indeed worrying. However, in the United States, since 2010, it is interesting to note that the growth rate of residential electricity prices has been slower than in European countries.



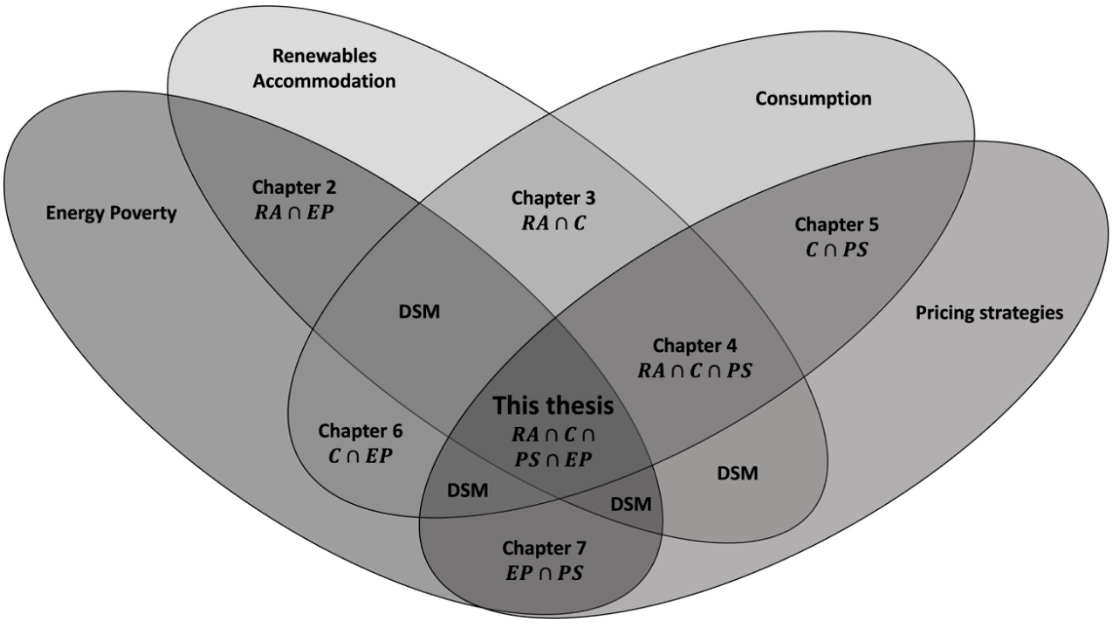
Notes: Own elaboration. Data source: EIA, EuroStat

Figure 1.2. European and US residential electricity prices growth rate

The motivation to write this thesis was driven by the challenges and barriers facing energy transition, namely understanding how to overcome its economic inefficiencies. On the one hand, fluctuations in electricity consumption throughout the day have intensified the need for readily available fossil fuels to satisfy it. Accordingly, demand uncertainty causes economic inefficiency, i.e., overcapacity. On the other hand, the effective generation by RES-I rarely matches its installed capacity. Therefore, to meet demand, further RES-I integration through the building of new wind farms and solar PV plants is not the answer. In other words, RES-I should not be driven by demand; if so, it will cause further economic inefficiencies in resources allocation. In turn, this will cause electricity prices to rise because the physical constraints of RES-I do not allow them to fully exploit their capacity. One solution to overcome this economic inefficiency is to improve the efficiency of RES-I technologies (Flora, Marques, & Fuinhas, 2014). However, this solution by itself is still insufficient due to RES-I's dependence on instantaneous natural resource availability. In fact, periods of high wind availability that do not match demand can lead electricity systems to shut down production when there is no storage option. The inability of the electricity sector, through demand, to fully exploit its scarce resources, especially those provided freely by green and natural resources, causes an even more exacerbated economic inefficiency.

The paradoxical situation discussed in the previous paragraph suggests the need for a paradigm change in the electricity market. Energy market decisions cannot just be about consuming and supplying more electricity. Decisions in this field should focus on which sources must be developed and assess their consequences on the electricity generation mix. Furthermore, the consequences alongside the policies of off-peak and peak-of-demand should also be considered. And finally, strategies to shift demand to best exploit the production of intermittent green energy sources should be designed. This would imply a shift from a demand-driven to a supply-driven electricity market where, the active participation of consumers is vital to both RES-I and RES-C, effectively substituting pollutant sources preserving a healthy environment and economic activity in the future. Therefore, the question previously presented must be inverted, leading to: how should society allocate its energy needs to exploit green energy resources fully? As Figures 1.1 and 1.2 indicate, energy transition apparently increases electricity prices for residential consumers, and consequently, it can contribute to increasing households' risk of energy poverty. This apparent trade-off between RES-I integration and energy poverty was the main motivation to develop this thesis further. Thus, this has led to the following main research question of this thesis: how can society be empowered to allocate its energy needs to exploit the benefits of green energy sources fully? This question inspired the motivation for this thesis.

This thesis aims to explore measures to provoke a mental state of willingness in consumers to shift their consumption needs towards periods of high green resources availability. In other words, consumers should be empowered to provide the necessary flexibility for RES-I accommodation. The reshaping of electricity consumption patterns to match the availability of RES-I may provide effective savings (or rewards) to consumers, thus motivating them to change their consumption patterns or habits. Thus, these potential savings are likely to increase consumer welfare and even reduce energy poverty. A key tool in bringing about these desired changes in electricity demand and market lies in demand-side management (DSM) and its pricing strategies. This is the main topic of this thesis and the last of the four dimensions analysed. The four dimensions assessed are: (i) Renewables Accommodation; (ii) Consumption; (iii) Energy Poverty; and (iv) Pricing Strategies. Figure 1.3 illustrates how these four dimensions are interrelated, highlighting the chapters of this thesis that result from them. The chapters of this thesis reveal the prominence of DSM to connect the four dimensions under analysis. In fact, DSM has the potential to furnish measures to overcome the challenges that both the energy system and society are facing. In short, this thesis intends to contribute with suggestions for energy policies and measures, mainly in terms of electricity demand, so that the diversification of the electricity mix is possible without exacerbating energy poverty.



Notes: Own elaboration, C means consumption, DSM means Demand-Side Management measures, EP means energy poverty, PS means pricing strategies, and RA means renewables accommodation, means intersection.

Figure 1.3. Thesis dimensions, interactions, and resulting chapters.

The formation of electricity prices in European countries includes the cost of generation, transportation, and RES surcharges. Meanwhile, electricity retailers have been obligated to accept and pay the FiTs fixed price, often above market prices, through long-term contracts of 15 to 20 years. In turn, these players have increased taxes and levies for both electricity prices and bills, i.e., through RES surcharges. The implementation of RES has been successful, but at what cost? In societies with a high level of income inequalities, energy transition can actually contribute to accentuating this issue. Overall, all the above-mentioned issues discussed have driven a keen curiosity, which led Chapter 2 of this thesis to ask:

(i) How have households withstood the costs of energy transition?
(ii) Can households continue to support the implementation of RES-I?

Chapter 2 is vital to understanding the effects of RES implementation on economies and overall society. In this, annual data for a panel of 15 European countries from 2005 to 2015 was assessed by using Stata tools. The Kao residual cointegration test was employed. The results indicate a long-run relationship between RES deployment and households' living conditions, namely income inequality, risk of poverty and social exclusion. Furthermore, a panel autoregressive distributed lag (PARDL) was carried out to apportion the effects on short-run dynamics and long-run equilibrium. To check the robustness of the PARDL results, a joint significance test was used. The most unexpected result found was the positive impact of solar PV on the risk of poverty and social exclusion of households. Regarding wind power, the results showed diverse effects. On the one hand, the installed capacity of wind power accentuates households' risk of poverty and social exclusion. On the other hand, the effective generation of wind power reduces the risk of poverty and social exclusion for households. Actually, electricity generation from wind power has a significant contribution to energy supply, reducing electricity generation costs and, consequently, the price of electricity. However, the phenomenon of intermittency is more noticeable with wind power, the main reason for these divergent effects being the difference between its installed capacity and effective generation.

RES-I inclusion reveals a growing trend despite its intermittent generation characteristic. However, this feature could offset its benefits, such as the reduction of greenhouse gas (GHG) emissions and the decline in the dependence on fossil fuels (Marques, Fuinhas, & Pereira, 2018). Compared to fossil fuels, the installed capacity of RES-I cannot always meet its effective generation, resulting in idle capacity. RES-I idle capacity has attracted much attention in the literature, as the notion of idle capacity is far from the traditional concept of excess capacity (Flora et al., 2014). The traditional economic concept of excess capacity is often defined as a market competition strategy by industrial economics. In it, demand uncertainty is mitigated by a pool of resources readily available to produce goods and services, i.e., the demand uncertainty is lessened by excess capacity. Notwithstanding, this competitive strategy from the field of industrial economics is pointless for RES-I players. On the one hand, the priority to dispatch to the grid is granted to them, cancelling any concerns about demand uncertainty. On the other hand, the long-term fixed revenues granted by FiTs contracts make this strategy even more useless for RES-I players. Consequently, unexploited RES-I capacity is an outcome of the absence of natural resources availability, not a market competition strategic behaviour.

In order to clarify whether there is a substitution effect of pollutant sources by RES, the author of this thesis chose to scrutinize 10 European countries (Marques et al., 2018). In that research, it was proven that installed capacity and effective generation capacity provided by RES-I cause dissimilar effects on fossil fuels dependency (Marques et al., 2018). It is argued that electricity generation from RES-I, mainly from wind power, provokes supply uncertainty. This supply uncertainty has thus cancelled out the expected and desired downward trend in electricity generation from fossil fuels. Fossil fuel plants, particularly those with a flexible generation capacity, are maintained in standby mode to balance the supply and demand in times of scarcity of RES-I availability or high demand. Flexible generation plants, like natural gas, hydropower, and even biomass plants, have the ability to ramp up their production in a matter of seconds, even in standby mode. Therefore, the compulsory balance between demand and supply in milliseconds, necessary to not jeopardize energy security or cause blackouts, often requires this distinctive ability from these plants; they are playing a backup role. It is clear that electricity consumption patterns reinforce the need to burn fossil fuels to satisfy electricity demand peaks, i.e., to satisfy high levels of demand in short time periods (Marques et al., 2018). Moreover, this proves that electricity demand peaks also hamper the integration of RES-I into the electricity mix (Marques et al., 2018).

When annual data is used, one must be conscious that some information is lost. For instance, annual data identifies peak demand as the one hour of the year with highest demand. However, electricity demand oscillates throughout the day. These intraday fluctuations in consumption are a daily concern for electrical systems, putting pressure on them to meet demand. Besides, electricity generation from RES-I could vary over intraday periods, and annual data are not able to provide evidence about the phenomenon of intermittency. Bearing in mind the relevance of these two facts and motivated to go further to provide enhanced empirical evidence, Chapter 3 introduces an innovative line of study. It analyses the interactions between electricity sources and periods with differing electricity demand. Chapter 3, by using high-frequency data, highlights the consequences of both implementing each source (RES and non-RES) and the peak and off-peak demand dynamics on the electricity mix diversification, and CO2 emissions mitigation. To furnish this empirical evidence, French electricity demand- and supply-side were analysed, and the following answers were answered:

(i) Could electricity demand contribute to diversifying the electricity generation mix and mitigating CO2 emissions?
(ii) What should be the daily incentives for France to dismantle its nuclear-powered baseload?
(iii) How effective have RES been in substituting both fossil fuels and nuclear sources?
(iv) How have the daily peaks and off-peaks of electricity demand been satisfied?

A vector autoregressive (VAR) model was employed in the Eviews software to answer these questions. Daily data from January 1, 2012, until December 31, 2018, was employed to assess the behaviour of electricity supply sources and electricity demand. The reasoning to study the French electricity sector was twofold. Firstly, this chapter aimed to focus on the Green Growth Act of 2015 targeted to decrease the nuclear contribution to electricity supply to 50% while increasing the RES contribution to 40% by 2030. The French electricity system is indeed an optimal case of study to assess this energy transition from nuclear power to RES. Secondly, intraday data on disaggregated electricity consumption are contemporary and scarce. At the time of the execution of this chapter, only the Réseau de transport d'électricité (French transmission system operator) published the start and end hours of the different periods of electricity demand. Indeed, these data were crucial to compute the consumption in the different periods of demand and proceed with this chapter. The empirical method applied in Chapter 3 confirmed the daily relationship between: (i) electricity sources; (ii) differing periods of electricity demand; (iii) degree of diversity in the electricity generation mix; (iv) CO2 emissions from electricity generation; (v) wholesale electricity market price; and (vi) imports and exports of electricity. It should be highlighted that the different periods of electricity demand were subdivided into: (a) morning off-peak, (b) morning peak; (c) middle off-peak, and (d) and night peak.

The findings in Chapter 3 are extensive, but 3 key points must be highlighted. French nuclear energy capacity was responsible, in the main, for the low levels of GHG emissions. The Fukushima accident and the pending long-term safety reviews were the only substantiated reasons for the reduction of nuclear contribution to electricity supply to 50%, decreasing it by more than 20%. Notwithstanding, Chapter 3 shows that increased pressure at peak demand and lack of consumption in off-peak periods exacerbate inefficiency in the exploitation of nuclear sources. In 2022, Emmanuel Macron's (French President) announcement of the 'rebirth' of the French nuclear industry was unexpected. French demand is not nearly smoothed; a condition needed to exploit the constant electricity production from nuclear energy fully. Chapter 3 proves that the shift in consumption from off-peak periods to peak night periods has greatly increased the need for more flexible plants. This flexibility was mainly powered by fossil fuels, increasing CO2 emissions during the night peak periods. In contrast, the electricity consumption in the morning peak is likely synchronized with the solar PV production curve, which is desirable. The RES mix used to satisfy the morning peak actually reduced the environmental impact of electricity consumption and even kept the wholesale electricity price low. The results culminate in the main basis and motivation for the development of the subsequent chapters of this thesis.

The main purpose of the DSM concept is to encourage consumers to adapt their electricity demand patterns, reducing their electricity consumption through efficiency or saving measures, or by shifting it to periods of high electricity produced from RES (Alasseri, Tripathi, Joji Rao, & Sreekanth, 2017; Meyabadi & Deihimi, 2017). DSM measures are introduced and promoted by governments and electricity retailers for customer use. Demand Response (DR) aims to involve customers through pricing strategies, e.g., price-responsive tariffs, time-based tariffs, or dynamic pricing programs (the definitions of these pricing strategies can be found in Table 7.1 in Chapter 7). DR instruments are focused on strategies that synchronize demand with RES-I generation and load smoothing through, for instance, peak clipping, valley filling, and load shifting (see Figure 5.1 in Chapter 5). To that end, reward mechanisms, or even penalties, should be employed to stimulate changes in consumer behaviour. In fact, economic theory often predicts that consumers will react to price differentiation. Consequently, greater price differentiation would generate a greater predisposition of consumers to change their electricity demand. In other words, consumers empowerment to break out their consumption habits would increase with price differentiation. Therefore, DR measures and their pricing strategies have the potential to provide demand flexibility, enhancing grid stability and the economic efficiency of electricity systems. In this line of study, Chapters 4 and 5 study how pricing strategies should evolve, in Germany and France, respectively.

In Germany, since 2017, RES represents more than 50% of installed electricity capacity, contributing more than 35% to the electricity supply. However, uncertain demand, which fluctuates per hour between 10.4453 megawatts and 79.062 megawatts, can hamper RES-I integration. This issue motivated Chapter 4 to unravel how to deal with highly intermittent supply and fluctuating demand. To do so, the German electricity market was studied from January 1, 2015, to November 20, 2019. This study involved two different analysis techniques, namely: an empirical and a mathematical approach. Firstly, in the empirical analysis, a seasonal autoregressive moving average with exogenous regressors and an exponential generalized conditional heteroskedasticity estimator was applied to assess the impact of both traditional demand and net demand on the wholesale electricity market price. Secondly, mathematical tools were used to develop a demand classification method. Electricity demand was classified into peak, valley, and flexible smoothed levels. It is noteworthy that the impact of the different levels of electricity demand on the wholesale market price was also assessed. Finally, Chapter 4 calculated heat maps to report the occurrence of hourly electricity demand levels depending on the season or day of the week. The mathematical and econometric procedures were performed using the MATLAB and Eviews software, respectively. Chapter 4 answered the following questions:

(i) Does net demand provides an enhanced explanation of the wholesale electricity market price?
(ii) Is the demand classification proposed able to explain the wholesale market price?
(iii) Should pricing strategies be designed through net or traditional demand classification?

The concept of net demand is quite different from the traditional concept of demand, i.e., just electricity consumption. The net demand concept ponders RES-I production as guaranteed, consisting of the deduction of RES-I production from total consumption. Basically, net demand refers to the consumption that controllable sources must satisfy or the demand where DSM should intervene. As expected, the estimations revealed that net demand has a greater explanatory power than the traditional demand on the German wholesale electricity market price. This discloses that net demand should become the main reference for all players in the electricity market. As Chapter 4 shows, net demand and traditional demand have a wide divergence. In fact, RES-I penetration provokes large variations in the shape of the well-known daily demand profile. This divergence was most noticeable at peak and valley demand levels. Thus, the traditional peak demand framework must be revised. Besides that, the concept of valley demand should be introduced, especially those of net demand. Therefore, as the levels of net demand classified in this chapter presented high explanatory power of the German wholesale electricity price, new pricing strategies should be projected by the net demand classification. To sum up, this chapter provides new insights into the net demand levels occurrence and the capacities required to satisfy them, as well as for the design of pricing strategies, affecting how the price should be differentiated throughout the day.

In France, as previously mentioned, and as Chapter 3 evidenced, oscillating and inflexible demand obstructs the integration of the world's second-largest nuclear power capacity. Electricity production from this source cannot be scaled up and down as desired. Nuclear power has indeed a rigid generation, although with low marginal costs. Therefore, its baseload role can provide potential benefits to consumers due to its significant contribution to electricity generation at lower costs. However, pricing strategies seems not to provide the desired effects on electricity demand. In fact, French electricity demand ranges from 20.085 megawatts to 95.064 megawatts (values observed in intraday 15-minutes data). These facts have motivated this thesis, in Chapter 5, to examine French intraday demand data and load profiles from January 1, 2013, until October 31, 2020, in more detail. The main goal of this chapter is to delineate and quantify the challenges and opportunities for DSM interventions. Considering the mathematical process proposed in Chapter 4 to classify electricity demand, this chapter has further developed it by classifying it into time periods using scatter and histogram plots. Furthermore, as this chapter highlights the interactions between the classified levels and time periods of demand, a more robust approach was employed to account for peak demand. Therefore, peak demand was classified as the demand that should be shifted to other periods, i.e., a consumption that is satisfied by peak power plants. The empirical analysis involved the estimation of four autoregressive distributed lag models with 256 lag lengths. Besides that, each short-run series was selected recurring to the stepwise least squares' estimator. The data download and cleaning process, the mathematical method, as well as the econometric analysis, were developed in the MATLAB program. This analysis aims to provide insights about:

(i) How should demand-side management policies evolve in France?

The results of Chapter 5 highlight that night peak demand, and morning valley demand, are restricting the occurrence of a smoothed demand. Furthermore, the desired shift in demand from the night peak towards the morning valley periods does not actually occur. In fact, night peak consumption has been similar every day. The residential sector is the main area responsible for this consumption pattern due to the use of a large number of electricity-intensive appliances for short periods of time. This consumption is made to meet the primary energy needs of households, such as cooking, washing, heating, lighting, and entertainment. Therefore, the price differentiation between night peak and morning valley periods should be high enough to compensate consumers' discomfort. In other words, the price differentiation between these periods should encourage consumers to change part of their demand habits, such as when they use washing machines, charge phones and laptops, or use other appliances. It is worth mentioning once again that the greater the price differentiation, the greater the consumer's empowerment to break with their demand patterns and habits.

Chapters 4 and 5 provide insightful perspectives through the analysis of high-frequency historical data, which were highly useful to outline and quantify opportunities for DSM intervention. In fact, the methods proposed can open new paths for understanding inefficiencies caused by both peak and valley demand levels. The concept of valley demand is still unexplored but needs to be better understood in order to find out how to increase consumption during this period. Currently, the detailed statistics about peak and valley demand are rather scarce. Therefore, the demand classification methods proposed in this thesis (see Chapters 4 and 5), can be used to produce statistics about them, having the advantage of also providing their daily time periods of occurrence. In this way, these statistics can be used in depth to understand which consumption needs to be cut, filled, or shifted towards other consumption periods. The most revealing finding in these chapters was the potential of Time-of-Use (ToU) tariffs to bring the desired changes in daily electricity demand. Besides, a ToU tariff combined with a critical-peak-pricing (CPP) tariff that is activated when the reliability of an electricity system is in jeopardy or when there is an unexpected shortage or excess of RES-I would also allow an immediate reaction from the demand-side to accommodate those situations.

Energy transition has caused a high dependence on natural gas, mainly because of its prominent role as a backup when RES-I are not producing and/or to deal with the uncertainty of electricity demand patterns. The unforeseen escalation in natural gas prices, due to issues related to geopolitics, financial and investment cuts, internal and external dependence on it, has led European countries to follow a natural gas conservation strategy. This strategy could cause an abrupt rise in natural gas prices and thus in electricity prices, causing those burdened with energy costs to fall into energy poverty. Consequently, it is mandatory to encourage households to switch from primary energy sources to electricity. This energy transition should be carefully projected and promoted. On the one hand, as proved by this thesis, electricity systems remain confronted with many challenges. Thus, it is crucial to promote efficient and cost-effective DSM measures in advance to influence changes in electricity demand, such as the pricing strategies presented in this thesis. On the other hand, the divergent energy needs of society can be a barrier to energy transition and consequent electrification. In this sense, Chapter 6 was driven to provide accurate information and guidance for decision-making with regard to energy transition policies from primary energy sources to electricity.

It is well-known that urban areas rely on electricity, whereas rural areas prefer primary energy sources, such as wood/biomass or natural gas. These rural areas' preference is often due to the lack of access to the electricity grid, but also due to the 'free' wood/biomass resources at their disposal. On this reasoning, a comparable cross-sectional and longitudinal analysis was carried out in Chapter 6. Econometrically, a panel of 12 European countries from 2005 to 2018 was used to estimate 24 first-difference models, employing a feasible generalized least squares estimator. The results of 12 models revealed the impact of forms of residential energy consumption (namely oil, natural gas, and wood/biomass) on both energy poverty and poverty by degrees of urbanization (divided into cities, towns and suburbs, and rural areas). The results of the remaining 12 estimations highlight the effects of residential electricity consumption by end-use activity, namely space heating, water heating, cooking, electrical appliances, and lighting, on both energy poverty and poverty, by urbanization degrees. The data download and cleaning processes were performed by using the tools of Python language, and the econometric procedures were carried out in Stata software. In Chapter 6, energy poverty disparities are analyzed by the degree of urbanization through the dynamics of residential consumption, and it aimed to answer the following questions:

(i) What form of energy or mix should be used to eradicate energy poverty in each urban degree?
(ii) Could electricity be a key form of energy for a transition towards a non-poor-energy society?
(iii) Does the impact of residential electricity consumption on energy poverty differ from its end use?
(iv) What are the policy precautions that should be put in place during energy transition to avoid intensifying energy poverty?

Chapter 6 highlights that energy poverty reduction and energy policies should not be designed at a national level. Such energy policies should be projected at a regional level, also taking advantage of the endogenous potential of any renewable resource. Specifically, in cities, electricity consumption for space heating and cooking has been advantageous, especially in reducing households' energy poverty. In fact, in cities, electric cooking and space heating technologies are widespread in new and renovated buildings. In contrast, in towns and suburbs, as well as in rural areas, electricity consumption has raised the number of families suffering from energy poverty. As expected, natural gas and wood/biomass consumption has played a crucial role in reducing energy poverty for these families. In the three urbanization degrees, the switch to electricity and the move away from primary energy sources must be gradual, accompanied by economic assistance and educational campaigns. Residential electricity consumption for water heating, electrical appliances, and lighting is indeed the primary concern. A positive impact of these end-use activities (powered by electricity) on both energy poverty and poverty was confirmed in the three urbanization degrees. This finding strengthens, even more, the urgency of adopting DSM policies, mainly focusing on energy efficiency and pricing strategies. In fact, water heating systems have an inherent potential to defer RES-I generation through efficient pricing strategies, also striving for a decrease in energy poverty.

The smart grid, i.e., an electricity system with two-way communication between consumers and suppliers, with a smart meter to record the consumption in different periods of time, has been implemented by developed countries around the world. The implementation of smart grid technologies has prompted the emergence of new pricing strategies. Pricing strategies, such as real-time pricing (RTP), variable peak pricing (VPP), critical peak rebate (CPR), CPP, and ToU (static tariff), have been introduced in the market to empower consumers. The price differentiation employed in these pricing strategies is based on the time of day, day-ahead and wholesale market prices, as well as on RES-I availability (Sousa & Soares, 2020; Stavrakas & Flamos, 2020). Among these, RTP is the most dynamic, commonly considered the best for delivering desired changes in both supply and demand sides (Eksin, Deliç, & Ribeiro, 2018; Omri & Nguyen, 2014). This argument is supported by the fact that RTP is linked to the day-ahead and wholesale electricity market price, reflecting both RES-I availability and instantaneous demand (Eksin et al., 2018; Omri & Nguyen, 2014). All pricing strategies pledge to reduce the inefficiency of the electricity system as a whole, contributing to a price reduction that would increase consumers' welfare. These announced benefits actually occur, specifically benefiting households suffering from energy poverty. In this line of thought, Chapter 7 answer the final research questions of this thesis:

(i) Are dynamic tariffs effective in reducing energy poverty?
(ii) If yes, are they effective in avoiding households falling into the energy poverty trap?

Chapter 7 analyses whether pricing strategies can reduce the energy burden for households, and consequently, diminish the number of households suffering from energy poverty in 51 states of the US from 2013 to 2019. The reason the US states was chosen to conduct this research was twofold. Firstly, the US is the most developed country in terms of pricing strategies implementation. This can be proven by the 4.5 billion dollars investment to deploy the world's largest smart grid, reaching 88% of the 150 million residential consumers, in 2020 (EIA, 2017). Secondly, RES-I penetration in the US market has been mainly generated by market instruments. Consequently, its electricity price is not constraint by high RES-I surcharges. A dynamic panel estimator, namely the Arellano & Bond consistent generalized method of moments, was used to assess the impact of RTP, VPP, CPR CPP, and ToU on households suffering from energy poverty. Besides, the impact of pricing strategies on non-energy-stressed households, i.e., those not suffering from energy poverty, was also evaluated. The procedures for downloading, cleaning, grouping, and merging the data were implemented through an SQL database in an algorithm developed in Python language. The econometric methods were performed in both Stata software and Python language. This strategy was followed to verify whether pricing strategies effectively prevent households from falling into energy poverty.

This chapter stresses that a household already threatened by energy poverty is 43% likely to remain in energy poverty in the following year. The main finding was the potential of ToU and CPP (the more static tariffs) to reduce energy poverty. The more dynamic, namely the RTP and VPP tariffs, revealed the opposite effect, increasing the number of households in energy poverty. This effect of RTP on energy poverty was actually unexpected. The RTP tariff is seen as the one with the greatest economic and environmental benefits. Besides, the literature argues that RTP will be the most widespread pricing strategy (Eksin et al., 2018; Omri & Nguyen, 2014). Notwithstanding, RTP application is a challenge for the average consumer to understand and rely on, as it delivers a large amount of complex data every single day. This bulky data challenges the average consumer to manage their electricity demand on a daily basis. Furthermore, one of the main barriers to electricity savings through the RTP tariff is the low time given to consumers to react ahead of price changes. This task is even more intrinsic for society with a low level of literacy, which is the case of most low-income households or households already threatened by energy poverty (Littlewood et al., 2017; Rehfuess & World Health, 2006). Therefore, the RTP tariff should be linked to DR programs, those that directly control residential appliances, like water and space heating and washing machines, or instead, linked to the Internet of Things (IoT) gadgets and appliances with delayed start options, or other schemes that require less consumer intervention.

The most revealing finding throughout this thesis was the potential of ToU on both supply and demand sides. Considering the supply side, ToU has shown the potential to provide the flexibility needed to accommodate RES-I and leverage its integration. This flexibility is provided by encouraging demand-side changes to accommodate a system with a high RES-I contribution in the electricity mix and a system with large rigid baseload production. Meanwhile, on the demand-side, the ToU discloses a potential to reduce the energy burden and, consequently, the number of households suffering from energy poverty. Therefore, involving consumers as active players in electricity markets can be achieved through ToU tariffs in an initial stage. The simplicity of these pricing strategies is more appealing for consumers to start taking an active role in energy transition and thus, promoting the beginning of the desired changes. However, this pricing strategy will only succeed if flat-rate tariffs, i.e., tariffs that charge the same price for each kilowatt-hour of electricity consumed, are progressively abandoned and even abolished in the future. As ToU period-blocks rates are settled beforehand, it allows consumers to adjust their demand pattern to the new prices in advance by reducing their risks aversion. Therefore, and to sum up, consumer empowerment must start with ToU tariffs, charges which increase their willingness to break existing electricity demand patterns and habits in exchange for savings and a healthier environment.

1.1 Contribution to the literature

This thesis presents several contributions to the existing literature in four main lines of research, namely: (i) RES integration and accommodation into the electricity generation mix; (ii) Demand-Side Management; (iii) DR pricing strategies; and (iv) energy poverty. This thesis opens new paths to provide evidence on how the demand-side can contribute to energy transitions towards RES and, consequently, impact energy poverty reduction. Furthermore, this thesis also shows how the design of energy transition policies should be in order to avoid threatening households with energy poverty. The central themes and innovative contributions of these thesis chapters, with an international perspective, are detailed in the following paragraphs.

Chapter 2 has added new knowledge to the literature by providing empirical evidence of the consequences of electricity mix diversification by integrating RES on income inequality and the risk of poverty and social exclusion. This chapter has considered these effects on several types of households, unlike the existing literature that has only assessed the impact of RES on low-income households. Chapter 2's real value lies in its ability to reveal the effects of RES on the economy and overall society. Furthermore, this chapter has disclosed the impact of households' income inequality on RES implementation, showing that this inequality is delaying the deployment of RES.

Chapter 3 contributes by unveiling how electricity demand could be a pivotal element to diversify the electricity mix and mitigate CO2 emissions. To the best of our knowledge, it is the first empirical analysis using high-frequency data, considering the daily individual characteristics of each source and each differing period of electricity demand and its interactions. In fact, this research broke new ground by presenting the consequences of peak and off-peak daily demand consequences. This chapter also focuses on France's nuclear phase-out and its RES-I implementation goals, projecting DSM measures to achieve an effective transition through demand-response capability.

Chapters 4 and 5 assess high-frequency data to disclose efficient pricing strategies that promote demand-side participation to provide flexibility to the electricity system. Chapter 4 added a new line of knowledge through a proposed demand classification method, classifying net demand into peak, valley, and intermediate levels. Moreover, the classified intermediate level mathematically and statistically simulated a flexible and smoothed demand curve. In this chapter, heat maps have been provided to detail the occurrence of both traditional demand and net demand levels, as well as a table providing information on baseload, flexible, and peak generation capacities to satisfy them.

Chapter 5 went further by classifying in detail the demand as a means of generating truly representative electricity demand profile data, especially with regard to the shape of load profiles and variability within daily time periods. In these, demand was classified into both levels and time periods, and its interactions were empirically analyzed. Therefore, DSM policies and pricing strategies to achieve a flexible, smoothed daily demand curve were projected. Lastly, it should be noted that both the classification methods proposed in Chapters 4 and 5 can be used to generate detailed statistics on electricity demand, which are scarce but valuable for researchers and policymakers.

Chapter 6 contributed deeper to the understanding of energy poverty by empirically analyzing the impact of residential energy consumption forms, like oil, natural gas, wood/biomass, and electricity, on both energy poverty and poverty. Furthermore, the residential electricity consumption effect by end-use activity, such as water heating, space heating, cooking, electrical appliances, and lighting, on both energy poverty and poverty was also assessed. The foremost originality of this chapter also comes from the comparison of the results between degrees of urbanization, such as cities, towns and suburbs, and rural areas, as well as the comparison of the findings between energy poverty and poverty.

Lastly, Chapter 7 fills a new gap and is, as far as we know, the first to extensively analyze the social and economic effects of pricing strategies, namely ToU, CPP, CPR, VPP, RTP. In fact, the impact of pricing strategies has only previously been evaluated through pilot programs or surveys in specific parts of the population without population representativeness. This chapter goes as far as data can allow, disclosing the effectiveness of pricing strategies on energy burden reduction and, consequently, in alleviating the phenomenon of energy poverty. The analysis of this chapter was crucial to assess the feasibility of the pricing strategies proposed in Chapters 4 and 5 on energy burden reduction and thus, verify their potential to reduce energy poverty.

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Chapter 2

Are renewables affecting income distribution and increasing the risk of household poverty?

This chapter was presented in two conferences and resulted in an article published in *Energy*, the international journal. This chapter outputs are:

Pereira, D. S., Marques, A. C., & Fuinhas, J. A. (2019). Are renewables affecting income distribution and increasing the risk of household poverty? Energy, 170, 791-803. https://doi.org/10.1016/j.energy.2018.12.199. WoS/Scopus; Impact factor - 7.147; CiteScore – 11.5; SJR – Q1; 10 citations; 7 Blogs/News mentions; 221 Shares, likes, and comments; and 74 tweets.

Pereira, D. S., Marques, A. C., & Fuinhas, J. A. (2017). Are the renewable energies affecting the income distribution and the risk of poverty of households? 15th IAEE European Conference - Heading Towards Sustainable Energy Systems: Evolution or Revolution?, Vienna, Austria

Pereira, D. S., Marques, A. C., & Fuinhas, J. A. (2018) Are renewables affecting income distribution and increasing the risk of household poverty? 1st International Conference of Energy, Finance and the Macroeconomy, Montpellier, France

Abstract

The worldwide electricity mix has become diversified, mainly through the exploitation of endogenous and green resources. However, doubt has been cast on the much-vaunted advantages of renewables due to some of their characteristics, such as availability, security, and affordability. In fact, growth in the installed capacity of renewable energy has increased electricity prices, which raises the question of how households have withstood the cost of energy transition. The main aim of this study is to empirically assess and discuss: (i) whether different types of households have suffered dissimilar effects from the promotion of renewables; (ii) the consequences of promoting renewables on household income; and (iii) if the promotion of renewables has reduced the risk of poverty and social exclusion. A panel data of European countries has been analysed using Kao's residual cointegration test, and an Autoregressive Distributed Lag approach, to assess the relationships. This paper proves that both income and risk of household poverty are directly linked with renewable energies, in both the short- and long-run. The energy transition to renewables has had negative consequences for households. Thus, the disadvantaged households should be helped to meet the increased cost arising from the energy transition.

2.1 Introduction

The world's population has been growing and developing, increasing the demand for energy, particularly electrical energy. Electricity is considered a key energy source for the future, playing a fundamental role in socio-economic and sustainable development. In the near future, it is expected that the residential, industrial, services, transport, and heating sectors will only consume electricity, as will public services such as education, health, and sanitation. It is hoped that cleaner, green electricity generation will take over as the primary energy source for consumption, to achieve the Millennium Development Goals, the Sustainable Development Goals, and the pledges of the Paris Agreement (United Nations, 2015; 70/1. Transforming Our World: The 2030 Agenda for Sustainable Development, 2015). In fact, electricity, particularly that generated from Renewable Energy Sources (RES), has also been seen as a potential solution to mitigate poverty and the poor's access to energy, mainly experienced in rural areas, and it is hoped that it will promote sustainable growth, and expand economic prospects (International Energy Agency, 2016; UNDP, 2005; United Nations, 2015; 70/1. Transforming Our World: The 2030 Agenda for Sustainable Development, 2015). Therefore, access to affordable and modern energy sources, like electricity produced from RES, could be a vital means for overcoming poverty, and increasing economic growth in a sustainable way (Omri, 2014; Shahbaz et al., 2014; UNDP, 2005).

To achieve development through an ecological electricity mix, European (EU) countries, have designed and implemented public policies to develop and deploy RES. The installed capacity of RES, and their contribution to energy supply has been growing rapidly (REN21, 2016). Feed-in Tariffs (FiTs) policies have been largely responsible for the deployment of Intermittent Renewable Energy Sources (RES-I), namely wind power and solar photovoltaic (PV), in EU countries (REN21, 2016). In fact, the literature argues that environmental concerns, represented by Carbon Dioxide (CO2) emissions, and economic wealth, represented by Gross Domestic Product (GDP), have not been effective in promoting RES (Aguirre & Ibikunle, 2014; Marques & Fuinhas, 2012; Polzin et al., 2015). This research aims to bring fresh new insights about the social and economic drivers of RES deployment, adding the income inequality of households, residential consumption of natural gas, and electricity prices for domestic users in the explanation of RES installed capacity and capacity effectively used, i.e. RES electricity production.

As previously mentioned, RES installed capacity growth has been underpinned by policies to subsidise them. These policies have affected both the economic profits and the economic surplus of economic agents, redistributing the economic surplus between incumbent and incoming electricity generators, and between producers and consumers (Hirth & Ueckerdt, 2013). So, the installed capacity of RES and its effective use, could actually have been hampering its expected benefits, such as energy security, affordability, and reduced CO2 emissions (Flora et al., 2014; Glasnovic & Margeta, 2011; Nel & Cooper, 2009). This research will be focused mainly on the energy affordability problem, because of the literature have warned that RES deployment would increase the cost of electricity for society overall (Frondel et al., 2010, 2015; Nelson et al., 2011, 2012). In fact, the literature has studied the affordability problem only to low-income households and solar PV, showing that the higher cost arising from both FiTs and solar PV deployment have threatened low-income households with energy poverty (Frondel et al., 2010, 2015; Nelson et al., 2011, 2012). Notwithstanding, the main purpose of this research is to provide and discuss empirical evidence about the effects of all RES deployment on households' income, and on their risk of poverty or social exclusion.

This paper analyses annual data for a panel of fifteen EU countries, from 2005 until 2015. A residual cointegration test was performed to verify the long-run relationship between the RES deployment and households living conditions, such as income inequality and risk of poverty or social exclusion. An Autoregressive Distributed Lag (ARDL) methodology was used, because of its ability of dividing the effects into short-run dynamics, and long-run equilibrium. A joint significance test was used to confirm the long-run relationships in the ARDL models. Besides, long-run models were made to prove the robustness of ARDL models long-run results. Therefore, the empirical results allows to answer the following research questions: (i) what is the effect of households' income on RES promotion?; (ii) what are the consequences of promoting renewables on households' income?; and (iii) what is the impact of RES on the risk of poverty or social exclusion of households?

This research provides new evidence and valuable knowledge about the effects of RES on living condition for several types of households, specifically the impact on their income, and their risk of poverty or social exclusion. In short, this research adds new knowledge to the literature, by: (i) the study of the relationships between RES deployment and income inequality; (ii) the analysis of the effects of RES promotion on the risk of poverty or social exclusion; and (iii) the focus on several households types, because of the literature to date has only assessed the effects of RES on low-income. In fact, it is essential to study the effects of RES on all kinds of households, so that policymakers and government fully understand these effects on the economy and on overall society. Therefore, this research aims to fill this gap in the existing literature, as well as to propose and discuss measures by which all consumers could share the economic benefits of the energy transition towards RES.

This paper's results show that solar PV implemented by big players, in the period under analysis, has not yet been beneficial for society. In fact, the solar PV deployed by major producers, has increased the risk of poverty in the overall society. However, the small-scale implementation of solar PV by consumers could bring them into Demand-Side Management (DSM) programs, which could afford them better living conditions, and decrease their risk of poverty. The electrification of home appliances has enhanced the potential for the economic autonomy of households with children, giving them greater security. The results also emphasize that producers have kept all the surpluses from the deployment of RES, and households are threatened with energy poverty. In order to mitigate this negative effect, it is vital that policies are devised to share with consumers the economic surpluses from the deployment of RES. For example, policies could reward consumers with lower electricity prices if they consume in periods with a higher availability of natural resources.

The rest of this paper continues as follows: Section 2.2 covers the literature on RES drivers, and the consequences of RES implementation on low-income households. The data and methodology are described in Section 2.3. Section 2.4 presents and discusses the results. Lastly, Section 2.5 concludes.

2.2 Literature Review

The literature has being studying the triggers for the deployment of RES. This literature can be divided into two main topics: public policies supporting RES, and economic, environmental, and social drivers of RES implementation (Aguirre & Ibikunle, 2014; Marques & Fuinhas, 2012; Polzin et al., 2015). The authors of these studies have concluded that fiscal and financial policies have been an effective driver of RES deployment (Aguirre & Ibikunle, 2014; Andor et al., 2015; Marques & Fuinhas, 2012; Polzin et al., 2015). In contrast, the empirical literature shows that concerns over the environment, energy dependence, and economic wealth have not been effective drivers of RES deployment (Aguirre & Ibikunle, 2014; Frondel et al., 2010; Marques & Fuinhas, 2012; Polzin et al., 2015). The literature often shows that the transition to electrical energy from RES has mainly been stimulated by two factors: (a) incremental energy consumption; and (b) social and political pressure for the development of cleaner and greener energy sources (Aguirre & Ibikunle, 2014; Marques & Fuinhas, 2012; Polzin et al., 2015; Valdés Lucas et al., 2016). So, the EU countries have replicated the German policy framework for energy transition through the introduction of RES, the Renewable Energy Sources Act (EEG). In fact, German energy policies to promote RES have been the most studied and cited (Andor et al., 2015; Frondel et al., 2010, 2014, 2015; Nelson et al., 2011, 2012). However, their results for society and economy have not been those expected or desired, because of their being based on a policy of subsidies, the much-discussed FiTs (Frondel et al., 2015; Grösche & Schröder, 2014; Jenner et al., 2013; Nelson et al., 2011, 2012; Polzin et al., 2015).

FiTs guarantee dispatch priority, and the production of RES subsidised by FiTs can only be switched off if the grid stability is an inherent concern (Ketterer, 2014). All RES generation subsidised by FiTs has a guaranteed price, generally above the market price, which allows high returns for investors (Andor et al., 2015; Frondel et al., 2014; Ketterer, 2014; Kyritsis et al., 2017; Nelson et al., 2011). Moreover, this policy guarantees all these advantages for producers for at least 20 years, allowing for long-term planning. Electricity utilities that sell electricity directly to consumers have been obligated to accept and pay this fixed price, recovering it through taxes and levies in the electricity price, the so-called RES surcharges. However, these RES surcharges are borne equally by all consumers in their electricity bills, only depending on their consumption. It is true that these policies have enabled less mature and more expensive technologies to be introduced into the market, but at what cost?

In the case of wind power, the wind turbine capacity has increased over time, enabling more electricity to be produced through wind power (Hirth & Ueckerdt, 2013; Kyritsis et al., 2017). By 2008, EU countries had a significant installed capacity of wind power, providing them a high share of RES in the electricity mix (International Energy Agency, 2016; REN21, 2016). Since then, dispatch priority and a high share of wind power in the electricity mix have increased the percentage of electricity production with a marginal cost close to zero. This led to the so-called merit order effect, putting pressure on, and decreasing the price of electricity generation. This effect has been more noticeable in the wholesale electricity market price (Hirth & Ueckerdt, 2013; Kyritsis et al., 2017). Nonetheless, the pressure caused by wind power has also had a significant effect on the price of electricity for households and industry. At certain times of the day, indeed, the reduction in the price of electricity has exceeded the additional cost of RES surcharges. So, all electricity consumers have benefited from the deployment of wind power, in contrast to what occurred with the implementation of solar PV (Frondel et al., 2008; Hirth & Ueckerdt, 2013; Kyritsis et al., 2017).

In the case of solar PV, the author of the first paper of this theme, Frondel et al. (Frondel et al., 2014), argued that solar PV deployment has been an “unfolding disaster”, in Germany. In 2015, the same author claimed that solar PV implementation had been a “license to print money” (Andor et al., 2015). In fact, the installed capacity of solar PV, in 2007 was almost insignificant. However, by 2015, it represented a considerable share of electricity production capacity. The capacity of solar PV has grown at a high rate and accumulated high cost, which must continue to be paid for 20 years (Andor et al., 2015; Frondel et al., 2014). These costs are mainly due to the high returns provided by FiTs (Frondel et al., 2014). Consequently, the literature argues that FiTs costs should be diverted to more cost-effective climate protection instruments, diminishing the overall burden of energy transition on the economy (Frondel et al., 2010, 2015; Kyritsis et al., 2017; Nelson et al., 2011).

It should be highlighted that FiTs are a technologic-specific policy, and that the FiTs for solar PV guarantee the highest financial support per kilowatt-hour (kWh). This financial support has been set, because solar PV modules are still inefficient, and geographical conditions are mostly unfavourable for them in EU countries outside the Iberian Peninsula (Frondel et al., 2010). The policy was implemented to offset the lack of competitiveness of this particular RES technology (Frondel et al., 2008). However, the literature has argued that the effect of incentivizing solar PV through FiTs has been harmful to households (Frondel et al., 2010, 2015; Nelson et al., 2011, 2012). In fact, solar PV deployment has greatly increased households’ electricity bills. Thus, the literature has been studying this effect, and how to mitigate it, particularly for low-income households (Frondel et al., 2010, 2015; Nelson et al., 2011, 2012).

The literature has only assessed the effects of PV implementation for two countries, namely Germany and Australia, by major players in solar PV (Frondel et al., 2010, 2015; Nelson et al., 2011, 2012). The authors of these studies noted that wealthy households have the opportunity to invest, indirectly through savings, or directly through the installation of PV panels in their homes (Frondel et al., 2010, 2015; Nelson et al., 2011, 2012). However, neither of the papers studied the direct impact of solar PV on wealthy households' income or budgets, and the impact of wealthy households on solar PV deployment. In assessing the impact of RES deployment through the price of electricity, studies have only focused on low-income households. This literature has pointed out that poorer households have financed the substantial cost of RES deployment, through their electricity bills (Frondel et al., 2010, 2015; Nelson et al., 2011, 2012). As the RES surcharges in electricity bills is proportional to the electricity consumed, both wealthy and poorer households pay the same surcharge (Frondel et al., 2010, 2015; Nelson et al., 2011, 2012). This redistribution of costs through surcharges, has led the authors to argue that the burden of RES implementation is higher for poor households than for wealthy households (Andor et al., 2015; Frondel et al., 2010, 2014, 2015; Nelson et al., 2011, 2012). Thus, the literature has been researching and discussing policies and measures for energy transition that do not threaten poorer households with energy poverty (Andor et al., 2015; Frondel et al., 2010, 2014, 2015; Nelson et al., 2011, 2012).

The shift from fossil fuels to RES in electricity generation systems, has virtually doubled the price of electricity, with this increase being split between the cost of generation and RES surcharges, since the introduction of FiTs policies (Andor et al., 2015; Frondel et al., 2010, 2014, 2015; Nelson et al., 2011, 2012). Studies of deploying wind power have only analysed its effect on the wholesale electricity market price (Hirth & Ueckerdt, 2013; Kyritsis et al., 2017). The effect of solar PV deployment through FiTs schemes has only been assessed for low-income households in Germany and Australia. However, it is crucial to analyse the effects of RES, disaggregated by source, on all household types. In fact, it is expected that the energy transition from fossil fuels to RES in the electricity generation, and the transition from fossil fuels towards electricity in households' consumption will have consequences on the overall society. This theme has not experienced much of the attention by the literature and scientific community. However, it is pertinent to understand the benefits and disadvantages that will be provoked in the households. Has the transition benefited the overall society, or it has benefited one type of households while harming other types? Therefore, it is crucial to realize the effects of the measures to deal effectively with global warming, and more important, if these measures could constitute an exclusion of most people from the new energies and their benefits. Energy policy makers should be aware of the benefits and potential disadvantages for society, protecting the low-income households through a fair redistributing of the benefits of RES production and electricity consumption between the high- and low-income households.

2.3 Data and Methodology

To accomplish the objectives of this study, the database of the European Union Statistics on Income and Living Conditions (EU-SILC) was used. This database allows the income and poverty of households to be analysed through comparable cross-sectional, and longitudinal multidimensional data. This research also used other drivers of income inequality in populations, such as work intensity, education levels, and natural gas consumption; and drivers of RES implementation in economies, namely gross domestic product, electricity prices, and energy intensity. The selection of EU countries was made according to the following requisites: (i) data on the installed capacities of wind power, solar PV, and hydro power being available and higher than zero; and (ii) accessible data about the income and risk of poverty of all types of households for the entire time-span without gaps, which the EU-SILC database contains. So, this analysis focuses on the following fifteen countries: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. Annual data was used for a time-span from 2005 until 2015.

The mean net income, the people at risk of poverty and social exclusion, and the percentage of people with very low work intensity was retrieved from the EU-SILC database by household type. The mean net income variable is the mean monetary value of wages, rents, and interests earned by each household type. The people at risk of poverty or social exclusion variable indicates the sum of persons who are at risk of poverty or being severely materially deprived or living in households with very low work intensity. This variable accounts for persons with an equivalised disposable income below the risk-of-poverty threshold, which is set at 60% of the national median disposable income. The people with very low work intensity variable designates the percentage of people living in households where the adults work 20% or less of their total work potential. Table A.2.1 in the appendix, shows the distribution of population by percentage of household type. The installed capacity of wind power, solar PV, and hydropower; the share of electricity produced through RES; the price of electricity for households; natural gas consumption in residences; gross domestic product; and the percentage of government expenditure on education, have all been retrieved from the Eurostat database. It should be noted that the electricity variables are only related to major producers and auto-producers, because of the non-availability of statistics on prosumers.

Table 2.1. Descriptive statistics of variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Percentage of household's mean disposable income in relation to the total mean disposable income (%)					
Single person	165	87.76	7.14	75.04	106.59
Single person with dependent children	165	71.23	5.32	58.72	88.32
Two adults	165	111.05	5.15	96.61	123.27
Two adults younger than 65 years	165	122.29	4.74	111.51	133.73
Two adults, at least one aged 65 years or over	165	96.94	8.64	79.31	119.18
Two adults with one dependent child	165	108.51	4.70	99.92	124.00
Two adults with two dependent children	165	100.31	5.27	89.21	115.14
Two adults with three or more dependent children	165	84.95	6.61	70.00	108.52
Two adults or more without dependent children	165	111.83	3.54	101.90	122.54
Two adults or more with dependent children	165	98.24	3.95	90.95	108.09
Three or more adults	165	113.24	5.05	99.93	130.24
Three or more adults with dependent children	165	92.20	7.95	73.15	123.29
Households without dependent children	165	104.63	3.42	97.33	114.14
Households with dependent children	165	95.56	3.15	89.46	102.96
Number of people at risk of poverty or social exclusion (number of people)					
Single person	165	32.16	5.58	16.70	47.00
Single person with dependent children	165	46.46	7.92	28.80	74.70
Two adults	165	16.65	6.51	7.90	36.60
Two adults younger than 65 years	165	17.51	6.08	9.50	36.40
Two adults, at least one aged 65 years or over	165	15.64	8.22	4.60	40.40
Two adults with one dependent child	165	14.85	5.85	5.00	37.50
Two adults with two dependent children	165	14.86	7.40	4.40	33.90
Two adults with three or more dependent children	165	27.50	10.73	9.80	51.20
Two adults or more without dependent children	165	15.73	5.90	8.00	33.50
Two adults or more with dependent children	165	17.78	7.21	7.80	38.30
Three or more adults	165	14.08	6.41	3.90	39.00
Three or more adults with dependent children	165	20.32	9.77	1.50	50.90
Households without dependent children	165	20.69	4.53	11.70	34.10
Households with dependent children	165	20.59	6.45	11.10	38.80
Percentage of people living with very low work intensity (%)					
Total households	165	9.60	2.79	4.70	18.10
Single person	165	22.26	6.00	9.90	35.10
Single person with dependent children	165	26.11	8.77	11.00	50.40
Two adults	165	12.88	4.55	4.30	25.30
Two adults younger than 65 years	165	10.87	3.45	3.90	20.20
Two adults, at least one aged 65 years or over	165	36.21	8.96	8.90	56.70
Two adults with one dependent child	165	5.17	1.92	1.70	11.70
Two adults with two dependent children	165	3.33	1.78	0.50	9.40
Two adults with three or more dependent children	165	6.86	4.03	0.00	19.20
Two adults or more without dependent children	165	10.97	4.06	4.40	26.90
Two adults or more with dependent children	165	4.92	2.32	1.90	13.40
Three or more adults	165	8.42	4.85	2.80	28.10
Three or more adults with dependent children	165	6.15	4.62	0.10	23.40
Households without dependent children	165	14.25	3.80	8.30	26.70
Households with dependent children	165	7.01	2.76	2.90	14.50

The mean net income by household has been divided by the total mean income, and multiplied by 100, to show the percentage of household income in relation to the total disposable income. This variable is able to measure income inequality by household, so it can be discovered if the income of a household is above or below the mean income. This variable neglect other economic effects, such as any increase in the national base salary, but this is not relevant to this analysis. Subsequently, all series were transformed into their natural logarithms, denoted by the prefix "*L*". Table 2.1 summarises the descriptive statistics of the EU-SILC data, and Table 2.2 shows the descriptive statistics of energy, social, and economic series.

Table 2.2. Descriptive statistics of energy and control variables

Variable	Definition and measure	Obs	Mean	Std. Dev.	Min	Max
RES_IC	Installed capacity of renewable energies (MW)	165	16662.19	18685.20	1193	95883
HYDRO_IC	Installed capacity of hydro power (MW)	165	8444.56	8245.70	7	25401
WIND_IC	Installed capacity of wind power (MW)	165	5433.82	8225.61	22	44670
SOL_IC	Installed capacity of solar (MW)	165	2717.82	6737.86	1	39788
RES_GEN	Electricity production from renewable energies (1000 TOE)	165	9212.81	8235.37	71.60	38886.10
HYDRO_GEN	Electricity production from hydro power (1000 TOE)	165	1696.80	1926.42	1.10	6786.90
WIND_GEN	Electricity production from wind power (1000 TOE)	165	893.69	1273.60	1.80	6810.50
SOL_GEN	Electricity production from solar (1000 TOE)	165	360.74	763.73	0.70	4001.10
PRICE_ELEC	Electricity price (euro per KWh)	165	0.18	0.05	0.07	0.31
GAS_CONS	Natural gas consumption in residences	165	6491.90	8575.19	26.30	30149.30
GEH_INTS	Greenhouse gas emissions intensity of energy consumption (index)	165	92.33	6.86	74.20	108.90
ENERG_INTS	Energy intensity of the economy (kg of oil equivalent per 1 000 EUR)	165	137.30	46.99	65.10	327
GDP	Gross domestic product *per capita* (constant LCU)	165	99185.23	133694.90	16028.16	405353.30
EDU_EXPS	Percentage of government expenditure in education	165	11.09	1.78	7.30	15.10

Note: TOE means tonnes of oil equivalent; KWh mean Kilowatt hour; LCU means local currency unit

The results of the CD-test proposed by Pesaran (2004), the CD-test is the most employed and accurate to test the cross-section dependence by variable (Eberhardt, 2011; Hoyos et al., 2006; Pesaran, 2004). The CD-test supports the presence of cross-sectional dependence in most series (see Table 2.3). However, in the hydro power series and income series, the CD-test does not support the presence of cross-sectional dependence. As a consequence of the CD-test results, both the first- and second-generation unit roots tests were performed. Only the second-generation tests are displayed (see Table 2.3), because of the conformity between the first- and second-generation tests. The results of the CIPS test proposed by Pesaran (2004), were robust in the presence of cross-sectional dependence, and revealed that all series are integrated of order one, i.e. I(1).

Table 2.3. Cross section dependence and unit roots test

	Cross section dependence			Unit roots test (CIPS)			
				Level		First differences	
	CD-test	Corr	Abs (Corr)	No trend	Trend	No trend	Trend
Percentage of household's mean disposable income in relation to the total mean disposable income (in natural logarithm)							
Single person	0.21	0.006	0.42	-0.661	1.087	-5.538***	-3.474***
Single person with dependent children	-0.57	-0.017	0.291	-0.531	-0.552	-5.309***	-1.762**
Two adults	3.92***	0.115	0.415	-1.244	1.153	-4.358***	-2.616***
Two adults younger than 65 years	1.39	0.041	0.319	0.215	1.151	-3.441***	-1.929**
Two adults, at least one aged 65 years or over	19.79***	0.582	0.601	15.421	13.817	-4.960***	-2.902***
Two adults with one dependent child	-0.71	-0.021	0.258	0.618	-0.09	-4.318***	-1.663**
Two adults with two dependent children	2.19**	0.064	0.274	-0.12	1.806	-3.087***	-2.080**
Two adults with three or more dependent children	0.74	0.022	0.37	-0.699	1.803	-6.916***	-4.310***
Two adults or more without dependent children	2.29**	0.067	0.342	-0.88	-0.579	-4.196***	-2.585***
Two adults or more with dependent children	0.64	0.019	0.407	-0.613	-0.723	-4.157***	-2.187**
Three or more adults	2.48**	0.073	0.286	15.421	13.817	-6.228***	-3.429***
Three or more adults with dependent children	1.54	0.045	0.321	-0.136	-0.037	-5.655***	-3.793***
Households without dependent children	-0.06	-0.002	0.419	-0.553	0.117	-3.478***	-1.560**
Households with dependent children	-0.16	-0.005	0.423	-0.796	0.015	-3.812***	-1.876**
Number of people at risk of poverty or social exclusion (in natural logarithm)							
Single person	-0.43	-0.013	0.406	-0.804	-0.21	-4.116***	-1.886**
Single person with dependent children	-1.59	-0.047	0.285	0.423	-0.017	-5.191***	-4.293***
Two adults	11.62***	0.342	0.425	-1.261	-0.876	-3.651***	-1.911**
Two adults younger than 65 years	0.5	0.015	0.4	-0.287	-1.245	-3.890***	-2.060**
Two adults, at least one aged 65 years or over	14.19***	0.418	0.561	15.421	-0.469	-3.947***	-1.669**
Two adults with one dependent child	5.27***	0.155	0.332	0.101	0.945	-4.551***	-1.644**
Two adults with two dependent children	3.05***	0.09	0.252	-0.676	-1.042	-4.481***	-2.169**
Two adults with three or more dependent children	0.05	0.002	0.274	1.137	2.708	-5.178***	-2.770***
Two adults or more without dependent children	2.68***	0.079	0.347	0.398	-1.113	-4.855***	-2.489***
Two adults or more with dependent children	6.88***	0.202	0.361	15.421	13.817	-4.486***	-1.739**
Three or more adults	6.86***	0.202	0.329	15.421	13.817	-5.300***	-2.684***
Three or more adults with dependent children	2.68***	0.079	0.368	-1.526	1.22	-6.181***	-3.638***
Households without dependent children	0.65	0.019	0.37	0.375	13.817	-4.682***	-2.591***
Households with dependent children	6.05***	0.178	0.384	15.421	-2.772	-5.108***	-2.133**
Percentage of people living with very low work intensity (in natural logarithm)							
Total households	8.48***	0.25	0.41	15.421	13.817	-6.010***	-4.147***
Single person	7.81***	0.23	0.416	-1.008	-0.761	-4.969***	-2.363***
Single person with dependent children	0.98	0.029	0.323	15.421	-0.667	-5.637***	-3.467***
Two adults	2.73***	0.08	0.487	0.156	-0.105	-3.116***	-1.637**
Two adults younger than 65 years	3.43***	0.101	0.481	0.545	-0.27	-3.312***	-1.191**
Two adults, at least one aged 65 years or over	-0.43	-0.013	0.401	-0.771	-0.789	-4.301***	-1.670**
Two adults with one dependent child	5.01***	0.147	0.316	0.588	-0.402	-3.584***	-1.650**
Two adults with two dependent children	2.32***	0.068	0.331	-1.101	-0.177	-5.394***	-3.656***
Two adults with three or more dependent children	2.04**	0.06	0.291	1.435	3.251	-5.194***	-2.717***
Two adults or more without dependent children	2.51***	0.074	0.404	-0.335	0.33	-5.347***	-3.733***
Two adults or more with dependent children	6.59***	0.194	0.366	0.424	0.246	-6.960***	-4.775***
Three or more adults	4.32***	0.127	0.32	0.588	-0.753	-5.859***	-3.698***
Three or more adults with dependent children	2.54**	0.075	0.355	-0.911	-0.684	-6.102***	-3.062***
Households without dependent children	6.99***	0.206	0.406	15.421	13.817	-6.692***	-4.143***
Households with dependent children	7.91***	0.233	0.377	-0.76	1.083	-6.041***	-3.529***
Energy and control variables							
LRES_IC	31.53***	0.928	0.928	0.371	0.957	-1.497***	-2.036**
LHYDRO_IC	-	-	-	2.174	3.857	-0.590**	-0.439***
LWIND_IC	31.19***	0.918	0.918	-0.599	1.599	-1.745***	-1.877***

LSOL_IC	30.33***	0.892	0.892	0.072	1.623	-1.408**	-0.072***
LRES_GEN	29.23***	0.866	0.866	-0.988	0.271	-3.077***	-0.989**
LHYDRO_GEN	3.76***	0.111	0.354	-0.394	0.147	-4.228***	-1.695**
LWIND_GEN	30.42***	0.9	0.9	-0.551	0.638	-2.143**	-0.960**
LSOL_GEN	31.89***	0.944	0.944	15.155	-0.768	-2.689***	-1.879***
LPRICE_ELEC	21.05***	0.619	0.725	-0.222	-1.135	-4.383***	-3.884***
LGAS_CONS	13.34***	0.393	0.512	-0.771	1.008	-1.599***	- 9.537***
LGEH_INTS	18.23***	0.536	0.662	-1.002	1.241	-1.978***	-1.778**
LENERG_INTS	24.97***	0.735	0.78	-0.8	-0.105	-2.693***	-1.688***
LGDP	12.96***	0.381	0.513	3.417	1.64	-1.099***	1.752***
LEDU_EXPS	1.08***	0.032	0.446	0.409	0.421	-4.567***	-3.052***

Notes: **, ***, denote statistical significance at 5% and 1% level, respectively. CD-test has N(0,1) distribution under H0: cross- section independence; panel unit roots test (CIPS) tests the H0: series are I(1).

To show the effects of household income and the usual RES drivers (Aguirre & Ibikunle, 2014; Omri & Nguyen, 2014; Romano et al., 2017; Valdés Lucas et al., 2016) on the deployment and use of RES, eight models were estimated, namely (with their respective dependent variable):

- *WIND_IC* – installed capacity of wind power;
- *SOL_IC* – installed capacity of solar PV;
- *HYDRO_IC* – installed capacity of hydro power;
- *RES_IC* – installed capacity of all RES;
- *WIND_GEG* – electricity generation from wind power;
- *SOL_GEG* – electricity generation from solar PV;
- *HYDRO_GEG* – electricity generation from hydro power; and
- *RES_GEG* – electricity generation from all RES.

To meet the main objective of this paper, 14 models were estimated to reveal the effects of the deployment of RES on household incomes, and also to reveal the effects on the households' risk of poverty and social exclusion, using as dependent variables the household' income and the risk of poverty, respectively. This research also tested the drivers of income inequality generally used in the literature (Gęstwicki & Wędrowska, 2016; Neumayer & Plumper, 2016; Page & Goldstein, 2016; Turnovsky, 2015).

Table 2.4. Kao residual cointegration test

Single person	*inc*	-5.201271***	Two or more adults with dependent children	*inc*	-4.880614***
	risk	-3.814086***		*risk*	-7.910950***
Single person with dependent children	*inc*	-3.513028***	Three or more adults	*inc*	-4.799234***
	risk	-7.464221***		*risk*	-7.586330***
Two adults	*inc*	-3.245477***	Three or more adults with dependent children	*inc*	-3.792484***
	risk	-3.757293***		*risk*	-3.490349***
Two adults younger than 65 years	*inc*	-5.837310***	Households without dependent children	*inc*	-4.080159***
	risk	-7.638724***		*risk*	-3.930485***
Two adults, at least one aged 65 years or over	*inc*	-4.939195***	Households with dependent children	*inc*	-4.410320***
	risk	-4.153939***		*risk*	-7.640866***
Two adults with one dependent child	*inc*	-5.592643***	*RES_IC*		-2.117332***
	risk	-6.265151***	*RES_GEN*		-3.854390***
Two adults with two dependent children	*inc*	-2.810666***	*HYDRO_IC*		-5.354045***
	risk	-8.446245***	*HYDRO_GEN*		-3.691919***
Two adults with three or more dependent children	*inc*	-4.091316***	*WIND_IC*		-5.343441***
	risk	-7.126844***	*WIND_GEN*		-4.871691***
Two or more adults without dependent children	*inc*	-3.580205***	*SOL_IC*		-5.120046***
	risk	-4.891898***	*SOL_GEN*		-4.276471***

Notes: *** denote statistical significance at 1% level;. inc refers to the percentage of household's mean disposable income in relation to the total mean disposable income, and risk refers to the number of people at risk of poverty or social exclusion.

As all variables are I(1), the Kao residual cointegration test (Gutierrez, 2003) was employed. This test is based on a Monte Carlo procedure, which outperforms the Pedroni's test when there is a small time series dimension in panel data (Gutierrez, 2003), as is the case of this analysis. The Kao tests suggest the existence of long-run relationships in all models. Thus, the analysis of both short-run adjustments and long-run equilibrium are recommended. An ARDL methodology has been applied to apportion the total effects into short- and long-runs. Furthermore, the ARDL methodology allows the use of I(1) variables, and is suitable for long memory patterns. The literature suggests that ARDL models applied in panel data produce consistent and efficient parameter estimations, even in small-samples (Fuinhas et al., 2015; Papageorgiou et al., 2016). The ARDL equation modelling and estimates the short- and long-run coefficients simultaneously, eliminating econometric problems associated with omitted variables and autocorrelation. The coefficients estimation provided by the ARDL equation, which is a cointegration method, are unbiased and efficient, mainly because of its avoidance of problems that might happen in the presence of serial correlation and endogeneity (Marques et al., 2017, 2018; Pesaran & Shin, 1999a; Phillips & Hansen, 1990). Moreover, traditional estimators, even traditional cointegration estimators, may produce erroneous results due to the endogeneity, meanwhile, with the ARDL method the independent and dependent variables could be distinguished and produced efficient results under endogeneity issues (Marques et al., 2017; Marques, Fuinhas, & Neves, 2018; Papageorgiou et al., 2016; Pesaran & Shin, 1999b; Phillips & Hansen, 1990; Rafindadi & Ozturk, 2017). Therefore, the general ARDL models used are stated below (eq. 2.1). To prove the existence of long-run relationships in the ARDL models, two Joint Significance Tests (JSE) were carried out, using a Wald test, an individual test (eq. 2.2) and a joint test (eq. 2.3).

$$D\boldsymbol{Y}_{i,t} = f(D\boldsymbol{X}_{i,t}, \boldsymbol{Y}_{i,t-1}, \boldsymbol{X}_{i,t-1}) \tag{2.1}$$

$$H0\colon \alpha i = \alpha i + 1 = 0 \tag{2.2}$$

$$H0\colon \alpha i + \alpha i + 1 = 0 \tag{2.3}$$

where, $\mathbf{Y}_{i,t}$ is the vector of dependent variables, $\mathbf{X}_{i,t}$ is the vector of independent variables, and the αi denotes the significant long-run coefficients in the models. The variables incorporated in the models are in natural logarithms, and first differences of logarithms, denoted by the operator "D", their coefficients are elasticities (long-run) and semi-elasticities (short-run). The elasticities are computed by dividing the coefficient of the long-run series by the coefficient of the Error Correction Mechanism (ECM), from the estimated models both lagged once, and then multiplied by -1.

The correlation matrix and the variance inflation factor statistics revealed that the income percentage of some households had to be excluded from the RES models, because of problems of collinearity and multicollinearity. Thereafter, the low correlation values and VIF statistics support the idea that collinearity and multicollinearity was no longer a concern. A battery of model specification tests were performed to show the properties of the models (see Table 2.5).

Table 2.5. Model specification tests

Models		**Hausman RE vs. FE**	**Modified Wald test**	**Wooldridge test**	**Pesaran's test**	**Frees' test**	**Friedman's test**
RES_IC		35.87***	809.92***	21.406***	-0.36	0.626***	5.953
RES_GEN		46.23***	234.68***	7.283**	0.575	-0.191	14.36
HYDRO_IC		53.05***	609.94***	75.659***	0.908	-0.097	13.022
HYDRO_GEN		73.04***	493.64***	66.014***	1.304	0.498**	13.691
WIND_IC		70.65***	132.92***	9.555***	-0.548	0.13	6.142
WIND_GEN		39.41***	49.37***	0.803	1.811*	0.183	18.491
SOL_IC		41.69***	585.79***	18.796***	-0.394	0.257*	7.393
SOL_GEN		50.63***	62.99***	39.344***	-0.369	0.697***	6.578
Single person	*inc*	47.80***	115.75***	23.058***	-1.213	0.213	4.135
	risk	44.54***	107.69***	26.516***	-1.275	-0.258	5.415
Single person with	*inc*	42.53***	96.82***	26.520***	0.709	0.159	8.76
	risk	61.32***	209.07***	17.624***	-0.892	0.594***	4.978

dependent children							
Two adults	*inc*	30.25***	116.16***	26.180***	-0.557	-0.363	11.349
	risk	39.03***	251.33***	23.343***	-1.006	0.122	4.847
Two adults younger than 65 years	*inc*	33.62***	255.18***	43.448***	1.001	0.137	12.862
	risk	56.10***	63.80***	83.311***	-0.935	0.029	5.327
Two adults, at least one aged 65 years or over	*inc*	42.72***	83.88***	56.349***	-0.747	-0.226	7.873
	risk	38.07***	207.26***	22.498***	-1.085	0.09	5.007
Two adults with one dependent child	*inc*	50.47***	213.47***	24.413***	-1.568	0.272*	2.476
	risk	54.52***	158.16***	48.203***	-0.566	0.308*	5.255
Two adults with two dependent children	*inc*	47.39***	136.61***	18.947***	-0.365	-0.072	9.153
	risk	75.26***	138.48***	9.679***	0.204	-0.201	5.371
Two adults with three or more dependent children	*inc*	43.12***	261.95***	31.386***	0.712	0.031	12.033
	risk	-	-	-	-	-	-
Two or more adults without dependent children	*inc*	38.08***	265.86***	46.422***	-0.163	-0.272	9.691
	risk	46.52***	480.59***	41.698***	0.949	0.450**	9.269
Two or more adults with dependent children	*inc*	49.87***	31.63***	39.720***	-0.909	-0.012	6.229
	risk	68.98***	37.07***	19.377***	0.582	-0.174	9.255
Three or more adults	*inc*	35.33***	42.72***	30.423***	0.582	-0.252	12.498
	risk	41.27***	277.63***	45.482***	-0.167	0.395**	6.564
Three or more adults with dependent children	*inc*	-	-	-	-	-	-
	risk	57.45***	899.47***	27.275***	0.371	0.053	9.022
Households without dependent children	*inc*	47.07***	190.63***	77.970***	0.006	0.012	6.593
	risk	34.41***	163.21***	39.214***	0.232	-0.113	10.942
Households with dependent children	*inc*	45.89***	35.91***	77.043***	-0.503	-0.13	4.978
	risk	68.73***	220.75***	35.899***	0.181	-0.004	7.291

Notes: inc refers to the percentage of household's mean disposable income in relation to the total mean disposable income, and risk refers to the number of people at risk of poverty or social exclusion. ***, **, * denote statistical significance at 1%, 5%, and 10% level, respectively; the modified Wald test has χ2 distribution and tests H0: , for c=1,...,N; the Wooldridge test is normally distributed N(0,1), and tests H0: no serial correlation; Pesaran, Frees and Friedman test the H0: residuals are not correlated; Hausman results for H0: difference in coefficient of FE and RE is not systematic including the constant.

The specification tests indicated the presence of: (a) heteroskedasticity; (b) panel first order autocorrelation in all models, except the WIND_GEG model; and (c) fixed effects. Accordingly, the specification tests suggested that the Driscoll and Kraay (Driscoll & Kraay, 1998) estimator with fixed effects was suitable to handle those data features. The

Driscoll and Kraay (Driscoll & Kraay, 1998) is a covariance estimator, and it deals with small-samples considerably better than alternative traditional estimators, when heteroskedasticity and panel first order autocorrelation are present (Hoechle, 2007).

2.4 Results and Discussion

The results of the ARDL models are shown in Tables 2.6, 2.7, and 2.8. The Driscoll and Kraay estimator was used, and the parsimonious principle was followed. The Kao residual cointegration test and the JSE test revealed the existence of long-run relationships among variables in the models. The negative and highly statistically significant ECM values emphasise the confidence of the econometric results and reveal that the models are stable and able to return to the equilibrium after a disturbance. Besides, it should be highlighted that the ARDL method allows us to understand two important aspects. Firstly, the short-run reaction of the dependent variable is to variations or shocks in explanatory variables. This means, how the households' income and risk of poverty reacts in the short-run dynamics of adjustment to changes in the RES, natural gas consumption, and electricity prices. Secondly, the long-run equilibrium discloses how the households income and risk of poverty will converge if nothing is changed, namely in the explanatory variables (Marques, Fuinhas, & Neves, 2018; Marques, Fuinhas, & Pereira, 2018; Pesaran & Shin, 1999a). The results show that on the equilibrium the majority of the effects is not desirable, mainly because of the increment of people at risk of poverty. Therefore, The energy transition towards RES and electricity should be well thought out, and the policy makers should change some policies and measures to not threaten the low-income households with energy poverty.

Table 2.6. Elasticities, semi-elasticities, and adjustment speeds of RES models

Models	***RES_IC***	***RES_GEG***	***HYDRO_IC***	***HYDRO_GEG***	***WIND_IC***	***WIND_GEG***	***SOL_IC***	***SOL_GEG***
Short-run (semi-elasticities)								
Percentage of household's mean disposable income in relation to the total mean disposable income (in first differences of natural logarithm)								
Single person					-0.5382*		-5.0417***	
Single person with dependent children			0.0645**		0.1702**		-1.2671**	
Two adults younger than 65 years	-0.3027*			0.9579			-4.0862**	
Two adults with one dependent child	-0.5667***				-0.9312***	-1.0261***	-3.6140***	-2.4065***
Two adults with three or more dependent children			-0.0917***		-0.2734***			
Three or more adults with dependent children	-0.1496***				0.2710**		-3.1733**	
Energy and control variables								
DLGAS_CONS	0.0686***	0.1274***		0.2895***	0.2284***		-0.6009**	
DLPRICE_ELEC					-0.1481*			1.3289**
DLGEH_INTS		-0.5014***		-1.4993***	-0.7291**	-1.6995***		
DLENERG_INTS	-0.4131***					-0.9763**		-2.4032**
DLGDP					-0.5696*			-1.8600**
DLEDU_EXPS	-0.3194***						-3.4323**	-2.5854**
People living with very low work intensity					0.0739*			-1.3340**
Speed adjustment								
ECM	-0.0728**	-0.1913***	-0.5133***	-0.9567***	-0.2050***	-0.2355***	-0.1402***	-0.2204***
Long-run (elasticities)								
Percentage of household's mean disposable income in relation to the total mean disposable income (in natural logarithm)								
Single person	-5.1716**	-2.3493**	.4045**		-8.6553***	-5.4519***	-41.7915***	-9.9253**
Single person with dependent children	-3.8170**	.9385***		-.5361***			-12.7726***	
Two adults younger than 65 years					-2.6176***	-3.2059**		
Two adults, at least one aged 65 years or over	-3.1987*		.2029***					
Two adults with one dependent child	-6.5265*	-3.2729***	.6274**		-6.7832***	-6.3002***	-43.908***	-16.8877***
Two adults with two dependent children			.8006**				34.6749**	23.2303***
Two adults with three or more dependent children	-2.0596**		-.3038***		-5.5383***	-2.5514**		6.0534**
Three or more adults			.6071*		-5.3669***			19.3352**
Three or more adults with dependent children	-3.2336*						-27.7752***	
Energy and Control variables								
LGAS_CONS			.05396***				-3.4753**	3.4853***
LPRICE_ELEC	1.5565***	.6382***	.04418***	.1180**				3.1089***
LGEH_INTS					-7.0005***	-7.1504***		-13.3714***
LENERG_INTS	-3.8491***				2.8937***			-19.1329***
LGDP	-6.9196***	-1.7157***	.3705***					-32.7049***
LEDU_EXPS	-3.6829***		-.3609*	-.8969***				-9.7587***
People living with very low work intensity	-1.9787*							-7.7170**
Constant	16.5943***	9.6275***	-3.277	10.0553***	32.5463***	28.0687***	62.6093***	95.7279***
Observations	150	150	150	150	150	150	150	149
R^2	0.3171	0.3099	0.4169	0.581	0.5259	0.508	0.4145	0.488
JSE individual	1800.21***	61.76***	546.34***	47.35***	3515.13***	315.39***	64.00***	92.17***
JSE	22.26***	51.84***	2.89	26.40***	24.44***	260.42***	37.63***	19.32***

Notes: ***, **, * denote statistical significance at 1%, 5%, and 10% level, respectively.

The results of the RES models highlight that: (a) income inequality may be delaying the deployment of RES, except for hydro power; (b) the income of large families has been effective in promoting solar PV; (c) energy intensity in economies has been the main driver of wind power deployment; and (d) no RES, other than wind power, need more subsidies. In fact, an increase of 1% in the price of residential electricity generates increases of 1.56%, 0.04%, and 3.11%, in the installed capacity of RES, hydro power, and solar PV generation, respectively. Both hydro power and solar PV could enter the market without being subsidised, due to household income, and electricity prices also have the potential to increase their deployment. Furthermore, the growing importance of hydro power and solar PV in electricity systems could further increase their competitiveness in the electricity market.

In households with children, there is empirical evidence for the following relationship; natural gas consumption decreases income and increases the risk of poverty, while higher electricity prices increase income and reduce the risk of poverty and social exclusion. In households without children, the contrary is shown to be true, contrary to what expected, that natural gas consumption decreases the risk of poverty, and higher electricity prices increase it. Electricity is accessible in the majority of cities, and metropolitan areas, and electricity can be used to power all home appliances. In contrast, access to natural gas is not always provided, and it can only be used for heating and cooking. Thus, the natural gas access excludes the consumption and use of households' appliances and electronic devices, which it is of growing importance on the society. Besides, home appliances for heating and cooking powered by electricity are safer than the home appliances powered by natural gas, which is an important concern for families with children. In fact, although studies are scarce, the literature shows that households with children generally consume more electricity and less natural gas than households without children (Brounen et al., 2012; Chalal et al., 2017; Longhi, 2014; Shirani et al., 2016). The positive effect of children on electricity consumption could be due to greater use by children of certain appliances, such as televisions, personal computers, game consoles, etc. (Brounen et al., 2012; Chalal et al., 2017; Longhi, 2014; Shirani et al., 2016).

The frequent use of the internet by the children to access social media, entertainment, and learning processes, influenced by external social effects, and educational challenges could increase their propensity to have successful careers. Many parents also learn from their children to use the internet more effectively. The expansion of internet resources to work processes, and the increased capacity for processing its information could increase the income of households, further decreasing the risk of poverty. Furthermore, the access to more information and social media reduce the risk of info exclusion and, consequently, decrease the risk of poverty and social exclusion. Therefore, this effect of the internet and electricity on economies could increase the income of households, and enable better living condition, as suggested in our results. Policymakers should realize the importance of electricity consumption to households, and help those households threatened by poverty, or with a large number of dependent children. This aid could be provided by nonlinear electricity prices according to the number of family members and their risk of poverty, for example, by giving discount vouchers for electricity based on the number of dependent children, poverty and social status.

In households with children, electricity prices have been decreasing the risk of poverty, so, electricity is providing them with greater well-being. Furthermore, if these households joined DSM programs and energy efficiency measures, they could channel the resulting savings to other categories in their budgets. Thus, electricity could help them to avoid falling into the poverty trap and ensure greater well-being. Conversely, the transition of home appliances from natural gas to electricity must be well thought out for households without children. The price of electricity, which has been supporting the penetration of RES, is generally higher than the price of natural gas. During a transition to electricity, this type of household might divert funds from other categories, such as food and hygiene, to compensate for rising expenditure on energy. As such, this will decrease their productivity and future income, increasing the risk of their experiencing a poverty trap, or energy poverty. Therefore, their transition to electric home appliances should be planned to include DSM and energy efficiency programs to mitigate this negative effect, helping them reduce their electricity bills, and avoid falling into the poverty trap.

Wind power deployment and electricity generated from RES have a distinct effect on a household's risk of poverty. Wind power does not offer them high FiTs. Wind power is the largest contributor to the RES, and the deployment of wind power and its share of RES in the electricity mix has been diminishing the cost of electricity generation. During some periods, the high quantities of electricity generated from RES, mainly by wind power, have decreased the cost of generation below the RES surcharge. In fact, this price reduction could benefit households, if they have a time-of-use electricity tariff instead of a flat rate. Thus, it is crucial to incentivize consumers to use real-time electricity tariffs and DSM programs, and then adapt their consumption to periods when there is a high availability of natural resources. The households would then benefit from lower electricity prices, which would decrease their risk of poverty and social exclusion.

Table 2.7. Elasticities, semi-elasticities, adjustment speeds of household models

Models	Single person		Single person with dependent children		Two adults		Two adults younger than 65 years		Two adults, at least one aged 65 years or over		Two adults with one dependent child		Two adults with two dependent children	
	inc	risk	inc	risk	inc	risk	inc	risk	inc	risk	inc	risk	inc	risk
Short-run (semi-elasticities)														
People living with very low work intensity	-0.0603***	0.1692***	-0.0771***	0.3152***		0.2327***		0.3356***		0.1223***	-0.0236***	0.2982***	-0.0148***	0.1709***
DHYDRO_IC	0.0737***	-0.2120*	0.2525***	-0.5854***			-0.0721*		0.1762***			0.3911**		
DWIND_IC								0.0405*			-0.0325***	0.1701**		
DSOL_IC	-0.0084**	0.0195**	-0.0114**	0.0111***	-0.0055**			0.0218**	-0.0053**	-0.0273***	-0.0059**	0.0407*		
DRES_GEN								0.0898*		-0.1826**				
DLGAS_CONS	-0.0408***	0.0472**	-0.1025***	0.1559***				-0.0941*				-0.1288***		
DLPRICE_ELEC	0.0396**												0.0670***	
DLGEH_INTS				-0.3276***			0.0425*	-0.2124**	-0.0965**					-0.4376**
DLENERG_INTS	0.1566***	-0.5226***				-0.2117**				-0.7942***	-0.0946**		-0.1115**	0.5691*
DLGDP					-0.1547***		-0.0592*		-0.2486***	-0.4439**			-0.1174**	0.3391**
DLEDU_EXPS	-0.2142***	0.4529***			-0.1893***		-0.1388**		-0.1996***	0.3620**	-0.1365*	0.6398*	0.1002**	
Adjustment speed														
ECM	-0.6545***	-0.4812***	-0.7246***	-0.9335***	-0.5196***	-0.5869***	-0.6323***	-0.7926***	-0.6213***	-0.4255***	-0.8272***	-0.8610***	-0.7082***	-0.9840***
Long-run (elasticities)														
People living with very low work intensity	-.0787***		-.1251***	.4183***	-.0253***	.2319***		.4256***			-.0414***	.3301***	-.0284***	.1981***
LHYDRO_IC							-.0975*	-.3797***		1.8462**				
LWIND_IC	-.0278***					-.0284**	.0193*	-.0648***	.01743***		-.0113***	-.0736***		
LSOL_IC	.0098***		-.01488***	.0113***				.0179***			-.0071***	.0444***	-.0042***	.0259***
LRES_GEN	-.0525***		.0712***			-.0837***				-.3709***	.0157**			
LGAS_CONS			-.1602***	.1559***		-.0924***		-.1324***		-.2715***	-.0287***	-.1800***	-.0386***	.0964***
LPRICE_ELEC				-.1010***							.0787***		.0317**	-.1519***
LGEH_INTS	-.1809***	.25897**	.2311**	-.2539**		.4937***	.0934***			2.2617***				.4571**
LENERG_INTS		-.3393***	-.2872**	.2655***	-.0569**		.2005***	-.4009***	-.4527***				-.1611***	
LGDP	-.4478***		-.3620***	.5305***	-.3112***		.1703***	-.4857**	-.7475***		-.3084***		-.3846***	
LEDU_EXPS	-.1052***	.6598***		-.1724***				-.4854***		1.0529***			.2099***	
Constant	7.3549***	1.1138***	6.9413***	-4.0834**	4.3780***	0.8795	1.3868**	11.5236***	9.1676***	-8.4002***	6.9732***	3.1779***	6.6843***	-0.7962
Observations	150	150	150	150	150	150	150	150	150	150	150	150	150	150
R²	0.5422	0.4508	0.4934	0.681	0.405	0.4149	0.4815	0.5832	0.3976	0.3734	0.5115	0.5729	0.4462	0.6773
JSE individual	302.36***	59.95***	363.28***	93600.39***	36.37***	11.54***	109.71***	142.68***	130.70***	1147.22***	1054.73***	110.49***	56.81***	293.17***
JSE	194.88***	8.31**	122.62***	0.79	94.55***	5.38**	10.89***	34.02***	195.02***	17.81***	67.46***	108.83***	35.30***	3.51*

Notes: inc refers to the percentage of household's mean disposable income in relation to the total mean disposable income, and risk refers to the number of people at risk of poverty or social exclusion. ***, **, * denote statistical significance at 1%, 5%, and 10% level, respectively.

Table 2.8. Elasticities, semi-elasticities, adjustment speeds of household models

Models	Two adults with three or more dependent children		Two or more adults without dependent children		Two or more adults with dependent children		Three or more adults		Three or more adults with dependent children		Households without dependent children		Households with dependent children	
	inc	**risk**	**inc**	**risk**	**inc**	**risk**	**inc**	**risk**	**inc**	**risk**	**inc**	**risk**	**inc**	**risk**
Short-run (semi-elasticities)														
People living with very low work intensity	0.0671***	-		0.2823***	-0.0094**	0.1880***	-0.0225**	0.4990***	-	0.1352***		0.2400***		0.1639***
DHYDRO_IC	-0.2226***	-				0.3357***	-0.1528***		-	0.7770**				0.1194***
DWIND_IC		-					-0.0286***	0.0992*	-	-0.1924**				
DRES_GEN		-					0.0806***	-0.2930**	-	0.7240**				
DLPRICE_ELEC	-0.0795*	-	-0.0305***		0.0181**		-0.0882***		-	0.8330**	-0.0194***		0.0208***	
DLGEH_INTS		-	-0.0509*			-0.2929***			-		-0.0280**	0.1077*		-0.2422***
DLENERG_INTS		-						-0.8524***	-					
DLGDP		-	-0.0973***		0.0469**		-0.1508**		-	-0.9051**	-0.0467*		0.0481**	
DLEDU_EXPS	0.3186***	-	-0.0620*		0.0939***		0.0855**		-		-0.0836***		0.1032***	
Adjustment speed														
ECM	-0.8544***	-	-0.6167***	-0.6345***	-0.6361***	-0.8380***	-0.8724***	-0.9431***	-	-0.8745***	-0.5918***	-0.4831***	-0.5853***	-0.8514***
Long-run (elasticities)														
People living with very low work intensity		-		.4006***		.1881***	-.0278***	.5627***	-			.2725***		.2051***
LHYDRO_IC		-						-.9327***	-	1.3386***				
LWIND_IC		-	.0105***					.0725***	-					
LSOL_IC		-			-.0016*		-.0088***		-	-.0746***	.0023**		-.0029***	.0106**
LRES_GEN		-				.0528***	.0658***	-.1402***	-	.6475***				
LGAS_CONS	-.0512***	-	.0269**	-.0694**	-.0358***	.0869***	.0287***	-.0841***	-		.0349***		-.0403***	.0776***
LPRICE_ELEC		-	-.0220**		.0208**	-.0985***	-.0215**	.1149***	-		-.0273***		.0298***	-.1199***
LGEH_INTS		-		.5636***					-	-1.2743**		.31859***		
LENERG_INTS		-				-.4472***			-					-.3067*
LGDP	.3774***	-				-.3781***			-	-2.0455***				-.3258***
LEDU_EXPS		-			.0767***				-		-.0601***		.0832***	
Constant	0.6287	-	2.7166***	-0.1889	2.9960***	6.3095***	3.5103***	9.7299***	-	13.0803*	2.6504***	0.408	2.7632***	5.7730***
		-							-					
Observations	150	-	150	150	150	150	150	150	-	150	150	150	150	150
R^2	0.4402	-	0.4203	0.4654	0.4684	0.6345	0.5407	0.6442	-	0.6651	0.4217	0.4271	0.4245	0.6133
JSE individual	22.51***	-	25.52***	20.22***	22.18***	268.99***	454.87***	90.88***	-	91.96***	22.64***	9.23***	22.99***	90.39***
JSE	62.16***	-	48.63***	0.82	93.20***	41.74***	152.37***	24.53***	-	5.39**	65.07***	5.21**	90.51***	32.76***

Notes: inc refers to the percentage of household's mean disposable income in relation to the total mean disposable income, and risk refers to the number of people at risk of poverty or social exclusion. ***, **, * denote statistical significance at 1%, 5%, and 10% level, respectively.

Solar PV deployment by major producers and auto-producers, has not yet produced the desired and expected effects, and has failed to positively affect economies and society overall. In fact, the installed capacity of solar PV has been decreasing incomes, and increasing the risk to households of poverty and social exclusion. This is an unexpected finding, and it deserves careful consideration. Firstly, this negative consequence could be a direct effect of the high FiTs awarded to promote solar PV. Indeed, the reduction of FiTs has not kept pace with reductions in the price of PV modules, which has led companies to install greater quantities of solar PV (Frondel et al., 2015; REN21, 2016). Consequently, the incentives to promote solar PV have permitted companies to benefit from higher returns, and, the economic benefits of RES deployment have not been shared with consumers, since the producers have retained all the profit.

Secondly, the majority of solar PV modules installed have been imported from non-European countries, such as China, Japan, and India. In fact, European solar panel producers have struggled to compete with non-European PV producers. For example, the price of PV panels produced in China was €0.47/Wp (watt-peak) compared to the European average of €1.10/Wp (ProSun, 2016). This led the European Commission to open antidumping investigations, and impose high trade restrictions to protect European PV manufactures (ProSun, 2016). However, several non-European manufactures and European PV companies have since merged. These international operations have been able to avoid the tariff restrictions, and enabled non-European modules to enter Europe at reduced prices (McCarthy, 2016). Therefore, with manufacturing operations still being run outside of Europe, potential benefits to the European economy, such as job opportunities, have been cancelled out.

Currently, electricity prices and bills include the costs of generation, transportation, and RES surcharges. Thus, consumers have been paying for RES implementation and generation, along with the cost of providing fossil-fuel standby capacity to backup both RES and consumption peaks. In fact, this will keep increasing electricity prices, and consequently, the risk to households of poverty, including energy poverty. Households, particularly those on low-incomes, must be helped to support the cost of energy transition, and the economic surplus arising from energy transition has to be shared with consumers.

Incorporating RES is no longer a simple question of dispatch priority and guaranteed returns. In fact, households could play an important role in accommodating intermittent RES generation. In return, they should benefit from lower electricity prices. Thus, the economic surplus and well-being from using RES could be shared between consumers and producers. To enable households to enjoy a green electricity mix at reduced costs, governments and policy makers must be prepared to: (i) promote electricity conservation; (ii) subsidise more efficient home appliances instead of RES deployment; (iii) reward changes in consumption routines, through schemes such as electricity tariff differentiation; and (iv) encourage people to generate their own electricity, not through subsidies, but through low-interest rates. Tariff differentiation, if properly explained to consumers, could help them to adapt their consumption to periods with a higher availability of natural resources. Thus, it would reduce electricity prices and bills, and prevent sections of European society from falling into a poverty trap.

2.5 Robustness check

As additional proof of the results' robustness, a new framework, based on a long-run model, was performed. To perform a long-run model equation, the data must comply with two assumptions: (i) the variables included in the model are integrated of order one, i.e. I(1); and (ii) the series are cointegrated. The integration order test (Table 2.3) confirmed that all variables are I(1), and the Kao residual cointegration test (Table 2.4) corroborate that the variables are cointegrated. Accordingly, the data of this research complies with the two requirements needed to perform the long-run models. In the data used the endogeneity, residual cointegration, and serial correlation is suspicious, and the small sample bias is a concern. To surpass these econometric problems, the long-run models have been estimated using the Fully Modified Ordinary Least Squares (FMOLS), and Driscoll and Kraay estimators. The FMOLS estimator is suitable to handle sample size bias, serial correlation, and endogeneity (Phillips & Hansen, 1990). Although the Driscoll and Kraay estimator, as mentioned before, is appropriate for handling sample size bias and serial correlation, instead of controlling endogeneity it controls heterogeneity between countries. In the FMOLS estimator the country fixed effects have been controlled manually, adding a dummy to each country. In the Driscoll and Kraay estimator the fixed effects are controlled automatically, choosing the option fixed effects. Therefore, the validity of ARDL long-run coefficients can be confirmed by the comparison with the coefficients of long-run models.

The long-run models results estimated by FMOLS and Driscoll and Kraay, validate the ARDL long-run coefficients, in terms of sign effects. This means that no change of signal effects between the two robustness estimators used and the ARDL models has been found. However, in terms of statistical significance, the long-run models estimated by Driscoll and Kraay reveal less statistically significant series, and different degrees of statistical significance when compared to either the ARDL models or the FMOLS results.

The one main difference between the Driscoll and Kraay estimator and both the FMOLS estimator and the ARDL models, is the control of endogeneity. Thus, it is shown that, if endogeneity is not properly addressed, the results can be biased. The comparison of long-run ARDL and FMOLS results verified that the ARDL modelling deals effectively with the endogeneity issue, because of the similar results obtained. Therefore, the FMOLS estimator corroborated that the ARDL methodology was properly applied to the data used, and does not lead to biased results. In addition, the ARDL models permitted a breakdown of the total effects into short-run dynamics and long-run equilibrium, which enabled the retrieval of more conclusions.

2.6 Conclusion

This research focuses on the relationships between the deployment of RES and both the income of households and their risk of poverty. To evaluate the impact of RES implementation on society, the installed capacities have been divided into wind power, solar PV, and hydro power, and studied along with the share of electricity produced from RES, and electricity prices for the residential sector. In addition, households have also been classified according to EU-SILC categories, and empirically assessed by category. A Kao residual cointegration test, and an ARDL approach was employed to study fifteen EU countries, over a time-span from 2005 to 2015. The results show that RES deployment is directly linked with the living conditions of households. A battery of model-specification tests was run, to choose the most suitable estimator, and to validate the long-run relationships. The long-run coefficients of ARDL models were subjected to a robustness check, corroborating the fact that the ARDL models have consistent and efficient parameter estimations. Furthermore, the robustness section highlights that endogeneity is present in the data used, and that it is properly addressed by the ARDL estimation.

In response to the questions proposed by this research it was found, firstly, that the income of different households has differing effects on RES promotion, benefiting hydro power, and solar PV. Secondly, the installed capacities of both wind power and hydro power, and the overall share of RES have dissimilar impacts on different households, but they have increased the income of some. However, the unexpected finding was the negative effect of solar PV deployment on household income. Thirdly, the capacity of wind and hydro power, and of all RES generation, have reduced the risk of poverty for some households, but have increased the risk for others. According to the income models for the period under analysis, solar PV has not yet been shown to reduce the risk of poverty. However, solar PV deployment by major players may have the potential to substitute fossil fuels during the day time, allowing for lower electricity prices. However, small-scale solar PV deployment, by consumers, could enhance the autonomy of their electricity consumption, and also improve these households' living conditions.

Access to modern and affordable electricity, through RES generation, will require an effort by society overall, particularly by consumers. Policymakers and electricity providers should raise people's awareness of the advantages of real-time tariffs over flat rates, and of self-generation through solar PV. They could encourage consumers to shift their consumption from peak periods, when electricity prices are higher, towards off-peak periods, when they will benefit from reduced prices. Furthermore, they could stimulate consumers to shift their consumption to periods with a higher availability of natural resources, by rewarding them with lower prices, and thus sharing the surplus of energy transition with them.

RES subsidies should be discontinued, and the savings used in cost-effective climate protection policies, or to subsidize household energy efficiency and saving measures. Indeed, the implementation and accommodation of RES should be accompanied by DSM programs, to involve consumers in the operation of RES, and share with them part of the economic surplus derived from the deployment of RES. Further research is needed to more precisely understand the impact of energy transition on household incomes and budgets, and how to mitigate any adverse consequences. Therefore, future research should focus on the impact of this transition on society, and also on policies, measures and programs, such as DSM and energy efficiency and saving, to overcome the negative implications of RES deployment.

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Chapter 3

Could electricity demand contribute to diversifying the mix and mitigating CO_2 emissions? A fresh daily analysis of the French electricity system

This chapter was presented as a poster at GAPEER17 – Desafios da Gestão Ativa da Procura de Energia: Eficiência e Resposta, earning the prize “Prémio para o melhor poster jovem investigador – APEEN”. It was also presented at two conferences and invited to be published in a special issue of the conference - VII International Academic Symposium: Smart Energy Systems from a New Energy Policy Approach – which has resulted in a publication in *Energy Policy*. This chapter outputs are:

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Prize: Prémio para o melhor poster jovem investigador – APEEN, Associação Portuguesa da Economia da Energia

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Abstract

This paper introduces an innovative line of study to the current literature, by assessing the interactions, in France, between electricity sources, and periods with differing electricity consumption; namely morning off-peak, morning peak, middle off-peak, and night peak, using high-frequency data, specifically, daily data. This paper also analyses the impact of these interactions on both the diversification of the electricity mix, and on carbon dioxide emissions. Thus, this research could help identify the conditions needed, in both supply and demand, for a successful transition towards renewable energies. A Vector Autoregressive model has been employed to detect the presence of endogeneity, and to show the interactions between electricity supply and demand. Consumption in France has been problematic for the management of a portfolio containing rigid and intermittent base load sources. High peak consumption at night has increased the necessity to deploy a flexible electricity generating source, in other words, fossil fuels, and is one of the reasons for nuclear de-activation. In comparison, high morning peak consumption is rational and desirable. Indeed, morning peaks have been satisfied by a portfolio of renewable energies, decreasing the harmful impact of electricity on the environment, and keeping electricity costs low.

3.1 Introduction

Over time, countries have been forced to use fossil fuels to satisfy an increasing electricity demand caused mainly by: (i) persistent population expansion; (ii) the extension of electrification in different regions (rural regions); and (iii) the increasing electrification of the industrial, residential, services, heating, and transport sectors. However, an increase in the use of fossil fuels to generate electricity has been undertaken without proper environmental weighting. The coming era of energy transition will require a shift from conventional to renewable energy sources (RES), within a context of the increasing electrification of economies. This energy transition will face several challenges and barriers, such as peaks in electricity demand and RES intermittency. Thus, it is imperative to provide careful guidance on policy that will provide flexibility in electricity systems, not just in terms of supply, but also in terms of demand. The diversification of national electricity mixes must not be a merely theoretical goal, it is essential to analyse and understand the conditions of both the supply and demand sides to achieve a successful diversification.

Decisions on energy cannot just be about consuming and supplying more electricity, the crucial decisions concern what sources to develop, the consequences of deploying each source, the consequences of peak and off-peak consumption, and how to shift consumption to best exploit production from intermittent renewable energy sources (RES-I). These issues constitute the main motivation for this paper. This research intends to contribute to the literature, by identifying the conditions needed to successfully diversify the electricity mix by integrating more RES. To do this, this research analyses the relationships between periods of differing electricity demand (morning and middle day off-peak, morning and night peak), electricity sources, carbon dioxide (CO_2) emissions, and the degree of diversity of electricity sources. It is crucial to understand the changes that must occur, in both supply and demand sides, to allow a higher penetration of RES and, consequently, an increase in diversification, and a reduction in CO_2 emissions. The main innovative contributions of this paper are thus: (i) its focus on France's nuclear phase-out, by assessing its transition from nuclear power to RES; (ii) its use of empirical evidence from jointly studying both supply and demand sides through high-frequency data, to identify key factors for successfully integrating RES, diversifying the electricity mix, and mitigating CO_2 emissions; and (iii) its discussion and suggestions regarding additional measures for demand-side management (DSM), to achieve an effective transition towards RES, without compromising sustainable development. In summary, this paper contributes by disclosing how electricity demand can be used to help diversify the electricity mix and mitigate CO2 emissions, in a country which is shifting from nuclear power to RES.

Typically, literature analysing the interactions between electricity sources by studying the electricity growth-nexus, uses only either monthly or annual data (Apergis & Payne, 2011; Tiba & Omri, 2017). However, when electricity sources and consumption are assessed using these data frequencies, the real-time interactions can be lost, in the sense that they are diluted in the sum and mean values. In contrast, when the analysis is carried out on a daily and hourly basis, factors such as, forecasts of electricity consumption, valley and peak period consumption, temperature, wind power, solar photovoltaic (PV) electricity generation, and capacity factors can be assessed in detail. In this way, considering that the management of electricity supplies is made on a daily and hourly basis, and given the emerging availability of high-frequency data, i.e. intraday and daily data on electricity supply and demand, a more accurate and trustworthy assessment of the interactions can be carried out. Literature analysing the electricity market has used high-frequency data before, but only to study the effects of consumption and RES-I on electricity prices (Croonenbroeck & Stadtmann, 2019; Graf & Wozabal, 2013). This paper aims to fill this gap in the existing literature, by analysing the interactions between electricity demand periods and electricity production sources through high-frequency data.

In this research, a Vector Autoregressive (VAR) model was used to analyse electricity supply and demand in France from 1 January 2012 until 31 December 2018. This method can reveal the daily relationships between electricity sources, differing periods of electricity demand, wholesale electricity market prices, CO2 emissions from electricity production, the degree of diversity in the electricity mix, and imports and exports of electricity. The electricity sources have been disaggregated into wind power, solar PV, biomass, hydro power, coal, oil, natural gas, and nuclear power. The differing periods of electricity demand have been disaggregated into morning off-peak, morning peak, middle off-peak, and night peak consumption. Consequently, this paper aims answer the following research questions: (i) Could electricity demand contribute to diversifying the mix and mitigating CO2 emissions?; (ii) What are the daily incentives for France to dismantle her huge nuclear powered base load?; (iii) How effective has RES been in substituting both fossil fuels and nuclear sources?; and (iv) How have the daily peaks and off-peaks of electricity demand been satisfied?

This paper takes into consideration the individual characteristics of each source, and each differing period of electricity demand. Consequently, it is able to confirm that each source and consumption period has different effects and challenges for the management of electricity generation. The results indicate that electricity consumption in France, which is mainly residential (IEA, 2017), has been problematic for the management of the electricity system as a whole. High peak consumption at night has increased the need for flexible plants powered by fossil fuels to instantaneously match supply with demand. In contrast, peak consumption in the morning is desirable, because it is satisfied by a mix of RES-I, namely wind power and solar PV, and controllable RES, such as hydro power and biomass. In fact, morning peaks have reduced the harmful impact of electricity generation on the environment, as well as keeping the wholesale electricity price low. Therefore, the key points highlighted and supported by the results of this research should attract the attention of policymakers and be considered when setting electricity price tariffs.

Hereafter, this paper is set out as follows. Section 3.2 discusses French electricity statistics, and Section 3.3 covers the literature on interaction between electricity sources and DSM. Section 3.4 presents the data and specifies the econometric technique used. The results are shown in Section 3.5 and discussed in Section 3.6. Finally, the conclusions are presented in Section 3.7.

3.2 The French electricity system

Since 2004, France has decreased its carbon intensity by around 30% (IEA, 2017). Nowadays, the carbon intensity of the French economy is half the average for the Organization for Economic Co-operation and Development (OECD) (IEA, 2017). France has been trying to fully decouple its energy consumption and CO2 emissions from the growth of both its population and economy. To accomplish this, the French electricity mix has undergone several changes over time. In fact, population growth, and increases in industrial, and services activity has forced France to deploy a high installed capacity of nuclear power (Mbarek et al., 2015). Over the last decade, nuclear power has played a dominant role in France, accounting for 77.5% of electricity generation, and allowing a low-carbon emission electricity mix (IEA, 2017; Saidi & Ben Mbarek, 2016). Currently, the 563.2 terawatt-hours of electricity consumed, is produced as follows: 77.7% nuclear, 9.7% hydro power, 3.8% wind power, 3.5% natural gas, 2.2% coal, 1.5% solar PV, 1.3% biofuels and wastes, and 0.3% oil (IEA, 2017).

France has the second-largest nuclear energy capacity in the world, which has now reached a 30-year average lifespan. In early 2017, France’s government announced the beginning of its nuclear phase-out, with a plan to cut the share of nuclear power to 50% by 2025 (IEA, 2017). Furthermore, the French government has yet to decide whether to continue long-term operation, pending safety reviews (IEA, 2017). Nonetheless, France intends to reduce its greenhouse gas emissions by 40% by 2030, which will require several initiatives, and significant investment, as set out in the Energy Transition for Green Growth Act (*Loi relative à la transition énergétique pour la croissance verte*, (LTECV).

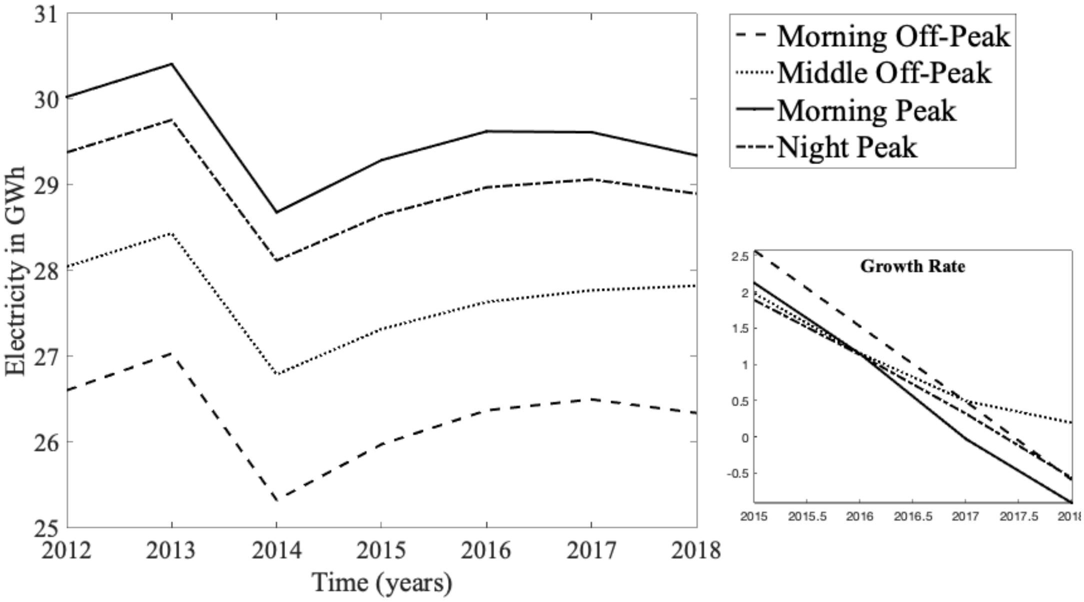

Figure 3.1. Evolution of electricity demand in the differing periods

Electricity demand peaks in France, can be observed in Figure 3.1. Morning and night peak consumption reached their maximums of 35 gigawatts/hour (GWh) and 28 GWh, respectively in 2013. These peaks are often caused by residential consumption, the sector which consumes the most electricity in France, representing 34.6% of total electricity demand (IEA, 2017). The commercial and public sectors account 32.9% and the industrial sector represents 25.8% of total electricity consumption (IEA, 2017). From 2013 to 2014, consumption in France has suffered an incremental reduction provoked by saving measures due to crisis periods (IEA, 2017). Consumption in both the morning and night peak periods remained above 28 GWh. However, since 2015, the growth rate graph in Figure 3.1 shows consumption in peak periods decreasing, while consumption in off-peak periods, mainly the middle off-peak period, was increasing. This reveals that electricity consumers may be changing their consumption patterns.

3.3 Literature Review

The need to evaluate the specific effects of RES and non-renewable energy sources (NRES) of electricity generation has prompted a change from aggregate analysis to investigating specific generation sources. This enables the evaluation of interactions between the technological characteristics of each electricity source (Marques et al., 2014). In formulating questions and hypotheses, the authors in the field have coined new terms to describe the interactions between electricity sources, such as the *baseload role*, the *backup role*, the *substitution effect*, and the *complementary effect*.

The literature has not unequivocally proved the substitution effect between RES and NRES (see Table 3.1). The literature often shows that RES generation causes electricity production from fossil fuels (Cerdeira Bento & Moutinho, 2016; Marques et al., 2014). However, unidirectional causality running from NRES to RES has been proven less frequently (Ben Jebli & Ben Youssef, 2015). The divergence in results and conclusions about the effects of RES had led some authors to argue that RES have not had the expected effect, and could continue to limit their desired benefits (Flora et al., 2014; Glasnovic & Margeta, 2011; Nel & Cooper, 2009). In contrast to fossil fuels, the installed capacity of RES-I does not represent their effective generation capacity, because of their physical restrictions, and their dependence on the availability of natural resources.

The need to understand how to integrate RES-I into electricity production systems, as well as their implications for economies and for the continued use of fossil fuels, has receive a good deal of attention. RES-I, and their negative consequences have prompted analysis of the drivers of both the capacity factor and idle capacity of RES (Boccard, 2009; Flora et al., 2014). The literature has also studied the impacts of RES on the environment and fossil fuel use, to ascertain the real influence of RES in reducing CO2 emissions (Tiba & Omri, 2017). Consequently, it has been argued in the literature that the expected benefits of RES-I will continue to be limited if their production technologies are not enhanced (Flora et al., 2014; Glasnovic & Margeta, 2011; Nel & Cooper, 2009). The difficulties encountered in attempting to match RES-I electricity generation with unpredictable electricity demand, and the unavailability of large electricity storage to defer consumption of RES-I generation, has stimulated the study of DSM policies and measures. Through these, the demand-side may be able to add flexibility to electricity management systems and harness RES-I production more precisely (Auer & Haas, 2016).

Table 3.1. Summary of the interactions between electricity sources

Author(s)	Period	Country(ies)	Methodology	Main results
(Apergis et al., 2010)	1984 - 2007	19 developed and developing countries	Panel Error Correction Model	RESNUC
(Apergis and Payne, 2012)	1990 - 2007	80 countries	Multivariate Panel Error Correction model	RESNRES
(Marques et al., 2014)	2004m8-2013m10	Greece	Johansen cointegration VECM	RESNRES HydroNRES HydroRES
(Al-mulali et al., 2014)	1980 - 2010	18 Latin American countries	DOLS Granger causality	RES NRES
(Salim et al., 2014)	1980 - 2011	29 OECD countries	Westerlund cointegration test Pooled Mean Group Panel Granger Causality	NRESRES
(Marques and Fuinhas, 2015)	2007m1-2012m10	Portugal	VAR Granger Causality	RESNRES
(Dogan, 2015)	1990 - 2012	Turkey	ARDL approach VECM Granger causality	NRESRES
(Ben Jebli and Ben Youssef, 2015)	1980 - 2009	Tunisia	ARDL bounds test VECM Granger causality	NRESRES
(Kahia et al., 2016)	1980 - 2012	5 MENA Net Oil Exporting Countries	FMOLS PECM	RESNRES
(Furuoka, 2016)	1992 - 2011	3 transition economies in the Baltic region	Homogeneous and heterogenous panel methods (granger causality)	NRESRES
(Dogan, 2016)	1988 - 2012	Turkey	ARDL Approach VECM Granger causality test.	RESNRES
(Cerdeira Bento and Moutinho, 2016)	1960 - 2011	Italy	ARDL approach Toda-Yamamoto causality test	RESNRES
(Mbarek et al., 2015)	1990 - 2013	9 developed countries	FMOLS and DOLS VECM Granger causality	RES Nuclear Nuclear RES
(Marques et al., 2016b)	2010m1-2014m11	France	ARDL approach	NUC Fossil RES NUC
(Marques and Fuinhas, 2016)	2006m1-2014m6	Portugal	ARDL approach	Hydro, Thermal SR Wind OR
(Asafu-Adjaye et al., 2016)	1990 - 2012	53 exporter and importer countries	Pooled Mean Group estimator	NRESRES RES NRES
(Marques et al., 2016a)	2004m8 – 2014m2	Greece	ARDL approach	NRES RES RES NRES
(Amri, 2017)	1980 - 2012	Algeria	VECM Granger causality	RES NRES
(Kahia et al., 2017)	1980 - 2012	11 MENA Net Oil Importing Countries	FMLOS and Panel VECM Granger causality	RESNRES
(Marques et al., 2018a)	2013m1 – 2016m1	Spain	ARDL approach	NRES RES
(Marques et al., 2018b)	1990 – 2014	10 European countries	ARDL approach through Driscoll and Kraay	Hydro NRES RES-I Coal RES-I Gas
(Marques and Fuinhas, 2018)	2008m7 – 2016m11	Germany	ARDL approach	NRES NUC NUC NRES RES NRES
	1 January 2015– 28 February 2017	Germany	VAR	RESNRES
(Bekun et al., 2019)	1996 - 2014	16 European countries	Pooled Mean Group ARDL approach	RESNRES
(Marques et al., 2019a)	2010m1 – 2017m2	Spain	ARDL approach	Sol NUC NUC Hydro
(Marques et al., 2019b)	1996 - 2017	46 countries	ARDL approach through Driscoll and Kraay	NRES RES Gas Solar

High levels of RES-I deployment have shown the crucial importance of matching electricity demand with supply availability. Thus, recent literature has presented one solution, DSM, to enable and enhance the flexibility of electricity system through the demand-side (Meyabadi & Deihimi, 2017). The main objectives of DSM are to shift electricity consumption patterns, and raise consumer awareness about the harmful effects of electricity generation on the environment (Alasseri et al., 2017; Bahl et al., 2017; Meyabadi & Deihimi, 2017). DSM programmes could be helpful in achieving the desired transformations in the electricity load shape, namely peak-clipping, valley-filling, and the synchronization of consumption with the availability of natural resources, such as wind power and solar PV (Alasseri et al., 2017; Bahl et al., 2017; Meyabadi & Deihimi, 2017). Therefore, the application of DSM measures, along with the advent of smart grids, and distributed energy sources, has been indicated as a way of mitigating the harmful effects of the electricity sector on the environment, energy access, energy affordability, and energy security.

Energy Load Management (ELM) aims to develop, implement, and monitor programmes intended to stimulate changes in electricity demand patterns. Furthermore, it aims to divert some electricity requirements from peak to off-peak periods, engaging consumers through tariffs, rewards or penalties, and individual indicators that can provide information (Meyabadi & Deihimi, 2017). ELM can be divided into three alternatives: (i) direct load control, through the implementation of technological measures by utilities; (ii) indirect control, through several forms of electricity tariffs and pricing schemes; and (iii) energy storage control, with the purpose of deferring consumption of RES generation (Kinhekar et al., 2014; Meyabadi & Deihimi, 2017). As this research also analyses the impact of wholesale electricity market prices, or so-called real-time electricity price, it is important to highlight Demand Response (DR) programmes. DR focuses on price-responsive programmes, and on incentive schemes to change consumption routines, with the aim of reducing electricity demand during critical grid condition periods (Meyabadi & Deihimi, 2017). These critical conditions occur when the electricity price is high, or when rapid or large changes in electrical charges could damage the electrical equipment of both generators and consumers, thus jeopardising energy security.

In summary, the literature has expanded the electricity growth-nexus by analysing it through disaggregating electricity sources. At the same time, academic papers have studied the interactions between electricity sources. The literature argues that, to effectively use RES-I, storage capacity and cost-effectiveness must be enhanced so that the dependence of RES-I on backup from fossil fuels is eliminated. In fact, the backup needed by RES-I provokes negative effects on economic activity, because of the significant economic inefficiencies in allocating resources, particularly those associated with idle capacity. Thus, DSM programmes are crucial to provide the flexibility required in electricity system management, and to increase the penetration of electricity generated from RES-I. Therefore, intervening in demand will be decisive for RES-I to effectively substitute fossil sources and preserve healthy economic activity in the future.

3.4 Data and Methodology

This research uses daily data from 1 January 2012 to 31 December 2018, totalling 2,557 observations. All the electricity supply and demand data has been obtained from the French transmission system operator, *Réseau de transport d'électricité* (RTE). RTE has provided data on electricity generated daily from each source, namely wind power, solar PV, biomass, hydro power, nuclear, oil, coal, and natural gas; daily imports and exports of electricity; CO2 emissions from electricity production; and the wholesale electricity market price; the intraday electricity consumption, in 30-minute periods; and the start and finish times of the morning and night peak periods. The daily average temperature, precipitation index, mean visibility index, mean wind speed, and the maximum wind gust were obtained from the National Oceanic and Atmospheric Administration database.

The morning peak, in the sample analysed, occurs in 21% of the days between 7:30 a.m. and 1.30 p.m., in 13% of the days between 9 a.m. and 3 p.m., in 9% of the days between 8:30 a.m. and 2:30 p.m., and in 9% of the days between 8 a.m. and 2 p.m. The night peak, in the sample analysed happens in 27% of the days between 6 p.m. and 8 p.m., in 14% of the days between 6:30 p.m. and 8:30 p.m., and in 5% of the days between 7 p.m. and 9 p.m. The off-peak consumption in the middle of the day is the consumption period between the finish of the morning peak and the beginning of the night peak. The middle off-peak period generally has flat electricity consumption. The off-peak consumption in the morning is the consumption period from the finish of night peak until the beginning of morning peak. On most days, the morning off-peak period has a valley consumption. The daily electricity peak consumption during morning and night periods, as well as the daily electricity off-peak consumption during middle and morning periods was calculated using the intraday consumption and the peak time data, given by RTE, through the equations (3.1), (3.2), (3.3), and (3.4).

$$PEAK\_AM_i = \sum_{h=AMI_i}^{AMF_i} cons_{i,h} \tag{3.1}$$

$$PEAK\_PM_i = \sum_{h=PMI_i}^{PMF_i} cons_{i,h} \tag{3.2}$$

$$OFF\_MID_i = \sum_{h=AMF_i+00:30}^{PMI_i-00:30} cons_{i,h} \tag{3.3}$$

$$OFF\_AM_i = \sum_{h=PMF_{i(-1)}+00:30}^{23:30} cons_{i(-1),h} + \sum_{h=00:00}^{AMI_i-00:30} cons_{i,h} \tag{3.4}$$

where, $cons_{i,h}$ is the electricity consumption on day i, at h hours, the AMI_i and the AMF_i are the start and finish times of the morning peak on day i, and the PMI_i and the PMF_i are the start and finish times of the night peak on day i. The degree of diversity of electricity sources was computed using the Shannon-Weaver index (see eq. 3.5), which is considered the most suitable measure of energy diversity, because it incorporates the concepts of variability and balance (Western, 1995).

$$Divers_{\mathrm{i}} = -\sum\nolimits_{k} p_{i,k} * \ln(p_{i,k}) \tag{3.5}$$

In this equation, $p_{i,k} = {}^{g_{i,k}}/_{G_i}$, $p_{i,k}$ is the share of electricity produced in day i by source k, $g_{i,k}$ is the total amount produced by the electricity source k on day i, and G_i is the total electricity produced on day i. This diversification index has been employed to reveal the effect of electricity sources and electricity consumption on the level of diversification of the electricity mix, as well as, to show the consequences of a diversified electricity mix on the supply and demand side. All the daily series used in this research are shown in Table 3.2, along with their definitions, units of measurement, and descriptive statistics. After this, all series have been transformed into their natural logarithm denoted by the "*L*" prefix. The "*G*" prefix represents the growth rate, which has been used to transform the degree of diversification index series.

Table 3.2. Series definition, and descriptive statistics

Name	Definition	Obs.	Mean	Max.	Min.	S.D.	Skew.	Kurt.	Jarque-Bera
WIND	Electricity produced from wind power (MWh)	2471	56183.33	270501.00	3585.00	40687.73	1.54	5.68	1722.863***
SOL	Electricity produced from solar PV (MWh)	2471	19142.99	54763.50	1044.50	11430.52	0.71	2.76	214.1905***
BIO	Electricity produced from biomass (MWh)	2471	21683.68	31923.00	11280.50	4193.59	-0.10	1.96	114.807***
HYDRO	Electricity produced from hydro power (MWh)	2471	175501.40	303401.00	50387.00	53612.16	0.00	2.02	98.1854***
COAL	Electricity produced from coal (MWh)	2471	29840.46	137207.50	0.00	28091.76	1.00	3.49	433.5524***
NUC	Electricity produced from nuclear (MWh)	2471	1094422.00	1460228.00	718316.50	160568.40	0.38	2.15	134.3328***
OIL	Electricity produced from oil (MWh)	2471	8292.91	93093.00	2274.00	6723.99	5.59	51.89	258963.6***
GAS	Electricity produced from natural gas (MWh)	2471	72975.75	225714.00	7671.00	55127.60	0.72	2.43	246.1865***
PUMP	Electricity consumption for pumping (MWh)	2471	19561.43	55123.00	1566.00	9237.58	1.21	3.90	684.1343***
PEAK_AM	Electricity consumption at morning peak hours (MWh)	2471	350888.18	642419.50	100924.50	106053.74	-0.14	2.64	22.318***
PEAK_PM	Electricity consumption at night peak hours (MWh)	2471	157992.91	457299.00	62525.00	52415.53	1.50	8.06	3557.8039***
OFF_AM	Electricity consumption at night and morning off-peak hours (MWh)	2471	560289.69	1114775.00	261634.50	166764.60	0.47	2.32	139.7023***
OFF_MI	Electricity consumption at middle off-peak hours (MWh)	2471	240910.66	548868.00	62921.50	69846.34	0.09	2.60	19.9094***
RXM	Coverage electricity imports by exports (ratio)	2471	0.31	17.79	0.00	0.71	9.81	176.69	3145712***
CO2	Carbon dioxide emissions (g/KWh)	2471	2570.75	6137.00	860.00	1096.53	0.42	2.30	121.8839***
PRICE	Electricity price (€/MWh)	2471	42.03	215.82	10.42	15.77	1.71	12.18	9882.388***
SHI	Degree of diversification of electricity sources (Shannon-Weaver Index)	2471	0.93	1.29	0.57	0.11	-0.12	2.77	11.1153***
TEMP	Mean temperature (Fahrenheit)	2471	54.14	79.14	21.96	10.99	-0.03	2.25	57.85098***
PRCP	Precipitation amount (0.1 inches)	2471	0.08	0.71	0.00	0.10	1.73	6.41	2432.31***
VISIB	Mean visibility (0.1 miles)	2471	8.82	15.51	2.28	1.80	-0.16	3.16	13.31079***
WDSP	Mean wind speed (0.1 knots)	2471	6.95	17.25	2.64	2.09	0.94	4.09	487.6663***
GUST	Maximum wind gust (0.1 knots)	2471	26.38	43.10	7.50	5.19	0.03	3.33	11.86058***

Notes: Obs. means observations, Max. maximum, Min. minimum, S.D. standard deviation, Skew. skewness, and Kurt. kurtosis.

Working with daily data brings several challenges, as is well recognised in the literature and demonstrated by Figure 3.2, specifically, white noise in the series, and extreme values. The literature argues that extreme values generate outliers and biased results (Aït-Sahalia & Xiu, 2017; At-Sahalia et al., 2011; Cao & Tay, 2001; Li et al., 2017; Zhong & Enke, 2017). Nevertheless, when studying both the supply and demand sides of electricity, it is inappropriate to call outliers extreme values. Extreme values of generation and consumption occur every day, and they are a genuine concern for the systems management services and transmission system operators who must respond to them. Therefore, the exclusion of these extreme values could produce erroneous and biased results, and it is important they are considered, to reflect the pressures experienced in the daily management of electricity systems, such as congestions and peak consumption.

Regarding seasonality, it can be seen that all series suffer from seasonality effects, and the seasonal pattern is closely related to the mean temperature. Solar PV production reacts very similarly to the mean temperature; when the temperature rises, solar PV production increases. However, the other variables react conversely, this means, when the temperature rises, generation and consumption decreases, and when the temperature drops, generation and consumption increases. This seasonality is a concern for the electricity systems, because it affects both the demand-side and RES-I. Therefore, in its estimations, this research will use the weather series to control the seasonal effects, using an approach that supports a complex multiple seasonality framework, such as the VAR (Ghysels & Osborn, 2001; Sims, 1980).

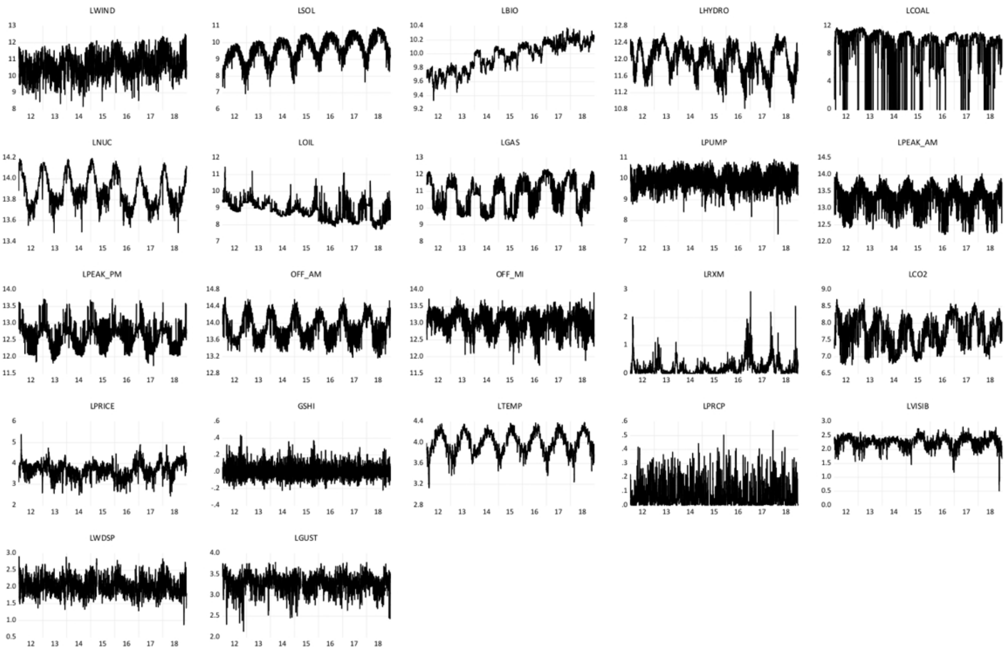

Figure 3.2. Series used in the research

The Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981), the Phillips and Perron (PP) test (Phillips & Perron, 1988), and the Kwiatkowski Schmidt Shin (KPSS) test (Kwiatkowski et al., 1992) were performed to assess the integration order of the series (see Table 3.3). The ADF tests were carried out under the null hypothesis of unit root, following the Schwartz information criterion. The PP and the KPSS tests followed the Bartlett Kernel Spectral estimation method and the Newey-West-bandwidth. The null hypothesis of the PP tests was the existence of a unit root, and the null hypothesis of the KPSS tests was the non-existence of a unit root. The results of the integration order tests reveal a lack of consensus with those from the KPSS, but it should be noted that this test is not robust in the presence of extreme values (Kwiatkowski et al., 1992). Overall, the integration order tests indicate that the series used are I(0) in their levels, with intercept, and with intercept and trend.

Table 3.3. Integration order tests results

Tests	ADF		PP		KPSS	
Series	**C**	**CT**	**C**	**CT**	**C**	**CT**
LWIND	-17.2661***	-18.396***	-27.4676***	-27.1199***	1.9311***	0.0463
LSOL	-3.4834***	-3.5933**	-14.62***	-19.1438***	1.9906***	0.0606
LBIO	-4.416845***	-6.3933***	-4.049311***	-8.6876***	5.5579***	0.2583***
LHYDRO	-3.9952***	-4.1233***	-15.2522***	-15.8693***	0.5376**	0.0685
LCOAL	-6.6702***	-6.7634***	-28.2336***	-28.228***	0.2709	0.1568**
LNUC	-3.5158***	-3.4065*	-8.6854***	-8.9066***	0.3204	0.0699
LOIL	-3.996***	-4.4425***	-20.552***	-23.5413***	1.8941***	0.2136**
LGAS	-3.1868**	-3.5198**	-15.6838***	-16.5413***	0.8376***	0.1693**
LPUMP	-6.1016***	-6.1019***	-40.4615***	-40.4541***	0.1463	0.1521**
LPEAK_AM	-4.1562***	-4.1399***	-50.453***	-50.4372***	0.0892	0.0352
LPEAK_PM	-3.6928***	-3.6595**	-61.6556***	-61.7568***	0.0994	0.0743
LOFF_AM	-2.7837***	-2.8126***	-31.8306***	-31.8469***	0.0518	0.0412
LOFF_MI	-5.5529***	-5.8353***	56.6681***	-56.4261***	0.7015**	0.0707
LRXM	-5.8296***	-5.9493***	-11.5072***	-11.7595***	0.6403**	0.1814**
LCO2	-4.2505***	-4.2536***	-19.0763***	-19.0946***	0.2876	0.2508***
LPRICE	-4.5757***	-4.6107***	-25.8535***	-25.9256***	0.4772**	0.4348***
GSHI	-14.2167***	-14.3012***	-88.9507***	-89.7326***	0.1419	0.0317
LTEMP	-5.5527***	-5.5515***	-5.7245***	-5.7096***	0.0791	0.0398
LPRCP	-28.2831***	-28.3039***	-28.6292***	-28.6323***	0.221	0.0724
LVISIB	-11.7268***	-11.7336***	-15.3004***	-15.3096***	0.0519	0.0434
LWDSP	-19.0876***	-19.215***	-23.8832***	-23.8249***	0.4614*	0.0567
LGUST	-29.0232***	-29.0388***	-34.4234***	-34.4087***	0.0853	0.0523

Notes: c means constant, CT constant and trend. ***, **, * indicate that the statistic is significant at 1%, 5% and 10% levels, respectively.

The VAR model was required because the series are integrated of order zero and there are complex multiple seasonality patterns which exhibit endogeneity due to: (i) the dependency of some sources on the availability of others; (ii) consumption periods triggering the use of different sources; and (iii) CO_2 emissions, the degree of diversification of electricity sources, and wholesale electricity market prices are all dependent on the daily electricity mix and consumption. The VAR methodology treats all series as potentially endogenous, and it assesses the relationships without needing to distinguish between endogenous and exogenous series. This property is a prerequisite of the simultaneous equation models. The VAR model were specified as follows:

$$\boldsymbol{Y}_t = \sum_{j=1}^{\alpha} \gamma * \boldsymbol{Y}_{t-1} + \varphi * \boldsymbol{X}_t + \omega_t \tag{3.6}$$

where, $\boldsymbol{Y}_t$ is the vector of the endogenous series, and $\boldsymbol{X}_t$ is the vector of the exogenous series, γ is the coefficient matrix of endogenous series, φ is the coefficient matrix of exogenous series, ω_t represents the residuals, and α is the optimal number of lags. The procedures followed in the VAR model estimation were to: (i) test the collinearity and multicollinearity using the correlation matrix and variance inflation factors (VIF) statistics; (ii) choose the optimal number of lags, supporting the choice through exclusion tests of lag number; (iii) test the stability condition of the models; (iv) carry out the Granger block exogeneity test; (v) perform residual diagnostic tests, to verify the normality, autocorrelation and heteroskedasticity of residuals; (vi) compute the Variance Decomposition (VDC); and (vii) estimate the Impulse Response Functions (IRF).

3.5 Results

After inspecting the correlation matrix and VIF statistics, it was concluded that the LSHI causes collinearity and multicollinearity, as was expected. To overcome this problem, SHI was transformed by the growth rate. Then, collinearity and multicollinearity were set aside (see Tables A.3.1 and A.3.2 in appendix). The VAR results revealed that all series are endogenous except the weather series (*LTEMP*, *LPRCP*, *LVISIB*, *LWDSP*, and *LGUST*), which are exogenous, as expected. The exogeneity demonstrated by the weather series reveals that electrical systems use them to anticipate potential RES-I generation, and some electricity demand patterns, such as the use of air conditioners and heating systems. In this way, the electrical systems could anticipate some supply and demand characteristics by activating or deactivating base loads, or putting flexible sources in standby mode, meaning that they are ready to operate when necessary. The VAR lag length was selected through the Schwartz, Hannan-Quinn, and Akaike information criteria, suggesting that the VAR(1), and VAR(8), respectively, were the best-fitting models. To overcome the non-consensual information criteria, the Wald lag exclusion test was employed, and showed that the optimal number of lags is one, i.e. VAR(1). This result is a sign of the absence of omitted-variable bias.

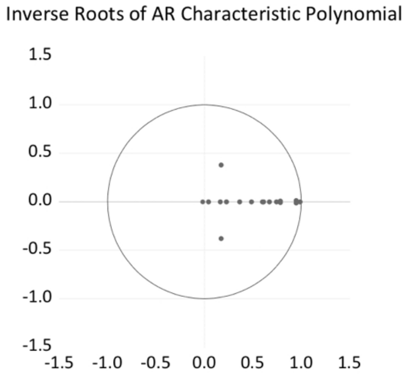

Figure 3.3. Eigenvalue stability condition

Financial econometrics, a discipline that often studies high-frequency series, as well as literature on electricity markets, suggests that it is difficult to separate underlying trends and patterns from random features, which are persistent in high-frequency data analysis (Brooks, 2008; Croonenbroeck & Stadtmann, 2019; Graf & Wozabal, 2013). In our analysis, these patterns and underlying trends are expected, because of; (i) the way the electricity system and market operates; (ii) the random path of RES-I generation; (iii) the way that electricity sources are managed; and (iv) the way that consumption routines and random patterns are recorded in the series. However, both the underlying trends and random features are essential to this analysis, but the use of weather series attenuates these problems.

This research data is not normally distributed (see Table 3.2), as it is in high-frequency financial econometrics data analysis, as is the norm with econometric techniques (Brooks, 2008). The extreme values, as mentioned previously, are a genuine concern for electricity system management, and result in distributions with fat tails in the series, which are indicated by their kurtosis values. These extreme values could provoke the non-normality of both the series and VAR model. However, in many cases extreme values have no other consequences than this non-normality of the series. In the study of electricity consumption and generation, extreme values should not only be seen from a statistical point of view. In fact, these extreme values are points of consumption that have to be met with supply, and it is therefore pertinent for system managers to understand the consequences these values bring to the challenge of managing the system as a whole. Besides, as this research performs a VAR, the non-normality of the series and extreme values are not a concern for confidence in the robustness of its results. Nonetheless, concerns regarding non-normal series with fat tails could be addressed by using quantile modelling statistics and quantile regressions, or by the application of extreme distribution based on Extreme Value Theory methods, which describe and design extreme scenarios.

Table 3.4. Granger causality and exogeneity blocks

	LWIND	LSOL	LBIO	LHYDRO	LCOAL	LNUC	LOIL	LGAS	LPUMP	LPEAK_AM	LPEAK_PM	LOFF_AM	LOFF_MI	LRXM	LCO2	LPRICE	GSHI
LWIND does not cause	-	***	***	**	NS	NS	**	***	NS	**	NS	***	**	**	***	***	***
LSOL does not cause	***	-	**	***	***	***	NS	NS	***	***	***	***	***	**	NS	***	NS
LBIO does not cause	***	***	-	***	***	NS	***	NS	***	***	NS	***	***	**	***	***	*
LHYDRO does not cause	***	***	***	-	NS	NS	***	**	NS	***	***	***	***	***	***	**	***
LCOAL does not cause	NS	**	*	NS	-	***	NS	***	NS	NS	***	NS	NS	NS	NS	NS	***
LNUC does not cause	*	***	NS	**	***	-	NS	**	**	***	NS	***	***	***	NS	NS	***
LOIL does not cause	**	***	NS	NS	**	*	-	NS	NS	NS	NS	NS	**	***	NS	*	***
LGAS does not cause	***	NS	NS	NS	NS	NS	NS	-	***	***	***	***	NS	NS	***	NS	***
LPUMP does not cause	**	**	***	***	***	***	***	***	-	***	NS	*	***	**	***	***	***
LPEAK_AM does not cause	NS	NS	***	***	***	***	***	***	***	-	NS	***	**	**	***	***	***
LPEAK_PM does not cause	NS	NS	NS	***	***	***	**	***	***	***	-	***	NS	NS	***	***	***
LOFF_AM does not cause	NS	***	**	***	***	NS	***	**	***	***	**	-	***	NS	**	NS	***
LOFF_MI does not cause	NS	***	***	NS	NS	NS	*	NS	NS	NS	***	***	-	NS	NS	NS	NS
LRXM does not cause	NS	NS	NS	NS	NS	NS	NS	***	***	***	**	***	***	-	***	**	***
LCO2 does not cause	NS	NS	*	NS	***	***	NS	NS	***	***	***	***	***	NS	-	***	***
LPRICE does not cause	***	***	NS	***	***	***	***	NS	**	NS	NS	***	NS	***	***	-	***
GSHI does not cause	NS	*	**	***	***	***	***	***	***	***	NS	NS	NS	***	***	***	-
All does not cause	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***	***

Notes: “ALL” denotes the causality test set for all independent series. ***, **, and * denote the statistical significance at 1%, 5%, and 10%, respectively, and NS denotes the non-statistical significance.

For the reasons, mentioned above, it was expected, though not desired, that the VAR model estimated would fail to reject the null hypothesis of all the diagnostic tests. However, the literature argues that it is still possible to estimate a feasible VAR model with high-frequency data that does not assume normality, homoscedasticity, and non-autocorrelation (Brooks, 2008). It is often shown that, when the sample contains a great deal of information, the violation of diagnostic tests is virtually inconsequential (Brooks, 2008). This argument is corroborated by the central limit theorem, which states that high-frequency statistics, and econometric procedures using them, will asymptotically follow the appropriate distribution, even when the diagnostic tests are rejected (Brooks, 2008). Thus, the violation and non-rejection of heteroskedasticity, normality, and autocorrelation are a minor concern and inconsequential in the assessment of a large sample, such as the one used in this research containing 2,471 daily observations.

The stability of the models (see Fig. 3.3), is supported once the p-values are inside the circle, i.e., the values are below one. This result corroborates what was previously stated about the extreme values in both electricity supply and demand. The large number of Granger causalities found (see Table 3.4), underlines that endogeneity is present in the interactions between the French electricity supply and demand sides, and can be seen as further enhancing confidence in the robustness of the results. Furthermore, the VDC (see Table 3.5) and the IRFs (Figure A.3.1 in appendix) also reveal the dynamic behaviour, which is a requirement of endogeneity. Both VDC and IRFs was computed following the Cholesky order, ordering the series from the most endogenous to most exogenous. The IRF corroborated the integration order tests, since all IRFs tended to zero.

Table 3.5. Variance decomposition

Period	S.E.	*LWIND*	*LSOL*	*LBIO*	*LHYDRO*	*LCOAL*	*LNUC*	*LOIL*	*LGAS*	*LPUMP*	*LPEAK_AM*	*LPEAK_PM*	*LOFF_AM*	*LOFF_MI*	*LRXM*	*LCO2*	*LPRICE*	*GSHI*
Variance Decomposition of LWIND																		
2	0.2642	98.0507	0.1431	0.6914	0.0746	0.0335	0.1024	0.1971	0.2207	0.0535	0.0860	0.0304	0.0239	0.0204	0.0690	0.0001	0.2022	0.0010
30	0.3120	70.5875	0.2451	14.4709	0.4437	1.2770	0.7475	0.9038	7.0425	0.6791	0.3025	0.2922	0.1505	0.1701	1.1501	0.3983	1.1054	0.0337
180	0.3527	55.3340	0.2695	23.6546	1.6368	1.7357	0.9715	0.7786	10.4517	0.7816	0.3092	0.5029	0.1926	0.2620	1.6043	0.5104	0.9547	0.0497
365	0.3539	54.9727	0.2699	23.8759	1.6749	1.7455	0.9796	0.7750	10.5245	0.7815	0.3087	0.5084	0.1934	0.2642	1.6132	0.5125	0.9498	0.0501
Variance Decomposition of LSOL																		
2	0.3405	0.0800	98.1334	0.1860	0.1987	0.0179	0.2464	0.1344	0.1344	0.1863	0.0480	0.0627	0.2382	0.0864	0.0066	0.0801	0.1517	0.0088
30	0.4724	0.0632	69.4035	7.6641	8.8372	0.0369	9.1337	1.3853	0.6948	0.5339	0.1971	0.1373	0.3295	0.4916	0.1765	0.0936	0.8072	0.0146
180	0.5078	0.1047	60.2938	13.9544	10.4993	0.2941	8.1213	1.2513	2.4648	0.4994	0.1781	0.3096	0.3056	0.4778	0.3786	0.1411	0.7034	0.0227
365	0.5088	0.1062	60.0630	14.1210	10.4874	0.3054	8.0985	1.2474	2.5381	0.5004	0.1783	0.3136	0.3056	0.4783	0.3885	0.1437	0.7015	0.0230
Variance Decomposition of LBIO																		
2	0.0388	0.4317	0.2636	90.8375	3.9111	0.2143	0.9814	0.0049	0.4292	1.2141	1.4855	0.0031	0.0757	0.1297	0.0000	0.0061	0.0003	0.0116
30	0.1359	0.5053	0.8407	62.5450	13.3191	2.1803	2.1655	0.0333	13.4063	0.5017	0.3294	1.3659	0.1675	0.4703	1.4471	0.6283	0.0086	0.0856
180	0.1927	0.4968	0.5725	59.9794	10.9506	2.6344	2.3149	0.1102	17.0347	0.5311	0.2524	1.3765	0.2318	0.5361	2.1122	0.6984	0.0716	0.0965
365	0.1942	0.4967	0.5687	59.9382	10.8970	2.6431	2.3132	0.1121	17.1025	0.5346	0.2521	1.3759	0.2331	0.5370	2.1251	0.7003	0.0738	0.0967
Variance Decomposition of LHYDRO																		
2	0.1571	0.8219	0.3194	1.9408	87.0097	0.0715	1.3085	0.0525	0.0018	3.7351	2.7627	1.4436	0.1008	0.0019	0.0012	0.1797	0.1056	0.1433
30	0.2708	0.4728	0.3802	1.5764	58.1423	1.7223	2.1949	3.2121	8.0443	14.4488	3.8604	0.6252	0.2904	0.1568	1.3437	1.0285	2.4349	0.0661
180	0.2790	0.4589	0.3763	2.4903	55.8256	1.8286	2.1182	3.2239	8.9606	14.3886	3.8137	0.5984	0.3072	0.1604	1.5700	1.0650	2.7496	0.0648
365	0.2791	0.4590	0.3763	2.5237	55.7961	1.8294	2.1183	3.2221	8.9682	14.3803	3.8115	0.5988	0.3072	0.1606	1.5708	1.0649	2.7481	0.0648
Variance Decomposition of LCOAL																		
2	2.5373	0.1525	0.1731	1.2084	6.2992	84.7666	0.3634	0.0182	1.0501	0.6222	1.2011	1.2255	0.0457	0.0025	0.0103	2.6794	0.0849	0.0971
30	2.9929	0.2062	0.3924	2.1578	7.6801	69.0547	2.2338	0.2713	3.8273	2.1215	2.4238	1.1935	0.0828	0.1246	0.1827	5.3076	2.6384	0.1013
180	3.0155	0.2069	0.3913	2.6177	8.0004	68.0383	2.4360	0.2752	3.8561	2.1619	2.4064	1.1989	0.0828	0.1300	0.1910	5.2317	2.6746	0.1009
365	3.0158	0.2070	0.3913	2.6308	8.0002	68.0228	2.4360	0.2752	3.8603	2.1615	2.4059	1.1989	0.0829	0.1301	0.1916	5.2306	2.6740	0.1009
Variance Decomposition of LNUC																		
2	0.0512	0.0782	0.0736	0.7362	12.5081	5.8362	75.0140	0.1200	0.1603	1.1996	1.9038	1.2960	0.0099	0.0307	0.0028	0.6643	0.1783	0.1880
30	0.0910	0.0471	7.5751	0.2880	4.5539	2.1796	74.7090	0.8693	0.1228	2.8502	2.6235	0.7001	0.0225	0.2687	0.0640	0.2575	2.7531	0.1155
180	0.0924	0.0469	7.7608	0.4209	4.9937	2.1269	74.0696	0.9622	0.1407	2.7814	2.5543	0.6830	0.0248	0.2731	0.0640	0.2506	2.7339	0.1131
365	0.0924	0.0469	7.7602	0.4255	4.9939	2.1270	74.0638	0.9622	0.1424	2.7812	2.5541	0.6831	0.0248	0.2731	0.0643	0.2507	2.7337	0.1131
Variance Decomposition of LOIL																		
2	0.3395	0.1346	0.0741	1.5514	2.4942	0.0072	0.6348	94.0032	0.0037	0.2401	0.2339	0.0797	0.1086	0.0895	0.0065	0.0201	0.2777	0.0408
30	0.4354	0.1205	0.9303	8.6062	8.0122	0.0847	0.5980	75.2031	1.4018	0.7174	0.3906	0.2842	0.1187	0.4748	0.0559	0.0768	2.8904	0.0345
180	0.4667	0.1631	0.8569	14.8361	8.8839	0.3993	0.8770	65.4646	3.4139	0.6625	0.3504	0.4447	0.1314	0.4855	0.3185	0.1392	2.5302	0.0429
365	0.4676	0.1643	0.8548	14.9993	8.8782	0.4101	0.8821	65.2136	3.4835	0.6628	0.3499	0.4481	0.1322	0.4860	0.3287	0.1418	2.5213	0.0431
Variance Decomposition of LGAS																		
2	0.4398	0.2872	0.2715	1.2450	10.2918	2.0511	0.8469	2.1862	77.8572	1.2909	2.2194	0.8945	0.0221	0.0242	0.2291	0.1410	0.0045	0.1374
30	0.6237	0.2118	2.6776	3.6244	7.2575	2.6070	0.6258	2.6888	69.0476	3.1782	2.7183	0.5564	0.2307	0.1950	3.0176	0.3726	0.8933	0.0976
180	0.6564	0.2370	2.4576	8.0545	6.8298	2.7376	0.6279	2.5282	64.9278	3.2610	2.5538	0.5872	0.2537	0.2274	3.1509	0.4607	1.0071	0.0976
365	0.6573	0.2377	2.4519	8.1841	6.8314	2.7389	0.6321	2.5222	64.8134	3.2544	2.5477	0.5892	0.2539	0.2284	3.1504	0.4617	1.0050	0.0977
Variance Decomposition of LPUMP																		
2	0.4060	0.5717	2.0693	1.6589	39.6090	3.2515	3.0526	0.6173	5.2814	38.3108	2.1798	1.9087	0.1674	0.0146	0.0472	0.8739	0.0768	0.3089
30	0.4228	0.7571	2.7886	1.7961	37.3746	3.0636	4.8015	0.7233	5.1696	35.6016	3.6847	2.0650	0.2412	0.2569	0.1521	1.0500	0.1502	0.3239
180	0.4235	0.7561	2.7913	1.8930	37.2661	3.0623	4.8930	0.7252	5.1979	35.4946	3.6742	2.0622	0.2414	0.2590	0.1568	1.0483	0.1552	0.3233
365	0.4235	0.7561	2.7912	1.8959	37.2645	3.0623	4.8929	0.7251	5.1988	35.4928	3.6740	2.0622	0.2414	0.2591	0.1570	1.0483	0.1552	0.3233

Period	S.E.	*LWIND*	*LSOL*	*LBIO*	*LHYDRO*	*LCOAL*	*LNUC*	*LOIL*	*LGAS*	*LPUMP*	*LPEAK_AM*	*LPEAK_PM*	*LOFF_AM*	*LOFF_MI*	*LRXM*	*LCO2*	*LPRICE*	*GSHI*
Variance Decomposition of LPEAK_AM																		
2	0.2856	0.1038	0.9241	0.8871	34.0105	5.3629	6.7890	0.8132	5.3125	3.0047	35.7593	4.6824	0.0670	0.0188	0.1154	1.6536	0.0536	0.4422
30	0.2970	0.2618	1.3242	1.0767	31.8717	5.1867	6.9300	0.8119	5.5547	4.6909	34.1868	4.9614	0.0965	0.2728	0.6036	1.6530	0.0553	0.4621
180	0.2972	0.2616	1.3312	1.1308	31.8856	5.1791	6.9330	0.8154	5.5532	4.6864	34.1293	4.9547	0.0965	0.2726	0.6034	1.6504	0.0554	0.4614
365	0.2972	0.2616	1.3311	1.1325	31.8849	5.1791	6.9328	0.8154	5.5537	4.6863	34.1283	4.9545	0.0965	0.2726	0.6035	1.6504	0.0555	0.4614
Variance Decomposition of LPEAK_PM																		
2	0.2465	0.0240	1.2073	0.3425	0.2578	0.5682	0.0482	0.1328	0.5377	0.3978	8.3582	87.0781	0.0439	0.2747	0.0554	0.6325	0.0397	0.0009
30	0.2534	0.0292	2.5857	0.3590	0.5746	0.6871	1.3515	0.2777	1.4863	0.4728	7.9277	82.4134	0.0759	0.3692	0.3090	0.8879	0.1866	0.0063
180	0.2538	0.0302	2.5863	0.4188	0.6205	0.6978	1.3911	0.2936	1.5560	0.4948	7.9056	82.1492	0.0777	0.3703	0.3214	0.8892	0.1909	0.0066
365	0.2538	0.0302	2.5862	0.4208	0.6207	0.6979	1.3911	0.2936	1.5567	0.4948	7.9054	82.1465	0.0777	0.3703	0.3215	0.8892	0.1909	0.0066
Variance Decomposition of LOFF_AM																		
2	0.1546	0.0827	1.8295	0.0421	7.8125	1.1480	4.8444	0.5108	3.4092	0.8811	9.0785	2.4032	40.7194	24.8804	1.9649	0.1613	0.2297	0.0023
30	0.1862	0.1333	6.8037	0.6777	7.9207	1.8745	8.5843	1.1105	9.0585	1.4890	6.9485	2.1411	28.5645	19.5023	3.7854	0.9046	0.3396	0.1618
180	0.1886	0.1418	6.6549	1.5753	7.8519	1.9373	8.5669	1.1611	9.5069	1.5850	6.7950	2.1028	27.8536	19.0251	3.8024	0.9153	0.3640	0.1607
365	0.1887	0.1420	6.6517	1.6034	7.8517	1.9380	8.5637	1.1606	9.5130	1.5846	6.7917	2.1025	27.8397	19.0158	3.8020	0.9153	0.3639	0.1606
Variance Decomposition of LOFF_MI																		
2	0.2825	0.1867	2.5502	0.3511	0.8335	0.1033	1.0929	0.1588	1.4024	0.3139	0.6077	11.0443	2.2060	78.8442	0.1155	0.1718	0.0148	0.0028
30	0.3012	0.2025	4.8044	1.2376	2.5967	0.2828	2.2001	0.4256	3.1889	1.5113	0.8068	9.7182	2.0499	70.1561	0.3071	0.2733	0.2318	0.0070
180	0.3041	0.2075	4.7201	1.9837	2.6253	0.3581	2.2099	0.4599	3.6474	1.5861	0.8129	9.5500	2.0222	68.8601	0.3890	0.2943	0.2646	0.0088
365	0.3042	0.2076	4.7182	2.0073	2.6274	0.3593	2.2099	0.4598	3.6550	1.5858	0.8127	9.5465	2.0215	68.8310	0.3901	0.2945	0.2646	0.0089
Variance Decomposition of LRXM																		
2	0.1493	2.2389	0.0666	0.6606	1.0891	0.1225	9.5243	0.9835	0.1279	0.2003	2.6757	0.5939	1.6069	0.3679	79.5176	0.0348	0.1233	0.0664
30	0.2149	1.3884	1.9729	0.6865	1.5585	0.1153	24.1348	0.5456	0.9437	1.7962	3.0726	0.3448	1.4513	0.2010	57.3814	0.1042	4.2595	0.0433
180	0.2179	1.3553	2.1564	1.4783	1.6795	0.1460	24.2644	0.5377	1.2183	1.8186	3.0296	0.3474	1.4151	0.1997	55.8925	0.1184	4.2999	0.0428
365	0.2179	1.3549	2.1556	1.5041	1.6822	0.1474	24.2542	0.5376	1.2277	1.8181	3.0283	0.3478	1.4146	0.1999	55.8680	0.1188	4.2980	0.0428
Variance Decomposition of LCO2																		
2	0.2613	0.8864	0.0500	1.5043	8.2239	17.9133	2.7145	2.7869	22.1341	0.6303	1.3219	1.0733	0.1411	0.0768	0.0706	40.0217	0.1506	0.3004
30	0.3643	0.5338	1.1634	1.3401	12.2413	11.9565	6.8166	2.7591	24.5339	2.7623	2.1936	0.7424	0.2973	0.0998	1.8296	25.4338	5.0826	0.2140
180	0.3678	0.5238	1.1813	1.3173	12.5377	11.7489	7.0956	2.7388	24.2180	2.9953	2.2305	0.7364	0.2960	0.0987	1.8496	24.9731	5.2492	0.2100
365	0.3678	0.5238	1.1813	1.3174	12.5377	11.7488	7.0956	2.7388	24.2180	2.9953	2.2305	0.7364	0.2960	0.0987	1.8496	24.9730	5.2492	0.2100
Variance Decomposition of LPRICE																		
2	0.2422	0.4712	0.3792	1.3614	14.8994	5.1146	2.2647	3.7635	1.6383	1.5686	0.7323	0.8509	0.3650	0.0061	1.3623	1.8316	63.1895	0.2015
30	0.3138	0.3704	0.4242	1.2050	11.7579	3.6765	4.0136	4.6874	1.2627	2.2602	1.2401	0.6654	0.4359	0.0714	2.1117	2.0464	63.6078	0.1635
180	0.3155	0.3674	0.4594	1.2770	11.8492	3.6405	4.3784	4.6418	1.2677	2.3307	1.2575	0.6687	0.4318	0.0747	2.0987	2.0287	63.0657	0.1622
365	0.3155	0.3675	0.4594	1.2789	11.8490	3.6405	4.3783	4.6416	1.2684	2.3306	1.2575	0.6687	0.4318	0.0747	2.0987	2.0286	63.0635	0.1622
Variance Decomposition of GSHI																		
2	0.0686	5.4843	1.5938	1.2852	32.0889	4.9236	5.5320	2.5869	16.1824	3.0201	5.0308	1.1203	0.2703	0.0230	0.5377	10.0584	0.3432	9.9191
30	0.0738	5.1647	1.9059	1.3976	31.5241	4.8226	5.2161	2.7654	16.1076	3.2250	5.0063	1.6295	0.2540	0.2218	0.5093	11.0745	0.4733	8.7023
180	0.0738	5.1642	1.9067	1.3996	31.5226	4.8222	5.2189	2.7653	16.1067	3.2247	5.0059	1.6294	0.2540	0.2218	0.5093	11.0736	0.4736	8.7016
365	0.0738	5.1642	1.9067	1.3997	31.5225	4.8222	5.2189	2.7653	16.1067	3.2247	5.0059	1.6294	0.2540	0.2218	0.5093	11.0736	0.4736	8.7016

VDC reveals how a series explains the variation of another series, as a percentage. For example, shocks to *LPEAK_AM* explain 9% of the forecast error variance in *LOFF_AM*, after a two-day lag. The IRF describes the evolution of a series of interest after a standard shock in another series at a given moment, over a specified time horizon. For example, a positive and standard shock to *LPEAK_AM* leads to a drop of 5 percentage points (pp) in the growth rate of *LOFF_AM*. It should be stressed that IRFs are analysed as a growth rate, because the series are used in natural logarithms. The lack of available space does not allow us to detail all the VDC and IRF effects. Thus, Figure 3.4 summarizes the relationships between periods of consumption and CO_2, Figure 3.6 shows the interactions between electricity sources, and Figure 3.7 reveals the interactions between consumption periods and electricity sources.

3.6 Discussion

When the French government announced the decommissioning of a part of their nuclear power capacity, it was believed that the reasons behind it were based on a combination of external and internal factors; namely the Fukushima accident, and pending long-term safety reviews. However, the results of this research demonstrate that the French government could have other reasons. The results highlight that solar PV and natural gas have the potential to decrease the use of nuclear power (see Figure 3.4). In fact, *LSOL* explains 8% of the forecast error variance of *LNUC* (see Table 3.5). Nevertheless, on the one hand, the current low installed capacity of solar PV is insufficient to allow a large reduction in the high capacity of nuclear power. On the other hand, natural gas capacity has been preserved, or kept on stand-by, to satisfy consumption when it reaches excessive levels, namely in the night peak periods. The *LPEAK_PM* explains almost 1% of the forecast error variance of *LGAS*, and a positive and standard shock on it increases the growth rate of *LGAS* by 4 pp (see Table 3.5 for VDC and Figure A.3.1 for IRF). After going deeper into the analysis, the nuclear phase-out seems have been stimulated by the need to satisfy aggravated pressure from demand peaks, which has required more flexible power plants. *LPEAK_AM* and *LPEAK_PM* explain 3% and 1% of the forecast error variance of *LNUC,* and a positive and standard shock on *LPEAK_AM* and *LPEAK_PM* leads to a drop of 0.7 and 0.6 pp respectively in the growth rate of *LNUC*. Electricity consumption in peak periods, and load transfers from off-peak to night peak periods, has prompted a rethink of the role of nuclear power in the country's electricity mix, leaving just four possible solutions to accommodate it: (i) turn off and decommission nuclear power capacity; (ii) induce increased electricity consumption in off-peak periods; (iii) implement technological measures to control loads (ancillary services), or electricity pricing strategy, to incentive consumers to shift their consumption from peak to off-peak periods; or (iv) a combination of (i) and (iii).

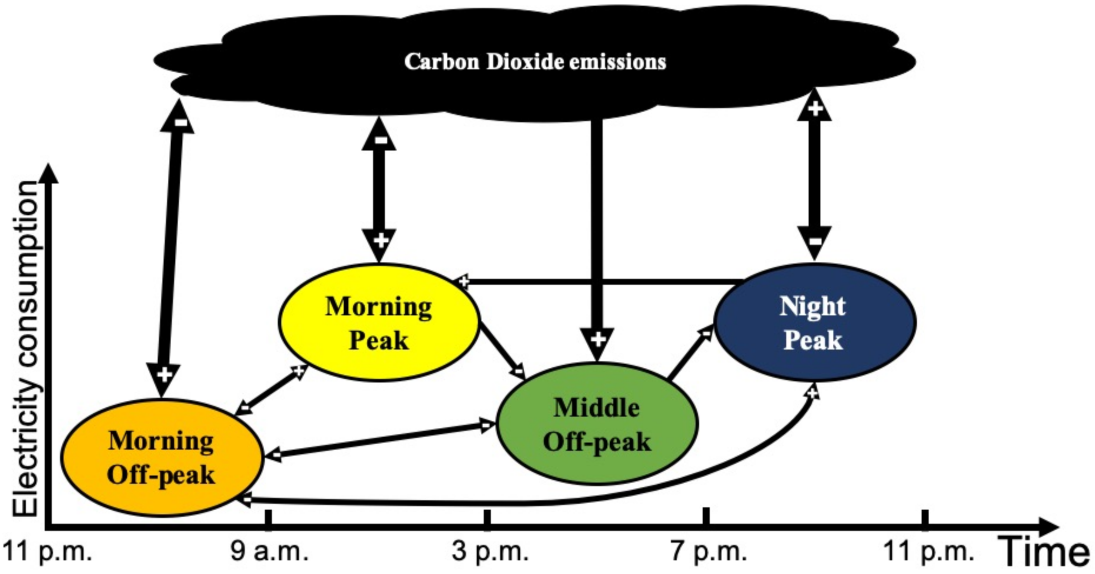

Figure 3.4. Summary of relationships between periods of consumption and CO_2 emissions

Both *LSOL* and *LBIO* explain 3% of the forecast error variance of *LCOAL*. A positive and standard shock on *LSOL* and *LBIO* provokes a drop of 6.4 pp and 18 pp in the growth rate of *LCOAL*, respectively. *LWIND*, *LBIO* and *LHYDRO* together explain 24% of the forecast error variance of *LOIL*, causing a drop of 7 pp in the growth rate of *LOIL*. Therefore, it is reasonable to argue that RES have been effective in substituting fossil fuels. See Figure 3.6 for other results of electricity source interactions. RES-I have been backed up by hydro power and biomass plants rather than fossil fuels. It should be stressed that, a positive innovation in either *LWIND* or *LSOL* leads to a rise of 0.8 pp in the growth rate of *LBIO*. A positive and standard shock on *LWIND* provokes a drop of 1.3 pp in the growth rate of *LHYDRO*, and a shock on *LSOL* causes a rise of 0.8 pp. The characteristics of hydro power, and biomass plants are similar to those of natural gas, in that they allow flexible generation, and provide storage capabilities. RES-I not only cause electricity scarcities, they can also generate excess electricity on the grid. France has used the excess from RES-I to pump water to upper reservoirs, and defer supply to night peak periods, when RES generation is needed to meet the demand. Direct access to Germany, an EU country with a high share of RES, has allowed France to import RES production at lower prices. So, the backup needed in night periods, when made through imports creates beneficial conditions for France, lower internal electricity prices and reduced CO_2 emissions. As France still requires backup powered by fossil fuels, policymakers should incentivise the deployment of hydro power with pumping system and biomass capacities.

Furthermore, France should also augment the capacity and the use of cross-border markets, with Germany, Iberian countries (Portugal and Spain), and the United Kingdom.

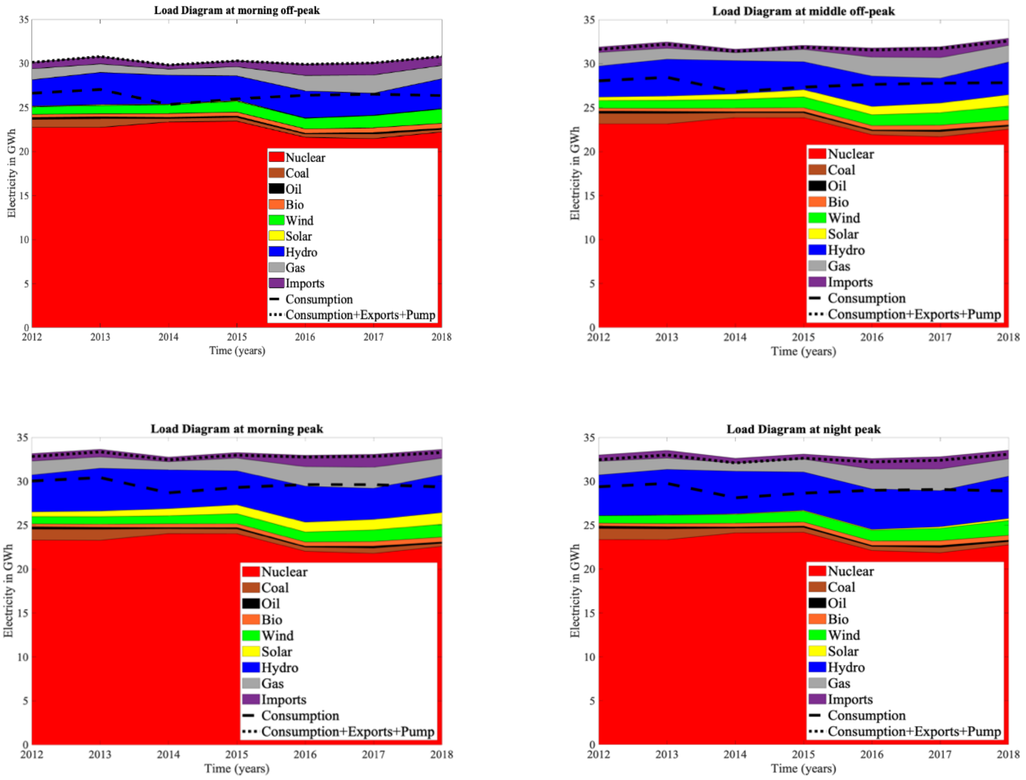

Figure 3.5. Daily mean demand coverage by technology in each differing period

Figure 3.5 shows the daily mean demand coverage for each technology by year. It can be seen that nuclear still satisfies most of the demand. However, the increasing integration of RES in the electricity mix can also be observed. Solar PV has increased its importance for consumption in the morning peak and the middle off-peak periods, while wind power covers consumption in morning off-peak and night peak periods. Comparing both the off-peak periods and peak periods, it can be concluded that hydro power has been used to accurately match supply with demand. In fact, hydro power production is higher in peak periods than in off-peak periods. Last but not least, the increasing use of natural gas can be seen to cover demand over the years. Indeed, this source's flexibility has been very useful in the energy transition. Figure 3.6 summarises the results of the interactions between electricity sources and consumption periods, showing and explaining them briefly. Through this figure it is easy to analyse the changes that must occur in consumption to accommodate RES-I in the electricity mix. What is more, it also reveals the consumption periods which increase the use of RES, i.e. increase electricity mix diversification. In addition, it shows the impact that each consumption period has on the use of both fossil fuels and nuclear.

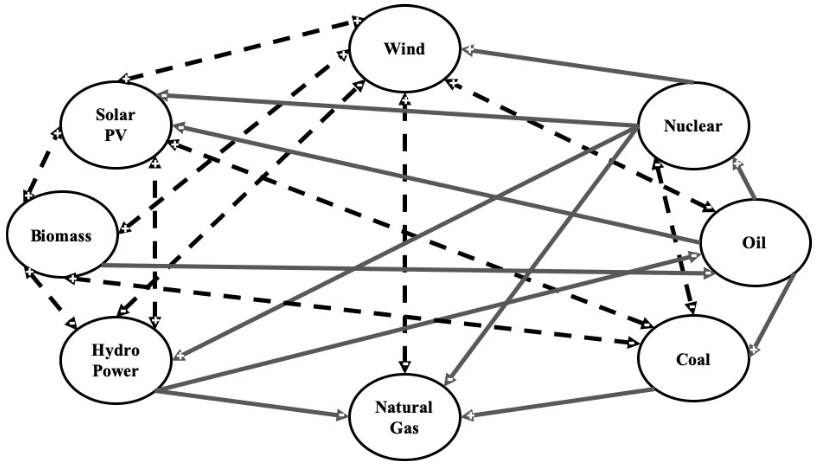

Figure 3.6. Summary of electricity sources interaction

In France, having peak consumption in the morning seems to be rational and desirable. In fact, there is a daily load transfer from both the night peaks and morning off-peaks towards the morning peak intended to exploit solar PV production. *LPEAK_PM* explains about 5% the forecast error variance of *LPEAK_AM*. A positive and standard shock on *LPEAK_PM* increases the growth rate of *LPEAK_PM* by 6 pp. Besides this, the share of RES in morning peaks, constituted mainly by biomass, hydro power, and solar PV, has allowed a reduction in the use of both nuclear power and fossil fuels (see Figure 3.6 and 3.7). In fact, the diversification of the electricity mix in this demand period has decreased CO_2 emissions; a positive and standard shock on *LPEAK_AM* provokes a drop of 3.5 pp in the growth rate of *LCO2*, explaining around 2% in forecast error variance. Furthermore, environmental concerns have increased consumption in this period; a positive and standard shock on *LCO2* leads to a rise of 4 pp in the growth rate of *LPEAK_AM*. Thus, higher penetration of solar PV should be pursued. Firstly, the lower capital investments needed to deploy solar PV on a small and medium scale, could create decentralized employment, distributed electricity generation and, in particular, promote the generation of electricity for self-consumption. Secondly, the large-scale deployment of solar PV along with energy storage systems, such as pumping systems, batteries, and electric vehicles, should be used to defer consumption of excess solar PV generation to periods when fossil fuels are currently required, namely night peaks. Thirdly, the large-scale implementation of solar PV could be key to moving the electricity mix from both nuclear power and fossil fuels towards RES, mainly solar PV. Nonetheless, this will require a shift in consumption from both night peaks and morning off-peak to morning peak, or even to the middle off-peak.

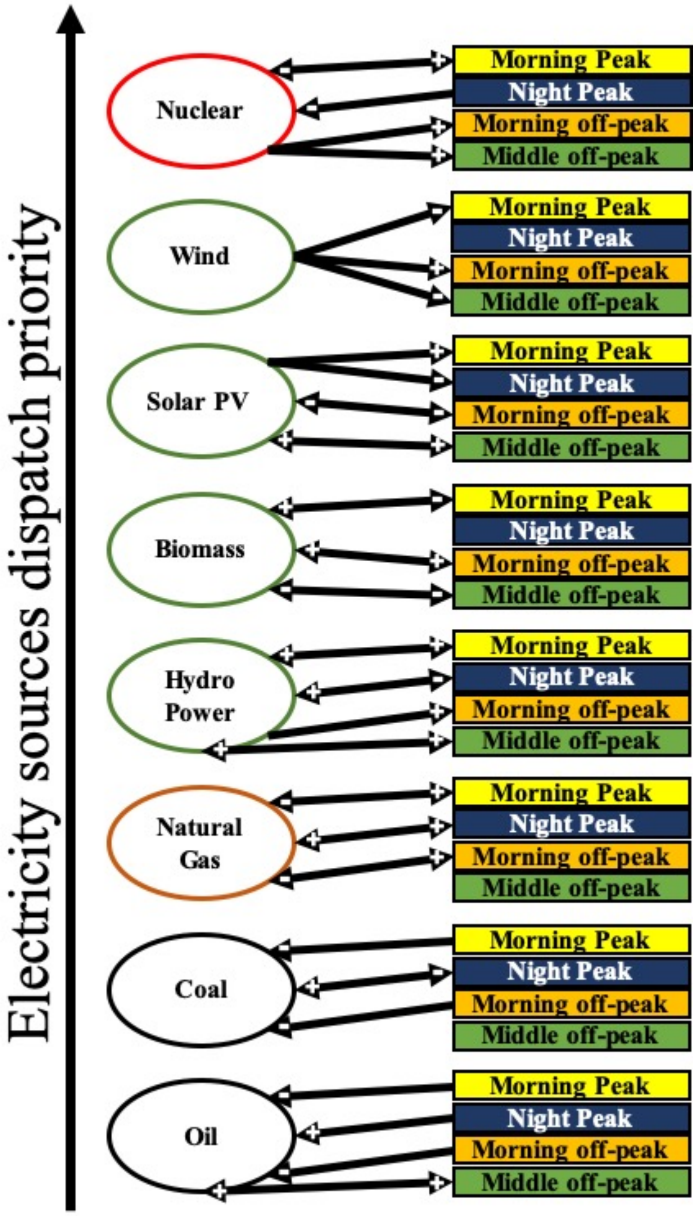

Figure 3.7. Summary of relationships between consumption periods and electricity sources

In contrast to the morning peaks, the night peaks have had harmful effects on the environment, as the large demand has had to be met by using fossil fuels. *LPEAK_PM* provokes a rise of 35 pp and 2 pp on the growth rate of *LCOAL* and *LOIL*, respectively (see Figure 3.7). Consequently, a positive and standard shock on *LPEAK_PM* provokes a rise of 3 pp in the growth rate of *LCO2*. Reducing night peak consumption has been a complex struggle, and one mainly incentivized by environmental concerns, with the aim of increasing the exploitation of wind power. In fact, the availability of natural resources, namely wind power, coincides with both the morning off-peak and night peak periods. As the results show, to benefit from the advantages of RES, it is necessary to reduce night peak consumption and increase morning off-peak consumption. However, the inverse effect was observed, in which consumption has been moved from the morning off-peak consumption towards the night peak periods (a positive and standard shock on *LOFF_AM* increases the growth rate of *LPEAK_PM* around 0.5 pp). In addition to this, policy guidance is needed on DSM policies to promote the shift from night peak towards morning off-peak, to allow endogenous and green resources to be used. Indeed, this consumption shift would benefit from the advantages of wind power that could decrease electricity prices during the night peak period.

The results underline that, for a diversified mix using wind power, off-peak consumption is needed, i.e. a smoothed electricity demand curve. Nonetheless, the advent of smart grids, information systems, and generation prediction, could be used to transmit the availability of wind power through price signals to consumers. They could then adapt their consumption to more fully use the power generated by wind power. The transition to using wind power could be quite complex when compared to the transition to solar PV. Consequently the economy should be prepared to: (i) increase the installed capacity and the capacity factor of wind power generation; (ii) reduce electricity consumption during night peaks, through policies of energy saving and efficiency; (iii) transfer peak night loads to off-peak periods; or (iv) increase the capacity of energy storage to defer the consumption of excess wind power generation from morning off-peaks to night peaks. These measures could initially result in higher costs for electricity systems, governments, and consumers, but in the future, it will reduce electricity prices, rewarding their efforts through harnessing the benefits of RES.

The results prove that electricity prices could even be reduced in peak demand periods, if the peak consumption is satisfied by a portfolio of RES-I and controllable RES. A positive and standard shock to the morning peak consumption causes a drop of 2 pp in the growth rate of the wholesale market price. In contrast, as the night peak has been satisfied by fossil fuels, a positive and standard shock to it provoked a rise of 3.34 pp in the growth rate of wholesale market price. This reveals that the cost of satisfying the night peak is higher than the cost of meeting the morning peak. These results should be taken into consideration when formulating both static tariffs, such as Time-of-Use (ToU), or dynamic ones. In fact, ToU tariffs impose the same price on both morning and night peaks, as well as critical peak time pricing schemes, and assign the same financial penalties to both demand peaks.

To sum up, this assessment of the daily dynamics between consumption periods, electricity sources, CO_2 emissions, and electricity mix diversification, proved to be valuable for identifying opportunities to improve the energy transition, in France. The results highlight opportunities to deploy RES-I without compromising either economic activity or the electricity market, such as: (i) the implementation of wind power installed capacity to satisfy consumption in off-peak and night peak periods when there is high wind power generation; (ii) the deployment of solar PV to meet consumption in morning peak, and middle off-peak periods; (iii) the expansion of biomass installed capacity to act as a baseload producer instead of fossil fuels, or even to play the backup role; and (iv) the use of hydro power with pumping systems, to manage the scarcities and surplus of electricity generated by RES-I, and match their intermittent supply with unpredictable demand. However, it will also be necessary to stimulate changes in consumption to successfully transition from both nuclear power and fossil fuels to RES (see Figure 3.7), namely: (a) a shift in consumption from night peak to off-peak periods; (b) an incremental reduction in overall consumption, specifically by reinforcing energy efficiency and energy saving measures; (c) adapting consumption to match RES-I production, specifically by co-ordinating morning peaks with solar PV generation, and off-peak and night peaks with wind power production; (d) providing price signals to consumers so they can anticipate the availability of RES-I production and adapt their consumption patterns accordingly; and (e) rethinking electricity tariffs to encourage the changes in consumption needed to accommodate RES-I. Furthermore, it should be stressed that peak pricing policy should be reanalysed. Indeed, it seems inconsistent to attribute the same price or financial penalties to morning and night peaks, as to morning and middle off-peaks.

3.7 Conclusions and Policy Implications

This research focused on the analysis of two exciting current research topics in energy economics. These are the interactions between electricity sources, and the interactions between consumption periods; namely morning peak, morning and middle off-peak, and night peak periods. This analysis uses daily data from 1 January 2012 to 31 December 2018, by using VAR modelling. VAR was required to cope with the phenomenon of endogeneity present in the data. This methodology has revealed new insights into the conditions needed to achieve a suitable energy transition, from both nuclear power and fossil fuels to a portfolio of RES-I, and controllable RES, namely hydro power and biomass.

France has plenty of opportunities to employ RES-I. On the one hand, there is evidence of load transfers to morning peak periods to harness solar PV production. On the other hand, the availability of wind coincides with off-peak and night peak periods. However, currently, RES-I only provides a small share of French consumption. The deployment of large levels of wind power and solar PV should be pursued, adapting them to the night and morning peaks, respectively. At the same time, DSM programmes should first emphasise peak-clipping at night, and valley-filling in the morning. Subsequently, real-time tariffing should be implemented to transmit price signals, through green generation forecasts. Then, consumers would be able to react more quickly, adapting their consumption to periods with a higher availability of natural resources, when they benefit from lower prices, something which should occur in the morning peak.

Residential consumers make up a major part of total consumption. Their engagement through DSM programmes is crucial for a successful energy transition away from fossil sources to RES. Firstly, the wider adoption by consumers of installing solar PV panels on their homes, could encourage them to shift their consumption needs to periods with a higher availability of sun, namely, morning peaks. Furthermore, the implementation of solar PV in homes within a proper DSM policy framework, could raise consumer awareness of electric mobility, and encourage them to install batteries, and enter into local energy communities. On the one hand, they could defer consuming their own generation to night peak periods, when they need greater amounts of energy to satisfy their routines. On the other hand, local communities, in buildings or neighbourhoods, could create small networks to share solar PV production during the day, as well as sharing backups through electricity stored in electric vehicles or home batteries, during the night. However, the autonomy and the quality of services in these communities must be regulated, to reflect the cost of providing the service to these communities in general electricity prices.

In the period analysed, morning peaks have contributed to reducing CO_2 emissions and consequently positively impacting the environment. This peak period has also decreased electricity prices due to the low cost of the effective use of RES-I, mainly solar PV. Thus, the results highlight the importance of a shift in consumption from certain periods towards periods with higher availability of RES-I. Electricity pricing schemes should not only focus on consumption in certain periods, but should also be based on the cost of electricity production. This will lead to price differentiation and encourage a shift in consumption towards the desired time periods. Consequently, electricity price in morning peak periods should be lower than in night peak periods, or even morning off-peak period. Thus, consumption in morning peak periods would increase, benefiting more fully from the advantages of solar PV, such as lower CO_2 emissions.

Conversely, as consumption in night peak periods is high and undesirable, electricity prices should then be higher than in other periods. In addition, electricity prices in morning off-peak periods should be lower to encourage consumers to shift their consumption from night periods. This shift in consumption will increase the propensity of consumers to benefit from all the advantages of wind power generation, such as lower electricity prices, and a benign environmental impact. However, as the availability of wind power is more inconsistent, real-time or dynamic tariffs should make more effective use of this endogenous resource, by combining them with market signals available in advance. Furthermore, this price differentiation, given that consumers have strict consumption needs in the night peak period, could encourage consumers to buy energy storage systems or more efficient home appliances, and also join DR programmes.

DR programmes operate specifically at end-user level. These programmes are intended to influence changes in consumption habits, and shift electricity loads from periods when the system is under major stress, to periods when there is no need to turn-on fossil fuel backup facilities. Demand Response programmes should be pursued in France, since the most disappointing result is the daily load transfer from morning off-peak to night peak periods. The major concern is that backup for this period has been mainly ensured by natural gas and coal. Strategies, such as peak-clipping, valley-filling, and load-shifting should be implemented, focusing on these two periods of differing demand. Indeed, as economic theory often predicts, consumers react more quickly to price differentiation than to financial penalties (Aghion & Bolton, 1992; Bolton Patrick & Dewatripont, 2005; Dewatripont et al., 2003). Thus, price tariffs, varying according to the periods in which electricity is consumed, are an efficient way to reduce harmful peak consumption. Even more important is increasing consumption during periods of high availability of RES-I, in other words, to periods with lower net-demand.

High consumption in night peak periods, as well as the transferring of electricity consumption from off-peak periods to night peak period, should be prevented. DSM measures should intervene to provide the electricity markets with a new balance between flexible demand and available wind power, matching demand with wind power availability. In practical terms, electricity systems and energy regulators should incentivise consumers to shift their consumption from night peak to morning off-peak periods, when there is surplus generation. Consumers will not respond immediately. Consequently, an integrated strategy is required, addressing not only the short-term, but also the long-term, which means considering the behaviour of future generations. Governments should begin with basic education, promoting children's environmental aware, and the positive impact of informed electricity demand on the environment. Thus, education and information policies, aiming to inform consumers about consumption habits and their impacts on the environment, should be a focus.

In fact, French electricity consumption has proved highly capable of accommodating a diversified electricity mix. This capability has mainly been demonstrated by the changes in consumption achieved to exploit solar PV generation. Contrary to what was expected, high consumption in the morning peak period is actually desirable, as it can be met by a range of RES. Therefore, DSM measures, in France, should now focus on promoting electricity self-generation, developing consumers awareness about the advantages of RES, not only in relation to the environment, but also the savings that RES can bring.

Last but not least, peak load pricing should be reanalysed. The results of this research reveal that it is contradictory to attribute an equal price or financial penalty to both morning and night peak periods, especially when this paper highlights that the morning peak period has largely contributed to the integration and accommodation of RES. Consequently, it follows that generation costs in morning peak periods have been lower than in the night peak period, as the latter requires backup power ensured by fossil fuels. In general, electricity consumption has an inelastic curve, and as such, consumers may not be particularly susceptible to financial incentives or price tariffs. However, consumer responsiveness will increase with greater price differentiation. The greater the price differentiation between demand periods, the larger the shift in consumption between them. Accordingly, more responsible consumers should be acknowledged by tariffs that reward their consumption in desired periods. This recognition could provoke rebound effects, but if electricity tariffs reflect not only the consumption levels, but also RES availability, the rebound effect will take different characteristics. Higher prices could be charged when RES generation potential is low, and lower prices when it is high. In fact, if additional demand is met by instantaneous supply from RES, then no additional stress to the system is implied. In this regard, this paper goes further by indicating that consumption in the morning peak period is an optimal strategy, because demand is fulfilled by nuclear sources and RES, i.e. low marginal cost energy sources. Therefore, pricing schemes should be rethought to share the surplus of electricity generation from these sources with consumers. However, the challenges of RES, particularly their investment risk, should also be shared with consumers. Accordingly, one of the strategies to incorporate these implications, is to rethink peak load pricing, adding the notion of net demand. Thus, a peak net-load pricing schemes should emerge, devised to take into account both RES and another sources with dispatch priority and low marginal cost, surplus and risk.

The new concept of net demand, which is the total load discounted by RES-I generation, should become a main reference for all players. Furthermore, this new concept should also become a main reference for research using high-frequency data, because it represents the total load discounted by the instantaneous RES-I supply. Consequently, further research is needed to study the consumption peaks more thoroughly and also analyse their impact on electricity source use, the environment, and the cost of electricity generation. In fact, this new daily analysis of the French electricity system has proved to be most useful for understanding the changes that must occur, in both the supply and demand-side, to achieve a diversified electricity mix through RES. This paper has taken the first steps in pursuing this line of research, and there are still limitations to overcome. These include modelling the assumption that different technologies do not operate equally throughout the day, or have the same potential to cover demand in differing periods, which is a complex challenge. In following this line of investigation, this paper is pioneering a new approach in the literature. Accordingly, this research and other research based on it, could provide a wider framework as a basis for policymakers and electricity system managers to devise more effective DSM policies and peak-load pricing schemes.

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Chapter 4

How should price-responsive electricity tariffs evolve? An analysis of the German net demand case

This chapter was presented in two conferences, being invited to be published in a special issue of the conference – 4th Annual APEEN Conference: Energy Demand-side Management and Electricity Markets – resulting in a publication at the *Utilities Policy* journal. This chapter outputs are:

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Pereira, D. S., & Marques, A. C. (2019). An innovative framework on the assessment of consumption by levels and time periods to design Demand- Side Management policies: Germany as a case study. Workshop: Economic Development Thinking the Environment, Coimbra, Portugal

Pereira, D. S., & Marques, A. C. (2019). An innovative framework on the assessment of consumption by levels and time periods to design Demand- Side Management policies: Germany as a case study. 4th Annual APEEN Conference: Energy Demand-side Management and Electricity Markets, Covilhã, Portugal

Abstract

This research proves, using daily data, that net demand has a higher impact on the German wholesale market price than the traditional concept of electricity demand. The aim of this paper is to develop a broader framework for the design of new tariffs for German consumers, taking net demand as its primary reference. To accomplish this, a classification of net demand by level was developed. The findings of this research provide new insights about the occurrence of net valley and net peak periods, something which is useful for designing tariffs, affecting how the price should be differentiated during the day.

4.1 Introduction

In the past, an electricity transmission system operator (TSO) would track demand, i.e. gross electricity consumption, and meet it by traditional and controllable plant generation. Even in periods of heavy demand, supply had to fulfil demand. In exceptional circumstances, the electricity systems curtailed the demand of some consumers, so as not to jeopardize the security of the system. Nowadays, the electricity systems and markets are very different from those in the past. On the one hand, growth in the capacity of intermittent renewable energy sources (RES-I) has changed interactions between electricity supply sources, impacting the market price of electricity and its behaviour (Aust & Horsch, 2020; Hu et al., 2018; Maciejowska, 2020; Martin de Lagarde & Lantz, 2018; Ribó-Pérez et al., 2019). On the other hand, consumers have reacted to developments in technology and communications. With regard to electricity consumption, they react to signals coming from the market. In fact, nowadays, consumers are able to adjust their demand to these signals, mainly from electricity prices (Andruszkiewicz et al., 2019; Ruokamo et al., 2019; Sundt et al., 2020; Wang et al., 2019; Wohlfarth, Klingler, et al., 2020; Wohlfarth, Klobasa, et al., 2020).

Germany has dramatically boosted RES-I capacity, namely wind power and solar photovoltaic (PV). Wind power capacity has doubled in the last ten years, from 25.7 gigawatts (GW) in 2009 to 61.2 GW in 2019 (Bundeskartellamt, 2019). Solar PV capacity rose from 10.57 GW in 2009 to 49.7 GW in 2019 (Bundeskartellamt, 2019). Renewable energy sources (RES), namely wind power, solar PV, hydropower, and biomass have, since 2017, represented more than 50% of German electricity capacity, and more than 35% of gross electricity generation (Bundesnetzagentur, 2019, 2018). The RES have progressively replaced generation from conventional plants. In fact, nuclear power capacity has decreased from 20.42 GW in 2009 to 9.52 GW in 2019 (Bundeskartellamt, 2018, 2019).

Nowadays, the electricity markets and TSOs have to deal with two new exogenous variables, namely oscillating demand and intermittent supply. As a result, the notion of load has to be reconsidered. Electricity market players, as well as policymakers, need to incorporate the concept of net demand (NDemand), i.e. net electricity consumption, or net-load as it is called in the literature, instead of the traditional concept of demand (TDemand) (Godoy-González et al., 2020; Kobylinski et al., 2020; Stainsby et al., 2020). The NDemand concept considers that RES-I production is guaranteed, while not underestimating its intermittent nature, and deducts it from demand. In other words, the NDemand concept consists of the deduction of RES-I production from total consumption. Consequently, NDemand is useful for determining the load that controllable sources have to meet, or which Demand-side Management (DSM) measures should intervene. In fact, the NDemand concept should now be a main reference for all electricity players. Accordingly, the traditional framework of periods categorized as peak consumption has to be revisited. Figure 4.1 illustrates the situation described above, by comparing NDemand and TDemand, in Germany during the week starting 6 May 2019.

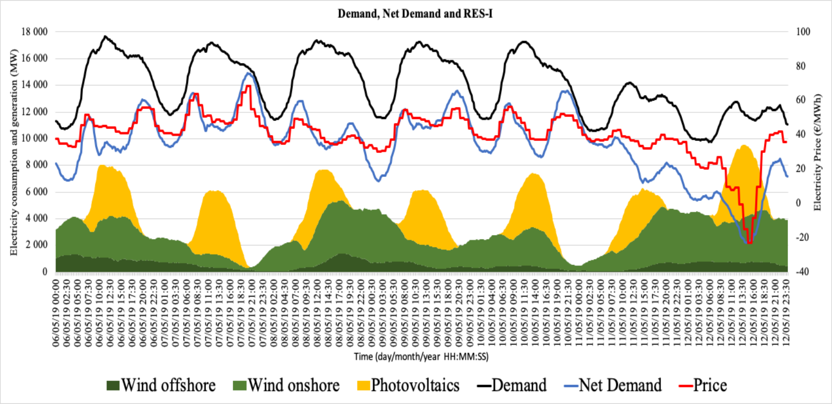

Figure 4.1. Demand vs. Net demand

Figure 4.1 shows the wide divergence between NDemand and TDemand, and reveals large variations from the shape of the well-known daily demand profile. In fact, high RES-I penetration causes large changes in the daily peak and valley of TDemand, i.e. the maximum and minimum daily demand, in terms of duration, size and timeline. The maximum demand of the week, i.e. the weekly peak demand occurred at 11:45 a.m. on 6 May 2019. However, wind power and solar PV cut peak TDemand by around 8 GW. Consequently, it should not be considered peak demand, but off-peak demand, as shown by the NDemand curve. This TDemand peak did not raise the price of electricity, indeed, it went down, accompanying the behaviour of NDemand. In contrast, NDemand peaks occurring during the week starting 6 May 2019, raised the electricity price.

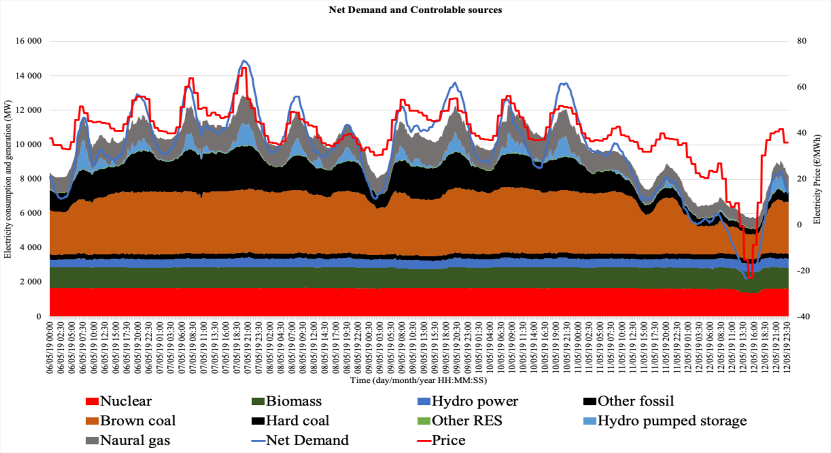

Figure 4.2. Net demand fulfilment by controllable sources

Figure 4.2 shows the production of controllable electricity sources, NDemand, and electricity price. This Figure highlights that NDemand peaks required production from controllable sources, mainly fossil fuels, provoking a rise in electricity prices. The NDemand peaks are shorter than the TDemand peaks, increasing and decreasing the load over a short period of time. This also requires controllable sources that can quickly ramp generation up or down. Consequently, the ramping generation needed, mainly provided by hard coal, natural gas, and hydro pumped storage, also increases the level and volatility of electricity prices. Therefore, NDemand should be expected to have a greater impact on the wholesale electricity price than TDemand. This question constitutes the prime motivation for this research. Its ambitious aim is to study the new concept of NDemand through high-frequency data, and verify that it does, indeed, have a greater impact on the price of electricity. This research can, thus, provide fresh new insights for devising price-responsive tariffs, and setting electricity regulations using the concept of net demand, mainly focused on reducing peak NDemand.

As can be seen in Figure 4.1, the breezy and sunny weekend of 11 and 12 May 2019 triggered a high divergence between the TDemand and the NDemand. In the breezy and sunny Sunday afternoon, RES-I generation satisfied more than 70% of the demand. This caused an excess of production from fossil fuels and controllable RES, namely biomass and hydropower. A large part of the excess was exported to the Netherlands, Austria, Poland and Switzerland at negative prices. Consequently, the minimum NDemand, i.e. the valley NDemand, also had a large impact. However, only cross-border countries benefited from Germany's high RES-I production, and no national benefit were experienced, particularly by residential consumers. This motivated us to analyse TDemand and NDemand by levels.

This research assesses the impact of both demand and net demand on the German wholesale electricity market price to answer the following question: Does net demand provides an enhanced explanation of the wholesale market price? Subsequently, a method of classifying demand is developed, classifying TDemand and NDemand according to differing levels, namely valley, peak, and intermediate. The purpose is to produce a broader framework for creating new price-responsive tariffs. Lastly, this research evaluates the explanatory power of this demand classification for changes in the wholesale electricity market price, in an effort to answer the following questions: Is this demand classification able to explain the wholesale market price?; Should price-responsive tariffs be designed through the classification of NDemand or TDemand? To this end, there is a careful analysis of the results, and subsequent discussion of how price-responsive tariffs should evolve.

Hereafter, this research is set out as follows. Section 4.2 summarizes the literature. Section 4.3 presents the econometric methodology and results of the preliminary analysis, explains the demand classification procedure, and lastly, checks their robustness. Section 4.3 presents and discusses the results of this research, with the aim of providing concrete suggestions for formulating price-responsive tariffs. Finally, Section 4.4 concludes.

4.2 Literature review

The German electricity market is typically characterised as a demand-driven system because of its quasi-inelastic demand, whereas, RES-I are dependent on the availability of natural resources, such as wind and sun. Consequently, their large-scale integration into a demand-driven system could provoke considerable challenges on the supply-side. It increases the volatility of supply, disturbing the stability of market prices (Sinn, 2017). The volatility of market prices caused by RES-I integration could drive conventional power plants out of the market due to their high marginal costs – they cannot compete with the near zero marginal cost of RES, particularly RES-I, and their dispatch priority (Gürtler & Paulsen, 2018). This effect has been widely studied in the literature through empirical and simulation analysis and is called the merit-order effect (MOE) (Sensfuß et al., 2008). Germany has received a good deal of attention on this matter because of its high share of RES-I (Aust & Horsch, 2020; Benhmad & Percebois, 2018; Gürtler & Paulsen, 2018; Maciejowska, 2020; Martin de Lagarde & Lantz, 2018).

One possible solution to deal with the volatility of RES-I is energy storage. The most prominent method in Germany is internal hydro pumped-storage (Sinn, 2017). We would argue that 6.89 terawatt-hours (TWh) of pumped-storage is required to cope with its RES-I volatility, and 42.93 TWh to cope with the volatility of both demand and RES-I. However, Germany only has the potential to reach a maximum of 0.045 TWh of pump-storage capacity (Sinn, 2017). Therefore, a market paradigm change is needed to incorporate RES-I into the German electricity mix on a large-scale. This implies a shift in the market from a demand-driven to a supply-driven system (Ambrosius et al., 2018; Katharina Grave et al., 2015; Olsthoorn et al., 2019; Venizelou et al., 2018; Wohlfarth, Klobasa, et al., 2020). It is often argued that green electricity sources in Germany could exceed their demand peaks. This argument is based on the positive link between RES-I, particularly solar PV, and volatile demand (Bundeskartellamt, 2019; Sinn, 2017; Stainsby et al., 2020; Wohlfarth, Klingler, et al., 2020). Accordingly, Energiewende should also focus on transition to a system based on flexible electricity demand linked to RES-I supply.

Flexible demand, consisting of flexible residential, industry, services, and transport sectors, combined with suitable DSM measures, could enhance network stability and the efficiency of electricity supply. Consequently, the advent of smart grids will be extremely important for managing demand with available green supply, and for fostering an active and dynamic role for consumers in the electricity market (Lockwood et al., 2020; Wohlfarth, Klingler, et al., 2020; Wohlfarth, Klobasa, et al., 2020). Demand flexibility could be promoted by price-responsive tariffs, namely static tariffs such as time-of-use (ToU) and super peak time-of-use (SPToU), and dynamic tariffs like critical peak pricing (CPP) and real-time pricing (RTP) (Alasseri et al., 2020; Dutta & Mitra, 2017; Elkasrawy & Venkatesh, 2020; Kaiser et al., 2020; Meyabadi & Deihimi, 2017; Olsthoorn et al., 2019; Wohlfarth, Klingler, et al., 2020) (Alasseri et al., 2018, 2020). In fact, price-responsive tariffs could increase the correlation between the RES-I supply and electricity demand. Price-responsive tariffs should stimulate consumers to curtail their demand during specific periods of the day, such as peak periods, or incentivize demand to shift from periods with higher demand to periods with lower demand (Alasseri et al., 2020; Conteh et al., 2020; Elkasrawy & Venkatesh, 2020; Sundt et al., 2020).

The main feature of DSM policies is to encourage consumers to modify their electricity consumption pattern, by reducing their consumption through saving or efficiency measures, and/or by shifting when they consume electricity. DSM programmes are generally for customer use, but they are encouraged and introduced by governments and utilities (Alasseri et al., 2018; Alasseri et al., 2017; Cardoso et al., 2020; Iliopoulos et al., 2020; Sahin et al., 2019; Yukseltan et al., 2017). Demand Response, the most prominent DSM instrument, aims to involve customers through pricing tariffs, using mechanisms of awards and penalties to modify their consumption pattern. DR initiatives are mainly strategies for load smoothing, like peak clipping, valley filling, or load shifting. Meyabadi and Deihimi (2017) established and described DSM, introducing and explaining the new terms and categories for DSM. A detailed literature review of DR optimization models and electricity tariffs has been provided by the literature (Alasseri et al., 2017; Cardoso et al., 2020; Dranka & Ferreira, 2019; Jordehi, 2019). However, the literature has only analysed demand response, specifically, price-responsive tariffs, in a qualitative way, or through theoretical modelling approaches (Cardoso et al., 2020; Elkasrawy & Venkatesh, 2020; Iliopoulos et al., 2020; Jordehi, 2019; Kaiser et al., 2020; Pacudan & Hamdan, 2019; Stainsby et al., 2020). To the best of our knowledge, in the literature there has been little empirical study that analyses demand through high-frequency data, exploring the barriers and opportunities to achieving a smoothed demand curve, or potential new price-responsive tariffs to achieve successful RES-I integration. Therefore, this research aims fill this gap in the literature, exploring high-frequency data to break new ground on price-responsive tariffs framework.

4.3 Methodology

This methodology section spotlights the relationship between the wholesale market price and both TDemand and NDemand, and their dissimilarities, in order to choose the appropriate concept to incorporate into price-responsive tariffs. Subsequently, the newly designed classification of electricity demand by levels is explained. Lastly, the impact of electricity demand classification on the wholesale market price is assessed

4.3.1 Traditional demand vs net demand to explain the wholesale market price

This preliminary analysis used hourly data on the German day-ahead market price of electricity, and TDemand and NDemand to reveal which type of demand has the greatest impact on this price. Table 4.1 shows the definitions, measures, and data sources. Electricity demand and the wholesale electricity price can compress multilevel seasonality depending on the hour of the day, day of the week, month, or season. Thus, this preliminary analysis will also focus on the assessment of seasonal effects.

Table 4.1. Series definition

	Definition	**Measure**	**Resolution**	**Source**
PRICE	Day-ahead electricity price for bidding zone DE/AT/LU until 30th September 2018, and for DE/LU from 1st October 2018	€/MWh	Hourly	SMARD
TD	Electricity demand	MW	Hourly	SMARD
WIND_OFF	Electricity generation from wind offshore	MW	Hourly	SMARD
WIND_ON	Electricity generation from wind onshore	MW	Hourly	SMARD
PHOTO	Electricity generation from solar PV	MW	Hourly	SMARD
ND	Net electricity demand (DMD-(WIND_OFF+WIND_ON+PHOTO))	MW	Hourly	Own calculation

Notes: MW means megawatt and MWh means megawatt-hour.

Table 4.2 displays the descriptive statistics of the raw data, and logarithm series denoted by the prefix "*L*". The timespan under analysis is from 1 January 2015 until 20 November 2019, totalling 43,080 hourly observations. The methodology employed requires a continuous timespan, consequently, all missing observations (173 observations) have been excluded.

Table 4.2. Descriptive statistics of raw and logarithm series

	Obs.	**Mean**	**Median**	**Max.**	**Min.**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**
Raw data									
PRICE	42907	36.02	34.80	163.52	0.00	15.04	0.72	5.32	13330.46***
TD	42907	55589.97	55365.25	79062.50	10453	10465.64	-0.39	3.75	2099.94***
WIND_OFF	42907	1802.37	1496.00	6813.00	0.00	1418.52	0.62	2.42	3376.04***
WIND_ON	42907	9156.39	6847.00	40389.25	130	7612.97	1.30	4.25	14785.12***
PHOTO	42907	4345.07	140.00	30028.50	0.00	6629.07	1.54	4.34	20175.59***
ND	42907	40301.20	40533.75	72475.50	3213.75	11602.43	-0.22	3.02	331.3256***
Logarithm series									
LPRICE	42907	3.50	3.58	5.10	0.00	0.54	-2.50	14.43	277927.8***
LTD	42907	10.88	10.92	11.28	9.25	0.58	-16.85	318.51	1.80E+08***
LND	42907	10.53	10.61	11.19	8.0755	0.62	-12.28	205.73	74555440***

Notes: Obs. means observations, Max. means maximum, Min. means minimum, Std. Dev. Means standard deviation. *** indicate that the statistic is significant at 1% level.

The Jarque-Bera test rejected the hypothesis that the series has a normal distribution. This was expected because the series had fat tails, as the Kurtosis values showed. Consequently, we had to find the most suitable distribution for the *LPRICE* series. This was found to be the t-student (see Figure 4.3), namely the 'tlocationscale' introduced using the built-in *fitdist* function of the Matlab software (Matlab, 2018), which features 23 parametric distribution types. The values of the 'tlocationscale' are the location parameter $\mu=3.58212$, scale parameter $\sigma=0.303447$, and shape parameter $\nu=2.76718$.

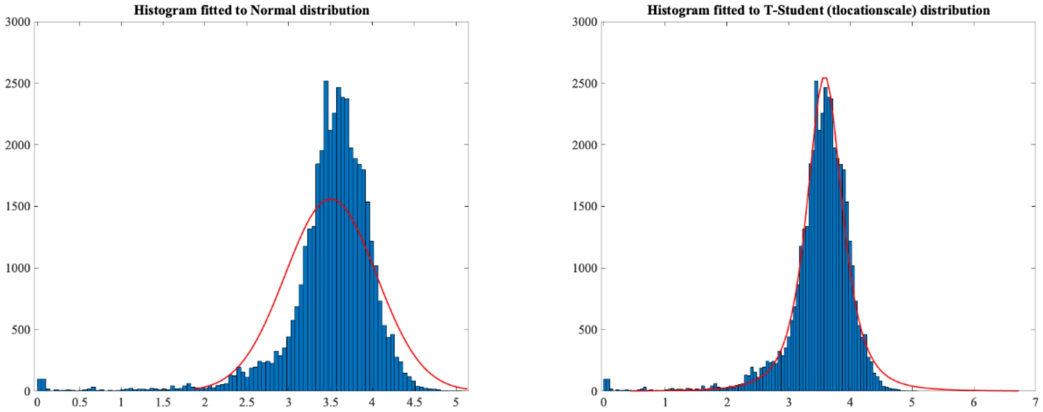

Figure 4.3. Histograms of *LPRICE* fitted to normal distribution (left-hand graph) and to 'tlocationscale' distribution (right-hand graph)

The integration order of the series was performed through the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981), the Phillips and Perron (PP) test (Peter & Perron, 1988), and the Kwiatkowski Schmidt Shin (KPSS) test (Kwiatkowski et al., 1992). The ADF and the PP tests were carried out under the null hypothesis of unit root, and the KPSS under the null of non-existence of a unit root. The ADF test followed the Schwarz Information Criterion (SIC). PP and KPSS tests followed the Bartlett Kernel Spectral estimation and the Newey-West-bandwidth. The three integration order tests were executed without a maximum limit for lags. The results of the integration order tests indicated that the three time-series under study are integrated of order zero, in their levels.

Table 4.3. ARCH-LM test and Ljung and Box (1978) statistics

	LPRICE
ARCH(1)	29610.02***
ARCH(12)	2619.315***
ARCH(24)	1328.231***
ARCH(48)	667.3237***
$Q_{LB}(1)$	33494***
$Q_{LB}(12)$	1632722***
$Q_{LB}(24)$	232332***
$Q_{LB}(48)$	294647***
$Q_{LB}(168)$	449853***

Notes: Q_{LB} represents the serial correlation test of standardized residuals, and *** denotes that the statistic is significant at 1% level.

The Ljung and Box (1978) test of serial autocorrelation revealed that the day-ahead electricity price is serially autocorrelated (see Table 4.3). The Lagrange Multiplier (ARCH-LM) test, developed by Engle (1982), showed that the LPRICE suffers from conditional heteroskedasticity (see Table 4.3). Accordingly, the most suitable estimator to cope with these data features belongs to the generalised autoregressive conditional heteroskedasticity (GARCH) regressor family.

The exponential generalised autoregressive conditional heteroskedastic estimator EGARCH(p,q) was developed by Nelson (1991) and it assumes asymmetric time-varying volatility. This volatility responds differently to positive and negative shocks. The choice of specifying an EGARCH was primarily due to its particular ability to determine the leverage effect. The leverage effect assesses which shocks, i.e. positive or negative (or even none), induce the greatest volatility in the day-ahead electricity price. This leverage effect is measured by a so-called asymmetry parameter, and can be interpreted in three ways: (i) if the asymmetry parameter values are less than 0, it means that the leverage effect exists, which means that negative shocks are likely to increase volatility more than positive ones; (ii) conversely, if the asymmetry parameter values are greater than 0, the inverse leverage effect applies, which means that increased volatility is essentially due to positive shocks; and lastly (iii) if the asymmetry parameter is equal to zero, the leverage effect does not exists. The stationary of the particular case EGARCH(1,1) is confirmed when the absolute value of the GARCH parameter (β) is less than one.

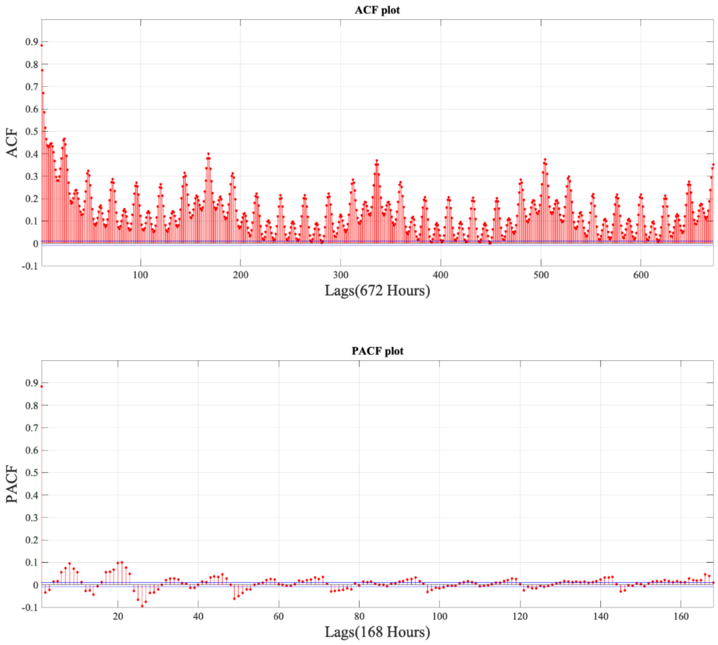

Figure 4.4. ACF and PACF plots of the logarithm of day-ahead electricity price

The correct specification of the mean and variance equation is fundamental for obtaining robust results. Therefore, the autocorrelation (ACF) and partial autocorrelation (PACF) plots of the wholesale electricity price were assessed (see Figure 4.4). Regarding the ACF plot, a high spike was observed at lag one, followed by a strong seasonality dependence in every five, seven, and twenty-four lags. This led to the inclusion of both autoregressive and seasonal autoregressive ($AR(p)$ and $SAR(q)$) processes in the mean equation. In relation to the PACF plot, a high spike could be seen at lag one. This prompted the introduction of a moving average $MA(q)$ structure with an $AR(p)$ process. Exogenous regressors were also included, such as electricity demand and net demand. Meanwhile, a set of dummies was also incorporated in both the mean and variance equations to deal with seasonality.

The method proposed in this study was a combination of a Seasonal Autoregressive Moving Average (SARMA) with exogenous regressors (SARMAX), and an EGARCH approach. Three diverse empirical specifications are presented in this section: *Model I* – a basic wholesale electricity price regression; *Model II* – includes TDemand in both the mean and variance equations; and *Model III* – incorporates NDemand in both the mean and variance equations. Furthermore, seasonality effects have been included, namely, a dummy to capture the effects of Sundays and holidays, along with a dummy to control for summer seasonality in models *I*, *II* and *III*. It was assumed in the three models that the error term follows a t-student distribution with μ=3.58212, σ=0.303447, and ν=2.76718.

Table 4.4. Results of SARMAX/EGARCH models

Model	***Model I***	***Model II***	***Model III***
Exogenous series	***none***	***LTD***	***LND***
Mean equation			
LTD		0.3276***	
LND			0.3437***
AR(1)	0.9732***	0.9343***	0.9533***
AR(9)	0.012***	0.0325***	
AR(12)	-0.0133***	-0.0095***	
AR(18)	0.0263***		
SAR(5)	-0.0996***	-0.078***	-0.0639***
SAR(7)	-0.0753***	-0.0474***	-0.0381***
SAR(24)	0.4261***	0.3123***	0.2956***
MA(1)	0.2092***	0.2304***	0.1911***
Sundays and holidays	-0.01***	-0.0094***	-0.0117***
Variance Equation			
ω	-0.5931***	-0.1806***	0.6335***
α	0.4975***	0.4105***	0.5979***
γ	-0.0749***	-0.1351***	-0.0765***
β	0.9265***	0.9187***	0.8363***
LTD		-0.0361***	
LND			-0.1571***
Sundays and holidays	0.0549***	0.0354***	0.0404***
Summer	-0.0368***	-0.0431***	-0.0949***
Diagnostic tests			
R^2	0.7333	0.7252	0.7334
SIC	-1.7592	-1.7809	-1.8676
AIC	-1.7622	-1.7841	-1.8706
Log likelihood	37783.27	38258.9200	40123.55
Durbin-Watson	2.6346	2.6487	2.6195
Q_{LB}	295.47 [9]	213.21 [8]	337.57 [6]
Q_{LB}^2	1.9775*** [1]	1.9775*** [1]	0.0613*** [1]
	13.245*** [18]	13.245*** [18]	29.561*** [23]
ARCH	1.9773*** [1]	1.9773*** [1]	0.0613*** [1]
	0.7254*** [18]	0.7254*** [18]	1.2943*** [23]

Notes: In an EGARCH model, the variance is typically driven by three parameters, α denotes the impact of new shocks, β reveals if previous shocks still persist, and γ represents the leverage effect, ω is the constant term. SIC and AIC represents the Schwartz and Akaike information criterion, respectively. Q_{LB} denotes the serial correlation test of standardized residuals, Q_{LB}^2 means the serial correlation test of standardized squared residuals, "[]" indicates the number of lags employed in the tests, and *** denotes statistical significance at 1% level.

Regarding the diagnostic test, all models rejected the hypothesis of serial correlation in standardized squared residuals; up to 18 lags for models *I* and *II*, and up to 23 lags for model *III*. This confirms that the clustering of volatility is well specified. Furthermore, the hypothesis of ARCH effects in the residuals was rejected; up to 18 lags for models *I* and *II*, and up to 23 lags for model *III*. It could be concluded from the Quantile-Quantile plots (see Figure 4.5), that model residuals follow the t-student distribution computed, since mostly of the data is positioned close to the theoretical line. All three models show a high R^2, emphasizing that *LPRICE* is well explained. However, the R^2, and the information criteria indicate that *Model III* is more suitable to explain *LPRICE* than the other models. Therefore, this proves that NDemand provides an enhanced explanation of the wholesale market price.

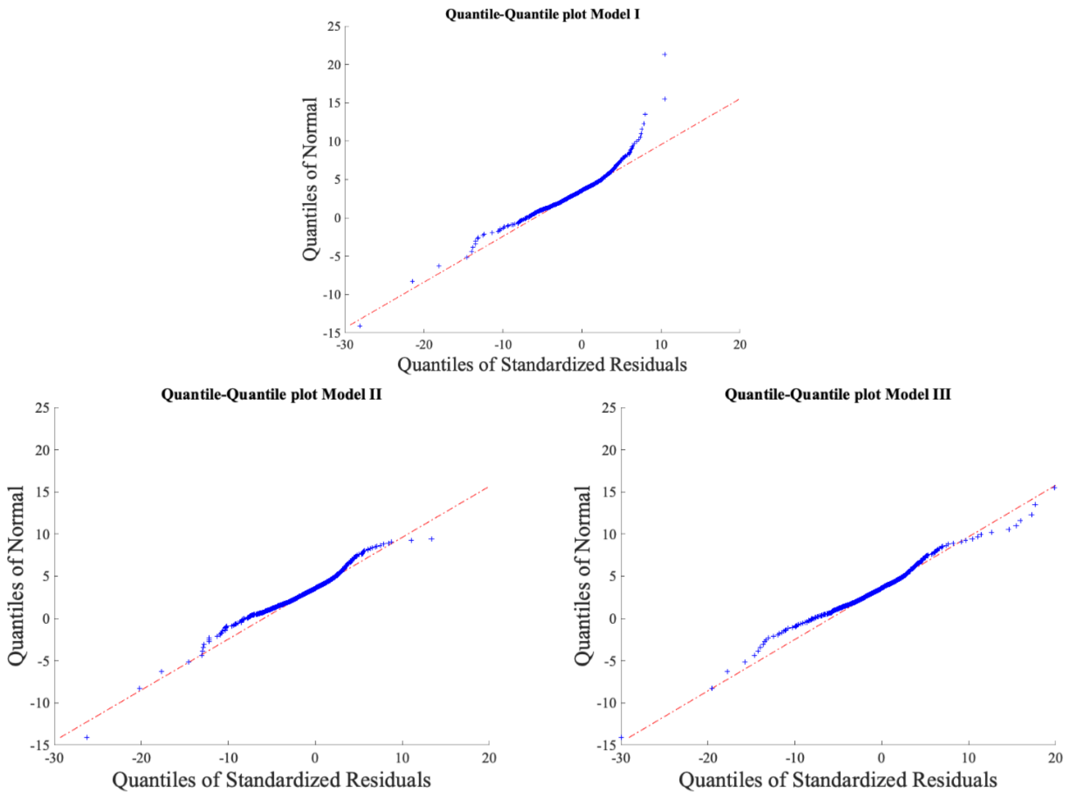

Figure 4.5. Quantile-Quantile Plots for Model *I* (up), *II* (down left), *III* (down right)

Regarding the mean equation, it shows that both TDemand and NDemand have a similar impact on the wholesale electricity market price. An increase of 1% in TDemand increases the price by around 0.33%. Whereas, an increase of 1% in NDemand raises the price by around 0.34%. Nonetheless, the impact of NDemand on price volatility differs from that of TDemand. An increase of 1% in NDemand reduces price volatility by around 0.16%. In contrast, when TDemand increases by 1%, it only slightly reduces price volatility by about 0.04%. Accordingly, one can conclude that NDemand has a higher explanatory power over the wholesale market price than TDemand. Therefore, this first outcome emphasizes the need to redesign electricity tariffs in line with NDemand, rather than TDemand. In fact, this finding also reveals that NDemand is more able to decrease the volatility of electricity prices than TDemand. Consequently, NDemand could help make the electricity market and regulatory framework more stable.

4.3.2 Demand classification procedure

This research will focus on different electricity demand levels (EDLs) and their daily time-periods, to shed new light on price-responsive tariffs. To do this, firstly, this research intends to coin a new concept in the classification of electricity demand, by considering demand by levels, as follows. Peak Electricity Demand Level (PEDL) is demand above a given or selected upper limit, during a determined period of time. Valley

Electricity Demand Level (VEDL) is demand below a given or selected lower limit, during a determined period of time. Intermediate Electricity Demand Level (IEDL) is demand between the two limits, where the superior limit is defined by the PEDL and the inferior limit defined by the VEDL, during a given period of time. These limits could be set to describe or simulate a flexible smoothed demand curve, or an inelastic demand curve. The limits could also be theoretically defined, or statistically and mathematically computed, or even determined by generation or demand characteristics. Consequently, the classification of peaks and valleys could vary according to the policy framework or research purposes.

The classifications were computed for TDemand, in traditional electricity demand levels (TEDLs), and for NDemand, by net electricity demand levels (NEDLS), although greater emphasis will be given to NDemand. This choice comes from the fact that NDemand has a higher impact on the wholesale market price than TDemand, as previously shown. Besides, it also enables price-responsive tariffs to be produced to synchronize demand with RES-I availability. The classification of demand was made using 15-minute period data from 1 January 2015 to 30 November 2019. This data was retrieved from the SMARD database. EDLs were classified by season, and weekdays, because the preliminary analysis denoted that wholesale electricity price formation and volatility suffers from these seasonal effects. This classification is in accordance with the literature (Aust & Horsch, 2020; Hinderks & Wagner, 2019, 2020; Maciejowska, 2020; Meyabadi & Deihimi, 2017; Wohlfarth, Klingler, et al., 2020). Furthermore, the ToU tariffs in Europe are mainly delineated by weekdays and seasons.

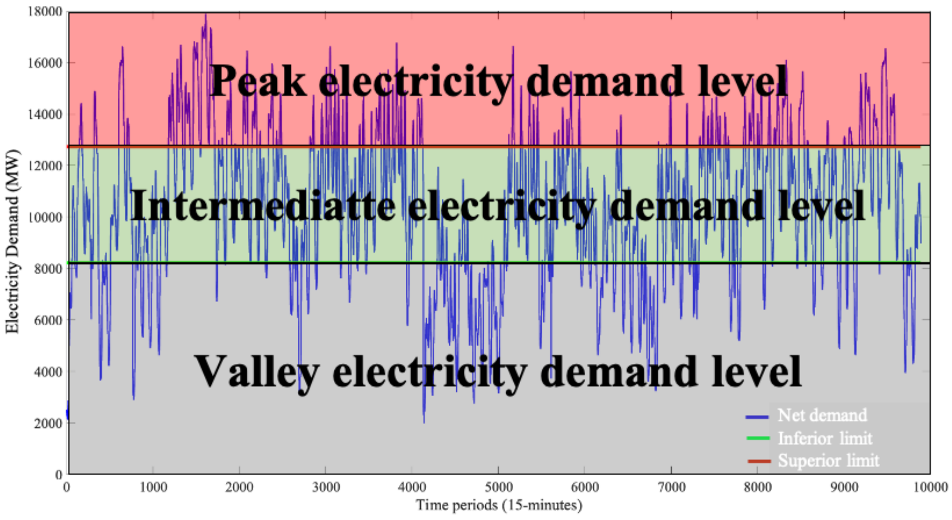

Figure 4.6. Demand classification of winter weekdays in 2019

The EDLs was classified through quartile ranges, a statistical method. The quartile ranges are suitable for computing the classification of EDLs because (i) they focus on the mean and median values which represent a hypothetical perfectly, and hypothetical near-perfectly smoothed demand curve, respectively; (ii) their limits are equidistant, so the PEDL and VEDL will have the same impact; and (iii) the interquartile range (IQR) makes it possible to both statistically and mathematically simulate a flexible smoothed demand curve, allowing demand to move around 25% above and below the median (Elzalabany et al., 2019; Grech, 2018). The quartile ranges split the data into three points, constituting four groups. The first quartile Q1, or lower quartile, represents the 25% with the lowest values; the second quartile (Q2) contains the lowest values above Q1 and below the median; the fourth quartile (Q4), or higher quartile, comprises the 25% with the highest values; and the third quartile (Q3) contains the highest values below Q4 and above the median. Accordingly, the quartile range is divided in three limits, i.e., the inferior limit (lim^{inf}), the middle limit (lim^{mid}), or median, and the superior limit (lim^{sup}). In this research Q1 will define the VEDL, Q4 the PEDL and IQR the IEDL, following the assumption below.

Assumption: The classification of EDLs has been performed through the inferior and superior limit of quartile ranges (see Table 4.4), depending on weekdays, season and year, with the VEDL, PEDL, and IEDL corresponding to Q1, Q4, and IQR (Q2+Q3), respectively.

$$DMD\_CLASS_{p(d)} = \begin{cases} PEDL_{p(d)}\ iff\ DMD_{p(d)} \geq lim^{sup}_{wkd(d),seas(d),year(d)} \\ IDCL_{p(d)}\ iff\ lim^{inf}_{wkd(d),seas(d),year(d)} < DMD_{p(d)} < lim^{sup}_{wkd(d),seas(d),year(d)} \\ VEDL_{p(d)}\ iff\ DMD_{p(d)} \leq lim^{inf}_{wkd(d),seas(d),year(d)}, \end{cases}$$

where, d denotes the days, $p(d)$ represents a 15-minute period of day d; $DMD\_CLASS_{p(d)}$ characterizes the demand in a 15-minute p of day d; $DMD_{p(d)}$ is the demand in a 15-minute p of day d; wkd represents the weekly days, grouped in weekdays, Saturdays, Sundays, and holidays; seas represent the seasons divided into summer (April to September inclusive) and winter (December to March); year represents the years 2015 to 2019; $PEDL$ is the peak electricity demand level; $VEDL$ is the valley demand level; $IEDL$ is the intermediate electricity demand level; $limit^{inf}_{wkd(d),seas(d),year(d)}$ and $limit^{sup}_{wkd(d),seas(d),year(d)}$ are the inferior and superior limits calculated using quartile ranges to determine wkd, $seas$ and $year$. Figure 4.6 illustrates the demand division for winter weekdays of 2019.

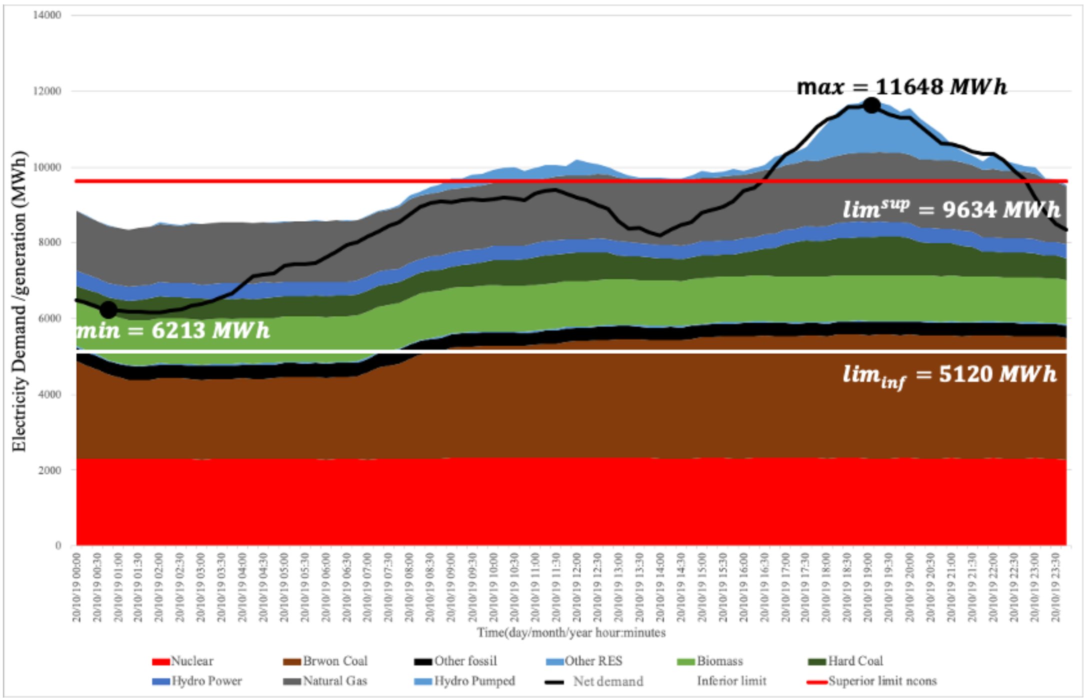

Figure 4.7. Classification of Net EDLs to 10 November 2019

Figure 4.7 illustrates the classification of NEDLs produced using NDemand to 10 November 2019 (random choice). It can be observed that the inferior limit can indicate the required baseload production; the area between the two limits, the required flexible production; and the difference between the maximum and superior limit, the peak production capacity. Accordingly, the requirements on 10 November 2019 were, a baseload capacity of 5,120 megawatt-hour (MWh); a flexible generation capacity of 4,514 MWh, and peak production capacity of 2,014 MWh.

Table 4.5. EDL limits for TDemand and NDemand

			TDemand				**NDemand**			
Year	Season	Day of the Week	Min.			Max.	Min.			Max.
2015	Winter	Weekdays	8522	12804	16950	19159	3122	10068	14118	17651
2015	Winter	Saturday	9135	11754	14008	15826	3838	8090	10913	13960
2015	Winter	Sunday and holidays	7459	10568	12987	18454	1563	6377	9785	13923
2015	Summer	Weekdays	8079	11883	15865	18402	3847	9432	12211	15521
2015	Summer	Saturday	8696	10483	12848	14806	3503	7814	9631	12473
2015	Summer	Sunday and holidays	7879	9617	11787	14266	2339	6803	9057	11902
2016	Winter	Weekdays	9173	12938	17014	18953	2302	10141	14116	18151
2016	Winter	Saturday	9027	11683	13857	15641	3236	8136	11289	14422
2016	Winter	Sunday and holidays	8633	10569	13072	18336	2110	7050	10261	14973
2016	Summer	Weekdays	8336	11842	15830	17501	4692	9608	12430	15553
2016	Summer	Saturday	8761	10588	12675	14601	2883	7760	9776	12455
2016	Summer	Sunday and holidays	7825	9708	11959	17478	1297	6423	9273	14021
2017	Winter	Weekdays	8846	13556	17563	19870	3834	9514	13949	18308
2017	Winter	Saturday	10259	12319	14665	16568	2889	6965	10869	14848
2017	Winter	Sunday and holidays	8670	11068	13699	18454	1790	5957	9973	15131
2017	Summer	Weekdays	9012	12105	16263	18237	3261	9235	12168	15351
2017	Summer	Saturday	9335	10785	13044	14968	3165	7296	9743	12608
2017	Summer	Sunday and holidays	8390	9834	12103	16818	1278	6136	9027	12355
2018	Winter	Weekdays	9291	13818	17708	19698	2896	9630	13623	17404
2018	Winter	Saturday	10335	12551	14795	16826	2149	7924	11353	14733
2018	Winter	Sunday and holidays	8026	11509	13841	19062	1509	6093	9974	15151
2018	Summer	Weekdays	9715	12809	16814	19235	3571	9482	12360	15925
2018	Summer	Saturday	10096	11490	13640	15919	2212	7396	9997	12308
2018	Summer	Sunday and holidays	8833	10456	12605	18035	1194	6456	9065	13767
2019	Winter	Weekdays	9041	13493	17147	19311	1994	8222	12738	17880
2019	Winter	Saturday	9788	12092	14209	16568	1770	5448	10167	14336
2019	Winter	Sunday and holidays	7349	11177	13523	17865	1339	5120	9634	16530
2019	Summer	Weekdays	8928	12123	15853	17705	2146	8523	11346	14395
2019	Summer	Saturday	9105	10785	12955	14534	1170	6051	9004	11438
2019	Summer	Sunday and holidays	8447	9959	11981	16355	623	4930	8082	11708
ALL	Winter	Weekdays	8522	13351	17272	19870	1994	9560	13789	18308
ALL	Winter	Saturday	9027	12071	14298	16826	1770	7374	11001	14848
ALL	Winter	Sunday and holidays	7349	10976	13450	19062	1339	6168	9953	16530
ALL	Summer	Weekdays	8079	12190	16122	19235	2146	9247	12114	15925
ALL	Summer	Saturday	8696	10877	13055	15919	1170	7214	9654	12608
ALL	Summer	Sunday and holidays	7825	9919	12117	18035	623	6175	8913	14021

Notes: All the values are in MWh; ALL means all years (2015 to 2019). Own elaboration.

Table 4.5 reveals all the minimum, maximum, lim_{inf}, and the lim^{sup} for both TDemand and NDemand classifications. The inferior and superior limit of NDemand, as well as the maximum NDemand, can reveal the capacities needed to meet demand with RES-I generation already discounted. Therefore, based on this, it is possible to formulate differential prices for price-responsive tariffs, such as ToU and CPP.

4.3.3 Robustness check of the classification of electricity demand levels

To check the robustness of the EDL classifications, the SARMAX-EGARCH(1,1) models were estimated using TEDLs and NEDLs to analyse their impact on the wholesale market price. *Model IV* – included the three TEDLs computed by TDemand, and *Model V* incorporated the three NEDLs, computed by NDemand. Table 4.6 shows the definitions of the series, and the descriptive statistics.

Table 4.6. Series definition and descriptive statistics of raw and logarithm series

Variables	Definition
TVEDL	VEDL computed by traditional demand
TIEDL	IEDL computed by traditional demand
TPEDL	PEDL computed by traditional demand
NVEDL	VEDL computed by net demand
NIEDL	IEDL computed by net demand
NPEDL	PEDL computed by net demand

Descriptive statistics

	Obs.	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
TVEDL	42907	11025.60	0.00	55030.00	0.00	18704.04	1.19	2.56	10528.15***
TIEDL	42907	28384.80	26068.50	70746.75	0.00	27449.17	0.11	1.23	5694.934***
TPEDL	42907	16179.57	0.00	79062.50	0.00	27146.89	1.22	2.67	10814.30***
NVEDL	42907	6893.11	0.00	40466.00	0.00	12112.91	1.40	3.31	14163.20***
NIEDL	42907	20388.96	19567.75	56442.25	0.00	19990.96	0.17	1.31	5311.101***
NPEDL	42907	13019.14	0.00	72475.50	0.00	22147.18	1.27	2.86	11603.77***
LTVEDL	42907	2.87	0.00	10.92	0.00	4.70	1.03	2.07	9176.543***
LTIEDL	42907	6.06	10.17	11.17	0.00	5.35	-0.24	1.07	7071.441***
LTPEDL	42907	3.12	0.00	11.28	0.00	4.92	0.95	1.91	8544.678***
LNVEDL	42907	2.74	0.00	10.61	0.00	4.49	1.03	2.07	9136.201***
LNIEDL	42907	5.81	9.88	10.94	0.00	5.20	-0.22	1.06	7069.125***
LNPEDL	42907	3.02	0.00	11.19	0.00	4.81	0.97	1.95	8695.505***

Notes: Obs. means observations, Max. means maximum, Min. means minimum, Std. Dev. Means standard deviation. *** indicate that the statistic is significant at 1% level.

The ADF, PP, and KPSS integration order tests revealed that they were all stationary in their levels. It should also be highlighted that collinearity and multicollinearity were assessed using correlation matrix and variance inflation factor statistics, thereby removing any doubt about collinearity or multicollinearity. It was also assumed in all three models that the error term follows a t-student distribution with $\mu=3.58212$, $\sigma=0.303447$, and $\nu=2.76718$.

Table 4.7. Results of SARMAX/EGARCH robustness models

	Model IV	*Model V*
	Mean equation	
LTVEDL	-0.004***	
LTIEDL	0.0002**	
LTPEDL	0.0012***	
LNVEDL		-0.0025***
LNIEDL		-0.001***
LNPEDL		0.0031***
Weekdays	0.0244***	0.0231***
Sundays and holidays	-0.0246***	-0.0182***
AR(1)	0.9387***	0.9426***
AR(9)	0.0602***	0.0522***
AR(12)	-0.0058***	-0.0068***
AR(18)	0.0046***	0.0095***
SAR(24)	0.3663***	0.3611***
MA(1)	0.2609***	0.2484***
	Variance Equation	
ω	-0.8586***	-1.167***
α	0.557***	0.5692***
γ	-0.089***	-0.0363***
β	0.9058***	0.858***
LTVEDL	0.0078***	
LTIEDL	0.0174***	
LTPEDL	0.005**	
LNVEDL		0.0455***
LNIEDL		0.0144***
LNPEDL		0.0167***
Saturdays	0.0236***	0.0482***
Sundays and holidays	0.0687***	0.1106***
Summer	-0.0453***	-0.0844***
	Diagnostic tests	
R^2	0.741487	0.743429
SIC	-1.786807	-1.786807
AIC	-1.791052	-1.791052
Log likelihood	37860.75	38407.73
Durbin-Watson stat	2.678068	2.65902
Q_{LB}	620.13*** [7]	703.92*** [7]
Q_{LB}^2	1.7709*** [1]	1.3665*** [1]
	17.33***[17]	22.262*** [15]
ARCH	1.7708*** [1]	1.3663*** [1]
	1.0019*** [17]	1.4614*** [15]

Notes: In an EGARCH model, the variance is typically driven by three parameters, α denotes the impact of new shocks, β reveals if previous shock still persist, and γ represents the leverage effect, ω is the constant term. SIC and AIC represents the Schwartz and Akaike information criteria, respectively. Q_{LB} denotes the serial correlation test of standardized residuals, Q_{LB}^2 means the serial correlation test of standardized squared residuals, in "[]" are the number of lags employed in the tests, and ***and ** denotes the statistical is significant at 1% and 5% level, respectively.

Regarding the diagnostic tests, all the models rejected the hypothesis of serial correlation in standardized squared residuals, and ARCH effects in residuals, up to 17 and 15 lags, for *Model IV* and *V* respectively. The Quantile-Quantile plots (see Figure 4.8) proved that the residuals of the models follow the t-student distribution computed previously. The robustness models (*Models* IV and V) revealed a higher R^2 than *Models I*, *II*, and *III*, demonstrating that the EDLs can provide an enhanced explanation of the wholesale market price. Regarding the comparison of the two robustness models, the R^2 and the information criteria demonstrate that the model with the computed NEDLs (*Model V*) improves the explanation of the wholesale market price.

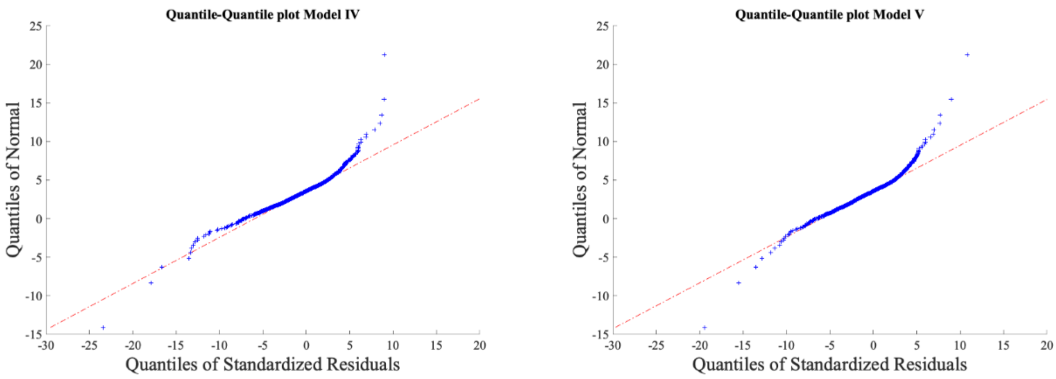

Figure 4.8. Quantile-Quantile Plots for Model *IV* (left) and V (right)

A smoothed NDemand, meaning a net intermediate electricity demand level (NIEDL), could reduce the wholesale market price by around 0.001%. In contrast, a traditional intermediate electricity demand level (TIEDL), or a smoothed TDemand, increases the price by 0.0002%. Moreover, the results also emphasise that NIEDL has less impact on price volatility than TIEDL. It is also important to perform a reality check on the EDL classifications. This could be made by comparing the results of net peak electricity demand level (NPEDL) with the traditional peak electricity demand level (TPEDL). Whereas in the mean equation, TPEDL has an impact of 0.0012% on the price formation, the NPEDL has a higher impact of around 0.0031%. Indeed, the TPEDL is satisfied by fossil fuels, RES-I, and controllable RES, but the NPEDL (in which the RES-I are already discounted) are only satisfied by fossil fuels and controllable RES. Therefore, it is expected that the NPEDL will have a greater impact on price formation. NPEDL increases volatility more than TPEDL (TPEDL: 0.005%, NPEDL: 0.0167%). Indeed, the NPEDL have a shorter duration, increasing volatility more. In contrast, TPEDL generally last longer, running from morning to afternoon. In short, this finding strongly corresponds to the reality.

Overall, NDemand has greater explanatory power for the wholesale market price than TDemand. This explanatory power is increased when evaluating it using NEDLs. Consequently, this means that the wholesale price could be useful to determine the price of NEDLs. Thus, a framework can be created for designing price-responsive tariffs for the retail market using NEDLs. The price-responsive tariffs designed using NEDLSs will have the advantage of being more able to synchronize demand with RES-I instantaneous availability. Therefore, this research provides an extremely useful methodology for planning the required capacity of controllable RES and fossil fuels in the mix, and for formulating retail prices based on these requirements.

4.4 Results and discussion

The inertia of German consumers has declined, and in 2018, only 27% of residential electricity customers were supplied using a default contract; this means on a flat-rate tariff (Bundeskartellamt, 2019). The remaining households were supplied using a ToU or RPT tariff, as were the majority of industrial and service sector customers (Bundeskartellamt, 2019). This suggests that German consumers have a high propensity for accepting new price-responsive tariffs. Consequently, ToU tariffs or real-time pricing schemes should be implemented, while at the same time, flat electricity tariffs progressively abandoned. This paper's analysis contributes to understanding both TDemand and NDemand patterns and their impact on the wholesale market price and, by this, provides a useful framework to design price-responsive tariffs. Table 4.8 and Table A.4.1., shown in the appendix, provide heat maps for the occurrence of NEDLs and TEDLs respectively. Both tables reveal the EDLs most likely to occur during a particular hour, depending on the season, day of the week, and year. In turn, Table 4.5 shows the baseload, flexible, and peak capacities required for each hour, depending on the season, day of the week, and year. Thus, the results of this research identify the block periods for devising ToU tariffs, as well as the correct price differentiation for each block period. Consequently, this discussion will focus on retail tariffs designed using NEDLs, intended to reduce the volatility and wholesale market price of the German electricity market

The heat maps reveal that weekends and holidays have NDemand pattern that diverge from those on weekdays (Monday to Friday). This could put stress on the electricity grid when it tries to fulfil demand with distinct patterns. Generally, demand on these days is mainly from residential, services, and commercial sectors, increasing NDemand volatility. This may jeopardize the reliability and security of the grid, and risk the demand not being met (Bahl et al., 2017; Cardoso et al., 2020; Elkasrawy & Venkatesh, 2020; Iliopoulos et al., 2020; Jordehi, 2019; Olsthoorn et al., 2019; Ruokamo et al., 2019). Therefore, the Germany electricity system should install automated metering infrastructures throughout the grid. A smart grid and smart meters allow detailed and disaggregated demand data to be obtained. This data could then be used to trace demand profiles and provide useful statistics to anticipate its patterns. This argument is well-established in the literature (Cardoso et al., 2020; Conteh et al., 2020; Iliopoulos et al., 2020; Kaiser et al., 2020; Wohlfarth, Klobasa, et al., 2020). These statistics would make it possible to anticipate demand needs, and adjust supply to meet them. Additionally, price-responsive tariffs could modify demand to correspond to the availability of RES-I (Alasseri et al., 2017; Meyabadi & Deihimi, 2017).

The inferior limit (lim_{inf}), is considered the minimum electricity production required, i.e., the baseload production, which can be provided by nuclear power, brown or hard coal, and even biomass. The difference between the superior limit and inferior limit ($lim^{sup} - lim_{inf}$) is seen as the flexible capacity needed to satisfy the variable NIEDL, which in Germany could be fulfilled through the dual structures of brown and hard coal plants, biomass, natural gas, and hydropower, mainly run-of-the-river. Taking the difference between the maximum and superior limits of NDemand ($max - lim^{sup}$) as the peak installed capacity required to fulfil the NPEDL, this is satisfied in Germany mainly by natural gas and pumped storage. The results highlight that price-responsive tariffs should distinguish between the winter and summer seasons. Indeed, the capacities required, baseload, flexible, and peak capacities, are all dependent on the season (see Table 4.5 and 4.8). For example, in 2019, the results show that the summer season required a higher baseload production than the winter season (winter: 6,263 MWh, summer: 6,501 MWh). This could lead one to conclude that the cost of electricity is higher in the summer than the winter. However, electricity is cheaper in the summer than in winter, because plants produce a constant amount of electricity, decreasing their marginal cost. In contrast, the flexible capacity required in the winter is 65% higher than in summer (winter: 4,583 MWh, summer: 2,976 MWh), moreover, peak capacity is 55% higher (winter: 4,583 MWh, summer: 2,976 MWh). The SARMAX-EGARCH models also corroborate these results, indicating that the summer season reduces wholesale market price volatility. Therefore, the design of price-responsive tariffs should take the season into consideration - with summer tariffs being cheaper than winter tariffs.

Table 4.8. Heat map of net electricity demand levels

Year	Season	Day of the Week	0h	1h	2h	3h	4h	5h	6h	7h	8h	9h	10h	11h	12h	13h	14h	15h	16h	17h	18h	19h	20h	21h	22h	23h
2015	Winter	Weekdays	I	I	I	V	V	V	I	I	I	I	I	I	I	I	I	I	I	P	P	P	P	P	P	I
2015	Winter	Saturday	V	V	V	V	V	V	I	I	I	I	I	I	I	I	I	I	I	P	P	P	I	I	I	I
2015	Winter	Sunday and Holidays	V	V	V	V	V	I	I	P	I	I	I	I	I	I	I	I	P	P	P	P	I	I	I	I
2015	Summer	Weekdays	I	I	I	I	I	I	I	I	I	I	I	I	V	V	V	V	I	I	P	P	P	P	P	P
2015	Summer	Saturday	V	V	V	V	V	V	I	P	P	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I
2015	Summer	Sunday and Holidays	I	V	V	V	V	I	I	P	P	I	I	I	I	I	I	I	I	I	I	P	P	I	I	I
2016	Winter	Weekdays	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I	I
2016	Winter	Saturday	V	V	V	V	V	V	I	I	P	P	I	I	I	I	I	P	P	P	P	P	P	I	I	I
2016	Winter	Sunday and Holidays	I	I	I	I	I	I	I	P	P	P	P	I	I	I	I	I	I	P	P	P	I	I	I	I
2016	Summer	Weekdays	I	I	I	I	I	I	I	I	I	I	I	V	V	V	V	V	V	I	I	P	P	P	P	I
2016	Summer	Saturday	V	V	V	V	V	V	I	P	P	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I
2016	Summer	Sunday and Holidays	I	V	V	V	I	I	I	P	P	P	I	I	I	I	I	I	I	I	P	P	P	P	I	I
2017	Winter	Weekdays	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	P	P	P	I	I	I
2017	Winter	Saturday	V	V	V	V	V	I	I	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I	I	I
2017	Winter	Sunday and Holidays	I	I	I	I	I	I	I	P	P	P	I	I	I	I	I	I	I	P	P	P	I	I	I	I
2017	Summer	Weekdays	I	I	I	I	I	I	I	I	I	I	I	I	V	V	V	V	V	I	P	P	P	P	P	P
2017	Summer	Saturday	V	V	V	V	V	I	I	P	P	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I
2017	Summer	Sunday and Holidays	I	I	I	I	I	I	I	P	P	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I
2018	Winter	Weekdays	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I	I
2018	Winter	Saturday	V	V	V	V	V	V	I	I	I	I	I	I	I	I	I	I	I	I	P	P	I	I	I	I
2018	Winter	Sunday and Holidays	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	P	P	P	I	I	I	I
2018	Summer	Weekdays	I	I	I	I	I	I	I	I	I	I	I	V	V	V	V	V	V	I	P	P	P	P	P	P
2018	Summer	Saturday	V	V	V	V	V	I	I	P	P	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I
2018	Summer	Sunday and Holidays	I	V	V	V	V	I	I	P	P	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I
2019	Winter	Weekdays	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	P	P	P	P	P	I	I	I
2019	Winter	Saturday	V	V	V	V	V	I	I	P	P	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I
2019	Winter	Sunday and Holidays	V	V	V	V	V	I	I	I	I	I	I	I	I	I	I	I	P	P	P	P	P	I	I	I
2019	Summer	Weekdays	I	I	I	I	I	I	I	I	I	I	I	V	V	V	V	V	I	I	P	P	P	P	P	P
2019	Summer	Saturday	V	V	V	V	V	I	I	P	P	I	I	I	I	I	I	I	I	I	I	P	P	P	I	I
2019	Summer	Sunday and Holidays	I	V	V	V	I	I	I	P	P	I	I	I	I	I	V	V	I	I	I	P	P	P	I	I
ALL	Winter	Weekdays	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I	I
ALL	Winter	Saturday	V	V	V	V	V	V	I	I	P	I	I	I	I	I	I	I	I	P	P	P	I	I	I	I
ALL	Winter	Sunday and Holidays	V	V	V	V	V	I	I	P	P	I	I	I	I	I	I	I	I	P	P	P	I	I	I	I
ALL	Summer	Weekdays	I	I	I	I	I	I	I	I	I	I	I	I	V	V	V	V	V	I	P	P	P	P	P	P
ALL	Summer	Saturday	V	V	V	V	V	I	I	P	P	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I
ALL	Summer	Sunday and Holidays	I	V	V	V	I	I	I	P	P	I	I	I	I	I	I	I	I	I	P	P	P	P	I	I

Notes: ALL means all years (2015 to 2019), V denotes valley electricity demand level, I represents the intermediate electricity demand level, and P designates the Peak electricity demand level.

With regard to the differences between days of the week, the results reveal that weekdays (Monday to Friday) require a higher capacity of both baseload and flexible plants than weekends and holidays. One reason for this outcome is the higher demand on weekdays due to the operation of the industrial and services sectors. In turn, Sundays and holidays demand more peak capacity than Saturdays and weekdays. This result is also corroborated by the SARMAX-EGARCH models, which identify that Sundays and holidays increase volatility in the wholesale market. The results also highlight that Sundays and holidays increase the volatility of the wholesale market more than Saturdays. A possible reason is that Sundays and holidays require a higher capacity of both flexible and peak plants than Saturdays, putting more stress on the electricity grid and markets. Additionally, the NEDL heat map also reveals that NPEDL occur at different times on weekdays. For example, in the summer of 2019, on weekends and holidays the NPEDL occurred during two distinct daily time-periods, firstly at 7 a.m. and 8 a.m., and after between 7 p.m. and 9 p.m. On weekdays the NPEDL mostly occurred between 6 p.m. and 12 p.m.

To summarise, ToU tariffs in Germany should be designed in a framework with a distinct price differentiation between weekdays, Saturdays, Sundays, and holidays. It is also important to highlight that the period blocks of ToU should be different for each day of the week. Nonetheless, Germany´s retail market should also pursue a CPP, or even incorporate a CPP in a ToU tariff; this means delineated a SPToU to diminish the high NPEDL on Sundays and holidays. If the price-responsive tariff for Sundays is successful, and decreases the NPEDL to NIEDL, the wholesale market price will decrease, benefiting both suppliers and consumers.

Finally, the results regarding the net valley electricity demand level (NVEDL) highlighted some specificities which are of great importance and relevance. In the winter of 2019, the minimum NDemand was 4 times lower than the baseload generation on weekdays (min:1,994 MWh, lim^{inf}: 8,222 MWh). This happened again in the summer weekdays of 2019, with the baseload capacity of around 8,523 MWh and NDemand minimum of 2,146 MWh. The NVEDL occurs on most days between 12 a.m. to 5 a.m. However, during winter weekdays, a NVEDL is less likely to occur and, in summer, the NVEDL occurs between 11 a.m. and 3 p.m. which coincides with maximum solar PV production (see Table 4.8). Therefore, the German retail market should design efficient valley-filling strategies to mitigate the economic inefficiency that NVEDL provokes in the electricity system. This economic inefficiency is not serious in Germany because it is the largest European net exporter of electricity, as noted by Sinn (2017). However, this problem could also be solved within the retail market. The ToU tariffs could be an efficient tool for resolving this difficulty. On the one hand, the TOU tariff could offer a lower price during NVEDL periods, incentivizing consumers to increase their demand in these periods. On the other hand, the ToU tariff could have a large price differential between NPEDL and NVEDL periods, encouraging consumers to shift loads from NPEDL periods to NVEDL periods. Consequently, this will reward the efforts of electricity consumers who shift from NPEDL to NVEDL periods, and penalize the wasteful. Therefore, through price differentiation, suppliers should publicize the great benefits of RES to consumers, mainly because there are strict demand needs in evening NPEDL periods.

4.5 Conclusion

By using two measures of electricity demand: traditional demand (TDemand), i.e. electricity consumption; and net demand (NDemand), i.e. TDemand minus RES-I production, this research uses high-frequency data (intraday and daily data) to show that NDemand has a greater impact on the wholesale electricity market price than TDemand. This research breaks new ground by developing a new classification of demand by level, to provide a proper framework for devising price-responsive tariffs. The NDemand levels (valley, intermediate, and peak) revealed a higher explanatory capacity for wholesale market prices than TDemand levels. Therefore, German policymakers and electricity retail companies should evolve their price-responsive tariffs, using as their primary reference, the concept of NDemand rather than TDemand.

In the best of our knowledge, German electricity retail companies only offer a ToU with two block periods, the peak period (6 a.m. to 10 p.m.) has a higher price; and the off-peak periods (remaining hours) have a lower price. This tariff plan is consistent with TDemand, as this research shows. However, our findings strongly suggest that tariff plans should be designed using the NDemand concept. This research contributes to the literature and, particularly, to tariff design, by showing that ToU tariffs should consist of three distinct block periods, corresponding to occurrences of the three NDemand levels. Furthermore, the price-responsive tariffs, their block periods, and respective prices should take into consideration the seasons and days of the week.

Price-responsive tariffs should aim to smooth the NDemand curve, and to lower the need for fossil fuel generation. They will also allow the NDemand to be met with a portfolio of controllable RES, particularly hydro power and biomass. Consequently, a smoothed NDemand curve will reduce electricity prices and their volatility. To achieve this, there should be a marked price differentiation between valley and peak periods of NDemand.

In the NDemand peak periods the demand needs are strict, and inelastic. Conversely, in the NDemand valley periods the demand needs are flexible, and elastic. Therefore, the price differentiation between NDemand valley and peak periods should be higher, to reward conscientious consumers and penalize the wasteful. Accordingly, this could lead residential consumers to adopt energy storage strategies in their homes, such as installing domestic batteries or acquiring electric vehicles. They could also connect their home appliances to Demand Response programmes, or even use the internet of things to benefit from lower electricity prices.

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Chapter 5

An analysis of the interactions between daily electricity demand levels in France

This chapter was presented at four international conferences, having also won the International Association of Energy Economics (IAEE) student prize at the conference - 6th Meeting on Energy and Environmental Economics, and resulted in an article published in *Utilities Policy* journal. This chapter outputs are:

Pereira, D. S., & Marques, A. C. (2022). An analysis of the interactions between daily electricity demand levels in France. Utilities Policy, 76. https://doi.org/10.1016/j.jup.2022.101368. WoS/Scopus; Impact factor – 2.813; CiteScore – 4.1; and SJR – Q1.

Pereira, D. S., & Marques, A. C. (2019). An econometric approach to assess and design policies and measures for electricity Demand-Side Management: France as a case study. 6th Meeting on Energy and Environmental Economics, Aveiro, Portugal

Prize: International Association of Energy Economics (IAEE) student prize – International Association for Energy Economics, and Associação Portuguesa da Economia da Energia

Pereira, D. S., & Marques, A. C. (2019). An econometric approach to assess and design policies and measures for electricity Demand-Side Management: France as a case study. 4th International Conference on Energy and Environment: bringing together Engineering and Economics, Guimarães, Portugal

Pereira, D. S., & Marques, A. C. (2019). An econometric approach to assess and design policies and measures for electricity Demand-Side Management: France as a case study. Workshop: Economic Development Thinking the Environment, Coimbra, Portugal

Pereira, D. S., & Marques, A. C. (2021). An econometric approach to assess and design policies and measures for electricity Demand-Side Management: France as a case study. 5th Annual APEEN Conference - APEEN2021 – Energy Transition and Sustainability, Lisboa, Portugal

Abstract

This research proposes a new system that classifies electricity demand in both levels and time periods, and uses intraday data to provide a deeper understanding and inform the design of appropriate demand-side management measures. This classification divides the day into three periods with contrasting levels of electricity demand; two with peaks, 6:15 a.m. to 5 p.m. and 5:15 p.m. to 11:45 p.m.; and one with a large drop in demand from 0 a.m. to 6 am. The interactions of daily levels of electricity demand in France, from 2013 to 2021, were empirically analysed, and revealed a need to implement demand-side management policies to shift demand from peak to valley periods.

5.1 Introduction

Electricity generation is becoming more dependent on the availability of renewable natural resources. Balancing intermittent generation with highly uncertain demand has triggered the installation of additional capacity in the form of fossil-fuel plants to meet peaks in demand. In fact, by backing up renewable energy sources (RES), flexible plants using fossil fuel, such as natural gas, have played a key role in the transition of electricity systems towards cleaner sources. These conventional fossil powered plants are maintained in stand-by, and only triggered when the intermittency of electrical production from renewable energy sources (RES-I) prevents them meeting highly fluctuating demand. However this continued dependence on fossil fuel plants, despite reductions in their financing, means that recent increases in the price of natural gas, due to geopolitical and other external factors, have led to large increases in electricity prices for consumers. Such increases in the cost of electricity represent a heavy burden for economies and society as a whole, and risk undermining the transition to cleaner energy. This paradoxical situation suggests the need for a change in the demand-side paradigm. The demand-side needs to become more responsive to the availability of renewable natural resources, and make electricity systems more flexible.

Influencing the demand-side is considered fundamental to successfully integrating RES-I into the electricity mix (Alasseri et al., 2018; Sahin et al., 2019; Thakur & Chakraborty, 2016). A key tool in bringing about the desired changes in electricity demand patterns is Demand-Side Management (DSM), particularly, the use of Time-Based Tariffs. TBTs have been employed all over the world in various forms, with benefits for both consumers and producers. However, despite the use of DSM and TBT measures, the consumption of electricity during peak periods still remains a problem in numerous electricity system and markets. Conversely, when the load diagrams of many countries are examined, large demand valleys can still be observed in the early hours of the day, when electricity generated by RES-I exceeds consumption. This is further evidence that TBT and DSM measures are failing to have the desired effect on electricity demand.

These failings were the primary motivation for this research. We realised there was a need to scrutinize intraday demand data and load profiles in more detail, in order to delineate and quantify the challenges and opportunities for demand control. Accordingly, the main objective of this work was to produce a new form of classifying electricity demand, divided into levels, to properly assess the impact of tariffs on smoothing consumption and provide knowledge to design effective and efficient TBT and DSM measures.

Thus, this research proposes adding a new body of knowledge, with an international perspective, by making the following novel contributions: (i) the classification of electricity demand divided into levels and time-periods using historical intraday data; (ii) the statistical simulation of a flexible and smoothed demand curve; (iii) the rigorous classification of demand as a way of generating truly representative electricity demand profile data, especially with regard to the shape of load profiles and variability within daily time periods; and (iv) the empirical analysis of interactions between the classified demand levels and time periods to produce easily understandable results and provide insights to help design policies to achieve flexible smoothed daily demand curves. In this paper, electricity demand in a specific national market was analysed to assess how DSM policies should evolve, in this case, France. However, this research methodology can be replicated to study demand in other countries, regions, or even households. Moreover, this classification method can also be used to generate detailed statistics on electricity demand, which are both valuable and scarce.

This research proposes a classification of the electricity demand in both levels and time periods. The lack of available data on peak and valley demand, led us to propose classification by electricity demand levels (EDLs). Electricity demand was divided into three levels: peak, valley, and intermediate. Furthermore, Peak Electricity Demand Levels and Valley Electricity Demand Levels (PEDLs and VEDLs, respectively) were subclassified into three time periods, namely morning, middle of the day, and night-time. A type of smoothed demand, we called the Intermediate Electricity Demand Level (IEDL), was statistically simulated using the interquartile ranges. Consequently, this EDL is not strictly constant but flexible, and moves around the daily median, i.e., a hypothetical, near-perfect, daily smoothed demand curve.

In this study, the daily interactions of French EDLs between 1 January 2013 and 10 October 2021 were analysed. To do this, an Autoregressive Distributed Lag (ARDL) model was used to reveal the short- and long-run interactions of EDLs. Four models were estimated to identify the barriers and opportunities to achieving a flexible smoothed daily demand curve in France. A battery of diagnostic and stability tests confirmed the models' goodness of fit.

The classification of demand proposed in this research, as well as the results of the empirical analysis, revealed several findings that can help in devising better DSM measures. The results showed that the demand patterns of residential consumption in France had changed very little. In fact, French households have caused peaks in consumption to grow, and increased even more in winter months, due to their heating needs. This suggests that DSM should be used to introduce Time-of-Use tariffs and incentivize residential customers to shift part of their consumption from the night PEDL towards the morning VEDL. In the meantime, real-time pricing (RTP) schemes should be incorporated into demand response (DR) programmes allowing households to benefit from the intelligent control of home appliances, such as heating systems. The latter DSM measure is intended to cut peak consumption during winter nights, and increase consumption during VEDL morning periods. France should also invest in Energy Efficiency (EE) policies across all sectors, to reduce the peak consumption it experiences in the middle of the day.

The rest of the paper is organised as follows: Section 5.2 offers a brief literature review, while Section 5.3 justifies why France was selected for this analysis. Section 5.4 explains and describes the demand classification procedure step by step. Section 5.5 presents the data, the econometric model, and the procedures followed, as well as the results and their interpretation. Section 5.6 discusses the results and proposed DSM measures. Lastly, Section 5.7 concludes.

5.2 Literature Review

DSM emerged in the 1970s to describe the planning, implementing, and monitoring of activities designed to influence the use of electricity by consumers/customers and produce desired shifts in the shape of electricity loads (Gellings, 2016; Strbac, 2008). DSM was intended to provide advantages for both electricity providers and consumers (Gellings, 1985; Gellings, 2016; Strbac, 2008). DSM measures were also intended to incentivize the active participation of consumers in adjusting their demand patterns and needs, to meet the constraints of electricity generation and provision. The aim of this adjustment, based on informed and conscious decisions, is to obtain optimal demand, specifically, by reducing peak load demand and increasing demand during valley periods (Alasseri et al., 2018; Alasseri et al., 2017; Pereira & Marques, 2020b; Sahin et al., 2019; Sharda et al., 2021). Consumer participation in DSM measures helps electricity providers maintain the reliability and stability of electricity generation and networks (Alasseri et al., 2017; Gellings, 1985; Holland & Mansur, 2008; Sharda et al., 2021). Cutting peak loads, known as peak clipping, reduces the need for installed capacity and the use of fossil-fuelled plants (Alasseri et al., 2018; Gellings, 1985; Pereira & Marques, 2020b; Sharda et al., 2021; Strbac, 2008). Conversely, valley filling leads to a reduction in RES-I exports and electricity storage needs (Pereira & Marques, 2020b). These two strategies reduce the overall cost of electricity production and transportation. DSM measures should also oblige electricity providers to share surpluses with consumers, thereby, reinforcing desirable consumer activity on the demand-side (Aneiros et al., 2016; Çakmak & Altaş, 2020).

The literature identifies the key categories of DSM as: Energy Efficiency (EE); Strategic Load Growth; Strategic Load Conservation; Spinning Reserves; Demand Response (DR); Time-Based Tariffs (TBTs); and Direct Load Management (Alasseri et al., 2018; Albadi & El-Saadany, 2007; Sahin et al., 2019). Consumers are positively encouraged by DSM and smart technologies (Andersen et al., 2017; Iliopoulos et al., 2020). Consumers, particularly residential consumers, are reluctant to hand over direct control of their electricity consuming equipment to electricity utilities and providers. Consequently, direct load management, strategic load growth, and spinning reserves are not appropriate DSM categories at the moment (Gołębiowska et al., 2021; Iliopoulos et al., 2020; Mesarić et al., 2017). This leaves DR and TBT as the key DSM categories for promoting modifications in demand patterns (Stavrakas & Flamos, 2020; Yu et al., 2017). EE, TBT, and DR have been the most efficient and cost-effective DSM measures for influencing changes in demand patterns (Sahin et al., 2019; Stavrakas & Flamos, 2020; Su et al., 2019). TBT, such as the Time of Use (ToU), inclined block rate, and day-ahead pricing tariffs, are set beforehand and allow consumers to adjust their demand patterns to the new prices in advance (Sharda et al., 2021; Stavrakas & Flamos, 2020; Su et al., 2019). On the other hand, DR and some TBTs, such as RTP, Critical Peak Pricing and Tariff Signalling, involve real-time demand adjustments (Holland & Mansur, 2008; Sousa & Soares, 2020; Stavrakas & Flamos, 2020; Su et al., 2019). Consequently, DR, RTP, and Critical Peak Pricing are effective ways to produce immediate changes in consumption during a network's critical periods, such as when RES-I generation is abundant (or scarce).

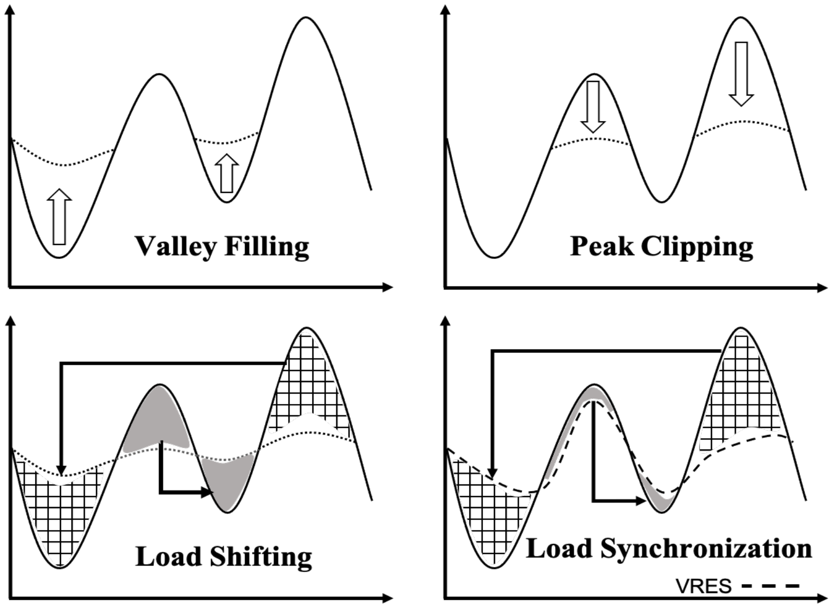


Figure 5.1 – Demand-Side Management consumption pattern shift objectives

DR and TBT are often considered to belong to the same DSM category (Borsche & Andersson, 2014; Stavrakas & Flamos, 2020), as they pursue the same DSM objectives, namely, valley filling, peak clipping, load shifting and load synchronization (see Figure 5.1). Generally, DR and TBT both encourage a reduction in the oscillation of demand curves, and help achieve more predictable and flexible demand. Furthermore, both DSM instruments reward customers for shifts in their demand patterns (Albadi & El-Saadany, 2007; Holland & Mansur, 2008; Sahin et al., 2019; Stavrakas & Flamos, 2020), Conversely, both DR and TBT penalize consumers if they do not change their demand patterns.

RES-I produce uncertainty and volatility in the electricity supply side, which also affects the price of electricity (Gürtler & Paulsen, 2018; Loureiro et al., 2019; Macedo et al., 2020). Consequently, DR and TBT use a load-synchronization approach, encouraging consumers to coordinate their consumption needs with the availability of RES-I (see Figure 5.1) (Pereira & Marques, 2020a, 2020b). To achieve this effectively, it is first necessary to understand how electricity demand can be smoothed. The literature has studied this subject in various ways, but, to the best of our knowledge, none of them has done so using an empirical analysis. Therefore, this research aims to fill this gap in the literature by analysing the interactions between EDLs in France.

5.3 Why France?

France is a country where the peak demand for electricity at night frequently occurs between 5 p.m. and 10 p.m. (see Figure 5.2). This peak occurs on all days of the week and in all seasons. However, the peak increases substantially on weekdays and in the winter (see Figure 5.2). In winter, the night-time peak is due to the prevalence of electrical heating systems in homes (Agency, 2018). Thus, it could be argued that residential consumers are responsible for the night-time peak, and the residential sector consumes the most electricity overall, accounting for 34.6% of total electricity demand (Agency, 2018). The peak demand in the middle of the day commonly occurs between 7 a.m. and 4 p.m., as Figure 5.2 shows. This peak occurs in all seasons and days of the week, but is less on weekends than during the week. This is probably because most of the industrial sector does not operate on weekends, although the commercial and public sectors do. Accordingly, it could be claimed that the industrial, services, and public sectors are responsible for the peak in demand that occurs in the middle of the day. The industrial sector represents 25.8% of electricity demand, while both the services and public sectors constitute around 32.9% (Agency, 2018). The electricity-intensive sectors in France, namely the residential, services, and public sectors, are the most likely to accept and comply with DSM measures and policies (Cardoso et al., 2020; Iliopoulos et al., 2020; Sahin et al., 2019; Vanouni & Lu, 2018; Vivekananthan et al., 2014).

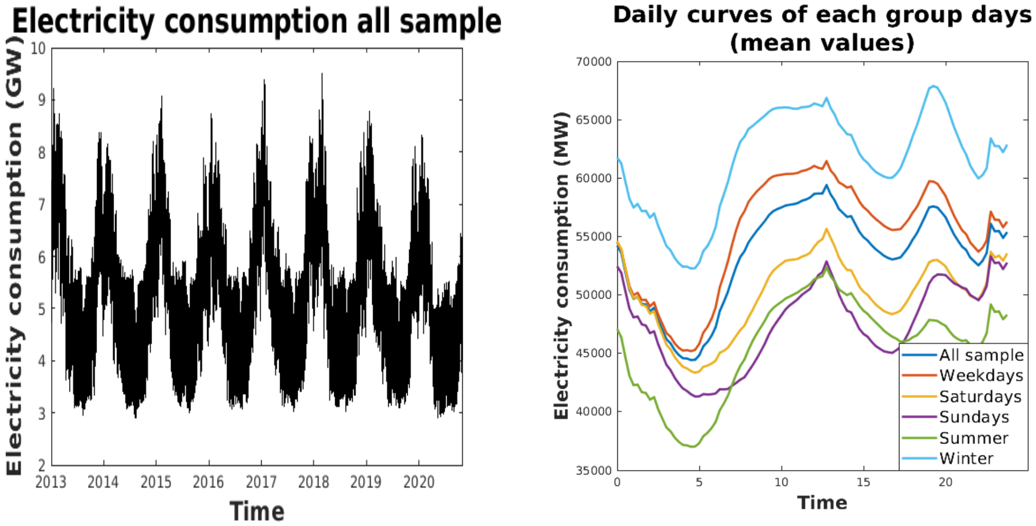


Figure 5.2. Daily curves of electricity demand in France

The nuclear component of France's electricity mix is the second-largest in the world (Agency, 2018). However, France intends to reduce its nuclear capacity, reducing the contribution of nuclear generation to the electricity supply to 50% by 2025. France also intends to reduce its greenhouse gas emissions by 40% by 2030 (Agency, 2018). To accomplish this, France intends to increase the penetration of renewable energy sources (RES), namely RES-I (Agency, 2018). The highly-rigid nature of the nuclear generation that provides France's base-load, makes it imperative to smooth the daily demand curve. In fact, the literature shows that highly oscillating daily demand in France has led to the re-activation of some nuclear power plants (Pereira & Marques, 2020a). In other words, excessively fluctuating demand cannot take advantage of the potential of nuclear sources. So far, it has proved difficult to manage electricity systems with a rigid baseload, and highly oscillating consumption, and has required support from flexible generation plants (Pereira & Marques, 2020a). To meet its oscillating demand, France has used natural gas, and hydropower plants, with and without pumping systems (Agency, 2018; Pereira & Marques, 2020a). Consequently, if the large-scale introduction of RES-I desired by the French government is combined with its currently undisciplined consumption, there will be an imbalance between demand and supply. This will be countered by the installation of more flexible plants using fossil fuels, such as natural gas, causing electricity prices to rise, and harming the environment. Thus, the research proposed in this paper could be of particular value to France by allowing insights into the characteristics of its intraday demand and providing tools for devising new, more effective TBTs, to smooth demand, make better use of nuclear power production, and advance the introduction of RES-I into its electricity mix.

5.4 Demand Classification Procedure

This paper aims to spotlight the different relationships between French EDLs in different time periods. For this, 15-minute period data on French consumption in megawatts (MW), from 1 January 2013 until 31 October 2020, was retrieved from the *Réseau de Transport d' Électricité* (RTE). If the observation of any 15-minute period during a day was unavailable, that day was excluded from the sample. In total, the study examined 273,888 observations, meaning that 2,853 days were analysed.

A large discrepancy was observed between the mean consumption (53,377 MW) and both the minimum (29,085 MW) and maximum (95,064 MW) for these 15-minute periods. The mean could be considered a perfectly smoothed demand curve for the sample under analysis. Of course, in this assumption, all consumption needs are satisfied and equally distributed over every 15-minute period. However, it is worth noting that a perfectly smoothed demand curve is difficult to achieve as it is virtually impossible to synchronize every consumer and their distinctive needs and habits. Therefore, this research aims to classify consumption through a procedure that allows demand to be flexible. To do this, the classification proposed by Pereira & Marques (2020b) was used as its starting point.

However, this was taken further in this study by using of modelling EDL classification that also divided the classification of demand into time periods.

5.4.1 Demand Classification by level

Electricity demand was classified into three levels: Peak Electricity Demand Level (PEDL), Intermediate Electricity Demand Level (IEDL), and Valley Electricity Demand Level (VEDL) (Pereira & Marques, 2020b). PEDL is consumption above a maximum superior daily limit. VEDL is the consumption below a minimum lower daily limit. IEDL is the consumption between the two daily limits. The classification of EDLs was carried out using intraday data, i.e., data on 15-minute periods. The main reason for adopting the classification proposed by Pereira and Marques (Pereira & Marques, 2020b) was its ability to simulate intermediate demand levels (IEDLs) restricted by maximum and minimum limits; in other words, a smoothed but flexible demand curve. Consequently, the study needed to determine the superior limit (lim^{sup}) and the inferior limit (lim^{inf}) for each day of the sample. It should be stressed that the PEDL only measures demand that exceeds the upper limit; while demand below the superior limit is considered IEDL (see Assumption 1). This permits the quantification of consumption that should be displaced to another period. During a peak period, it is not necessary to displace all the consumption, just the consumption that would otherwise require the use of peak plants, mainly powered by fossil fuels. Thus, to achieve a smoothed demand curve, consumption above the superior limit should be shifted away from these periods and, ideally, to periods when there are valleys in electricity demand curves.

Assumption 1: *The classification of EDLs was performed using daily quartile ranges, in which VEDL corresponds to the lower quartile, PEDL to the higher quartile, and IEDL to the interquartile range, as follows:*

$$DMDclass_{p(d)} = \begin{cases} PEDL_{p(d)} = DMD_{p(d)} - \lim_{\mathrm{d}}^{sup} \quad iff\ DMD_{p(d)} \geq \lim_{\mathrm{d}}^{sup} \\ IEDL_{p(d)} = \begin{cases} DMD_{p(d)} \quad iff \lim_{d}^{\mathrm{inf}} < DMD_{p(d)} < \lim_{\mathrm{d}}^{sup} \\ \lim_{d}^{\mathrm{sup}} \quad iff\ DMD_{p(d)} \geq \lim_{\mathrm{d}}^{sup} \end{cases} \\ VEDL_{p(d)} = DMD_{p(d)} \quad iff\ DMD_{p(d)} \leq \lim_{d}^{\mathrm{inf}} \end{cases}$$

where, d denotes the days, $p(d)$ is the 15-minute period of day d, $DMD_{p(d)}$ is the consumption in a 15-minute period p of day d , $DMDclass_{p(d)}$ is the demand classification function for each 15-minute period p of day d , lim_{d}^{sup} is the superior limit of day d, and $\lim_{d}^{\mathrm{inf}}$ is the inferior limit of day d.

Figure 5.3 illustrates the classification for the day with the lowest consumption during a 15-minute period (17 August 2018), and the day with the highest consumption during a 15-minute period (28 February 2018).

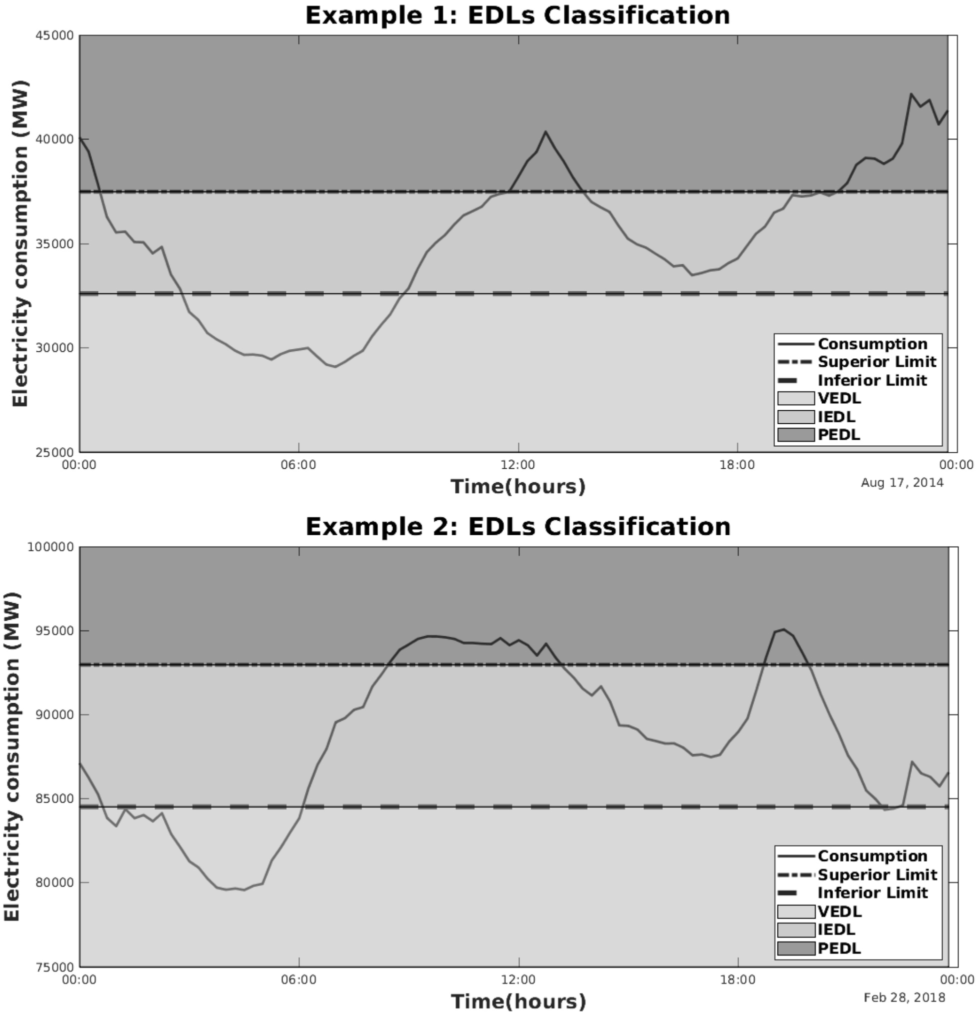


Figure 5.3. EDLs classification examples

One can observe that the demand curves for these two days are quite distinct, and required very different responses from the generation sources. 17 August 2018 was a summer day with lower consumption than 28 February 2018, which was a winter day. The inferior limit could be taken to represent baseload production, while consumption that exceeds the superior limit could denote the flexible generation needed to meet peaks in demand. Similarly, the area between the two limits, or the smoothed flexible demand, could be considered consumption that could be covered by baseload sources and flexible generation powered by RES, or low carbon-intensive sources.

5.4.2 Demand Classification by time-period

In the literature, the data is usually analysed to discover the time periods when certain levels of demand occur (Anderson & Torriti, 2018; Dlamini & Cromieres, 2012; Sakah et al., 2019), and methods have been proposed to determine these time-periods theoretically (Guo et al., 2017; Thakur & Chakraborty, 2016). In the present paper, data was also used to classify the EDLs, in line with (Anderson & Torriti, 2018; Dlamini & Cromieres, 2012; Sakah et al., 2019). To do so, scatter and histogram graphs were produced to enable the starting and ending times of the three EDLs to be determined (see Figures 5.4, 5.5, and 5.6).

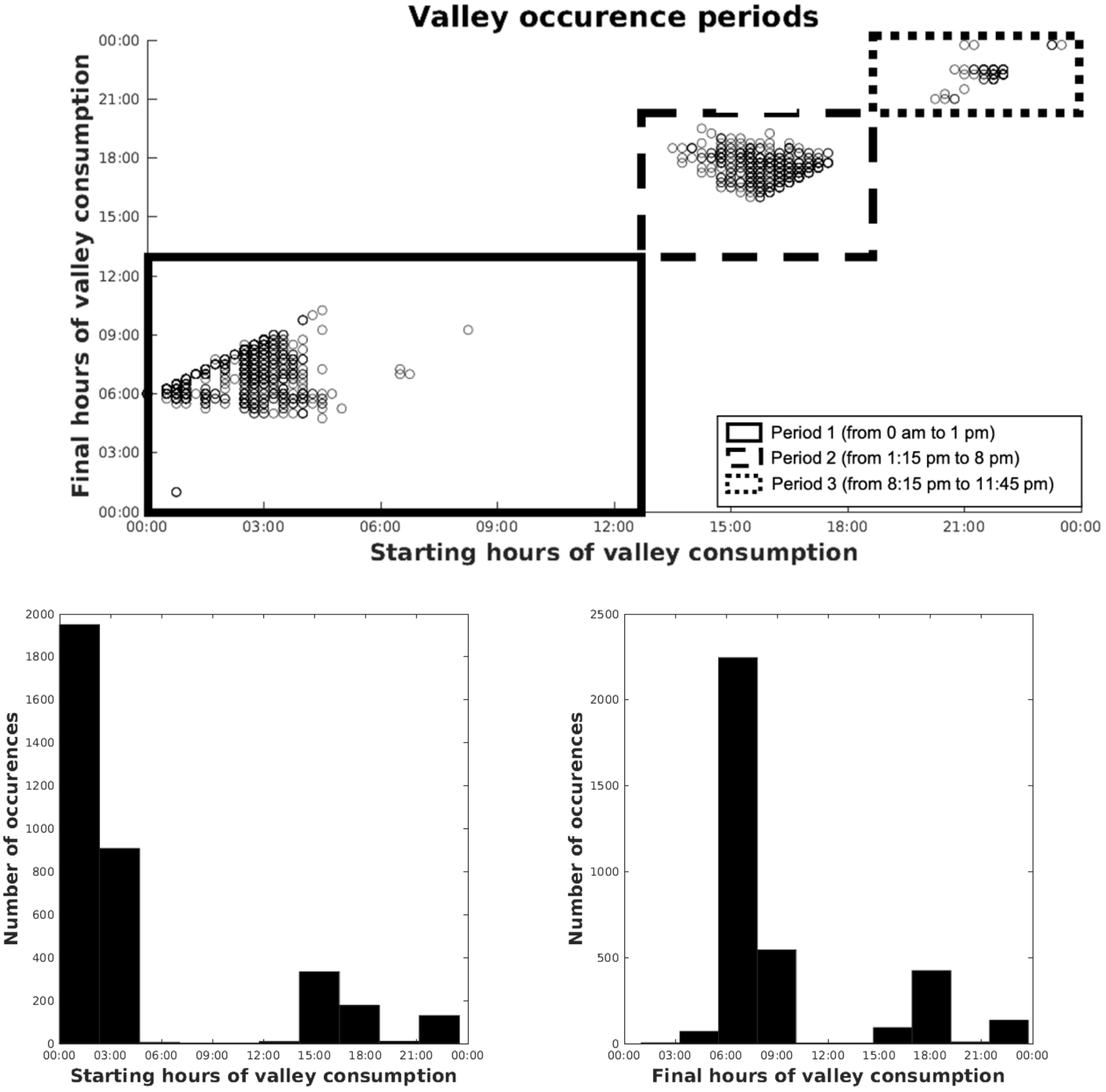


Figure 5.4. VEDL time-period classification

Figure 5.4 shows that VEDLs can be divided into three time periods: (i) from 0 a.m. to 1 p.m.; (ii) from 1:15 p.m. to 8 p.m.; and (iii) from 8:15 p.m. to 11:45 p.m.. The histograms revealed that, when VEDLs occur, more than 70% of the time they start between the hours of 1 - 4 a.m. and end at 6 - 7 am. This result was expected, as it is in line with the data provided by RTE and studied by Pereira and Marques (2020a). Indeed, it was presumed that periods of lower consumption would mostly occur during the night (commonly known as valley consumption). Nevertheless, the data also revealed some other periods when the level of consumption was lower than the inferior limit, as defined above. Thus, the VEDLs were further classified by time-period, using the following assumption:

Assumption 2: *The VEDL was classified into morning VEDL (VEDL_MRG) from 0 am to 1 p.m., middle-of-the-day VEDL (VEDL_MDD) from 1:15 p.m. to 8 p.m., and night-time VEDL (VEDL_NGT) from 8:15 p.m. to 11:45 p.m..*

$$VEDLclass_{p(d)} = \begin{cases} VEDL_{p(d)}^{MRG} = VEDL_{p(d)} \quad iff\ 00{:}00am \leq p(d) \leq 01{:}00pm \\ VEDL_{p(d)}^{MDD} = VEDL_{p(d)} \quad iff\ 01{:}00pm < p(d) \leq 08{:}00pm \\ VEDL_{p(d)}^{NGT} = VEDL_{p(d)} \quad iff\ 08{:}00pm < p(d) \leq 23{:}45pm \end{cases}$$

where, $\mathrm{VEDLclass}_{\mathrm{p(d)}}$ is the VEDL time-period classification for each 15-minute period p of day d, $\mathrm{VEDL}_{\mathrm{p(d)}}^{\mathrm{MRG}}$ is the VEDL in morning periods, $\mathrm{VEDL}_{\mathrm{p(d)}}^{\mathrm{MDD}}$ is the VEDL that occurs in the middle of the day, and $\mathrm{VEDL}_{\mathrm{p(d)}}^{\mathrm{NGT}}$ is the VEDL in night periods.

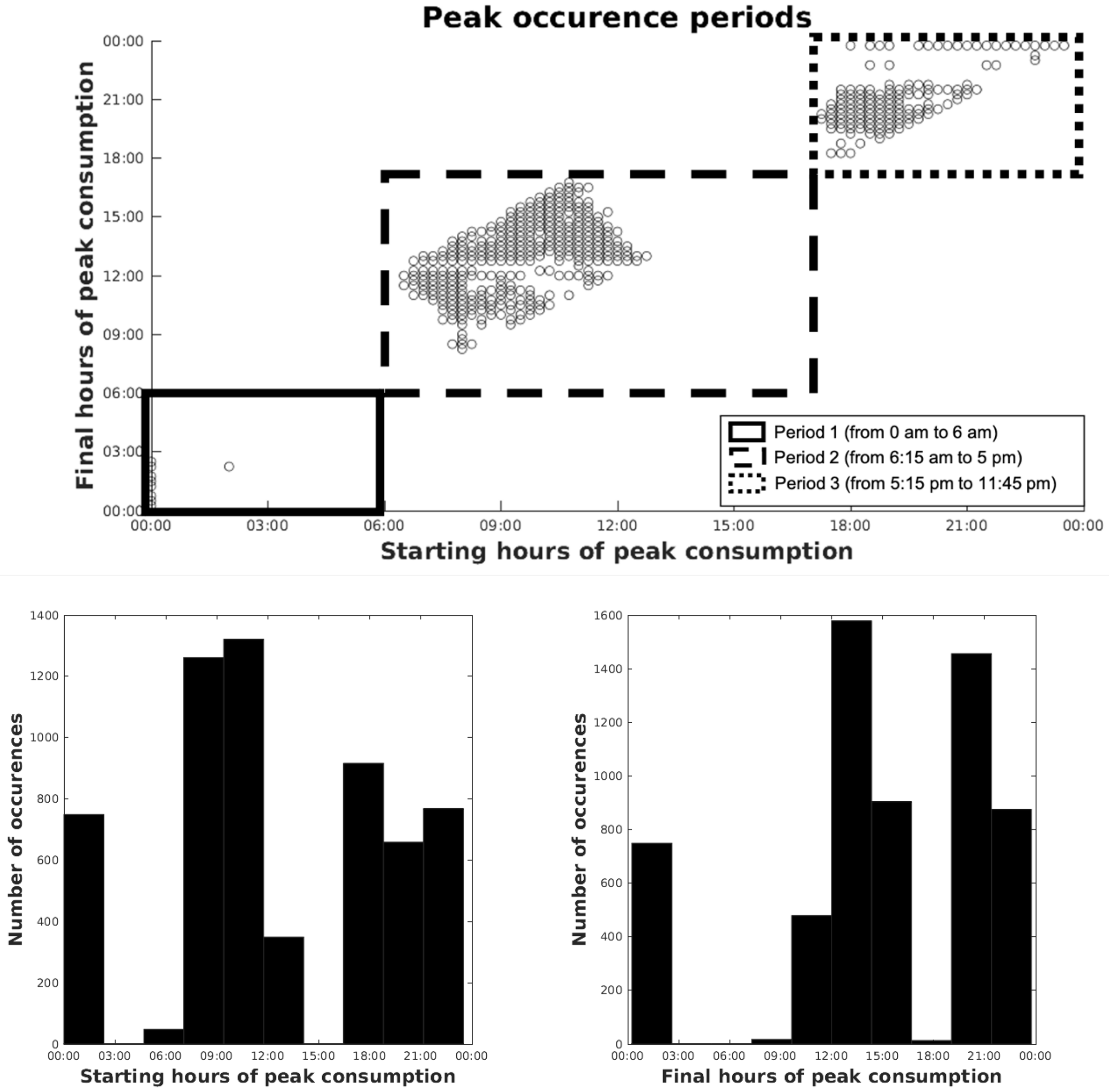


Figure 5.5. PEDL time-period classification

Figure 5.5 suggests that PEDL should be classified into 3 time periods: (i) from 0 a.m. to 6 a.m., (ii) from 6:15 a.m. to 5 p.m.; and (iii) from 5:15 p.m. to 11:45 p.m.. As expected, PEDL occurs mostly during working hours and at night. It could be argued that the middle-of-the-day PEDLs are due to the industrial, services and public sectors, while the night time peaks are mainly caused by the residential sector (Yu, 2021). These results are in line with the RTE and the study by Pereira and Marques (2020a). Thus, the classification of the PEDL by time-period was made using the following assumption:

Assumption 3: *The PEDL was classified into morning PEDL (PEDL_MRG) from 0 a.m. to 6 a.m., middle-of-the-day PEDL (PEDL_MDD), which corresponds to working hours, from 6:15 a.m. to 5 p.m., and night PEDL (PEDL_NGT) from 5:15 p.m. to 11:45 p.m.*

$$PEDLclass_{p(d)} = \begin{cases} PEDL_{p(d)}^{MRG} = PEDL_{p(d)} & iff\ 00{:}00am \leq p(d) \leq 06{:}00am \\ PEDL_{p(d)}^{MDD} = PEDL_{p(d)} & iff\ 06{:}00am < p(d) \leq 05{:}00pm \\ PEDL_{p(d)}^{NGT} = PEDL_{p(d)} & iff\ 05{:}00pm < p(d) \leq 23{:}45pm \end{cases}$$

where, $PEDLclass_{p(d)}$ is the PEDL time-period classification for each 15-minute period p of day d, $PEDL_{p(d)}^{MRG}$ is the PEDL in morning periods, $PEDL_{p(d)}^{MDD}$ is the PEDL that occurs in the middle of the day, and $PEDL_{p(d)}^{NGT}$ is the PEDL in night periods.

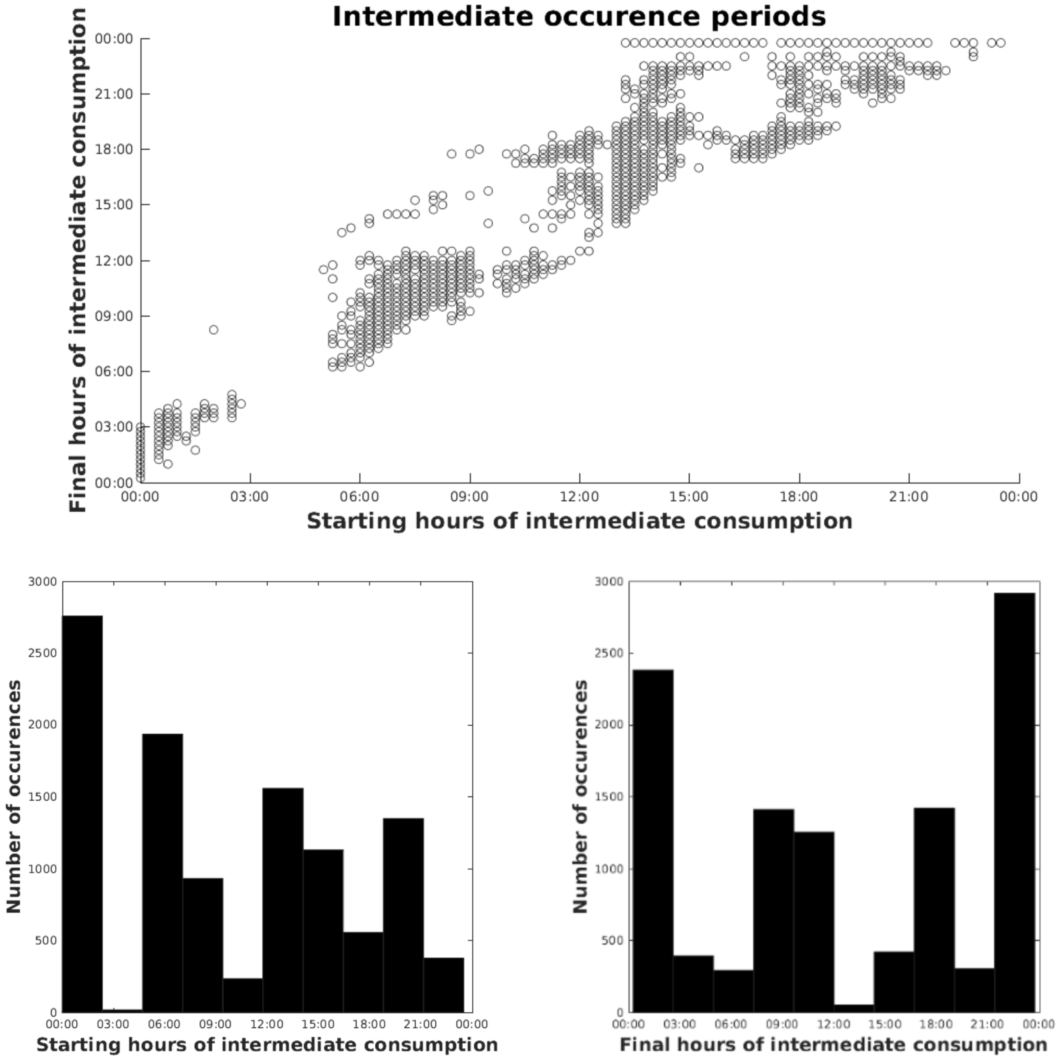


Figure 5.6. IEDL time-period classification

At first glance, the scatter plot shows that the IEDL can be classified into 2 time-periods, the first from 0 a.m. to 5 a.m., and the second, the remaining time (see Figure 6). However, the IEDL histograms show no breaks (see Figure 5.6). Consequently, the IEDL time-periods should not be divided to avoid overlaying periods. As this research aims to diagnose the barriers and identify opportunities for achieving flexible and smoothed demand curves, it is more advantageous to study the IDEL without disaggregating them into time-periods. It should be noted that IEDL mainly occurred between the middle of day and night, and indicate when the French demand curve is more smoothed and flexible.

5.4.3 Demand classification by level and time-periods

Next, both VEDL and PEDL were classified by level and time-period, whereas IEDL were only classified by level, as shown in the following equations.

$$PEDL_{p(d)}^{MRG} = DMD_{p(d)} - \lim_{\mathrm{d}}^{\mathrm{sup}} \quad iff\ DMD_{p(d)} \geq \lim_{\mathrm{d}}^{\mathrm{sup}} \cap\ 00:00am \leq p(d) \leq 06:00am \tag{5.1}$$

$$PEDL_{p(d)}^{MDD} = DMD_{p(d)} - \lim_{\mathrm{d}}^{\mathrm{sup}} \quad iff\ DMD_{p(d)} \geq \lim_{\mathrm{d}}^{\mathrm{sup}} \cap\ 06:00am < p(d) \leq 05:00pm \tag{5.2}$$

$$PEDL_{p(d)}^{NGT} = DMD_{p(d)} - \lim_{\mathrm{d}}^{\mathrm{sup}} \quad iff\ DMD_{p(d)} \geq \lim_{\mathrm{d}}^{\mathrm{sup}} \cap\ 05:00pm < p(d) \leq 23:45pm \tag{5.3}$$

$$IEDL_{p(d)} = \begin{cases} DMD_{p(d)} & iff \lim_{d}^{\mathrm{inf}} < DMD_{p(d)} < \lim_{\mathrm{d}}^{\mathrm{sup}} \\ \lim_{\mathrm{d}}^{\mathrm{sup}} & iff\ DMD_{p(d)} \geq \lim_{\mathrm{d}}^{\mathrm{sup}} \end{cases} \tag{5.4}$$

$$VEDL_{p(d)}^{MRG} = DMD_{p(d)} \quad iff\ DMD_{p(d)} \leq \lim_{d}^{\mathrm{inf}} \cap\ 00:00am \leq p(d) \leq 01:00pm \tag{5.5}$$

$$VEDL_{p(d)}^{MDD} = DMD_{p(d)} \quad iff\ DMD_{p(d)} \leq \lim_{d}^{\mathrm{inf}} \cap\ 01:00pm < p(d) \leq 08:00pm \tag{5.6}$$

$$VEDL_{p(d)}^{NGT} = DMD_{p(d)} \quad iff\ DMD_{p(d)} \leq \lim_{d}^{\mathrm{inf}} \cap\ 08:00pm < p(d) \leq 23:45pm \tag{5.7}$$

It should be noted that the classification of levels and time periods performed in this analysis is not the only classification possible. The classification of both levels and time-periods can be adapted and applied to other research questions, countries, electricity system characteristic, or policy frameworks. For example, to analyse the efficiency of a ToU or other TBT on demand, the time periods could be defined by the TBT in force. Alternatively, to study the synchronization of demand with RES-I, the time-periods could be defined by RES-I availability (high and low availability). Similarly, the EDL could be defined by non-RES and RES-I generation to evaluate how synchronized demand is with their respective availability.

5.4.4 Conversion of intraday data to daily data

After classifying the demand into levels and time periods, the data was converted from 15-minute-period data into daily data. The conversion was performed by calculating the mean values, as shown by equations (5.8) to (5.14).

$$PEDL_d^{MRG} = \frac{1}{N_{PEDL_d^{MRG}}} \sum_{m=00:00}^{06:00} PEDL_{p(d)}^{MRG} \tag{5.8}$$

$$PEDL_d^{MDD} = \frac{1}{N_{PEDL_d^{MDD}}} \sum_{m=06:00}^{17:00} PEDL_{p(d)}^{MDD} \tag{5.9}$$

$$PEDL_d^{NGT} = \frac{1}{N_{PEDL_d^{NGT}}} \sum_{m=17:15}^{23:45} PEDL_{p(d)}^{NGT} \tag{5.10}$$

$$IEDL_d = \frac{1}{N_{IEDL_d}} \sum_{m=00:00}^{23:45} IEDL_{p(d)} \tag{5.11}$$

$$VEDL_d^{MRG} = \frac{1}{N_{VEDL_d^{MRG}}} \sum_{m=00:00}^{13:00} VEDL_{p(d)}^{MRG} \tag{5.12}$$

$$VEDL_d^{MDD} = \frac{1}{N_{VEDL_d^{MDD}}} \sum_{m=13:15}^{20:00} VEDL_{p(d)}^{MDD} \tag{5.13}$$

$$VEDL_d^{NGT} = \frac{1}{N_{VEDL_d^{NGT}}} \sum_{m=20:15}^{23:45} VEDL_{p(d)}^{NGT} \tag{5.14}$$

where, N represents the number of observations. It should be noted that, to perform the econometric analysis, the intraday data was converted to daily data using the mean, and is thus expressed in MWh (megawatt hours). It was converted to daily data because the high number of zeros in each intraday time series could have led to erroneous or biased results, and also because it is easier to analyse and interpret the EDLs using daily data.

5.5 Econometric procedures

The econometric model used, the Autoregressive distributed lag (ARDL) model, enables the verification of both the short and long-term conditions and obstacles to smoothing the demand curve. The econometric procedures carried out were as follows. Firstly, the characteristics of the data were analysed through descriptive statistics and unit root tests. Secondly, the theoretical ARDL model was designed and estimated. After that, the ARDL models' quality and stability were assessed through a series of diagnostic tests. Lastly, the results were analysed, and their respective explanations determined.

5.5.1 Data analysis

The EDLs previously classified by the intraday data, only described specific parts of the day, whereas the main aim of this study was to analyse the interactions between EDLs, and produce easily understandable results. To accomplish this, only the daily data (2,841 daily observations) was used in the empirical analysis. All the series were transformed into their natural logarithms and first differences of natural logarithms denoted by the prefix “L” and “D”, respectively. Table 5.1 shows the descriptive statistics for all daily series, and Figure 5.7 shows the graphs of all series.

Table 5.1. Summary statistics of the daily data

	Obs.	Mean	Max.	Min.	S.D.	Skewness	Kurtosis	Jarque-Bera
LIEDL	2841	10.6119	11.1209	10.2061	0.1918	0.2716	2.1952	111.6336***
LPEDL_MRG	2841	1.0186	5.8563	0.0000	1.6769	1.1765	2.6268	671.9055***
LPEDL_MDD	2841	5.1888	6.9765	0.0000	0.8934	-1.705	8.6268	5124.883***
LPEDL_NGT	2841	3.1579	6.5395	0.0000	2.2886	-0.397	1.4928	343.3683***
LVEDL_MRG	2841	9.2523	9.8766	6.8313	0.2639	-1.261	10.391	7220.717***
LVEDL_MDD	2841	1.7309	9.3828	0.0000	3.2566	1.3866	3.0069	910.3636***
LVEDL_NGT	2841	0.6709	9.0384	0.0000	2.0674	2.7883	8.8894	7787.119***

Notes: Obs. means observations, Max. means maximum, Min. means minimum, S.D. means standard deviation, and *** indicate the statistic is significant at 1% level

First of all, a visual inspection of the series was carried out to assess the seasonality, stationarity, and extreme values of the series (see Figure 5.7). As is well established in the literature, the analysis of high-frequency or intraday data brings several challenges, namely white noise, seasonal trends according to the day of the week, month, year, and other specific trends linked to holidays. These characteristics of intraday data have led the literature to suggest that they could produce outliers and biased results (Aït-Sahalia & Xiu, 2017; Li et al., 2017; Zhong & Enke, 2017). However, in the analysis of electricity consumption and generation, it is unhelpful to consider extreme values to be outliers, as they occur almost every day. Indeed, if the rationale of the literature were strictly followed, both peak and valley consumption values could be considered outliers. However, these extreme values are a genuine concern for electricity management services, given that they must respond to them (through clipping or filling). Consequently, in the case of this study, excluding these extremes would not only provoke erroneous and biased results, but would defeat the object of the research, as an electricity system cannot be analysed by disregarding one of its most critical and challenging phenomenon.

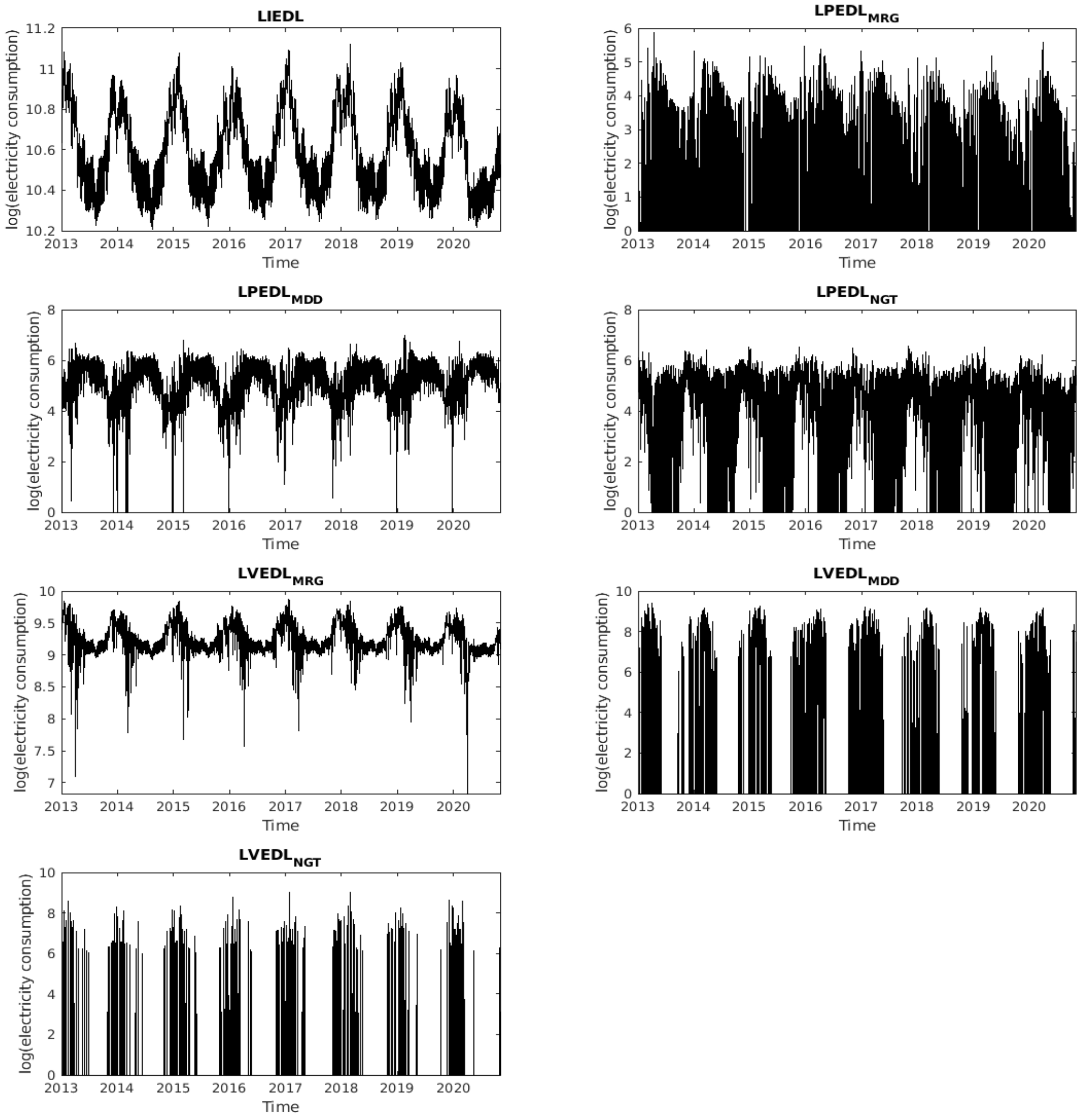


Figure 5.7. Daily series graphs

With regard to the phenomenon of seasonality, one can observe that all the series suffer from seasonality effects. The seasonal effects are more marked in *LIED, LPEDL_MDD, LPEDL_NGT,* and *LVEDL_MRG* than in the other series. VEDL in the middle of the day or at night are a rare occurrence, but occur during every morning. PEDL in the middle of the day occurs almost every day. However, the occurrence of PEDL in the morning and at night is highly correlated with the seasons. Lastly, the correlation matrix and variance inflation factors statistics had to be checked for any collinearity issues. The highest value in the correlation matrix (Table A.5.1 in the Appendix) was -0.73, and the highest variance inflation factor (Table A.5.2 in the Appendix) value was 4.0. Therefore, we were able to set aside concerns about collinearity and correlation between the series.

5.5.2 Unit roots tests

The integration order was verified using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981), the Phillips and Perron (PP) test (Phillips & Perron, 1988), and the Kwiatkowski Schmidt Shin (KPSS) test (Kwiatkowski et al., 1992). The three traditional integration order tests were executed without a maximum limit of lags, and for the series in levels and first differences. The results of traditional integration order tests (see Table A.5.3 in the Appendix) revealed that the majority of the series were integrated of order zero, i.e., I(0). However, the *LPEDL_NGT* and *LVEDL_MDD* integration order tests results were inconclusive, suggesting that both series could be borderline (I(0)/I(1)) or integrated of order one, i.e., I(1). The results of these tests could have been biased by seasonal effects. Consequently, as the majority of the series suffered from seasonality, seasonal integration order tests were performed, namely the traditional Hylleberg-Engle-Granger-Yoo (HEGY) test (Hylleberg et al., 1990), and the Likelihood-Ratio (HEGY) test proposed by (Smith & Taylor, 1999). The seasonal integration order tests (see Table A.5.4 in Appendix) confirmed the results obtained by the traditional integration order tests. Therefore, it could be concluded that all the series were I(0) except *LPEDL_NGT* and *LVEDL_MDD*.

5.5.3 Models and estimators

To meet the main goal of this research, four models were estimated. Table 5.2 presents the models and the dependent and independent series. In the French electricity system, the largest disparities in the allocation of resources occur during the morning valley in demand and during the peaks at night and in the middle of the day (Pereira & Marques, 2020a). These disparities could be addressed by increasing demand during morning periods and decreasing it in peak periods. To increase the penetration of RES-I in its electrical system, France needs to adjust these imbalances in consumption and obtain a smoothed demand curve. Therefore, a *Smooth Demand* model was devised for this study to diagnose the barriers to smoothed but flexible demand and identify opportunities for achieving it. Additionally, *Peak at night* and *Valley in the morning* models were formulated to analyse peaks in consumption at night, and valleys in consumption during the morning, respectively. The purpose of these models was to better understand these periods and identify opportunities for shifting consumption between them. Lastly, the *Peak in working hours* model was designed to discover opportunities for shifting industrial consumption to other time periods.

Table 5.2. Model description

Name	Dependent series	Independent series
Smooth demand	*DLIEDL*	*LPEDL_MRG, LPEDL_MDD, LPEDL_NGT, LVEDL_MRG, LVEDL_MDD, and LVEDL_NGT*
Peak in working hours	*DLPEDL_MDD*	*LIEDL, LPEDL_MRG, LPEDL_NGT, LVEDL_MRG, LVEDL_MDD, and LVEDL_NGT*
Peak at night	*DLPEDL_NGT*	*LIEDL, LPEDL_MRG, LPEDL_MDD, LVEDL_MRG, LVEDL_MDD, and LVEDL_NGT*
Valley in the morning	*LVEDL_MRG*	*LIEDL, LPEDL_MRG, LPEDL_MDD, LPEDL_NGT, LVEDL_MDD, and LVEDL_NGT*

Preliminary analysis of the data revealed four main characteristics that could lead to biased results if not addressed in the econometric model. The presence of seasonality and endogeneity was expected, due to interactions between EDLs. Dynamic effects in daily data could also arise from daily adjustments in consumption habits and needs, as could static effects on a weekly, monthly, or even yearly basis. To handle these data features, the ARDL approach developed by Pesaran & Shin (1999) was considered best suited. In short, the main advantages of the ARDL methodology are: (i) its flexibility and the potential to analyse models with mixed integration order series; (ii) as a single equation set, it is easy to implement, and its results are easy to interpret; (iii) the use of different lag-lengths for each series in the model allows the daily, weekly, monthly, and yearly seasonal effects of the series to be captured; (iv) its ability to separate total effects into short-run effects (dynamic effects) and long-run effects (static or equilibrium effects); (v) its ability to address endogeneity issues correctly, in contrast to traditional cointegration estimators that lead to erroneous results; and (vi) its elimination of econometric problems associated with omitted series and autocorrelation issues.

In its generic formulation, a seven-variable $ARDL(l_1, l_2, l_3, l_4, l_5, l_6, l_7)$ can be represented by the following equation (5.15).

$$Y_t = \sum_{i_1=1}^{l_1} \alpha_{i_1} Y_{t-i_1} + \sum_{i_2=0}^{l_2} \beta_{i_2} X_{t-i_2} + \sum_{i_3=0}^{l_3} \gamma_{i_3} Z_{t-i_3} + \sum_{i_4=0}^{l_4} \delta_{i_4} Q_{t-i_4} + \sum_{i_5=0}^{l_5} \eta_{i_5} W_{t-i_5} + \sum_{i_6=0}^{l_6} \theta_{i_6} R_{t-i_6} + \sum_{i_7=0}^{l_7} \lambda_{i_7} P_{t-i_7} + \tau + \varepsilon_t \,, \qquad (5.15)$$

where $i_1, i_2, i_3, i_4, i_5, i_6$ and i_7 are indices of lags, t denotes the time periods $t = 1,2,3, \dots, T$, Y_t is the dependent variable, $X_t, Z_t, Q_t, W_t, R_t,$ and P_t are the explanatory variables, α_{i_1} is the coefficients of the lags of the dependent variable, β_{i_2}, γ_{i_3}, δ_{i_4}, η_{i_5}, θ_{i_6} and λ_{i_7} denote the coefficients of the lagged explanatory variables, τ is the constant term, and ε_t is the error term. Furthermore, equation (5.15) can be re-parameterized and expressed in an error-correction model, as shown below in equation (5.16). This model, in which the coefficients are unrestricted, enables the dynamic relationships between the variables to be captured.

$$\begin{aligned}\Delta Y_t &= \tau + \omega_1 Y_{t-1} + \omega_2 X_{t-1} + \omega_3 Z_{t-1} + \omega_4 Q_{t-1} + \omega_5 W_{t-1} + \omega_6 R_{t-1} + \\ &\omega_7 P_{t-1} + \sum_{i_1=1}^{l_1-1} y_{i_1} \Delta Y_{t-i_1} + \sum_{i_2=0}^{l_2-1} x_{i_2} \Delta X_{t-i_2} + \sum_{i_3=0}^{l_3-1} z_{i_3} \Delta Z_{t-i_3} + \sum_{i_4=0}^{l_4-1} q_{i_4} \Delta Q_{t-i_4} + \\ &\sum_{i_5=0}^{l_5-1} w_{i_5} \Delta W_{t-i_5} + \sum_{i_6=0}^{l_6-1} r_{i_6} \Delta R_{t-i_6} + \sum_{i_7=0}^{l_7-1} p_{i_7} \Delta P_{t-i_7} + \varepsilon_t \,,\end{aligned} \tag{5.16}$$

where, $\omega_1 = (1 - \sum_{i_1=1}^{l_1} \alpha_{i_1})$ is the error correction mechanism (ECM), and $\omega_2 = \sum_{i_2=0}^{l_2} \beta_{i_2}$, $\omega_3 = \sum_{i_3=0}^{l_3} \gamma_{i_3}$, $\omega_4 = \sum_{i_4=0}^{l_4} \delta_{i_4}$; $\omega_5 = \sum_{i_5=0}^{l_5} \eta_{i_5}$, $\omega_6 = \sum_{i_6=0}^{l_6} \theta_{i_6}$; $\omega_7 = \sum_{i_7=0}^{l_7} \lambda_{i_7}$, $\omega_8 = \sum_{i_8=0}^{l_8} \pi_{i_8}$, and $\omega_9 = \sum_{i_9=0}^{l_9} \chi_{i_9}$ are the long-run coefficients. The appropriate values for the maximum lags, $l_1, l_2, l_3, l_4, l_5, l_6, l_7$ were determined by the SIC and Hannan-Quinn (HQ) criteria. The optimal lag value was indicated by the ARDL model which presented the lowest value for one of the information criteria. The ARDL log-log functional specification for the models, *Smooth demand*, *Peak in working hours*, *Peak at night*, and *Valley in the morning* are represented by equations (5.17), (5.18), (5.19), and (5.20), respectively, in accordance with equation (5.15).

$$\begin{aligned} LIEDL_t = {} & \sum_{i_1=1}^{256} \alpha_{i_1} LIEDL_{t-i_1} + \sum_{i_2=0}^{256} \beta_{i_2} LPEDL\_MRG_{t-i_2} + \sum_{i_3=0}^{256} \gamma_{i_3} LPEDL\_MDD_{t-i_3} + \sum_{i_4=0}^{256} \delta_{i_4}\, LPEDL\_NGT_{t-i_4} + \sum_{i_5=0}^{256} \eta_{i_5} LVEDL\_MRG_{t-i_5} \\ & + \sum_{i_6=0}^{256} \theta_{i_6} LVEDL\_MDD_{t-i_6} + \sum_{i_7=0}^{256} \lambda_{i_7} LVEDL\_NGT_{t-i_7} + \tau + \varepsilon_t \end{aligned} \tag{5.17}$$

$$\begin{aligned} LPEDL\_MDD_t = {} & \sum_{i_1=1}^{256} \alpha_{i_1} LPEDL\_MDD_{t-i_1} + \sum_{i_3=0}^{256} \gamma_{i_3} LIEDL_{t-i_3} + \sum_{i_2=0}^{256} \beta_{i_2} LPEDL\_MRG_{t-i_2} + \sum_{i_4=0}^{256} \delta_{i_4}\, LPEDL\_NGT_{t-i_4} \\ & + \sum_{i_5=0}^{256} \eta_{i_5} LVEDL\_MRG_{t-i_5} + \sum_{i_6=0}^{256} \theta_{i_6} LVEDL\_MDD_{t-i_6} + \sum_{i_7=0}^{256} \lambda_{i_7} LVEDL\_NGT_{t-i_7} + \tau + \varepsilon_t \end{aligned} \tag{5.18}$$

$$\begin{aligned} LPEDL\_NGT_t = {} & \sum_{i_1=1}^{256} \alpha_{i_1} LPEDL\_NGT_{t-i_1} + \sum_{i_4=0}^{256} \delta_{i_4}\, LIEDL_{t-i_4} + \sum_{i_2=0}^{256} \beta_{i_2} LPEDL\_MRG_{t-i_2} + \sum_{i_3=0}^{256} \gamma_{i_3} LPEDL\_MDD_{t-i_3} \\ & + \sum_{i_5=0}^{256} \eta_{i_5} LVEDL\_MRG_{t-i_5} + \sum_{i_6=0}^{256} \theta_{i_6} LVEDL\_MDD_{t-i_6} + \sum_{i_7=0}^{256} \lambda_{i_7} LVEDL\_NGT_{t-i_7} + \tau + \varepsilon_t \end{aligned} \tag{5.19}$$

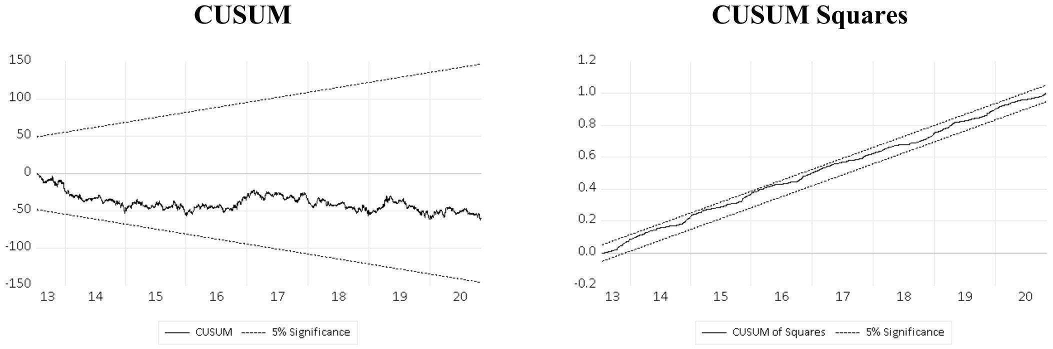
$$\begin{aligned} LVEDL\_MRG_t = {} & \sum_{i_1=1}^{256} \alpha_{i_1} LVEDL\_MRG_{t-i_1} + \sum_{i_5=0}^{256} \eta_{i_5} LIEDL_{t-i_5} + \sum_{i_2=0}^{256} \beta_{i_2} LPEDL\_MRG_{t-i_2} + \sum_{i_3=0}^{256} \gamma_{i_3} LPEDL\_MDD_{t-i_3} \\ & + \sum_{i_4=0}^{256} \delta_{i_4}\, LPEDL\_NGT_{t-i_4} + \sum_{i_6=0}^{256} \theta_{i_6} LVEDL\_MDD_{t-i_6} + \sum_{i_7=0}^{256} \lambda_{i_7} LVEDL\_NGT_{t-i_7} + \tau + \varepsilon_t \end{aligned} \tag{5.20}$$

It should be noted that all models included 256 lag-lengths. for each short-run series, to estimate the models, and the Stepwise Least Squares (STEPLS) estimator was used to select the statistically-significant short-run coefficients. The unidirectional method was employed with the STEPLS estimator, and a 10% level of statistical significance was chosen with a maximum of 100,000 replications. The 10% level was chosen enabled broader-reaching models and revealed additional impacts that needed to be considered in the analysis, following the most recent literature (Merrill et al., 2020; Sadeghian et al., 2022). Thus, the models began with 256 lag-lengths for each short-run series. Next, backward induction was used in the estimator to remove the series lag-lengths that were not statistically significant at the 10% level. After that, the best models were selected using the SIC and HQ information criteria. Thus, the model and estimator also allow distinct day effects, as well as daily, weekly, and monthly seasonal effects to be controlled for, without needing to use dummy variables.

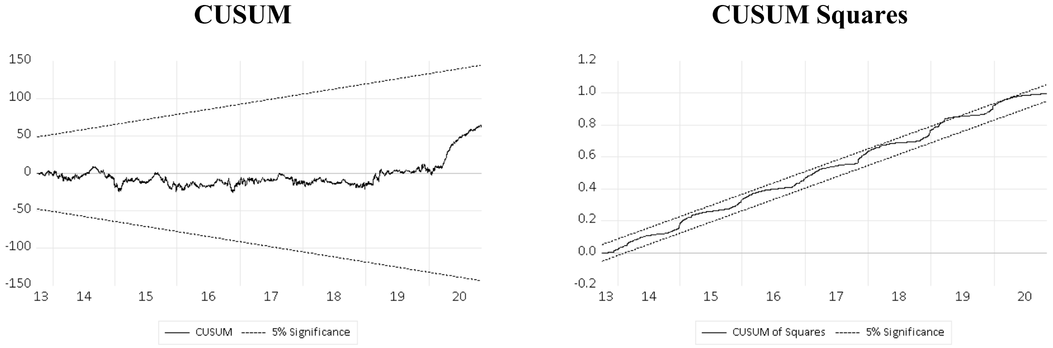
5.5.4 Diagnostic tests

The diagnostic tests, shown in Table A.5.5 in the Appendix, assess the quality of the models. It was found that all the models satisfied almost all the econometric requirements. However, the ARCH and Jarque-Bera tests indicated that the model errors were heteroscedastic and are not normally distributed. This was expected, since the sample under analysis contained a large number of observations. However, the autocorrelation LM and the Ramsey RESET tests indicated that the models were correctly specified. Consequently, the models and estimators used were considered suitable for dealing with the data under analysis. The Bounds test demonstrated that there were long-run relationships between the series under analysis, i.e., it corroborated that there was equilibrium between the series. This further confirmed that the models were appropriate for data being studied.

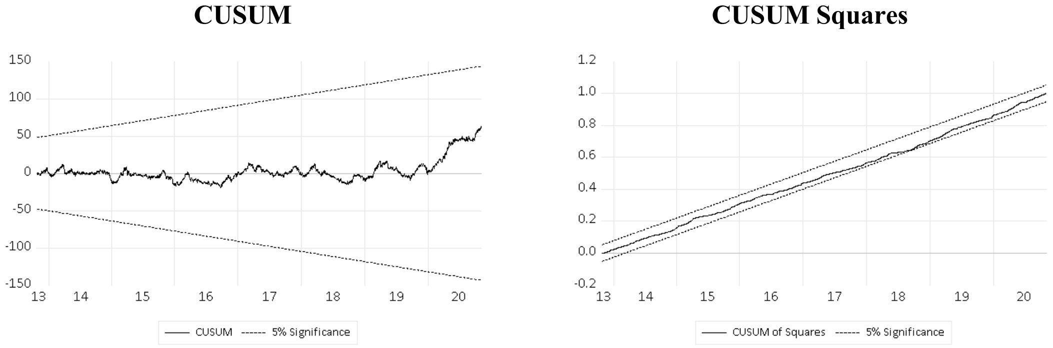
Smooth demand



Peak in working hours



Peak at night



Valley in the morning

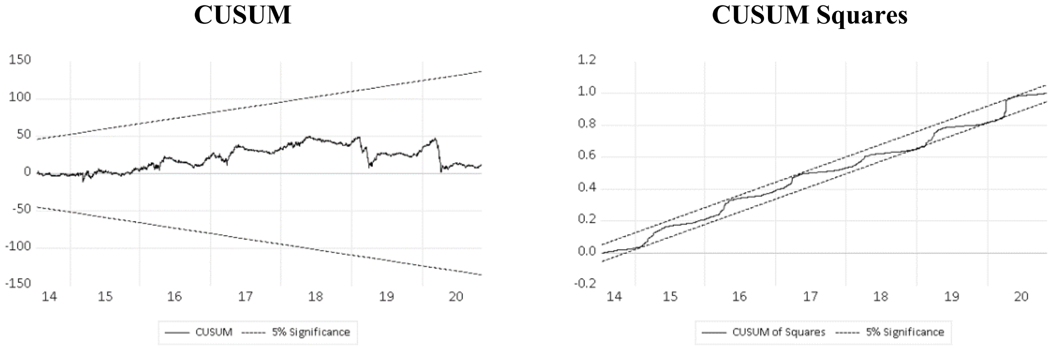


Figure 5.8. CUSUM test

Lastly, both the CUSUM and CUSUM Squares tests proved that the models were stable throughout the sample. This result was important for two main reasons. Firstly, the time sample under analysis was large, comprising daily data for about 8 years. Secondly, the time sample under analysis included daily data from 2020; the year when SARS-COV2 first affected global populations and economies. Consequently, the models were re-estimated excluding data from 2020, to avoid risking any distortion due to the impact of SARS-COV2. However, there were no significant differences in the results with or without data from 2020. Therefore, this study made use of the most recent available data up to 31 October 2020.

5.5.5 Results

The complete models are shown in Tables A.5.6, A.5.7, A.5.8, and A.5.9, in the Appendix. Table A.5.10, in the Appendix, summarizes the results of all models. It should be noted that Table A.5.10 only shows the coefficients of the short-run series for 1 and 8 lags, and the long-run coefficients. Table 5.3 shows the results of the elasticities of the models. As previously mentioned, the ARDL model breaks down the total effects into short-run (semi-elasticities) and long-run (elasticities). The semi-elasticities reveal the short-run dynamic of adjustment. For example, an increase of 1 percentage point (pp) in the consumption of IEDL on the same day (*DLIEDL*), on the day before (*DLIEDL(-1)*), and two days before (*DLIEDL(-2)*), cause a drop of 10.8007, 1.6308, and 2.1888 pp respectively, in the consumption of PEDL at night, (see Table A.5.8 model *Peak at night*). Elasticities, in contrast, reveal equilibrium or future trends. This arises when independent series continue to impact the dependent variable if nothing is changed. In other words, if consumption patterns do not change, the elasticities indicate what will continue to happen in the future. For example, if nothing changes, an increase of 1% in the consumption of VEDL in the morning will only provoke a rise of 0.7553% in the consumption of IEDL.

The highly statistically significant ECM values in all the models corroborated confidence in the suitability of the modelling used. Furthermore, the ECM values confirmed there was long memory in the data. All the models were stable and able to return to equilibrium after a disturbance. In the models of *Smooth demand*, *Peak in working hours*, *Peak at night*, and *Valley in the morning*, disturbances were substantially corrected within a day in 9.73%, 41.19%, 22.16%, and 59.63%, of cases, respectively. This reveals that IEDL consumption is harder to adjust. This result was expected, because IEDL neither puts additional load on the system, nor causes excess supply.

Shocks in the consumption of PEDL during working hours and VEDL in the morning were corrected and internalized more quickly than shocks in consumption during PEDL at night. This confirms confidence in the models in terms of their adherence to reality.

In fact, residential demand (evident in PEDL at night) has strict needs and habits, such as cooking, heating, lighting, charging of electric equipment, and entertainment (Andersen et al., 2017; Borsche & Andersson, 2014; Çakmak & Altaş, 2020; Iliopoulos et al., 2020; Vanouni & Lu, 2018). Thus, shocks in consumption in PEDL during working hours and VEDL in the morning are quickly internalized.

Regarding Figure 5.9, the grey curves behind all graphs represent the curves of all the daily electricity demand in the sample used. The black curves represent daily electricity demand for each group of days in the analysis, along with their functional average represented by the dotted white lines. The purpose of Figure 5.9 is to illustrate characteristics to consider when planning TBT or DR programmes, and to show some of the trends in daily electricity demand. For example, Figure 5.9 shows that the national daily electricity demand curves in summer periods have different characteristics from those found in the winter ones. Overall consumption, and night demand peaks are narrower in summer than in winter, revealing the need for price tariffs to differentiate between them. Figure 5.9 also shows that peaks in the middle of the day occur in every season, but are higher on weekdays than on weekends. This indicates that this peak is mainly due to industrial activity that is more intense on working days. Consequently, DSM measures should focus on increasing energy efficiency in the industrial sector. Additionally, France should also introduce electricity tariffs to encourage the transfer of some industrial workload to periods when there are valleys in demand.

5.6 Discussion

It is important to be able to classifying different types of peak demand, because simply identifying peak demand as the one hour of the year with the highest demand is clearly inadequate (Agency, 2018). Peak demand is a matter of daily concern for electrical system managers, who are under great pressure to satisfy it. Understanding which loads need to be cut or shifted towards other consumption periods, requires a more useful system of classification. This is the motivation behind the new classification of electricity demand levels proposed in this research, a classification that can open new paths for understanding, quantifying, and managing peaks in demand. By discriminating between different types of peak, the insights afforded by the proposed method can be an invaluable tool in reducing the economic inefficiencies caused by peak demand, such as the high redundant capacity of plants kept on stand-by just for backup.

Conversely, low demand, represented by valleys in the demand curve, which usually occurs in the early hours of the morning, is indicative of a failure to take advantage of the capacity of the electricity system. Valley demand can lead to economic inefficiencies and the ineffective allocation of resources. Like the peaks, these valleys in electricity demand also need to be better understood, to determine how best to fill them, but currently, there is little in the way of detailed statistics for their analysis. Consequently, this study also proposes a method for classifying levels of valley demand, so that the hitherto inexistent statistics can be produced and the problem more effectively analysed.

As part of this more-detailed classification, this study has further classified levels of electricity demand by time period. In this, endogenous classification has proved highly useful, as it is able to provide information about the distribution of both peak and valley periods throughout the day, as well as the probability of their occurring, and the findings of our study have been insightful.

For example, they indicate that Time-of Use (ToU) schemes could be devised to bring about desired changes in the daily load curve, particularly if combined with Critical Peak Pricing (CPP) that is activated when the reliability of an electricity system is in jeopardy, or there is unexpected shortage of RES-I. This finding diverges from the literature, which generally argues that Real Time Pricing (RTP) provides higher economic and environmental benefits than ToU (Eksin et al., 2018; Holland & Mansur, 2008; Nguyen et al., 2015), because RTP is closely linked to the wholesale, day-ahead electricity markets, and instantaneous demand (Eksin et al., 2018; Nguyen et al., 2015). However, the implementation of RTP is challenging for both suppliers and consumers, a challenge exacerbated by the requirement for a two-way-flow of information between them, in real-time, and the inevitable gaps in information that arise. More importantly, it is hard for the average consumer to understand the large amount of complex data which this system presents to them every day, and to manage their electricity demand accordingly. Our findings suggest that, to encourage consumers to make appropriate changes in their consumption habits, policymakers, regulators, and retailers should focus more on Time Based Tariffs (TBTs) like ToU, whereas RTP should primarily be used in automated systems that directly control load, or other schemes that require less consumer intervention.

Table 5.3. Elasticities

Models	***Smooth demand***	***Peak in working hours***	***Peak at night***	***Valley in the morning***
LIEDL(-1)	-	1.5231***	-5.9634***	1.112***
LPEDL_MRG(-1)	-0.0747***	-0.0667	-0.4546**	0.0241**
LPEDL_MDD(-1)	-0.0619***	-	-3.1447***	0.0014
LPEDL_NGT(-1)	0.0354***	-0.3372***	-	0.0089***
LVEDL_MRG(-1)	0.7553***	-1.1975***	5.0653***	-
LVEDL_MDD(-1)	0.0174***	-0.0641***	0.056369	-0.0409***
LVEDL_NGT(-1)	-0.0576***	0.0604***	-0.4311***	-0.0085***

Notes: **, *** denotes the statistical significances at 10%, and 1% level, respectively.

In the empirical analysis of electricity demand levels and time-periods, the ability to outline and quantify opportunities to control load can be very useful. Our findings regarding historical French load profiles alert us to the difficulties and challenges of attaining a smoothed demand, but also reveal opportunities. As mentioned previously, Figure 5.9 shows a peak in the middle of the day that is mainly due to industrial activity. Attenuating this peak will require a cocktail of DSM policies and measures. Firstly, energy efficiency should be encouraged in this sector, to incrementally reduce middle-of-the-day peak consumption. This can be accomplished through investment in R&D and more energy-efficient industrial machinery, so fiscal, and financial incentives should be used to incentivize industries to introduce more efficient machinery. Furthermore, a strategic policy to promote the self-generation of electricity using cogeneration from heat wasted by industrial machineries would also cause an incremental reduction in loads. Solar photovoltaic systems should also be promoted, particularly as generation is most effective during daytime working hours. Table 5.3 shows that an increase of 1% in consumption during the morning valley causes a drop of 1.1975% in peak consumption during working hours. This result highlights the potential for strategies that shift loads between these periods. Consequently, electricity retailers and regulators in France should introduce pricing tariffs to encourage the industrial sector to shift at least 236 MWh (see Table A.5.11 in the Appendix) from the peak, to the morning valley period. The price differentiation between these periods, would need to be large enough to offset the cost of rescheduling working hours.

The peak that occurs during working hours can also be reduced by the residential sector. Residential consumption in this period is mainly by appliances that consume a constant amount of electricity during the day, like refrigerators and freezers (Andersen et al., 2017; Iliopoulos et al., 2020). This consumption, which we can call residential-based consumption, cannot be shifted to other periods. However, there are other strategies to incentivize the residential sector to cut peak consumption during working hours. Policymakers could encourage the purchase of energy-efficient household appliances through financial and tax benefits. Additionally they could incentivize the installation of solar PV capacity, which is most productive during the PEDL of working hours and could, thus, cover the base consumption of the residential sector during this period.

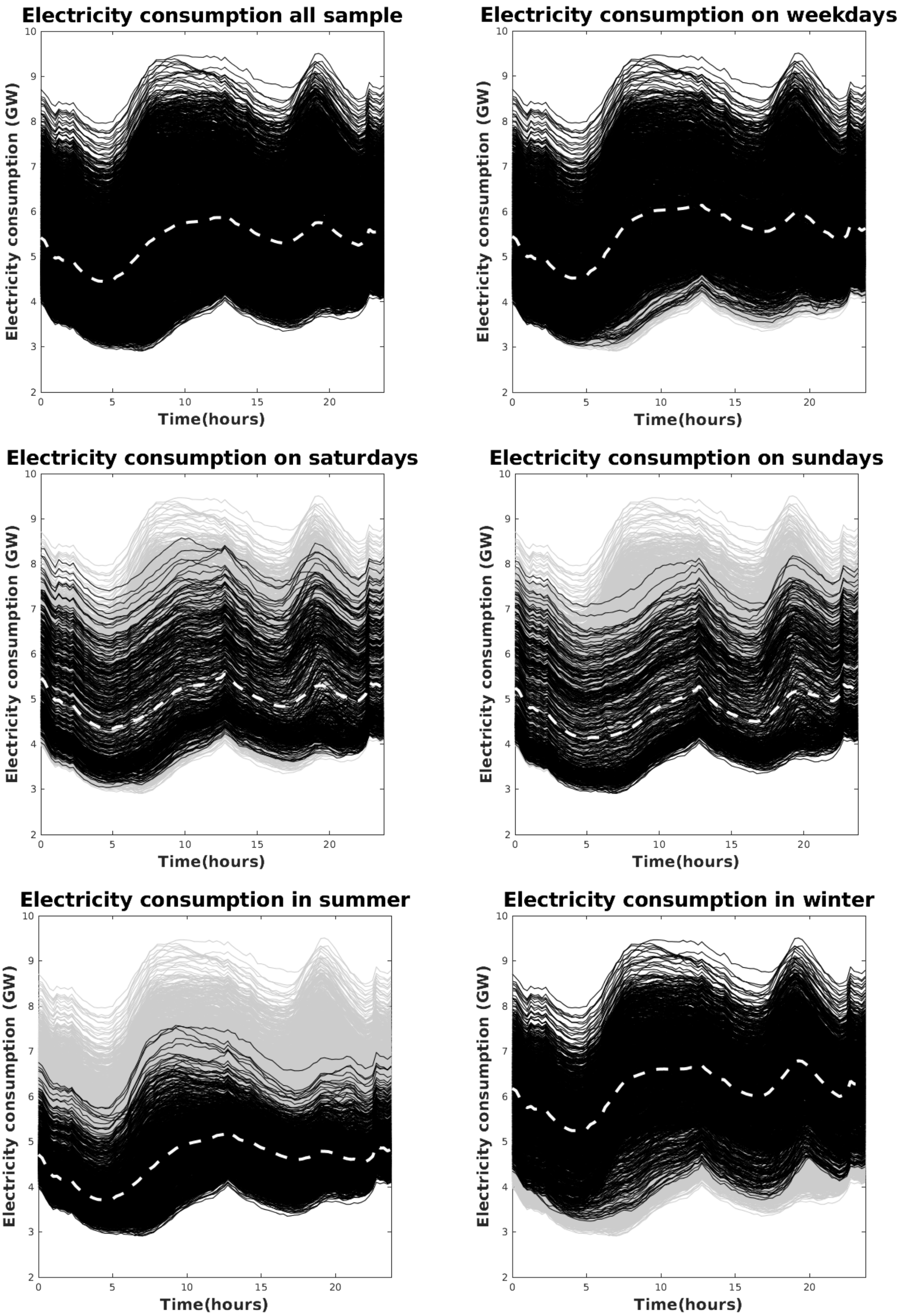


Figure 5.9. Daily curves of electricity demand

(The grey curve represents the entire sample, and the dotted white lines indicate the functional mean values for each group of days)

Night-time peak consumption is similar every day of the week. This peak is largely due to residential consumption, arising from the use of a large number of energy-intensive appliances for short periods of time. This consumption is to meet the primary needs of households, such as cooking, washing, heating, lighting, and entertainment (Andersen et al., 2017; Iliopoulos et al., 2020). Consequently, measures to shift these consumption patterns and needs are difficult to design. However, our findings revealed that there is a substitution effect between peak consumption at night and during working hours. An increase of 1% in the peak during working hours causes a drop of 3.1447% in the night-time peak (see Table 5.3). In contrast, an increase of 1% in the night-time peak only causes a drop of around 0.3372% in the working-hours peak (see Table 5.3). This shift in consumption towards the period of working-hours is highly desirable. It could both increase efficiency by reducing the need for installed capacity, and make use of the electricity generated by households from ‘free’ solar resources. This strategy would also be beneficial for suppliers because it would decrease night-time peak consumption, while bringing savings for consumers through solar PV generation.

Night-time peak consumption in France should be reduced by between 103 MWh and 691 MWh (see Table A.5.11 in the Appendix). From Figure 5.9 it can be concluded that this reduction should be larger in the winter. The findings of this research prove that the TBT used in France has not had the desired impact on demand patterns, but the study also suggests how they could be improved. Analysis of this paper’s classification of electricity demand indicate that there should be three daily pricing periods. The first period (P1), or the valley-demand period, should cover the hours between 0 a.m. and 6 a.m. The second period (P2), or the middle peak period, should last from 6 a.m. to 5 p.m. Lastly, the third period (P3), or the night-time peak period, should range between 6 p.m. to 0 a.m. It should be noted that the price of P3 should be higher than P2 but the price differentiation should be relatively small. In contrast the price differentiation between P1 and both P2 and P3 should be high enough to encourage consumers to alter their consumption habits, for example, changing when they use washing machines, charge phones and laptops, or use other appliances. It is well known from economic theory that consumers react to price differentiation. Thus, the greater the price differentiation, the higher the predisposition of consumers to change their patterns of electricity consumption.

The TBT scheme proposed above, or any other, will only be effective if flat rate tariffs are abandoned. Therefore, flat rate tariffs should be gradually replaced by TBTs, and even abolished in the future. ToU tariffs can encourage a desirable shift of consumption in the French residential sector. However, it should be highlighted that TBT will not change some types of residential consumption, such as cooking, lighting, and entertainment in the early stages. For now, energy storage is the only solution for shifting consumption that serves the strict needs of the residential sector. Home batteries or even e-vehicle batteries could be used to meet the demand for household consumption during the night-time peak. Afterwards, these batteries could be recharged during the morning valley periods. It should be noted that machine-learning technology could be used to understand and forecast patterns of consumer consumption, and select charging and discharging strategies with limited intervention from consumers. The critical point is that TBT must reward consumers for their efforts and investments. Consumers must feel that their good behaviour is rewarded, and this will increase the speed and impact of policies.

5.7 Conclusion

Focusing on the challenges posed by various aspects of electricity demand and their consequences for the management of electricity systems, this work proposed a new classification for levels of electricity demand, and used it to analyse the short- and long-run interactions between them. The country chosen for the study, France, is attempting to reduce its high nuclear capacity while incorporating RES-I, and to smooth the peaks and valleys of its electricity demand curve by shifting demand loads. The analysis in this paper of intraday data on the interactions between demand levels in France between 2013 and 2021, produced new insights into the current characteristics and future trends of demand. The findings also showed that public policies introduced to smooth the demand curve using demand-side management have been unsuccessful and need to evolve.

The innovative system used to classify demand levels sheds light on a particular problem of imbalanced demand for the electricity system; the morning valley. This large drop in demand during the early hours of the morning leads to both economic inefficiencies and the misallocation of resources in the electricity system. For now, France would be advised to export electricity during these periods, so as not to ‘waste’ electricity generated from nuclear power.

Conversely, the new classification system used in this study also highlighted the major concerns for the electricity system associated with two peaks in demand: one during working hours, and the other at night, with the latter becoming particularly acute in the winter. Peaks in demand require electricity systems to maintain an installed capacity of flexible plants on stand-by, mainly powered by fossil fuels, ready to satisfy high peaks in demand at short notice. This also leads to economic inefficiencies as these resources are only used at times of peak demand. The study highlights the clear benefits of shifting demand from peak periods to valley periods. This would enable the electricity systems to reduce the installed capacity required to meet peaks in demand and make fuller use of electricity generated internally from baseload sources, such as nuclear power and RES-I. To reduce peak consumption during working hours, public policies should focus on increasing the energy efficiency of the industrial sector, through measures such as financial and fiscal benefits to industries to invest in more efficient machinery.

Public policies must also evolve with regard to the residential sector, to successfully encourage desired changes in patterns of demand. Policymakers and electricity providers should implement measures focusing on: (i) the energy efficiency of large appliances, such as freezers and refrigerators; (ii) direct control of specific appliances, like heating systems; (iii) changing consumer habits to shift consumption from peak to valley periods, such as using major appliances and charging electrical devices during the day time; and (iv) raising the awareness of consumers and informing them about the economic and environmental effects of electricity demand and supply.

Electricity suppliers and regulators should devise ToU tariffs for the residential sector as ToU tariffs are simpler than RTPs, and this simplicity would make it easier and more attractive for consumers to start adopting desired demand patterns. The price differentiation of the ToU tariff should be high enough to reward consumers efforts and investments, particularly in appliances with delayed start options linked to the Internet of Things (IoT). The price of off-peak electricity should initially be similar to the peak demand price, so that consumers are encouraged to install self-generation systems, such as rooftop solar panels, and off-peak tariffs should reward those who have installed them. Lastly, but no less essential, electricity providers and regulators should implement a DR program linked with RTP tariffs that directly control residential heating systems during winter months and reduce peak demand at night. To sum up, a new demand level classification system was developed in this study and applied to specific data for France. Its findings show that this classification can enable the daily interactions of load levels in an electrical system to be more accurately identified and evaluated, and that it can be an invaluable tool for devising effective solutions for the problems identified

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Chapter 6

How do energy forms impact energy poverty? An analysis of European degrees of urbanisation

This chapter has been presented at an international conference, at the date of delivery this thesis, it is still in the review process, having already been submitted a first revision on a Web of Science indexed journal. The output of this chapter is:

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Abstract

The access that households have to various forms of energy depends on their level of urbanisation, which leads to distinct preferences in the forms of energy they consume. Consequently, different forms of residential energy consumption should have different impacts on energy poverty, when analysed for each degree of urbanisation. Verifying this was the underlying motivation for this study. Thus, it investigates how forms of residential energy consumption (oil, wood/biomass, natural gas, and electricity) impact energy poverty in (a) cities; (b) towns and suburbs; and (c) rural areas. To do so, data from 2005 until 2018 for twelve European countries was analysed using three-panel data sets, one for each urbanisation degree. The results, estimated using Feasible Generalised Least Squares, indicated that, in sparsely populated areas (towns, suburbs, and rural areas), primary energy sources, such as wood/biomass and natural gas alleviate energy poverty. Conversely, in cities, residential electricity consumption has been the key form for decreasing both poverty and energy poverty. The results of this research highlight that energy forms have differing impacts on energy poverty in areas with different levels of urbanisation. Therefore, energy policies should be planned at a disaggregated regional level within countries, and not at a national or European level.

6.1 Introduction

According to the European Energy Poverty Advisory Hub (EPAH), around 34 million European citizens suffer from energy poverty (EPAH, 2022b). The definition of energy poverty has been extensively discussed in the literature (Fabbri and Gaspari, 2021; Moore, 2012; Sareen et al., 2020; Thomson et al., 2017), as has the way it is measured (Sareen et al., 2020; Siksnelyte-Butkiene et al., 2021; Villalobos et al., 2021). However, the contentious nature of the academic debate on the subject further demonstrates the difficulty of precisely defining energy poverty, its measurement, and the best indicators for quantifying it. Even though the need for a common definition and form of quantifying energy poverty is generally agreed (particularly in Europe), there is no consensus on the wording of this definition or the indicator to be used to measure it (Bardazzi et al., 2021). Furthermore, the widely varying information and estimations on energy poverty in the literature makes devising and developing suitable policies extremely difficult. Faced with this ambiguous range of concepts regarding energy poverty, we decided, for this study, to follow the definition and form of measurement used by both the EPAH and the United Nations. This was to enable the study to produce accurate information and provide guidance for decision-making consistent with EPAH objectives and Sustainable Development Goals (SDGs).

This research is focused on SDG 1.2: “by 2030, reduce at least by half the proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions”. In July 2017, the General Assembly of the United Nations requested the adoption of global indicators for each SGD (Nations, 2017). As an indicator for SDG 1.2, it was suggested: (i) “Proportion of population living below the national poverty line, by sex and age”; and (ii) “Proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions” (Nations, 2017). As the primary data for evaluating energy poverty, the EPAH chose consensual, expenditure-based indicators, namely, arrears on utility bills, low absolute energy expenditure, high share of income spent on energy, and inability to keep homes adequately warm (EPAH, 2022a). Therefore, in this study of energy poverty, we also focused on energy expenditure and poverty thresholds, and considered that energy poverty occurs when energy expenses account for a percentage of a household’s income high enough to impact its ability to meet basic needs, such as nutrition. This definition of energy poverty highlights the choice some households face between spending their budget on energy consumption and costs, or on food, hygiene and other related items. To better understand this phenomenon, this paper studied the impact of various forms of residential energy consumption (oil, natural gas, wood/biomass, and electricity) on energy poverty in European countries.

The aim of EPAH, the central platform of energy poverty expertise in Europe, is to “eradicate energy poverty while accelerating energy transition”. This objective is also shared with SDG 7 - “ensure access to affordable, reliable, sustainable and modern energy for all”. The objectives of the EPAH, and of SDGs 1.2 and 7 are in line with current European policy, and were included in the Clean Energy for all Europeans package adopted in 2019 (Commission, 2019). The Clean Energy for all Europeans package aims to move consumption away from fossil fuels toward cleaner energy sources, while protecting vulnerable consumers from energy poverty. This scope of this package is broad, and involves the energy performance of buildings, energy efficiency, the integration of renewable energy sources, and the design of the electricity market. Understanding how this objective of accelerating the energy transition while alleviating energy poverty can be achieved was the primary reason for undertaking this study. The ongoing energy transition from traditional, more polluting sources towards renewable energy sources in Europe will imply increasing dependence on electricity. This means that the residential sector will have to adjust the way it consumes energy. To more fully understand the risks of energy poverty that may arise from electrification, the study also assessed the consequences of residential electricity consumption by end-use, such as space heating, water heating, cooking, household appliances, and lighting.

Residential energy needs and habits vary between countries, but also within them. For instance, it is well-known that urban areas (cities) tend to rely on electricity, while rural areas prefer primary energy sources, such as wood/biomass and gas. The latter preference is often due to the inaccessibility of the electricity grid, the easy availability of ‘free’ wood/biomass, or simply long-standing traditional ways of living. Consequently, the compulsory switch from primary energy sources to electricity implicit in the energy transition, may increase the risk of energy poverty for some households., making it crucial to assess whether electricity can provide greater well-being for households than other, less expensive, energy forms. For example, comparing the energy costs for households in rural areas, costs will apparently be lower and well-being greater if they consume wood/biomass rather than electricity. As this may hinder the objectives for energy transition set out above, we were prompted to study the impact that residential energy consumption (or preferences) has on energy poverty in areas with different degrees of urbanisation. Accordingly, this research analysed each European country divided into three degrees of urbanisation, namely (a) cities, (b) towns and suburbs, and (c) rural areas.

The main objective of this research is to provide an accurate knowledge base for devising energy policies by which the energy transition can be implemented without exacerbating energy poverty or traditional poverty (poverty caused by the low-income or low well-being of households). Furthermore, this research also seeks to discover how the energy transition could be beneficial to households, by alleviating energy poverty. Thus, this research aims to answer the following questions: (i) does energy poverty depends on the mix of forms of residential energy consumption? (ii) what form of energy or mix should be used to alleviate energy poverty for each degree of urbanisation? (iii) could electricity be a key form of energy for a transition towards a society without energy poverty? This research breaks new ground in the literature on the subject by (a) studying the impacts of forms of residential consumption on both energy poverty and traditional poverty; (b) analysing the impact of residential electricity consumption by end-use activities on both energy poverty and traditional poverty; and (c) assessing and comparing these results by the three degrees of urbanisation. Therefore, this work fills a gap in the literature that, to the best of our knowledge, has not yet considered the influence of an area’s degree of urbanisation in the analysis of both energy poverty and traditional poverty.

Twelve European countries were analysed by degree of urbanisation, using three data panels, one contained the data for cities in each country, another for towns and suburbs, and the last for rural areas. They were analysed using two indicators for both energy poverty and traditional poverty. The indicators were obtained from Eurostat, and are explained in the Data Subsection of the Data and Methodology Section. The time span studied runs from 2005 until 2018. The results of this research show that policies for promoting the energy transition and for reducing energy poverty, should not be devised monolithically at a national level. In fact, the results stress that forms of residential consumption impact energy poverty in a variety of way, and depend on an area's degree of urbanisation. In rural areas, as well as in towns and suburbs, primary energy sources (wood/biomass and natural gas) have been key to alleviating both energy poverty and traditional poverty. In contrast, in cities, residential electricity consumption has been the main way to decrease both energy poverty and traditional poverty. In addition, this research revealed that the energy-inefficiency of electric water heating systems and household appliances can limit the potential benefits electricity brings for households. Therefore, the current transition towards a green energy mix, and the ongoing electrification of economies, should be carefully planned so as not further increase energy poverty.

The rest of the paper is organised as follow. Section 2 briefly summarises the literature on energy poverty, and identifies the gap in it that this paper fills. Section 3 presents the data and describes the methodology used to analyse it. The results are set out in Section 4 and discussed in the Section 5. Lastly, Section 6 contains the conclusions.

6.2 Literature Review

The term energy poverty has several alternative labels, namely fuel poverty, energy vulnerability, energy deprivation, energy precariousness, and energy burden. All of these terms are applied in the literature depending on their context and subject (Fabbri and Gaspari, 2021). Energy poverty is an increasingly urgent problem, and has led to frequent discussions in the literature over the last few years (Bednar and Reames, 2020; Frank et al., 2006; Mould and Baker, 2017; Wang et al., 2021). The definition of energy poverty generally implies that a household has to pay a disproportionate cost for energy use (Bednar and Reames, 2020; Wang et al., 2021). The literature argues that this disproportionate cost may be caused by high energy prices, low household income, or inefficient energy use (Bednar and Reames, 2020; Frank et al., 2006; Mould and Baker, 2017; Wang et al., 2021). Energy poverty can also imply that a household cannot afford to consume the energy needed to keep their home adequately warm (Fabbri and Gaspari, 2021; Gouveia et al., 2018). This definition is often used in the European context.

The definition of energy poverty has been twofold and, to measure it, a wide range of affordability indicators have been agreed on (Wang et al., 2021). These affordability indicators measure energy poverty by analysing the percentage of a household's total income used for energy. In 1991, the first definition of energy poverty was coined, along with the first measurement to quantify it – the 10% indicator (Boardman, 1991). The definition described energy poverty as the condition in which a household spend more than 10% of its income on energy services (Boardman, 1991). The 10% indicator was further defined as the heating-related energy expenditure required to maintain an adequate level of warmth in homes (Moore, 2012). Criticism of the 10% indicator led to the United Kingdom (UK) Fuel Poverty strategy (in which the first energy poverty indicators were introduced), and three other energy poverty definitions and indicators were developed (Hills, 2011, 2012; Moore, 2012). However, these indicators also received criticism, mainly for reducing the number of households classified as energy-poor, and for aggregating the indicators of fuel poverty and energy efficiency (Bednar and Reames, 2020; Wang et al., 2021). Multi-index energy poverty measures have been explored by the literature (Siksnelyte-Butkiene et al., 2021; Villalobos et al., 2021). These energy poverty definitions also consider aspects such as the inefficiency of buildings and appliances, energy affordability, public energy-related services, and the quality and reliability of national energy systems (Siksnelyte-Butkiene et al., 2021; Villalobos et al., 2021).

The literature often argues that energy poverty has been caused by an economic crisis, unemployment, low income, and the poor energy-efficiency of housing (Fabbri and Gaspari, 2021; Gouveia et al., 2018; Siksnelyte-Butkiene et al., 2021). Economic assistance, in the form of subsidies, has been the main policy of European countries to minimise the burden of energy costs for households with low incomes or threatened by energy poverty (Santamouris, 2016). However, this solution does not provide energy-poor households with a long-term solution. On the contrary, it merely minimises the risk of poverty in the short term (Gouveia et al., 2018; Santamouris, 2016). This subsidy policy does not generate consistent and sustainable savings for low-income households, that would allow them to improve the energy-efficiency of their homes. In studies on this aspect, the quality of insulation materials, window frames, and household appliances are taken into consideration, and it is argued that the cost of increasing the energy-efficiency of homes is likely to be too high for households already in need (Gouveia et al., 2018; Santamouris, 2016). Therefore the literature argues that policymakers should promote rehabilitation programmes or subsidies, to improve the energy performance of buildings, thereby providing a long-term solution for households threatened by energy poverty and poverty (Koomson and Danquah, 2021).

From the extensive literature on this subject, it can be concluded that energy poverty occurs when lack of income forces individuals to choose between energy consumption and basic needs, such as food and hygiene. The Covid-19 pandemic and resulting government emergency measures like lockdowns, are expected to aggravate energy poverty worldwide (Bardazzi et al., 2021; Bienvenido-Huertas, 2021). In fact, lockdowns have provoked an increase in residential energy consumption as families spend more time at home. Consumption has also increased due to the rise of the home office and of e-learning by children. Given all these changes, it is more important than ever to gain a more detailed understanding of patterns of domestic energy consumption and how they might impact energy poverty, something the literature has not yet done. Consequently, this research into energy poverty in Europe also analyses the various forms of residential energy and its end-use.

The literature suggests that households in areas with different degrees of urbanisation may have dissimilar energy needs, with differing impacts on energy poverty. This divergence was identified in research on the relationship between population density and energy use (Glaeser and Kahn, 2010; Larson and Yezer, 2015). However, this literature did not specifically look at energy poverty (Mahumane and Mulder, 2022). Conversely the literature on energy poverty and its various aspects, has not yet considered the role of urbanisation or the impact of population density on energy poverty (Mahumane and Mulder, 2022; Pelz et al., 2018). Consequently, the impact of urbanisation on energy poverty is still underexplored (Mahumane and Mulder, 2022). Therefore, this research also aims to fill this gap in the literature by taking into account the levels of urbanisation within European countries and analysing its respective impact on energy poverty.

6.3 Methodology

Three panels of data were used to study the impact of various forms of residential energy and residential electricity consumption by end use on both energy poverty and traditional poverty, and were analysed by three degrees of urbanisation: (a) Cities; (b) Towns and Suburbs; and (c) Rural Areas. The initial intention was to study all European Union countries, but the absence of national observations for the core dependent variables led to the exclusion of 15 countries. The criterion used meant that countries with data on less than 50% of the temporal sample in two or more dependent variables were excluded. This criterion was employed because panel econometrics best practice suggest that, for a viable comparison from which conclusions can be drawn, panel models should be estimated using the same countries and timeframe. Therefore, only twelve European countries were analysed, namely: Austria, Belgium, France, Greece, Ireland, Italy, the Netherlands, Poland, Portugal, Spain, Sweden, and the United Kingdom over a period from 2005 until 2018. This section describes how the characteristics of the data and model specification tests were evaluated, and how the models and estimators were determined, but begins by indicating the data used and assessed.

6.3.1 Data

The Eurostat tables computed by the European Union on Income and Living Conditions (EU-SILC) database were used to obtain the indexes of both energy poverty and traditional poverty. The data obtained was already disaggregated by degree of urbanisation from the Eurostat database. Table 6.1 shows the name of the Eurostat table and respective index and table code of the variables retrieved. It should be noted that all variables are measured annually. The research undertaken here focused on two indicators of energy poverty and two indicators of traditional poverty, and are described in detail below. The suffixes C, TS, and RA represent the three degrees of urbanisation: Cities, Towns and Suburbs, and Rural Areas, respectively. The prefixes L and D denote the natural logarithms and first differences of the variables. Table 6.2 contains the descriptive statistics of the raw data, while Figure 6.1 shows in graphical form, the indexes of energy poverty and traditional poverty by degree of urbanisation.

Table 6.1. Eurostat data details

Table name	**Measure**	**Table code**
At-risk-of-poverty rate by degree of urbanisation[2]	Annual percentage	ilc_li43
People at risk of poverty or social exclusion by degree of urbanisation[3]	Annual percentage	sdg_01_10a
At-risk-of-poverty rate after deducting housing costs by degree of urbanisation[4]	Annual Percentage	ilc_li48
Housing cost overburden rate by degree of urbanisation[5]	Annual Percentage	tessi165
Average number of rooms per person by degree of urbanisation[6]	Annual average	ilc_lvho04d
Mean and median income by degree of urbanisation[7]	Annual Euro	ilc_di17
People living in households with very low work intensity[8]	Annual number of households	tipslc40

The at-risk-of-poverty rate and people at risk of poverty and social exclusion were the indicators used to measure traditional poverty as indicated by the literature (Brunner et al., 2012; Karpinska and Śmiech, 2020b). At-risk-of-poverty describes people with an income below the risk of poverty threshold, specifically, households with an equivalised income after social transfers below 60% of the national income (European standard of relative income poverty threshold). People at risk of poverty and social exclusion are those families or individuals who (a) are at risk of poverty; (b) have worked less than 20% of their potential during the previous 12 months (People living with very low work intensity); or (c) are severely materially deprived. The Severely materially deprived are those households/individuals who are unable to afford at least four of the following items: (i) mortgage or rent; (ii) utility bills (energy poverty indicator); (iii) heating to keep the home adequately warm (the most studied energy poverty indicator in Europe); (iv) unexpected expenses; (v) regular consumption of meat or protein; (vi) holidays; (vii) television set; (viii) washing machines (energy poverty indicator); (ix) car; and (x) telephone. Although the people-at-risk-of-poverty rate and the social-exclusion-variable rate are traditional poverty measures, it is indeed a subjective index that contains indicators of energy poverty, as noted. It should be highlighted that People at risk of

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[2] https://ec.europa.eu/eurostat/web/products-datasets/-/ilc_li43
[3] https://ec.europa.eu/eurostat/web/products-datasets/-/sdg_01_10a
[4] https://ec.europa.eu/eurostat/web/products-datasets/-/ilc_li48
[5] https://ec.europa.eu/eurostat/web/products-datasets/-/tessi165
[6] https://ec.europa.eu/eurostat/web/products-datasets/-/ilc_lvho04d
[7] https://ec.europa.eu/eurostat/web/products-datasets/-/ilc_di17
[8] https://ec.europa.eu/eurostat/web/products-datasets/-/tipslc40

poverty and social exclusion is the main indicator for monitoring the European 2020 Strategy poverty target and the EU 2030 target on energy poverty and social exclusion (Eurostat).

In this study, the indicators used to measure energy poverty were the at-risk-of-poverty after deduction of housing-costs rate and the housing-costs-overburden rate. The at-risk-of-poverty rate after deduction of housing-costs shows the percentage of families or individuals whose disposable income after deducting housing costs is below the standard European relative income poverty threshold (60% of median national income). Housing-costs are those linked to the right to live in accommodation (rents or loans), including the costs of utilities (energy expenses), namely the costs of electricity, gas, and heating consumption. The Housing-costs overburden rate shows the percentage of families or individuals who spend more than 40% of their disposable income on housing costs. In this indicator, disposable income includes all earnings, wealth, social, and insurance transfers, and also accounts for transfers by public intervention, such as subsidies to aid households to meet their housing costs. In addition to helping evaluate the benefits of energy subsidies, the Housing-costs overburden rate is also comparable to the ten per cent rule index. However, as it includes other housing costs, such as rent and loans, the threshold is raised to 40%. Both these energy poverty indicators reveal how excessive consumption by inefficient electric water heating can increase energy expenses. and reduce disposal income for other crucial budget items, such as nutrition. Households or individuals are likely to face a trade-off between supporting the increase in electricity expenditures and spending their budget in food and hygiene, or other related items. In addition to being the main indicators of energy poverty used to monitor progress toward the European objectives for social protection and social inclusion (Committee, 2015), these two indicators are also used by academic literature on the subject (Deller et al., 2021; Karpinska and Śmiech, 2020a, b).

Three control variables were used, namely, the average number of rooms per person, mean income, and people living with very low work intensity. The control variables were also obtained broken down by degree of urbanisation. The average number of rooms per person reveals the number of rooms per individual in a household, as the size of dwellings is often considered an indication of wealth and an important factor in the risk of poverty and social exclusion (Thomson, 2018). People living with very low work intensity describes households with individuals working less than 20% of their work potential. Mean income is the mean income within a country by degree of urbanisation. According to the classification of Villalobos et al. (Villalobos et al., 2021) both income and percentage of people living in a household with low work intensity have a first-order impact. It was expected that lower income would raise a household's likelihood of suffering from energy poverty, and higher income would lower it. The relationship between individual work intensity and energy poverty, is linked to the impact of individual productivity. Individuals with low productivity will have lower earnings from labour (wages), and their households will have less disposable income to meet energy expenses. Therefore, the greater the number of people in a household living with very low work intensity, the greater the risk of both traditional poverty, and energy poverty.

Table 6.2. Descriptive statistics of urbanisation degrees variables

Variable	Degree of urbanisation	Obs.	Mean	SD.	Min	Max
Poverty						
At-risk-of-poverty rate (ARP)						
ARP-C	Cities	168	15.90655	3.552534	9.6	25.5
ARP-TS	Towns and suburbs	168	15.42024	3.933513	8.3	24.5
ARP-RA	Rural areas	168	18.56071	5.882095	5.2	28.2
People at risk of poverty or social exclusion (PARPSE)						
PARPSE-C	Cities	168	23.32679	4.582059	13.4	38.6
PARPSE-TS	Towns and suburbs	168	21.83869	6.519009	12.4	47.2
PARPSE-RA	Rural areas	168	24.36548	8.085583	6.5	50.6
Energy Poverty						
At-risk-of-poverty rate after deducting housing costs (ARP_DHC)						
ARP_DHC-C	Cities	168	31.45833	6.050619	19.7	47.8
ARP_DHC-TS	Towns and suburbs	168	30.10595	4.928321	19.4	48.3
ARP_DHC-RA	Rural areas	168	33.00893	7.216273	19.4	53.1
Housing cost overburden rate						
HCO-C	Cities	168	12.85119	7.870281	3.3	49
HCO-TS	Towns and suburbs	168	9.9	7.968689	2.5	48.1
HCO-RA	Rural areas	168	8.752381	7.338145	1.6	41.2
Control variables						
Average number of rooms per person (RPP)						
RPP-C	Cities	168	1.619643	.3323404	1	2.2
RPP-TS	Towns and suburbs	168	1.709524	.3452393	1	2.3
RPP-RA	Rural areas	168	1.800595	.3952559	1	2.7
Mean income (INC)						
INC-C	Cities	168	18827.79	4194.454	6864	26379
INC-TS	Towns and suburbs	168	17721.35	4606.879	5431	26267
INC-RA	Rural areas	168	16566.9	5016.091	4769	25691
People living in households with very low work intensity (HLWI)						
HLWI-C	Cities	168	1154.982	1130.105	87	4511
HLWI-TS	Towns and suburbs	168	569.8929	545.5836	1	2485
HLWI-RA	Rural areas	168	472.9524	433.1783	5	2227

The analysis of Table 6.2 shows that densely populated areas, i.e., urban zones, have the highest share of households in both energy and traditional poverty. However, poverty and social exclusion is also a widespread phenomenon in rural areas, i.e., thinly populated areas throughout the European Union. In fact, the highest maximum values for both energy and traditional poverty indicators are found in rural areas.

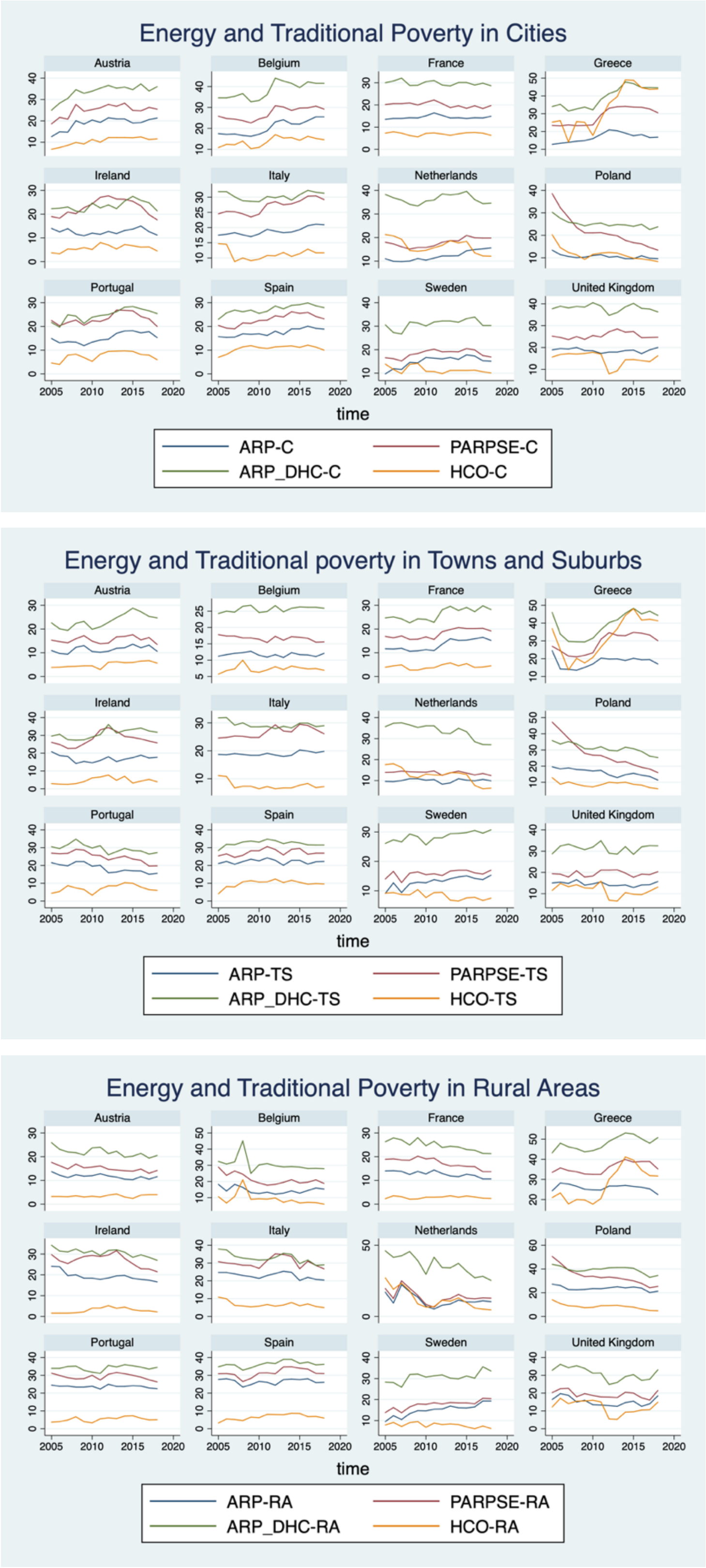

Figure 6.1. Energy and Traditional Poverty by urbanisation degree

Figure 6.1 shows that for all three degrees of urbanisation, the indicator At-risk-of-poverty rate after deducting housing costs (ARP_DHC) is high in all countries. This shows that energy poverty is a society-wide problem, regardless of geographic location. Moreover, the more subjective indicator for traditional poverty measure used in this research, the PARPSE, closely follows the ARP_DHC, in terms of magnitude and trend. This further highlights the prevalence of household poverty as a consequence of energy prices/consumption. The percentage of households spending more than 40% of their income on housing costs, by all degrees of urbanisation, was relatively low in all countries (except Greece). In contrast, the other indicators of poverty measures had higher percentages, suggesting that both energy and traditional poverty may be more related to income than to energy consumption habits. This is one of the areas this study sought to scrutinise.

To the best of our knowledge, the impact on both energy and traditional poverty of forms of residential consumption of energy and of electricity by end-use is unexplored. To discover their impact the study tested various forms of residential energy consumption, namely, oil, natural gas, wood/biomass, and electricity, and various end-uses of residential electricity consumption, such as space heating, water heating, cooking, electrical appliances and lighting. These variables were retrieved from the ODYSSEE-MURE database (ODYSSEE-MURE, 2021). The descriptive statistics of the raw data for the energy related variables are presented in Table 6.3. The energy-related variables measure annual residential consumption in million tonnes of oil equivalent. It should be noted that the energy-related variables and the indicators of energy poverty and traditional poverty are all measured annually. Residential coal consumption in Europe is relatively inconsequential, as shown by (Thonipara et al., 2019) and by Table A.6.2 in the appendix, registering around 0% in all European countries except the Czech Republic and Poland. Consequently, in this research, residential coal consumption was not considered.

Table 6.3. Descriptive statistics of energy related variables

Variable	Definition	Obs.	Mean	SD.	Min	Max
Residential sector						
OIL	Oil consumption	168	2.035735	1.925819	.0358	9.646
GAS	Gas consumption	168	6.345861	7.923479	.0302	30.1493
WOOD	Wood consumption	168	2.168101	2.369035	.0198	9.1178
ELEC	Electricity consumption	168	4.10478	3.7455	.646	14.0243
Residential sector electricity consumption						
SPACE	for space heating	168	.7237923	.9551975	.0735	3.997
WATER	for water heating	168	.4237708	.503305	.0245	2.1556
COOK	for cooking	168	.305431	.2561703	.0653	.9946
APP_LIGH	for electrical appliances and lighting	168	2.628878	2.298794	.2954	7.4597

Notes: All variables are expressed in annual million tonnes of oil equivalent

Table 6.3 reveals that natural gas is the main form of residential consumption, followed by electricity. Natural gas can be used for space and water heating, and for cooking, whereas electricity can be used for both these activities and also to power household appliances and lighting, which, as Table 6.3 shows, consume the most residential electricity.

6.3.2 Cross-sectional dependence and unit roots tests

As this research intended to analyse energy poverty and traditional poverty in European countries, common shocks and spatial dependence were expected. Common shocks could be provoked by the common European policies and guidance on eradicating social exclusion and poverty, including energy poverty. Furthermore, European levels of urbanisation share certain features, such as population density and forms of access to energy, which may also cause spatial dependence. Therefore, it was highly advisable to check for the presence of cross-sectional dependence in the data (Pesaran, 2004). A battery of cross-sectional dependence tests were carried out, including the Breusch-Pagan LM and Pesaran CD tests, which are two of the most frequently used in the literature (Abban and Hasan, 2021; Dogru and Bulut, 2018). The four cross-sectional dependence tests, (i) the Breusch-Pagan LM (Breusch and Pagan, 1980); (ii) the Pesaran Scaled LM (Pesaran et al., 2008); (iii) the Bias-corrected scaled LM (Baltagi et al., 2012); and (iv) the Pesaran CD (Pesaran, 2004), were performed on variables in both levels and first differences. Table A.6.1, in the appendix, shows the cross-sectional dependence tests.

The data used in this research was for a fixed number of time periods (T = 13) and cross-sections (N = 12), which meant the panel were neither small nor large (Baltagi et al., 2012; Pesaran et al., 2008). The Breusch-Pagan LM is robust when both T and N are small, and the remaining cross-sectional dependence tests are valid for large N and T. The results indicated the presence of cross-sectional dependence in all variables at levels and in most of the first-difference variables. Consequently, the integration order of the series was assessed using the CIPS second generation unit roots test proposed by (Pesaran, 2007). The results are shown in Table 6.4.

Table 6.4. Second generation unit root tests

	Level		First differences	
	Without trend	**With trend**	**Without trend**	**With trend**
LARP-C	-1.9**	-0.74	-5.838***	-4.101***
LARP-TS	-1.73**	-1.96**	-7.136***	-4.781***
LARP-RA	-0.89	-1.27	-7.594***	-5.565***
LPARPSE-C	-1.81**	-1.14	-5.602***	-5.07***
LPARPSE-TS	-0.6	-2.45***	-5.783***	-3.551***
LPARPSE-RA	0.05	-0.2	-5.895***	-4.033***
LARP_DHC-C	-4.76***	-2.11**	-6.161***	-4.461***
LARP_DHC-TS	-2.42***	-3.52***	-7.618***	-4.812***
LARP_DHC-RA	-3.48***	-3.29***	-8.052***	-5.7***
LHCO-C	-2.56***	-0.39	-4.772***	-3.736***
LHCO-TS	-3.79***	-4.66***	-8.014***	-6***
LHCO-RA	-1.55*	-1.22	-6.44***	-4.646***
LRPP-C	-0.32	0.67	-4.494***	-3.126***
LRPP-TS	-3.08***	-0.94	-5.697***	-3.913***
LRPP-RA	-1.56*	-2.74***	-7.201***	-5.807***
LINC-C	-0.33	1.51	-3.842***	-2.007**
LINC-TS	-0.11	0.87	-5.469***	-4.248***
LINC-RA	-0.26	-0.04	-5.723***	-4.612***
LHLWI-C	-1.68**	-0.51	-5.793***	-6.065***
LHLWI-TS	-1.15	-0.5	-5.416***	-3.985***
LHLWI-RA	-1.95**	-0.42	-5.303***	-4.22***
LOIL	-2.26**	0.09	-3.585***	-2.108**
LGAS	-2.14**	-1.19	-4.956***	-3.061***
LWOOD	-0.75	-0.95	-4.481***	-2.243**
LELEC	0.06	-2.02**	-5.298***	-3.065***
LSPACE	-0.92	0.76	-4.262***	-3.28***
LWATER	-0.16	0.84	-3.343***	-2.728***
LCOOK	-0.9	0.9	-5.122***	-4.535***
LAPP_LIGH	0.89	-0.44	-5.024***	-3.4***

Notes: *, **, *** denotes the statistical significance at the 10%, 5%, and 1% level, respectively. The null hypothesis of the CIPS test is the series integrated of order one.

As Table 6.4 shows, the CIPS test indicated that most of the variables are integrated of order one, I(1), and the others are I(0). Therefore, all the estimations are performed with the variables at first differences.

6.3.3 Models

To accomplish one of the main objectives of this work, two groups of models were performed to analyse traditional poverty (Traditional Poverty models) and energy poverty (Energy Poverty models) and were estimated for each degree of urbanisation. The variables in the Traditional Poverty models are at-risk-of-poverty rate (ARP) and people at risk of poverty and social exclusion (PARPSE). While in the Energy Poverty models, the dependent variables are at-risk-of-poverty after deducting housing costs rate (ARP_DHC) and housing-costs overburden (HCO). The correlation matrix revealed a strong correlation between the variables for forms of residential energy consumption and the variables for residential electricity consumption by end-use. Additionally, the variance inflation factors indicated that the models should not be estimated using all the energy-related variables, because of multicollinearity issues. Consequently, the models were divided into two subgroups, namely End-use of electricity models and Forms of energy models. Table 6.5 summarises the groups and subgroups of models and presents their nomenclature to aid in their identification.

Table 6.5. Models' nomenclature

		Explained variable	**Degree of urbanisation**	**Models' nomenclature**
Forms of energy models	*Traditional Poverty*	At-risk-of-poverty	Cities	FEP-ATP-C
			Towns and suburbs	FEP-ATP-TS
			Rural areas	FEP-ATP-RA
		People at risk of poverty or social exclusion	Cities	FEP-PPSE-C
			Towns and suburbs	FEP-PPSE-TS
			Rural areas	FEP-PPSE-RA
	Energy poverty models	At-risk-of-poverty after deducting housing costs	Cities	FEEP-ATP-C
			Towns and suburbs	FEEP-ATP-TS
			Rural areas	FEEP-ATP-RA
		Housing cost overburden	Cities	FEEP-HCO-C
			Towns and suburbs	FEEP-HCO-TS
			Rural areas	FEEP-HCO-RA
End-use electricity models	*Traditional Poverty*	At-risk-of-poverty	Cities	EEP-ATP-C
			Towns and suburbs	EEP-ATP-TS
			Rural areas	EEP-ATP-RA
		People at risk of poverty or social exclusion	Cities	EEP-PPSE-C
			Towns and suburbs	EEP-PPSE-TS
			Rural areas	EEP-PPSE-RA
	Energy poverty models	At-risk-of-poverty after deducting housing costs	Cities	EEEP-ATP-C
			Towns and suburbs	EEEP-ATP-TS
			Rural areas	EEEP-ATP-RA
		Housing cost overburden	Cities	EEEP-HCO-C
			Towns and suburbs	EEEP-HCO-TS
			Rural areas	EEEP-HCO-RA

The possible presence of the collinearity and multicollinearity was ruled out after energy. related variables were divided into different models. The highest correlation value recoded was 0.65, and the highest variance inflation factor was 3.7.

6.3.4 Models' specification tests and estimator selection

It is always advisable to analyse a model's characteristics before it is estimated. Therefore, a battery of tests were conducted to evaluate the models' characteristics, particularly, to determine if they are appropriately specified (see Table 6.6). The Ramsey Reset test (Ramsey, 1969) indicated that the models had no omitted variable problems. The Modified Wald test for groupwise heteroskedasticity (Baum, 2001) detected the presence of heteroskedasticity in all models except two (C-II and C-VI). Regarding serial correlation, the Wooldridge test (Wooldridge, 2010) only revealed its existence for model RA-I. To detect the phenomenon of contemporaneous correlation, four distinct tests were performed; (i) the Breush-Pagan LM test (Greene, 2003), (ii) the Pesaran's test (Pesaran, 2004); (iii) the Frees test (Frees, 1995); and (iv) the Friedman test (Friedman, 1937). The results were not consensual, and contemporaneous correlation was detected in only a few models. Lastly, the Hausman test suggested the presence of random effects in all models.

Table 6.6. Models specification tests

Models			RESET	Modified Wald	Wooldridge	Breusch-Pagan LM	Pesaran	Frees	Friedman	Hausman RE vs. FE
Forms of energy models	*Traditional Poverty*	FEP-ATP-C	2.08	109.92***	1.401	66.23	0.59	0.01	16.36	2.49
		FEP-ATP-TS	1.92	124.94***	0.201	96.57***	1.09	0.38**	16.92	1.71
		FEP-ATP-RA	2.58	2323.38***	13.43***	70.37	-0.54	0.13	9.94	1.66
		FEP-PPSE-C	1.99	17.67	0.45	84.71*	4.15***	-0.02	28.21***	9.82
		FEP-PPSE-TS	1.54	32.80***	0.46	75.90	2.06**	-0.01	17.52*	3.67
		FEP-PPSE-RA	1.84	2142.08***	1.86	71.98	-0.67	-0.01	9.03	2.68
	Energy poverty	FEEP-ATP-C	2.34	128.37***	1.18	69.08	0.51	0.04	16.18	0.41
		FEEP-ATP-TS	2.04	57.57***	1.18	95.69***	2.19***	0.22*	21.61**	0.72
		FEEP-ATP-RA	0.52	160.20***	0.15	74.82	3.49***	0.05	25.61***	1.83
		FEEP-HCO-C	1.41	109.15***	2.56	79.76	-0.77	-0.01	16.09	0.7
		FEEP-HCO-TS	0.87	30.39***	0.19	61.56	-0.99	-0.01	10.26	0.38
		FEEP-HCO-RA	1.45	54.23***	1.55	64.8	0.68	-0.18	15.17	1.81
End-use electricity models	*Traditional Poverty*	EEP-ATP-C	0.72	131.99***	1.3	63.9	0.58	-0.05	15.09	2.52
		EEP-ATP-TS	1.88	91.02***	0.04	92.37**	1.34	0.41	16.51	0.39
		EEP-ATP-RA	1.26	2255.1***	1.53	79.72	-0.66	0.14	8.35	0.85
		EEP-PPSE-C	0.97	17.13	0.55	84.09*	4.37***	-0.02	28.32***	10.88
		EEP-PPSE-TS	1.88	34.87***	0.01	69.34	1.71*	0.03	17.52*	2.58
		EEP-PPSE-RA	1.96	2432.73***	0.19	70.66	-0.28	-0.08	9.97	1.93
	Energy poverty	EEEP-ATP-C	1.25	155.07***	0.35	68.58	0.47	0.12	15.92	1.02
		EEEP-ATP-TS	1.35	45.32***	0.65	101.46***	2.43**	0.25*	20.15**	0.79
		EEEP-ATP-RA	0.81	258.54***	0.57	69.09	3.67***	0	27.66***	2.05
		EEEP-HCO-C	1.79	102.66***	1.89	74.79	-0.31	-0.03	15.47	1.25
		EEEP-HCO-TS	0.97	30.1***	0.79	64.98	-0.25	0.04	9.92	1.82
		EEEP-HCO-RA	0.46	46.53***	1.49	63.89	2.06**	-0.17	17.01	3.17

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. the Ramsey RESET tests H0: the model is well-fitted, with no omitted variables; the modified Wald test has distribution and tests H0: ; the Wooldridge test is normally distributed N(0,1), and tests H0: no serial correlation; Pesaran, Frees and Friedman test the H0: residuals are not correlated; Hausman results for H0: difference in coefficient of FE and RE is not systematic including the constant.

The Panel Corrected Standard Error (PCSE) and the Feasible Generalised Least Squares (FGLS) estimators are both suitable for dealing with random effects panel data. The PCSE estimator is more suited to analysing finite samples than the asymptotically efficient FGLS (Chong et al., 2019; Reed and Ye, 2011). However, the FGLS estimator is more efficient and robust for analysing panel data with a larger number of time observations than cross-sections (Beck and Katz, 1995; Reed and Ye, 2011). Furthermore, the FGLS is more efficient for evaluating data on first differences, i.e., first differentiated models (Beck and Katz, 1995; Reed and Ye, 2011). The characteristics of the data, namely the larger number of time observations than cross-sections, as well as the integration order of the variables which led to the use of first differentiated variables, suggested that the FGLS was the most suitable estimator. Furthermore, the FGLS can still estimate models with heteroskedastic and correlated-error structures, a phenomenon highlighted in the models in the specification tests.

6.4 Results

The results of the analysis of the impact of forms of residential energy consumption on energy poverty by degree of urbanisation are set out in Table 6.7 and summarised in Figure 6.2. The results of the analysis of the impact of residential electricity consumption by end-use on energy poverty by degree of urbanisation are shown in Table 6.8 and graphically displayed in Figure 6.3. The results of the analysis of the impact of forms of residential consumption, and of residential electricity consumption by end-use, on traditional poverty, by each degree of urbanisation are reported in Tables 6.9 and 6.10, respectively. Table A.6.2, in the appendix, shows the average consumption of households by energy form, in each European country.

Table 6.7. Energy forms impact on energy poverty

Models **Variables**	***FEEP-ATP-C***	***FEEP-HCO-C***	***FEEP-ATP-TS***	***FEEP-HCO-TS***	***FEEP-ATP-RA***	***FEEP-HCO-RA***
ΔLINC	-0.2705***	-0.4805***	-0.4711***	-0.7292***	-0.7876***	-1.7089***
ΔLHLWI	0.0839***	0.1298***	-0.0218***	-0.0308	-0.0438***	0.0727***
ΔLRPP	-0.23***	-0.6386***	-0.1486***	0.0485	-0.5971***	-0.4242**
ΔLOIL	0.0391*	0.0639	0.0278***	0.1900***	0.0858***	0.0559
ΔLGAS	0.0186	-0.0198	-0.0649***	-0.1824***	-0.0734***	-0.0717
ΔLWOOD	-0.0204*	-0.051	-0.0401***	-0.1035*	0.0124	-0.2060***
ΔLELEC	-0.1903***	-0.5858***	0.0394**	-0.4477**	0.0553*	0.5716***
Trend	-0.0031***	-0.0077***		-0.0078***		-0.0114***
Constant	0.0316***	0.0658***	0.0122***	0.0889***	0.0164***	0.1089***

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Overall, the results show that different forms of residential energy consumption have dissimilar impacts, and vary between areas with differing degrees of urbanisation. This reveals that the households in areas with different levels of urbanisation attribute different uses to each form of residential energy consumption. Some forms of energy consumption lower their risk of experiencing energy poverty, while others increase it.

For instance, Table 6.7 shows that electricity consumption increases a household's risk of energy poverty in rural areas, while natural gas and wood/biomass decrease the percentage of households suffering from energy poverty. It should be noted that wood/biomass has the ability to alleviate energy poverty in all degrees of urbanisation but with different magnitudes of impacts. Conversely, residential oil consumption increases the percentage of households threatened by energy poverty for every degree of urbanisation.

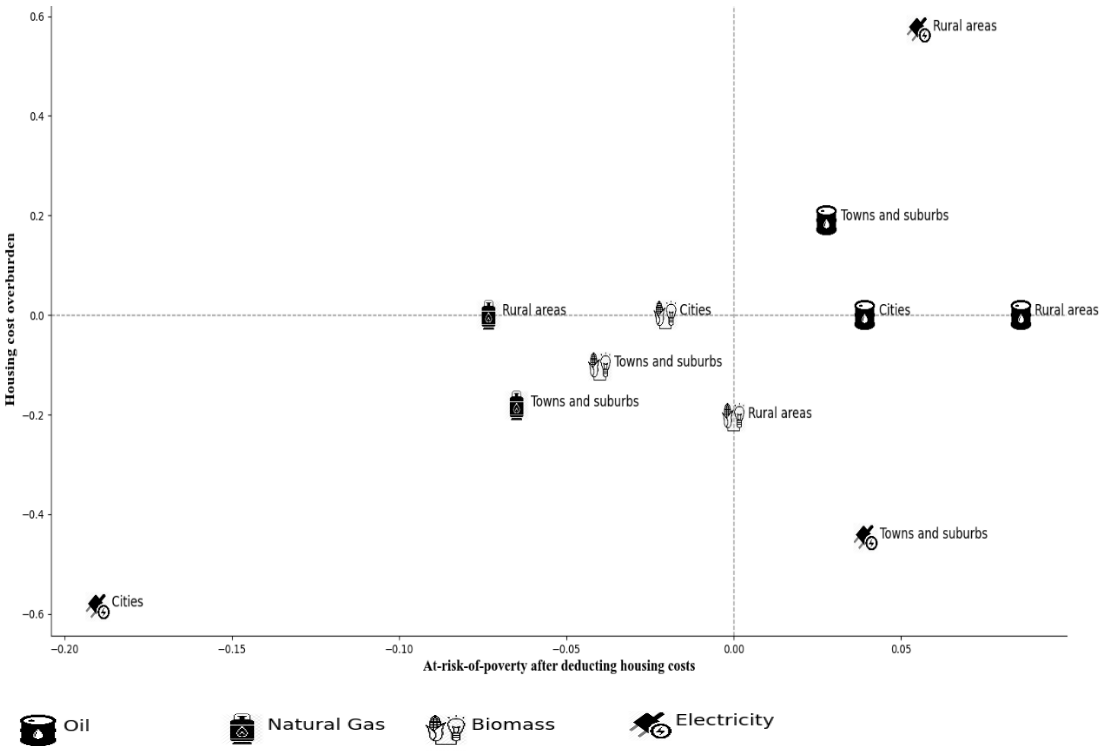

Figure 6.2. Energy forms impact on energy poverty

Table 6.8 and Figure 6.3 show the impact of residential electricity consumption in detail, by exploring its impact by end-use activity. For instance, Figure 6.2 shows that residential end-use consumption in towns and suburbs increases the risk of energy poverty. Figure 6.3, takes this further, and shows that this negative impact is mainly caused by electricity consumption by appliances, lighting, and water heating. In fact, in towns and suburbs, electricity consumption for water heating and households appliances and lighting tends to increase the *at-risk-of-poverty rate after deducting housing costs* (see Table 6.8). At the same time, electricity consumption for cooking and space heating tends to reduce the risk of poverty. In rural areas, the increased risk of energy poverty due to residential electricity consumption (shown by both indicators used) is also mainly due to electricity consumption for water heating, household appliances, and lighting. In rural areas, residential electricity consumption for cooking and for space heating seems to reduce the housing-costs overburden. Nonetheless, if these end use activities are powered by electricity, they do not help reduce a household's risk of energy poverty in rural areas.

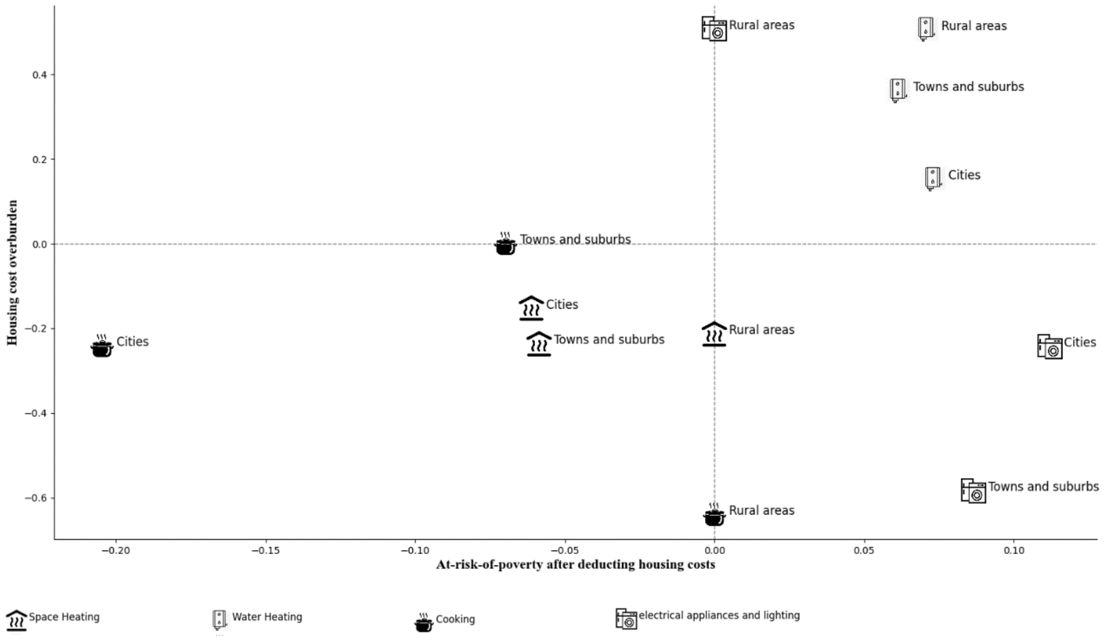

Figure 6.3. End-use electricity consumption impact on energy poverty

Electricity is considered the most promising form of green energy to achieve a low carbon economy because of its potential exploitation of natural resources such as wind and sun. In addition, electricity is the form of energy most consumed by European countries (see table A.6.2 in the appendix). Nevertheless, the energy transition and the electrification of economies it entails, may put even more pressure on households already threatened by energy poverty. The results of this research highlight that electricity only played a crucial role in decreasing energy poverty in cities, and even there, residential electricity consumption for water heating, household appliances and lighting still increased the risk of energy poverty (see Table 6.8 and Figure 6.3). These results reveal that energy poverty may be more related to infrastructure (stock) and energy-related education (stock) than to low-income (flow). In view of this, energy efficiency measures, and time-of-use tariffs, could alleviate energy poverty issues in cities (policies further discussed in the next section).

Table 6.8. End-use electricity consumption impact on energy poverty

Models **Variables**	***EEEP-ATP-C***	***EEEP-HCO-C***	***EEEP-ATP-TS***	***EEEP-HCO-TS***	***EEEP-ATP-RA***	***EEEP-HCO-RA***
ΔLINC	-0.2480***	-0.4576***	-0.5030***	-0.8182***	-0.7523***	-1.6487***
ΔLHLWI	0.1149***	0.1519***	-0.0353***	-0.0297	-0.0444***	0.1012***
ΔLRPP	-0.2019***	-0.6715***	-0.1637***	-0.0864	-0.4629***	-0.1400***
ΔLSPACE	-0.0612***	-0.1530***	-0.0586***	-0.2363***	-0.0006	-0.2135***
ΔLWATER	0.0733***	0.1523***	0.0615***	0.3604***	0.0709**	0.5057***
ΔLCOOK	-0.2048***	-0.2412***	-0.0698***	-0.0889	0.0153	-0.6409***
ΔLAPP_LIGH	0.1120***	-0.2433*	0.0866**	-0.5842***	0.0636	0.5073***
Trend		-0.0060***				
Constant	0.0094***	0.0499***	0.0144***	0.0269***	0.0102***	0.0183***

Notes: ***, **, * denote statistical significance at 1%, 5%, and 10% level, respectively.

Wood/biomass is often used for space heating and cooking, and can also be used for water heating. Table 6.8 shows that this form of residential energy consumption reduces the risk of energy poverty whatever the degree of urbanisation. However, the use of this energy form is linked with increasing traditional poverty in both cities, and towns and suburbs. These dissimilar outcomes could be due to the limited availability of wood/biomass in more urbanised areas, in contrast to rural areas, where it is not subject to the same availability issues or costs for transportation and storage, and reduces both energy and traditional poverty. Furthermore, the availability of biomass in rural areas may even generate business opportunities, leading to more social cohesion and environmental protection.

Table 6.9. Energy forms impact on poverty

Models	***FEP-ATP-C***	***FEP-PPSE-C***	***FEP-ATP-TS***	***FEP-PPSE-TS***	***FEP-ATP-RA***	***FEP-PPSE-RA***
Variables						
ΔLINC	0.0219	-0.2184***	-0.5141***	-0.7193***	-0.4780***	-0.4817***
ΔLHLWI	0.1677***	0.1901***	-0.0589***	0.0368***	0.0455***	0.1299***
ΔLRPP	-0.3118***	-0.2463***	-0.1392**	-0.074	-0.6220***	-0.3594***
ΔLOIL	-0.0491***	-0.0166**	0.0013	0.0655***	-0.0533***	-0.0260**
ΔLGAS	0.0538***	0.0352***	-0.1284***	-0.1050***	0.0052	-0.0336**
ΔLWOOD	0.0353**	0.0778***	0.01	0.0506***	-0.2418***	-0.2121***
ΔLELEC	-0.0881*	-0.1545***	0.1952***	0.1821***	0.2855***	0.2249***
Trend				-0.0030***		
Constant	0.0038	0.0029	0.0170***	0.0313***	0.0109***	0.0022

Notes: ***, **, * denote statistical significance at 1%, 5%, and 10% level, respectively.

It seems that residential oil consumption, mainly used to power old space heating equipment, tends to increase energy poverty (see Table 6.7 and Figure 6.2). Nevertheless, it should be pointed out that, in cities and rural areas, this form of energy consumption apparently reduces poverty (see Table 6.9). This could be explained by the fact that bigger oil-fired boilers can be shared between households in large residential buildings, allowing them to adequately heat their homes more cheaply and thereby reduce traditional poverty. However, if the installation/equipment is old or poorly maintained, families may still be unable to maintain an adequate temperature in their rooms, or avoid rising costs, increasing both energy and traditional poverty. This research reveals that using electricity for space heating leads to a decrease in energy poverty and traditional poverty, so that the replacement of inefficient old oil-fuelled systems with electrical systems might represent a solution for large buildings.

Table 6.10. End-use electricity consumption impact on poverty

Models **Variables**	***EEP-ATP-C***	***EEP-PPSE-C***	***EEP-ATP-TS***	***EEP-PPSE-TS***	***EEP-ATP-RA***	***EEP-PPSE-RA***
ΔLINC	0.0133	-0.3332***	-0.5052***	-0.7359***	-0.4462***	-0.3829***
ΔLHLWI	0.1728***	0.1617***	-0.0793***	0.0275***	0.0165	0.1312***
ΔLRPP	-0.2450***	-0.2370***	-0.2153***	-0.0769*	-0.5216***	-0.3911***
ΔLSPACE	-0.0269*	0.0279*	0.0303**	0.0931***	-0.1860***	-0.1122***
ΔLWATER	-0.0095	-0.0216	0.0631***	-0.011	0.2108***	0.1883***
ΔLCOOK	-0.1144***	0.0507	0.1443***	0.1241***	-0.1498***	-0.0311
ΔLAPP_LIGH	0.0763***	-0.1620***	-0.1915***	-0.0513*	0.1931**	0.0848*
Trend		-0.0030***		-0.0039***		
Constant	0.0122***	0.0285***	0.0175***	0.0395***	0.0039	-0.0055***

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

The results of analysing energy poverty and traditional poverty with respect to the end-use of residential electricity consumption, suggest ways of alleviating the poverty. For instance, using electricity for cooking could reduce both energy and traditional poverty in cities, where electric cooking technologies are already widespread for new and renovated buildings However, it would not yet have any noticeable effect in rural areas, or towns and suburbs, as areas with this level of urbanisation still lack of access to these new technologies. The greatest concern at every level of urbanisation is residential electrical water heating, as the study's results stress that electricity consumption for water heating has the greatest impact on increasing the percentage of households suffering from both energy poverty, and traditional poverty. Once again, this reinforces the idea that energy poverty is more a consequence of lack of stock rather than a consequence of flow (or income).

6.5 Discussion

This research highlights the importance of studying the impact of different forms of residential energy consumption on both energy and traditional poverty by degree of urbanisation. It shows that, depending on the degree of urbanisation, certain forms of residential energy consumption can be more useful and improve the well-being of households and it confirms that energy poverty is dependent on the type of energy consumed and the level of urbanisation. Therefore, energy policies should not be planned uniformly on a European or national scale. Policy guidelines or targets, such as the share of renewables in the energy mix, and energy poverty reduction targets, should be devised at a suitably local level. The accessibility and prices of different forms of energy differ widely between countries, and within countries, by region, and degree of urbanisation. For example, the accessibility of energy in rural areas of southern Europe is quite different from that in northern Europe. Consequently, energy policies and measures should be planned at a more disaggregated level of sub-national regions, whose households have divergent energy needs, and varying access to forms of energy. Furthermore, the results of this research also confirm that no single form of energy consumption can reduce energy poverty for every degree of urbanisation. These results clearly show that the energy transition, and the higher residential consumption of electricity it entails, requires well-informed policy. This research also went one step further and analysed the impact on poverty of residential electricity consumption by end-use, and provided important knowledge for more accurately targeted policy planning to assist households during the coming energy transition. The energy transition can provide benefits for households, but governments need to tailor policies to match the varying needs and circumstances of households.

Some forms of residential energy consumption can provide households or individuals with better living standards, while others can have the reverse impact, as this research shows. For instance, in rural areas, wood/biomass is an endogenous and mostly freely available energy form. The consumption of this energy form can be used for basic households needs, such as water heating, space heating, and cooking. It can also provide greater well-being for families because its low or nearly zero costs reduces energy expenses. It should also be noted that the consumption of wood/biomass can also substitute the use of gas. Consequently, the higher the consumption of wood/biomass in rural areas, the more of the household budget remains available for other primary needs. This means that wood/biomass can reduce the risk of energy poverty, traditional poverty and social exclusion. In contrast to rural areas, the results show that in cities, and in towns and suburbs, the consumption of wood/biomass has cost limitations. In these areas with greater levels of urbanisation, wood is not freely available and may involve transport costs and storage restrictions. This is confirmed by the fact that wood/biomass was found to increase energy poverty in more urbanised areas such as cities, towns and suburbs.

Gas consumption constituted almost half of total household energy consumption (see Table 6.3). The results show that this form of energy was generally preferred by households in rural areas, and in towns and suburbs, making natural gas is a key form of energy for reducing energy poverty in these less urbanised areas. When we turn to cities, the results show that natural gas has no impact on the indicators for energy poverty, but tends to increase the traditional poverty indicators. This means that natural gas has been increasing traditional poverty in city households. The high dependence of certain households on natural gas is also a major vulnerability. The unforeseen recent escalation in natural gas prices due to geopolitical issues, cuts in financial investment, and internal and external dependence, has led European countries to switch to a strategy of conserving natural gas. This strategy of conservation may cause abrupt rises in natural gas prices and thus in electricity prices, causing those struggling with energy costs to fall into energy poverty. Consequently, it is essential to encourage households to switch from primary energy sources to electricity, an energy source that can be generated using indigenous green energy sources.

The results show that electricity consumption increases energy poverty and traditional poverty in both rural areas, and towns and suburbs, whereas, in cities, electricity consumption can reduce energy poverty. This divergence arises because city lifestyles are more compatible with electricity consumption than those of households in non-urban areas. In cities, there is widespread access to modern and energy-efficient technologies powered by electricity which can increase the well-being of families and reduce their energy and traditional poverty. For instance, the use of modern electric cooking technologies has decreased energy poverty in cities. Electricity can power household appliances and devices, such as televisions, phones, laptops, and other gadgets, thereby improving individual well-being. These devices can be used to access entertainment and learning processes for adults and children, potentially increasing their present and future productivity and income. In other words, electricity consumption could reduce their propensity to suffer from both energy and traditional poverty. However, the results of our research also show that electricity consumption for certain kinds of end use can increase energy poverty, suggesting that the impact of electricity consumption on energy poverty may be more related to energy-related infrastructure and education (stock) than to low income (flow).

This research also found that the biggest driver of energy poverty was the use of inefficient technologies in water heating systems, and household appliances, such as washing machines, lighting, and entertainment. Inefficient technologies can cause high electricity consumption while reducing their usefulness and the well-being of families. In contrast, highly energy-efficient technologies consume less electricity and are at least as useful and beneficial to households as less efficient technologies. Consequently, policymakers should consider subsidies for the rehabilitation of energy-inefficient dwellings and appliances. This funding would benefit households through the potential savings of energy efficiency. Rehabilitation measures should be introduced for single-family and large residential buildings. These measures could be modest, for instance, painting the facades and roofs with thermochromic colours. or more extensive, such as applying better wall insulation, installing thermally efficient glazing, and exchanging household appliances for more energy-efficient ones, or those with deferred start to take advantage of time-of-use pricing strategies. This cost-effective funding of energy-efficiency improvements for households would enable a long-term and sustainable energy poverty solution.

The decentralisation of electricity production is another potential solution for reducing the threat energy poverty represents to households in rural areas, cities, and suburbs during the energy transition. In other words, the integration of decentralised electricity generation from renewable sources could be a step towards overcoming both energy and traditional poverty. Additionally, this decentralisation could also be a way of encouraging consumers in rural areas to switch from primary energy sources to electricity, by providing them with ‘free’ electricity generation. Solar photovoltaic (PV) panels can be installed on the roofs of houses or buildings make it possible to produce electricity locally. The main barrier to this solution is the initial investment. Vulnerable households, such as those on low incomes or those threatened by energy poverty, cannot afford the cost of solar PV panels. Policymakers should provide funding schemes to increase the penetration of solar PV panels in single or multi-family residential buildings. The capacity of solar PV panels should be sufficient to satisfy residential-based consumption, i.e., the continuous consumption of electricity during the day to power refrigerators, freezers, and other appliances. This will contribute to overcoming energy poverty and could even provide savings to overcome traditional poverty issues.

In summary, the results of this research show that energy policies should not be uniformly applied at a national level. The impact of forms of residential consumption and the impact of residential electricity consumption by end-use vary between areas with differing degrees of urbanisation. Consequently, energy policies aimed at alleviating poverty, and encouraging the energy transition and consequent electrification of economies, should be planned at a regional level, or by level of urbanisation. This planning could also take advantage of the strengths of local forms of clean energy. Areas with high solar exposure could promote the installation of both solar PV panels to generate electricity, and solar thermal collectors, to reduce electricity consumption for water heating systems. It should also be emphasised that, in rural areas, towns, and suburbs, strategies for reducing the reliance on wood/biomass and natural gas can trigger effects on both poverty and energy poverty. Therefore, the energy transition and the consequent electrification of economies should be carefully planned so as not to worsen both poverty and energy poverty in these areas.

6.6 Conclusion

This research used the Eurostat database to perform an analysis of the impacts of forms of residential energy consumption and residential electricity consumption by end-use on energy poverty and energy poverty. Traditional poverty and energy poverty in twelve EU countries were assessed for a period from 2005 to 2018 by degree of urbanisation. A battery of tests were conducted to evaluate the characteristics of the panel data and the specification of the models. The tests indicated that the FGLS estimator was best suited to handling the characteristics of the data and the specifications of the 24 models. The findings of this research provide a solid foundation from which decision-makers can gain insights on energy poverty policies.

Overall, the results prove that different forms of energy have differing effects on areas with different degrees of urbanisation. In other words, there is no single energy form for eradicating both poverty and energy poverty. Up until now, energy policies have generally been planned and executed at a national level. However, it would be better if these policies were planned within countries at a regional level, taking into account the local characteristics of residential consumption and its impact on energy poverty. In cities, residential electricity consumption was found to reduce energy poverty, while in rural areas, towns and suburbs, natural gas and wood/biomass were the crucial forms of energy for reducing energy poverty. In fact, residential electricity consumption in these less-urbanised areas increases both poverty and energy poverty. To understand residential electricity consumption in more detail, it was further disaggregated by end-use. Water heating, household appliances and lighting were found to be the key elements increasing energy poverty in rural areas, towns and suburbs.

The findings of this research suggest that energy poverty is more due to a lack of knowledge and financial investment than a consequence of low-income. Energy policies need to evolve to protect households threatened by energy poverty during the ongoing energy transition and electrification of the economy. Therefore, governments ought to be prepared to support public investment through: (i) the provision of energy-efficient appliances; (ii) the installation of solar PV panels; (iii) the installation of solar thermal collectors; (iv) a combination of both (ii) and (iii) with energy storage options and incorporated in energy communities; (v) education campaigns about the use of technologies in (ii), (iii), and (iv); (vi) information campaigns and training about price-responsive tariffs and demand response programmes; and (vii) the rehabilitation of low energy-efficient buildings, particularly those occupied by families threatened by energy poverty.

Further research is needed to address some of the limitations encountered in this study, primarily the limited number of countries under analysis and the short time span studied. To overcome these obstacles, a single energy poverty measure should be defined by the EU. A data set on energy poverty could then be set up, making it easier to compare the drivers of energy poverty in EU countries and their regions. It should also be noted that microeconomic data sets, such as the EU-SILC, based on surveys of families could also produce more useful statistics about this topic. As the local circumstances of households have been shown to be so important, future EU inquiries about energy poverty should include questions about the forms of energy they consume and their expected costs, as well as the consumer's preferences. Lastly, this study was unable to take into account the coping strategies that some households perform to combat energy poverty (such as only heating one room). Further research is needed to study both these coping strategies and, to measure other forms of hidden energy poverty.

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Chapter 7

Are dynamic tariffs effective on energy poverty reduction? Empirical evidence of US households

This chapter has been presented at an international conference, at the delivery of this thesis, it is still in the review process. The output of this chapter is:

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Abstract

Statistics from the United States (US) Energy Information Administration and the US Census Bureau reveal that a growing number of households are threatened by energy poverty. Both argue that energy poverty is becoming more common than traditional poverty. The increasing use of smart meters tracking energy use in homes and businesses further integrates consumers into the electricity system. This research aims to determine if dynamic pricing programs are able to reduce energy burden for households, and consequently, diminish the number suffering from energy poverty. The Annual Electric Power Industry Report and the American Community Survey was merged by state and year to assess the impact of dynamic pricing on energy poverty eradication for 51 US states from 2013 until 2019. The findings show that time-of-use and critical peak pricing tariffs are capable of reducing the number of households in energy poverty. Notwithstanding, policymakers and utilities should develop services to stimulate consumers to modify their consumption habits. In turn, they should provide electricity grids with enhanced flexibility to manage the scarcity and excess of electricity production provoked by intermittent renewable energy sources.

7.1 Introduction

Residential energy poverty has attracted considerable attention from researchers and policymakers. In the United States (US), most evidence in this field has been derived from the statistics of the Residential Energy Consumption Survey (RECS), published by the US Energy Information Administration (EIA). The last RECS published is from 2015, and it indicated that 17 million US households could not afford their energy bills, and had received a disconnection notice from their energy providers, i.e., 14% of the sampled households (EIA, 2015). Furthermore, 11% of them, to reduce their energy bill, kept their homes at uncomfortable and unhealthy temperatures (EIA, 2015). This portrayal of stress shows that 25 million households have had to make difficult choices in order to pay their energy bills, sometimes forgoing food and medicine to heat their homes (EIA, 2015; Wang et al., 2021). In fact, energy poverty has been seen to be more widespread than general poverty in the US (Brown, Soni, Doshi, et al., 2020; Wang et al., 2021). Nevertheless, the US federal government still does not recognise energy poverty as a distinct problem from low-income poverty (Bednar & Reames, 2020).

Climate change and the integration of renewable energy sources (RES) into the electricity mix have raised concerns about residential energy use. In developing countries, these concerns lie in unequal access to clean and modern energy sources. While, in developed countries, concerns reside in access to clean and modern energy sources at affordable prices. Furthermore, the electrification of economies and its consequent energy intensity is highly correlated with energy poverty (Wang et al., 2021). Even after decades of weatherisation programs and retrofit subsidies, US households, on average, continue to spend a higher share of their income on electricity and gas bills (Brown, Soni, Doshi, et al., 2020; Brown, Soni, Lapsa, et al., 2020; Wang et al., 2021). The most concerning consequence is that energy burden remains persistently high and onerous for low-income households, particularly those in South (American rural states), and among minority households (Brown, Soni, Doshi, et al., 2020; Brown, Soni, Lapsa, et al., 2020; Wang et al., 2021).

In the past, mass-market electricity consumers, namely residential, only had at their disposal meters to record their electricity consumption accumulated over time. Data from these were collected manually over monthly cycles for billing purposes. As a result, consumers only had fixed tariffs available, at which consumption was charged at the same price per kilowatt-hour (KWh). These rates did not reflect the variability of electricity marginal costs. Consequently, they provoked consumers' indifference, because the price of having a distributed consumption or not is equal, provoking the emergence of consumption peaks. Peaks of consumption have been met mainly by fossil fuels, causing negative impacts to the environment. This negative outcome has led to a worldwide search for a shift from fossil fuels towards RES, also implying a shift in focus from the supply side to the demand-side, i.e., consumer empowerment. Therefore, smart grids, including smart meters, have been installed to enable new business models and services to engage consumers and to provide enhanced flexibility to electrical systems (Agüero & Khodaei, 2018; Batalla-Bejerano et al., 2020; Zhou, 2021).

Dynamic pricing programs were introduced to replace flat rates. These programs empower the consumers. They are encouraged to modify their consumption habits to provide flexibility to the grid and accommodate RES intermittency by adjusting their consumption to RES availability. The price differentiation employed in dynamic pricing programs is mainly based on time of day, wholesale and day-ahead electricity market prices and periods, or even RES availability. This requires the dissemination of smart meters capable of capturing consumption in different time periods. Therefore, the US. has been modernizing its electricity grid to disseminate dynamic pricing programs throughout all states (EIA, 2021; Zhou, 2021). The dynamic pricing programs, through price differentiation, can provide savings to consumers, benefiting them. In fact, the literature has already explored the benefits of dynamic pricing programs to consumers, namely on its savings and behavioural consumption (Batalla-Bejerano et al., 2020; Zhou, 2021). Nevertheless, these analyses were based only on pilot programs or small population data (Batalla-Bejerano et al., 2020; Faruqui & Sergici, 2010).

Dynamic pricing programs can generate potential savings for consumers as they encourage consumption adjustment. Consequently, dynamic pricing programs could be seen as one of the solutions to overcome energy poverty. This line of reasoning has motivated this research to break new ground, that is, the analysis of the effect of dynamic tariffs, i.e., the peak pricing problem, on energy poverty. Accordingly, this research fills a new gap in the literature and is, as far as we know, the first research that extensively studies the economic and social impacts of dynamic pricing programs. To achieve our aim, 51 US states were evaluated over a period from 2013 to 2019 using dynamic panel estimators to answer the following research questions: (i) are dynamic tariffs effective in reducing energy poverty?; and (ii) if yes, are they effective in avoiding households falling into the energy poverty trap? One proves that dynamic pricing schemes can reduce energy poverty. Nevertheless, not all dynamic tariffs are able to fulfil this target. In fact, the results stress that the more static ones, like time-of-use (toU) and critical peak pricing (CPP), have a higher propensity to keep more households from energy poverty than the more dynamic ones, such as real-time pricing (RTP).

Thereafter, the rest of the paper develops as follow. The following section presents the literature results and arguments about energy poverty and dynamic tariffs. Section 7.3 includes the data and the methodology. The results are given and discussed in Section 7.4. Lastly, Section 7.5 concludes.

7.1 Literature Review

The massive penetration of RES, specifically the intermittent ones, the growing electrification of economies, and the need to progressively abandon fossil fuels due to their negative impacts on the environment, has shifted the focus of electricity distribution from the supply side to the demand-side. Until now, electricity consumers have had a passive role. Nowadays, they should play a proactive role in the electrical system through responsible consumption (Batalla-Bejerano et al., 2020; Martinez-Pabon et al., 2017). In fact, it is crucial that consumers allow greater flexibility within the electricity system, specifically to manage the scarcity and excess of electricity production caused by RES intermittency. This would imply empowering consumers with their consumption data and/or with signals about RES availability (Batalla-Bejerano et al., 2020; Zhou, 2021). The Advanced Metering Infrastructure (AMI), with its so-called ‘smart meters’, is in a position to provide this necessary consumption information to both consumers and utilities. Indeed, these smart meters can measure electricity consumption at frequent time intervals (every hour, 15 minutes or even 5 minutes) and provide this data to both consumers and utilities in real-time (FERC, 2006).

The integration of an information and communication network within an electrical system, i.e., a smart grid, has been developed and deployed through both public and private financial resources (Batalla-Bejerano et al., 2020; Brown et al., 2018; FERC, 2006; Zhou, 2021). In the US, a $4.5 billion investment, one of the world's largest public initiatives for grid modernization, has driven the deployment of a large smart grid infrastructure, with the installation of AMI and AMI within customers' home area network (AMI-HAN). The AMI-HAN is capable of recording and transmitting data instantaneously, allowing the AMI to communicate with customer’s household appliances and other devices in real-time (EIA). At the end of 2016, 71 million AMIs were installed in the US, representing 47% of the 150 million customers (EIA, 2017). By 2020, AMI penetration represented around 88% of the residential installations (EIA, 2021). These smart meters and grids have the potential to reduce the operational costs of metering and reading. At the same time, they can improve customer experience in managing electricity flows and billing and encourage better consumer engagement in the responsible use of electricity (Boisvert, 2013).

Successful smart grid deployment enables diverse market opportunities and services, also allowing the implementation of new utility business models (Agüero & Khodaei, 2018). Indeed, utilities have been focused on new business models and services to promote the active participation of consumers (Agüero & Khodaei, 2018; Batalla-Bejerano et al., 2020; Zhou, 2021). A typical example of them is the new forms of electricity pricing, i.e., dynamic pricing (Brown et al., 2018). Dynamic pricing, often called time-based rates, time-varying retail pricing, time-differential retail rates, time-variant pricing, and advanced pricing programs, exposes consumers to some level of electricity price variability (Agüero & Khodaei, 2018; Batalla-Bejerano et al., 2020; Brown et al., 2018; Zhou, 2021). In these, the price differentiation conveys the variability of electricity marginal costs and grid conditions, with the aim of modifying electricity usage patterns, including electricity demand timing and level (Agüero & Khodaei, 2018; Batalla-Bejerano et al., 2020; Zhou, 2021). Therefore, dynamic pricing has the potential to encourage consumers to have an effective and efficient response to electric rates options, allowing both utilities and customers to benefit from the advantages of the wholesale market price variability and the capabilities of smart grids.

A variety of dynamic pricing programs have been employed in the US, like CPP, CPR, VPP, and RTP (Office of electricity). ToU tariffs are often considered one of the dynamic pricing programs. However, this electricity tariff is not dynamic. Indeed, its rate schedule is static and predetermined at the time of hiring or one season in advance. Table 7.1 presents all the electricity pricing programs, their definitions and acronyms, from the most static to the most dynamic.

Table 7.1. Electricity rates definitions

Rates/tariffs	Definition
Flat rate	Each KWh consumed is charged at the same price over the billing period.
Tiered rate	Consumption is priced differently depending on usage blocks during a billing period. For example, the price of the first 500 KWh is higher than the next 500 KWh, or the other way around.
Time-of-use (ToU)	Consumers pay different prices depending on blocks of hours. The prices for each block of hours are predetermined and fixed, defined for each day of the week, season, and time of day. Generally, the peak prices are higher than off-peak prices, and off-peak prices are lower than the 'standard' flat rate.
Critical Peak Pricing (CPP)	This tariff is intended to reduce consumption during periods of high wholesale market prices (in peak periods or RES scarcity) or system contingencies. In these periods, a pre-specified rate is imposed for a limited number of hours; its prices can be 3-10 times higher than the flat rate. Customers are noticed from utilities about these periods a few hours ahead. Typically, a CPP tariff is combined with a ToU rate but is not mandatory.
Critical Peak Rebate (CPR)	Its mechanism is similar to the CPP. The consumer has a base rate plan, such as a flat rate or a ToU, which sets its price for the entire period. However, when critical peak events occur, the consumer earns a rebate on a limited number of days and for a limited number of hours, at the request of the electricity provider. This rebate or refund may be several times lower than the average price for any consumption reduction related to the baseline customer usage.
Variable Peak Pricing (VPP)	Is a form of ToU, where the prices for each block of hours of the day, especially those related to the peak periods, are defined, and noticed on the previous day (typically late afternoon). Its peak prices are often set through the day-ahead wholesale market price, and by the utility.
Real Time pricing (RTP)	This retail price structure reflects the prices of the wholesale market price on either day-ahead or hour-ahead market price. Its price blocks can fluctuate hourly or more often.

Notes: KWh means kilowatt hour. Own elaboration based on Energy International Agency and U.S. Department of energy (EIA; Office of electricity)

Dynamic pricing diffusion in the US, has been relatively slow (FERC, 2020). The Federal Energy Regulatory Commission (FERC), in 2021, reported that only 9.5 million US customers were actively participating in dynamic programs, which represents a small percentage of customers (FERC, 2020). The literature shows that a 10% increase in AMI penetration only causes an increase of around 0.5% in the participation of customers in dynamic pricing programs (Zhou, 2021). Consequently, one of the most promising benefits of smart grids, that is, price-responsive demand derived from dynamic pricing, is still absent (Batalla-Bejerano et al., 2020; FERC, 2020; Good et al., 2017; Zhou, 2021). In the literature, several empirical analyses about the impact dynamic pricing programs have on savings and consumption behaviour are observed (Batalla-Bejerano et al., 2020;

Zhou, 2021). However, most of these studies are based on pilot programs (Batalla-Bejerano et al., 2020; Faruqui & Sergici, 2010). This research is a leap forward through the massive analysis of the impact of dynamic pricing options on one of the major societal challenges, i.e., on energy poverty.

The correlation between household energy use and needs and household well-being has been studied, mainly from three standpoints: energy security/insecurity, energy justice, and fuel/energy poverty. Energy security definition is twofold. On the one hand, it was defined as 'sustainable energy for all' in the 65th session of the United Nations General Assembly Resolutions. On the other hand, it was defined as 'an inability to adequately meet basic residential energy needs' (Hernandez, 2016; Hernandez & Siegel, 2019). Its definition implies that a household is threatened by insufficient or inadequate energy consumption to meet its basic needs (Hernandez, 2016; Phoumin & Kimura, 2019; Wang et al., 2021). Regarding the health matter, the energy security thematic was expanded to study other impacts, as in environmental health and food insecurity (Cook et al., 2008; Eichelberger, 2010; Nord & Kantor, 2006; Smith et al., 2007).

Energy justice refers to the fair distribution of energy burdens and benefits, referring to the accessibility and affordability of energy for analysing health and well-being (Guruswamy, 2010; Hall, 2013; Sovacool & Dworkin, 2015; Sovacool et al., 2013; Wang et al., 2021). In developed economies, energy justice is mainly employed to address energy affordability issues (Hall, 2013). In this matter, the literature argues that energy should be supplied and consumed in a manner that does not compromise the capacity of households to obtain other basic needs, such as food, hygiene, studying, and health care (Sovacool & Dworkin, 2015; Sovacool et al., 2013). Whereas, in developing countries, this term is used to address energy access issues (Guruswamy, 2010; Wang et al., 2021). In fact, energy access is fundamental to driving human development and increasing the quality of households' life (Sovacool & Dworkin, 2015; Sovacool et al., 2013). This is particularly true in the sub-developed and developing economies where many households do not have access to life-sustaining energy or an uninterrupted energy supply (Sovacool & Dworkin, 2015; Sovacool et al., 2013). Accordingly, energy justice presupposes that the following four rights are ensured: the right to sustainable energy production; to the best energy infrastructure available; to affordable energy; and to an uninterrupted energy supply (Hernández, 2015; Wang et al., 2021).

Energy poverty is an increasingly urgent problem, which has provoked frequent discussion in the literature for the last ten years (Bednar & Reames, 2020; Frank et al., 2006; Mould & Baker, 2017; Wang et al., 2021). The definition of energy poverty implies that a household has to pay a disproportionate price for energy use. This disproportion is often caused by high energy costs, low household income, or inefficient energy use (Bednar & Reames, 2020; Frank et al., 2006; Mould & Baker, 2017; Wang et al., 2021). Energy poverty measurement is twofold and has a wide range of consensual and affordability measures (Wang et al., 2021). The consensual measure focuses on energy-related deprivation. In this case, energy poverty is a consequence of residential energy inefficiency or low income.

The affordability measure analyses the percentage of energy cost in the total household disposable income, i.e., energy burden. The first measure of energy poverty, proposed in 1991, was the 10% indicator (Boardman, 1991). This measure considers a household energy poor if it spends more than 10% of its income on energy expenses (Boardman, 1991). The first measure of the United Kingdom (UK) Fuel Poverty Strategy only considers heat-related energy expenditure to maintain an adequate level of warmth (Boardman, 1991; Moore, 2012). The UK fuel poverty strategy developed three other definitions and measures of energy poverty because of the criticisms made towards the 10% indicator (Hills, 2011, 2012; Moore, 2012). However, the other measures also received criticism, mainly for reducing the number of households classified as energy poor, or for aggregating the measure of fuel poverty and energy efficiency (Bednar & Reames, 2020; Wang et al., 2021).

Regarding the energy poverty literature focused on the US, in 2005, the literature recommended an affordability standard of 6% of gross household income for energy costs (Fisher et al., 2003). Nevertheless, in 2006, the literature pointed out that low-income households spent 10% or more of their income on fuel expenses in that country (Kaiser & Pulsipher, 2006). Many studies have analysed the impact of racial disparities, energy bill and weatherization assistance programs on energy poverty in the US (Dogan et al., 2021; Heindl & Schuessler, 2015; Tonn et al., 2021; Tonn et al., 2018; Wang et al., 2021). Notwithstanding, neither in the US nor in Europe has the impact of dynamic pricing programs on energy poverty been analysed. In other words, what inspired us was the eventual potential of the pricing strategies to mitigate the phenomenon of energy poverty. Consequently, this research aims to fill this gap in the literature by assessing the effectiveness of dynamic pricing on energy poverty reduction.

7.2 Data and Methodology

The dataset about dynamic prices and smart meters was built on the dynamic pricing and net metering tables of the Annual Electric Power Industry Report, Form EIA-861 survey (EIA). This survey collects information on the status of players involved in the generation, transmission, distribution, and retail sales of the US electric power industry (EIA). One of the main strengths of this survey is its impressive representativeness of US electric players. This is due to the mandatory participation in this survey of all industry players (Graff et al., 2021; Lehr, 2013; Zhou, 2021). In fact, fines, penalties, and other sanctions may apply in the case of failure to complete the survey. In 2013, the EIA-861 survey form was updated, covering the technological and pricing trends, specifically dynamic pricing, advanced metering, net metering, and distributed generation. Consequently, dynamic pricing and smart grid technologies deployment data are only available from 2013 to 2019, the last year of available data. EIA-861 survey data has been widely used in the literature to analyse the diffusion of both dynamic pricing and advanced metering, as well as their impacts (EIA; Graff et al., 2021; Lehr, 2013; Zhou, 2021).

The American Community Survey Public Use Microdata Sample (ACS–PUMS) was used to obtain household socio-economic, demographic, and energy characteristics. The ACS-PUMS is a nationally representative survey carried out annually by the US Census Bureau, providing relevant and up-to-date data for researchers and government institutions. The ACS-PUMS generates periodic estimations, representing the characteristics of the population and housing in a specific data collection period. The ACS-PUMS estimates available are 1-year, 1-year supplemental, 3-year, and 5-years. Regarding the 1-year estimates, they reflect the most current data, which is very useful when studying states with a fast-developing status or recent thematic. It should be noted that 1-year estimates are based on a smaller sample size, which can lead to higher error margins. Conversely, the 5-year estimates comprise a larger sample with data collected in earlier years, providing smaller error margins. Although the 5-year estimates have high reliability for smaller geographic areas and smaller population groups, they lose the validity of most current data. As this research aims to explore the effects of dynamic pricing and smart grid implementation, both current effects, ACS-PUMS 1-year estimates from the year 2013 to 2019, were used.

Energy burden (Burden) was calculated from the ACS-PUMS dataset following the equation (7.1).

$$BURDEN = \frac{\left(12 * (ELE + GAS)\right) + OFUL}{INC} * 100 \tag{7.1}$$

where, *ELE* is the monthly electricity cost, *GASP* is the monthly gas costs, *OFUL* is the monthly costs of fuels other than electricity and natural gas, *INC* is the annual household income. Households with a burden equal or higher than 10% (BURDEN≥10%) are considered energy poor households, following the literature (Boardman, 1991; Kaiser & Pulsipher, 2006; Moore, 2012). The remaining households, i.e., with a burden lower than 10% (BURDEN<10%), are the non-energy-stressed households (Agbim et al., 2020; Brown, Soni, Lapsa, et al., 2020; Tonn et al., 2021).

Table 7.2. Variable definition and source

Variable	Definition	From
EPOV	Number of households suffering from energy poverty	ACS-PUMS
NESH	Number of non-energy-stressed households	ACS-PUMS
TOU	Number of retailers with ToU tariffs	EIA
RTP	Number of retailers with RTP tariffs	EIA
VPP	Number of retailers with VPP tariffs	EIA
CPP	Number of retailers with CPP tariffs	EIA
CPR	Number of retailers with CPR tariffs	EIA
RENTEDWTOPAY	Number of families living in a rented house without payment	ACS-PUMS
CHILD	Number of households living with children under 6 years	ACS-PUMS
NOCHILDS	Average number of children by family	ACS-PUMS
GAS_COSTS	Average monthly gas costs	ACS-PUMS
GAS_INELE	Number of households with a dual gas and electricity plan	ACS-PUMS
ELE_NOTUSED	Number of households not using electricity	ACS-PUMS
CWDDA	Number of households with digital access to their smart meter	EIA

The ACS-PUMS data is presented by household, and the EIA-861 survey data is disaggregated by electric retailers. Consequently, both datasets were grouped by state and year and merged, totalling 357 observations, 7 time periods observations (from 2013 to 2019) for 51 states of the US. Table 7.2 shows the variables definition and dataset source, whereas Table 7.3 shows their descriptive statistics, and the cross-section test results.

Table 7.3. Data descriptive statistics and cross-sectional test

Variable	Obs.	Mean	S.D.	Min	Max	CD-test
EPOV	357	398993.80	362690.80	20225	1796273	74.70***
NESH	357	1939954.00	2175372.00	133434	12100000	82.71***
TOU	357	5.54	7.14	0	55	-
RTP	357	0.24	0.50	0	2	-
VPP	357	0.15	0.38	0	2	-
CPP	357	0.50	0.94	0	5	-
CPR	357	0.24	0.62	0	3	-
RENTEDWTOPAY	357	43066.13	40422.63	2324	195427	12.61***
CHILD	357	159255.50	174487.50	11711	961786	26.03***
NOCHILDS	357	0.51	0.09	0	1	66.15***
GAS_COSTS	357	48.64	15.50	7	87	58.15***
GAS_INELE	357	204048.10	388804.90	333	2414018	41.07***
ELE_NOTUSED	357	28778.32	35099.44	2160	199089	19.91***
CWDDA	357	17657.42	29691.56	0	247469	14.98***

Notes: *** denotes the statistical significance at 1% level. CD-test has N(0.1) distribution under H0: cross-section independence.

The cross-section dependence test proposed by Pesaran (2004) strongly supports the presence of cross-section dependence in all variables. It should be noted that the test (Pesaran, 2004) produced unreliable results in two cases when the distribution of the errors was not symmetric and when the variables lacked power for some directions (Pesaran, 2004; Sarafidis et al., 2009). In fact, dynamic pricing variables comply with these two specific cases, mainly because they contain zeros at the beginning and in the middle of the sample. Consequently, the test Pesaran (2004) results for these variables are not robust. In a database with a short time span, as the database used in this research, the evaluation of unit roots cannot be performed (Boozer, 1997; Karlsson & Löthgren, 2000). Nevertheless, in panels with a low number of temporal observations, stationarity is not a noteworthy problem (Boozer, 1997; Karlsson & Löthgren, 2000). In pursuing the main objective of this research, two models were estimated, namely the *energy poverty model* and the *non-energy-stressed model*. The *Energy poverty* model makes it possible to assess the impact of dynamic pricing programs on energy poverty reduction. The second one, the *energy-stressed model*, aims to evaluate whether dynamic pricing is effective in preventing households from falling into the energy poverty trap.

Table 7.4. Specification tests

Tests	*Energy Poverty model*	*Non-Energy-Stressed model*
Persistence tests		
Lag 1	258.170***	48.592***
Lag 2	9.978***	0.054
Lag 3	3.944	-
Max(corr)	0.56	0.76
Max(VIF)	4.44	3.93
Mean(VIF)	2.47	2.85
Breusch-Pagan LM	599.75***	412.01***
Modified Wald test	5758.54***	59081.87***
Wooldridge test	64.049***	132.956***
Hausman RE vs. FE	53.46***	145.91***
Pesaran test	3.505***	16.957***
Frees test	3.989***	6.603***
Friedman test	16.168	49.345

Notes: The persistence test performed is based on the Wooldridge test with the independent variable lagged multiple times under the H0: not-persistence; the Breush-Pagan LM test for random effects results for H0: variances across entities are zero; the Modified Wald tests H0: residuals are homoscedastic; the Wooldridge tests H0: no serial autocorrelation; Pesaran's, Free's and Friedman's test the h0: residuals are not correlated. *** denotes the statistically significant at 1% level.

A battery of model specification tests was performed to appraise the properties of the models and dependent variables. The persistence test conducted following (Drukker, 2003) showed that both *EPOV* and *NESH* are persistent over time, depending thus on their past. The low correlation matrix values and variance inflation factors (VIF) statistics revealed that collinearity and multicollinearity problems are set aside. The models' specification test disclosed: (a) the presence of panel effects, following the (Breusch & Pagan, 1980) test; (b) heteroskedastic errors revealed by the (Greene, 2003) test; (c) panel first-order correlation detected in all models by the (Drukker, 2003); (d) fixed effects; and (d) contemporaneous correlation perceived by (Frees, 1995; Friedman, 1937; Pesaran, 2004). Consequently, the results indicate that the models should be estimated by autoregressive dynamic estimators, such as the estimator proposed by Arellano & Bond (Arellano & Bond, 1991). The *energy poverty* and the *non-energy-stressed* dynamic panel models were established as follows in equations (7.2) and (7.3), respectively.

$$\begin{aligned} EPOV_{i,t} = \beta_0 &+ \beta_1 EPOV_{i,t-1} + \beta_2 EPOV_{i,t-2} + \beta_3 TOU_{i,t} + \beta_4 RTP_{i,t} + \beta_5 VPP_{i,t} \\ &+ \beta_6 CPP_{i,t} + \beta_7 CPR_{i,t} + \beta_8 GAS_{COSTS_{i,t}} + \beta_9 RENTEDWTOPAY_{i,t} \\ &+ \beta_{10} NOCHILDS_{i,t} + \beta_{11} GAS_{INELE_{i,t}} + \beta_{12} ELE_{NOTUSED_{i,t}} \\ &+ \beta_{13} CWDDA_{i,t} + \mu_{i,t} + \theta_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{7.2}$$

$$\begin{aligned} NESH_{i,t} = \beta_0 &+ \beta_1 NESH_{i,t-1} + \beta_2 TOU_{i,t} + \beta_3 RTP_{i,t} + \beta_4 VPP_{i,t} + \beta_5 CPP_{i,t} \\ &+ \beta_6 CPR_{i,t} + \beta_7 GAS\_COSTS_{i,t} + \beta_8 CHILD_{i,t} + \beta_9 GAS\_INELE_{i,t} \\ &+ \beta_{10} ELE_{NOTUSED_{i,t}} + \beta_{11} CWDDA_{i,t} + \mu_{i,t} + \theta_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{7.3}$$

where, β_0 represents the constant terms, i is the cross-section running from 1 to 51, $\mu_{i,t}$ is the state-specific effects, $\theta_{i,t}$ is the time-specific effects, and $\varepsilon_{i,t} \sim iid\ N(0, \sigma^2)$ is the identically distributed and independent idiosyncratic random disturbance. t is the time period. In *energy poverty*, the model ran from 1 to 4 because the two-period lagged a number of households suffering from energy poverty ($EPOV_{i,t-1}$, $EPOV_{i,t-2}$). In the *non-energy-stressed* model values were taken from 1 to 5 due to a one-period lagged number of non-energy-stressed households ($NESH_{i,t-1}$).

The dynamic estimators are more efficient than traditional panel models, mainly: (i) when unobserved factors influence both the dependent and explanatory variables; (ii) when explanatory variables are lined with past values of the dependent variable; or (iii) when the dependent variables are persistent. This is likely to be the case for the models performed in this research. The standard approach to deal with these econometric phenomena is to estimate models through an instrumental variable estimator. The central concept behind these estimators is to choose a set of instruments that are highly correlated with the independent variable but uncorrelated with the error. Then, the selected instruments are used as a replacement for the correlated independent variables. The Arellano & Bond consistent generalized method moment was selected to estimate the models. Both models were estimated with conventional and robust standard errors (Arellano & Bond, 1991). Further, the validity of both models was assessed through the Sargan Hansen tests of over-identification and the first- to third-order serial autocorrelation, following the literature (Canarella & Miller, 2018; Sarafidis et al., 2009).

7.4 Results and Discussion

The results of *energy poverty* and *non-energy-stressed* models are shown in Table 7.5. Overall, it has proven that dynamic tariffs have dissimilar effects on energy poverty reduction. In other words, there is not a single tariff for eradicating energy poverty. The results also reveal that tariffs have different impacts to prevent families from falling into the energy poverty trap. The most concerning outcome is that a household threatened by energy poverty is 43% more likely to remain in energy poverty in the next year (see Table 7.5). However, this probability decreased to 12.5% in the second year. Conversely, a non-energy-stressed household is 92.7% likely to remain so. This means that non-energy-stressed households have only a 7.3% chance of falling into the energy poverty trap. The results also highlight that more static tariffs, such as ToU and CPP, have a higher impact on energy poverty reduction than the more dynamic ones, like RTP. This is a relevant outcome that deserves to be further discussed below, considering its potential of framing energy and poverty policies. The model's diagnostic test attested to the suitability of estimators to deal with the data (see Table 7.6). Besides, the outcomes of these analyses are in line with research performed in pilot projects (Batalla-Bejerano et al., 2020;

Faruqui & Sergici, 2010). The control variable's impact, such as the number of dependent children, home rented without payment, and children age, are in accordance with those found in the literature (Brown, Soni, Doshi, et al., 2020; Brown, Soni, Lapsa, et al., 2020; Graff & Carley, 2020; Tonn et al., 2021; Tonn et al., 2018). This gives confidence to this research's estimation results.

Table 7.5. Results of energy poverty and non-energy-stressed models

	Energy Poverty model		***Non-Energy-Stressed model***	
	CSE	*RSE*	*CSE*	*RSE*
EPOV(-1)	.4258785***	.4258785***		
EPOV(-2)	-.12503522***	-.12503522***		
NESH(-1)			.92733372***	.92733372***
TOU	-8743.0951***	-8743.0951***	3208.9777***	3208.9777***
RTP	10355.816**	10355.816**	23277.977	23277.977
VPP	19798.774***	19798.774***	-20417.134***	-20417.134***
CPP	-15605.635***	-15605.635***	9691.8866***	9691.8866***
CPR	-4008.5159	-4008.5159	-7534.8326	-7534.8326
GAS_COSTS	2679.5905***	2679.5905***	-2581.4314***	-2581.4314***
RENTEDWTOPAY	1.7281048***	1.7281048***		
NOCHILDS	307850.54***	307850.54***		
CHILD			-.72519231***	-.72519231***
GAS_INELE	-.37051414**	-.37051414**	0.25362527	0.25362527
ELE_NOTUSED	1.9421061***	1.9421061***	-3.2205545***	-3.2205545***
CWDDA	-.16360411***	-.16360411***	0.04927074	0.04927074
Constant	-55240.903***	-55240.903***	358440.17***	358440.17***
No. of instruments	26	26	26	26
No. of States	51	51	51	51

Notes: ***, **, * denotes the statistical significance at 1%, and 5% levels. CSE are conventional standard errors, and RSE are the robust standard errors. The suffix (-1) and (-2) indicates the first- and second-order lag of the variable.

The results show that both ToU and CPP tariffs contribute to reducing the number of households in energy poverty. An increase of one CPP by a retailer provokes a drop of 15605 households in energy poverty (see Table 7.5). In contrast, the number of households in energy poverty reduces by around 8743 when a utility in a state provides a ToU tariff for consumers. These results are in line with those found by a pilot program of 3 investor-owned utilities in California, which concluded that a ToU reduces the energy consumption in peak periods by 5%, whereas CPP reduces it by 15% (George & Faruqui, 2005). In that pilot program, the peak block price was twice above the standard 13 cents/KWh, and the CPP peak rate was five times higher (George & Faruqui, 2005). Therefore, consumers consider losses more relevant than potential profits, following the theory of consumer loss aversion (Spurlock, 2015). In fact, this corroborates the non-statistically significance of CPR found in the outcomes of this research.

Key functionalities of smart meters, like real-time consumption information and two-way communication between retailers and consumers, can allow various forms of dynamic pricing, such as RTP. The literature often argues that RTP tariffs will be the most widespread tariffs, providing higher economic and environmental benefits (Eksin et al., 2018; Holland & Mansur, 2008; Nguyen et al., 2015). However, the results of this research noted that an increase of one RTP in a state provokes a rise of 10355 households in energy poverty. In fact, it is a challenging task for a consumer to understand and manage their hourly consumption based on such bulky and complex price data provided by RTP. Furthermore, one of the main barriers to energy savings through RTP is the low time given to consumers to react ahead of price changes. This is an even more intrinsic challenge for people with a low level of literacy, which is the case of most low-income households, or households threatened by energy poverty, such as noted by (Littlewood et al., 2017; Rehfuess & World Health, 2006).

Although dynamic tariffs with the exception of the CPP have not had the desired effect in reducing energy poverty, as this research reveals, the potential of these tariffs may not be being used in the best way. Therefore, dynamic tariffs, specifically RTP tariffs, should be further developed or redesigned to allow effective savings for consumers. These policies should take into consideration that consumers will be more predisposed to react to cost savings than to rewards. Besides, it should be noted that dynamic tariffs could provide a more stable and sizable demand reduction, such as noted by the analysis of pilot programs data (Batalla-Bejerano et al., 2020; Faruqui & Sergici, 2010; Wolak, 2011). In fact, more dynamic tariffs are crucial to smooth electricity demand, having more impacts on consumer behaviour discipline. Accordingly, dynamic tariffs are needed to achieve a sustainable electricity mix without unbalanced supply and demand. Notwithstanding their negative effect found in this research, dynamic tariffs must not be abandoned but reformulated to provoke the desired changes. For example, RTP could be combined with demand response programs, namely those aimed at direct control of the households' appliances, like heating systems and washing machines, with few interventions from consumers.

Table 7.6. Model diagnostic tests

	Energy Poverty model		*Non-Energy-Stressed model*	
	CSE	*RSE*	*CSE*	*RSE*
AR(1) test	-4.1165***	-3.7525***	-3.6241***	-3.4823***
AR(2) test	-1.2262	-1.1343	-1.636	-1.6258
AR(3) test	1.5387	1.4783	-1.3599	-1.3411
Sargan test	9.97 (0.267)		4.35 (0.360)	
Hansen test	9.17 (0.328)		5.29 (0.259)	

Notes: *** denotes the statistical significance at 1% level. CSE are conventional standard errors and RSE are the robust standard errors. AR(1), AR(2), and AR(3) denotes the first, second, and third order of serial correlation.

Economic assistance, in the form of subsidies, has been the leading US policy to minimize the burden of energy costs for households, mainly those with a low income. Despite the absence of federal recognition about energy poverty, in many US states, energy bill assistance programs have been implemented. The Low-Income Home Energy Assistance Program (LIHEAP), has been financed by the federal government since the 1973 oil crisis, - which is the key reason for LIHEAP establishment. LIHEAP aims to subsidize high energy expenditures, providing bill assistance for low-income households (Bednar & Reames, 2020; Tonn et al., 2021; Tonn et al., 2018). Nevertheless, this solution does not provide households with a long-term solution. Indeed, it just minimises the risk of energy poverty in the short term. Energy bill assistance does not generate consistent and sustainable savings for energy-poor households, and it, in fact, hinders the energy efficiency of their homes. Instead of the US government promoting a subsidy policy, they ought to consider funding the rehabilitation of energy-inefficient habitations. This funding scheme should focus primarily on low-income households, as they are the ones most likely to fall into the energy poverty trap. This path has already begun, in the US, through the Weatherization Assistance Program (WAP), which provides households with the opportunity to reduce high energy bills through a cost-effective energy efficiency upgrade. The literature evidenced that WAP is an effective and sustainable solution towards household energy affordability, enabling multiple benefits (Bednar & Reames, 2020; Cook & Shah, 2018; Tonn et al., 2021). Nevertheless, its funding is far short of the LIHEAP program. This reflects that the US takes a policy approach based on the notion that energy poverty is just temporary adversity that a form of debt recovery can remedy. Therefore, US policymakers should focus on WAP, enabling a long-term and sustainable energy poverty solution.

To sum up, this research determined the impact of dynamic tariffs on energy poverty. Furthermore, it provides insights for policymakers and retailers to develop dynamic pricing programs further. However, this research has some limitations. Despite using all available data, the time span remains relatively short. This research relied upon a database from the states and on a single energy poverty measure. Consequently, further research is needed, notably the use of microdata on household characteristics, to analyse the willingness to accept dynamic prices and their impact on energy poverty.

It is noteworthy that more research is needed to develop mechanisms and services, such as mobile apps and interfaces, home automation, integration of energy strategies into smart home systems to provide consumers with tools to understand price fluctuations and signals and quickly adjust their consumption. For example, it has been found in the literature that smart meters and their direct connection to smartphone/ web applications increase the effectiveness of ToU and CPP, even though these rates does not require an advanced meter for billing purposes (Faruqui et al., 2012; Hartway et al., 1999; Olmos et al., 2011). Therefore, both the benefits of a smart grid and dynamic pricing should be explored, empowering consumers with tools to allow them to obtain effective savings through their consumption behaviours while contributing to the sustainability and economic efficiency of the electricity system.

7.5 Conclusion

This research used American Community Survey microdata from the US Census Bureau to determine household energy burden and classify the households by energy poverty status. After that, the Annual Electricity Power Industry Report, containing electricity retailers' characteristics and services available, was used to retrieve data about dynamic pricing tariffs. After proper data treatment, both datasets were merged and grouped by state and year. Accordingly, panel data for the 51 US states with a time span from 2013 to 2019 was used to assess the impact of dynamic pricing on energy poverty reduction. After a battery of variables and model specification tests, an autoregressive dynamic model was chosen as the most suitable estimator to deal with the data characteristics.

Overall, this research provides valuable contributions to the literature and for policymaking. This study proves that consumers prefer dynamic pricing programs with a higher level of price predictability. Moreover, more static tariffs, such as ToU and CPP, do not require a high level of literacy, and they make it easier to adjust consumer demand to their prices. Conversely, the more dynamic tariffs, such as RTP and VPP, have not produced the expected effects on energy poverty reduction. These dynamic pricing schemes have a high level of price uncertainty, making consumption adjustment difficult, especially if the adjustments have to be performed in real-time. Accordingly, this innovative line of research can verify that dynamic pricing schemes, namely the more static ones, effectively reduce energy poverty and prevent households from falling into the energy poverty trap. In contrast, the results of this research stress that RTP, or more dynamic tariffs, crucial for the economic efficiency of the electricity system, as they adjust consumption to the instantaneous availability of electricity, should be reviewed and redesigned to effectively reward consumers for the cost reduction and flexibility provided.

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Chapter 8

Conclusion

Energy transition from primary energy sources towards RES implies a profound restructuring of the design of electricity markets as electricity supply shifts to endogenous and green energy resources. Hitherto, energy transition may not deliver the expected and desired benefits for the environment that are utterly vital for the well-being of society. In addition, society is burdened by high energy costs (e.g., high electricity, natural gas, and diesel fuel prices), which are actually threatening households with energy poverty. The undesired hike in electricity prices has been mainly triggered by: (i) the high cost of RES deployment; (ii) the continued dependency on fossil fuels to generate electricity, and (iii) the issue of electricity consumption patterns not being synchronized with RES-I availability. These factors could represent severe challenges for the new era of energy transition, undermining the efficient integration of cleaner energy sources. The emergence of novel and sustainable measures for electricity consumers is crucial for the diversification of the energy mix compatible with economic development and reduced energy poverty. This thesis brings novel insights and guidelines for decision-making regarding energy policies, aiming to provide guidance for sustainable measures.

This thesis focuses its assessment on four dimensions, namely: (i) renewables accommodation; (ii) consumption; (iii) energy poverty; and (iv) pricing strategies. DSM policies framework is indeed a key connector of these four dimensions. As this research notes, the DSM concept, and its pricing strategies, could provide crucial instruments to encourage demand responsiveness to effectively integrate RES-I. Thus, energy transition can benefit consumers, and RES-I could be accommodated in electricity systems without harming households' income and living conditions. The literature has, over time, resorted to historical data to assess severe economic and financial phenomena. However, assessing the implications of energy transition for society and the environment has not strictly followed the framework usually observed in the literature. For instance, DR (in particular pricing strategies) were essentially analysed mostly through qualitative or theoretical modelling approaches. To the best of our knowledge, there are few empirical studies in the literature that assess the behaviour of electricity demand, and its implications in RES-I accommodation, through high-frequency historical data. Chapters 3, 4, and 5 have filled this gap by exploring high-frequency data to break new ground on both pricing strategies frameworks and novel guidance for DSM measures. Chapters 2, 6, and 7 have added new knowledge to the literature by assessing how energy transition impacts household living conditions. These chapters provided careful guidance for energy transition towards electricity generation from RES, ensuring the well-being and equity of societies.

In this thesis, two new methods that classify electricity demand were developed and applied to specific country data. The proposed classification methods made it possible to accurately identify and evaluate how the daily interactions of load levels affect an electricity system. In fact, these methods have proved to be an invaluable tool for devising effective solutions to accommodate both RES-I intermittency and nuclear power rigidity. The proposed methods are extremely useful to plan the required capacity of RES-C in the electricity generation mix, as well as to design specific pricing strategies depending on the baseload, flexible, and peak capacity requirements. Furthermore, the demand classification methods developed in this thesis reveal the exact distribution of electricity demand throughout the day. This detailed information can be used to further develop valley and peak demand statistics, which are utterly useful in research about pricing strategies or DSM measures. Numerous econometric models (and procedures) to assess different data structures, namely: panel data and time-series data (i.e., high-frequency data such as intraday and daily) were employed in this thesis. A broad portfolio of mathematical software, econometric software, and programming languages were used, namely MATLAB, Stata, Eviews, SQL, Python, and C++. The panoply of econometric methods employed was required to ensure the robustness of the results obtained and to provide a reinforced answer to the research questions proposed. Furthermore, in each chapter, a battery of diagnostic tests, as well as model specification tests were carried out to produce robust econometric results.

8.1 Final remarks

Creating homes where their basic needs and lifestyle activities are powered solely by electricity is of great importance for the development of societies. Electricity can power all households' appliances and user devices (e.g., phones, laptops, and other gadgets). For instance, electricity allows the use of televisions, personal computers, and the internet by children and adults to access entertainment and learning processes. In fact, as the results of Chapter 2 reveal, electricity use in homes is likely to increase households' income by providing better living conditions and less information exclusion (this effect is mainly observed in households with children). However, electricity consumers are implicitly supporting the implementation of RES capacity through high energy prices. Chapters 2 and 6 reveal that households are likely to face a trade-off between supporting an increase in energy expenditures and spending their budget on food and hygiene or other related items. This impact is highlighted by one of the most heard soundbites in the 2000s, namely, to eat or to heat? This catchphrase is often linked to energy poverty, which means that households have to choose between maintaining an adequate level of indoor thermal comfort or meeting their basic needs, such as nutrition. The analysis of Chapter 2 goes further, and it reveals that the reduced monetary conditions of households (to pay the exacerbated electricity prices) is likely to diminish their productivity (this effect is evidenced through income reduction). Meanwhile, households' risk of poverty and social exclusions is prone to increase. Therefore, the deployment and integration of RES in electricity systems should be well thought out to ensure greater well-being of society, not threatening their economic and social living conditions.

Chapter 3 stresses that pricing strategies, for example, the *Tarif Blue* (French electricity tariff), have been ineffective and inefficient in France. In other words, pricing strategies have not provoked the desired changes on the demand-side. In fact, French electricity demand is not synchronized with RES-I generation nor with large-scale nuclear baseload generation. This tendency was revealed by the propensity of the peak demand to be satisfied by fossil fuels. Conversely, off-peak demand, especially in the early morning, shows a downward trend, provoking valley demand levels. High volatility patterns in electricity demand levels have been observed in the load diagrams of many countries (e.g., Portugal, France, Spain, and Germany). This further reveals from an international perspective that pricing strategies and DSM measures may be failing to have the desired effects on the demand-side. The analysis provided in Chapter 3, where an assessment of the French daily dynamic between differing consumption periods, electricity sources and CO_2 emissions was considered, was valuable to also identify opportunities for energy transition. The most impressive outcome occurs in the morning peak demand. In this period, electricity demand is likely to be met by a mix of RES-I and RES-C, not causing harmful impacts on the environment. Besides, the outcomes also show that during the morning peak of demand, French wholesale electricity price seems to drop. This evidence emphasises that the notion of traditional load, i.e., electricity demand, should be reconsidered.

The notion of load was reassessed in more detail in Chapter 4, and the high contribution of RES-I to the German electricity mix was studied. The demand classification method proposed in this Chapter was applied to both traditional demand and net demand concepts. One proves that net demand, and its computed demand levels, has a greater explanatory power on electricity market price than the traditional demand concept and its estimated demand levels. The peak and valley demand levels from traditional demand were compared with those of net demand, and their distinct roles are evident in the results. This difference is clearly discernible in the heat maps for each hour of the day and more pronounced when baseload, flexible, and peak generation capacities required are compared. Historical high-frequency electricity demand data analysed in Chapter 4 was useful in determining the demand levels where DSM measures should intervene, i.e., in periods when electricity demand has to be met by controllable and pollutant sources. It was observed that net demand should become the reference for classifying both peak and valley demand levels, especially in an electricity system with a high generation capacity of RES-I. The results obtained in this Chapter also revealed that a static pricing strategy, such as the ToU tariff, would enable the necessary demand-side flexibility. In other words, a ToU tariff may provide the desired demand shifts from periods of low RES-I production to periods of high RES-I generation.

Given the desire to scrutinize the efficient measures and pricing strategies that could smooth electricity consumption patterns, the analysis provided in Chapter 5 went further compared to Chapter 4. A new form of classifying electricity demand was proposed, i.e., electricity demand was divided into daily levels and subclassified in time periods endogenously. It was found that this classification method provides valuable and detailed statistics on the behaviour of electricity demand, which is still scarce in the literature. The daily interactions of the French electricity demand levels and time periods were then evaluated in Chapter 5. This assessment was carried out to identify, as well as quantify, the challenges and opportunities to achieve a flexible and smoothed daily demand curve. The results of this Chapter suggest that one of the efforts that the demand-side must endure is to fully exploit the benefits of the announced ‘rebirth’ of nuclear power in the French electricity mix. The major barriers are related to the two electricity demand peaks. These peaks occur predominantly during working hours and at night time (this latter is especially pronounced in the winter months). The morning valley demand should also not be disregarded, as in this period, not even the nuclear power supply is absorbed by the demand. Despite the barriers of the two demand peaks and the valley demand in the early morning, and the inability to store electricity large scale, to defer electricity production in time, it is also shown that a ToU tariff can provide the desired flexibility and a smoothed daily demand curve.

Electricity generated from zero-carbon energy sources, such as RES and nuclear power, is considered the most promising form of energy to achieve a low carbon economy. However, policymakers should be aware that this energy transition should not put further pressure on households threatened by energy poverty. Chapter 6 analyses the European statistics on the Income and Living Conditions database, and it reveals that there is no single energy form to eradicate both poverty and energy poverty. It is clear that different forms of energy have dissimilar impacts on energy poverty for each urbanization degree. In cities, households have benefited from energy transition to electricity, and their energy poverty has reduced. Notwithstanding, in towns and suburbs, as well as in rural areas, the reverse result is found. In these latter urbanization degrees, an increase in electricity consumption has provoked a rise in the number of households suffering from energy poverty. The observed results are even more worrying when analysing electricity consumption by end-use activity. It was evidenced that electricity consumption used for heating water, powering appliances, and lighting increased energy poverty. It is evident that energy poverty is actually more a lack of knowledge, capital, and financial investment than a low-income consequence. Therefore, policies encouraging energy transition to a world 100% powered by electricity must evolve to protect households threatened by energy poverty. Besides, these policies should be planned at a disaggregated level (e.g., by regions), such is highlighted in Chapter 6.

The advent of smart grids enables the emergence of shifting pricing strategies, from static (e.g., ToU tariffs) to more dynamic ones (e.g., RTP tariffs). Smart meters can record consumption in different time periods and hours. Consequently, this may ease electricity price differentiation based on the time of day, depending on the hourly wholesale electricity price, or even on RES-I availability. Pricing strategies aim to bring about the desired changes in electricity consumption patterns and habits. Pricing strategies are ideal for stimulating electricity consumers to adapt/change their consumption patterns and habits, and thus, potential savings could be generated. In this line of reasoning, consumers can adjust their consumption to hours when RES-I is available, reducing their energy expenses and the propensity to suffer from energy poverty. Chapter 7 assessed pricing strategies in 51 states of the US to verify whether they would reduce energy poverty. The outcomes unveil that electricity consumers are more interested in pricing strategies with a higher level of price predictability, such as the ToU and CPP tariffs. In fact, these pricing strategies do not require a high level of energy literacy and it is easier for consumers to adjust their demand in order to reduce their electricity bills. Notwithstanding, with dynamic pricing strategies (such as the RTP tariffs), consumers have to make a greater effort in adjusting their electricity consumption, mainly due to high price uncertainty and the real-time adjustments required. Consequently, these pricing strategies seems not to provoke an energy poverty reduction, as concluded in Chapter 7.

After these brief concluding remarks for each chapter, how can society be empowered to allocate its energy needs to exploit the benefits of green energy sources fully? So, what are the choices open to us to smooth the electricity consumption or synchronize it with RES-I generation and, simultaneously, prevent (or even reduce) energy poverty? Beginning with the latest concluding remark, it is true that consumption adjustment in real-time through the bulky and complex data provided by RTP is an arduous task. However, this pricing strategy could allow greater flexibility in electricity systems, adjusting demand to real-time availability of RES-I and instantaneous national electricity demand. The findings of this thesis suggest that policymakers, regulators, and retailers should focus on the role of RTP in automated systems. RTP tariffs should be combined with DR programs, especially those aimed at direct control of households' appliances, e.g., heating systems and washing machines. These DR programs should require few interventions by consumers. This strategy may increase the flexibility of electricity systems by reducing large peak demand in winter periods. Consequently, electricity consumers would benefit from lower electricity prices while not relinquishing adequate levels of indoor temperature, for instance. Furthermore, households with energy storage options, such as home batteries, e-vehicles, or thermo accumulators, and linked through the internet of things could use machine-learning algorithms combined with RTP. This method provides an understanding of forecasting patterns of household consumption, as well as selecting charging and discharging strategies based on real-time prices, with limited intervention from consumers.

Policymakers and governments cannot see energy poverty as just one temporary adversity, which a form of debt recovery can remedy. Economic assistance, in the form of subsidies to high energy expenditures or low-income households, cannot be the central policy to minimize the energy cost burden for society. Energy bill assistance actually only reduces the risk of both poverty and energy poverty in the short term. This economic assistance may not provide consistent and sustainable savings for households, blocking their potential investments in energy efficiency. In fact, households burdened by high energy expenditures are not able to afford the high costs of energy efficiency in rehabilitation measures. Instead, policymakers should promote a subsidy policy that ought to consider funding for the rehabilitation of energy-inefficiency habitations. Consequently, this funding would benefit households through potential savings of energy efficiency. Rehabilitation measures should be applied both to single habitations and large residential buildings. These measures can be modest, for instance, painting the facades and roofs with thermochromic colours. Or, in case of less modest ones, applying new wall insulation, installing thermo-efficient glazing, exchanging households' appliances for more energy-efficient ones, or those with deferred start to take advantage of time-of-use pricing strategies. This cost-effective energy-efficiency financing for households would enable a long-term and sustainable energy poverty solution.

Through the integration of RES-I in electricity systems, the decentralization of electricity production could be a step in the right direction to overcome energy poverty and poverty. Furthermore, this decentralization could also be a solution to encourage consumers in rural areas to switch their consumption from primary energy sources towards electricity. In fact, solar PV panels are ideal for producing electricity locally, for example, when they are installed on the roofs of houses and/or buildings. The main barrier of this solution is the initial investment needs. Vulnerable households, such as low-income or those threatened by energy poverty, cannot afford the cost of solar PV panels. Policymakers should provide funding schemes to increase the penetration of solar PV panels in single or multiple residential buildings. The capacity of solar PV panels should satisfy, at least, residential-based consumption, i.e., the constant consumption of electricity during the day to power refrigerators, freezers, or other appliances. In other words, the electricity demand that cannot be shifted to other periods should be met by the self-production. Solar PV capacity in households can surpass the residential-based consumption if and only if: (i) its generation excess is shared in nearby energy communities; (ii) its generation excess can be injected into the local or national electricity grid; or (iii) it is installed along with storage options, such as batteries or e-vehicles, to defer its excess to other periods.

In the past, electricity consumers only had meters to record their accumulated consumption over time at their disposal. Consequently, consumers only had flat-rate tariffs, where each kilowatt-hour of consumption is charged at the same price. These types of tariffs do not reflect the variability of marginal electricity costs, so consumers are indifferent to when they consume more or less electricity, whichever the hour of the day. This has provoked the emergence of both peak and valley demand levels. Electricity systems operators have to carefully track electricity demand in these periods because the demand is traditional met by controllable fossil fuels plants. This backup strategy causes continued environmental degradation. Given this, the integration of RES worldwide is being propelled so that an environmentally-friendly electricity generation system will eventually be replaced the burning of fossil fuels. Nowadays, electricity markets display different structures and dynamics from those in the past. On the one hand, the growth of

RES-I capacity has changed the management of electricity production, which has provoked impacts on electricity price (e.g., the well-known merit-order effect) and on its behaviour (e.g., increased volatility). On the other hand, smart grids and meters have been developed and deployed to stimulate consumers' reactions to electricity market signals.

The proposed demand classification algorithms show that electricity tariffs should have at least three daily pricing periods. The first period (P1) should cover the early hours of the day, where valley-demand periods are likely to occur. The middle peak period or the working hour peak hours, i.e., between 6 a.m. and 5 p.m., must be considered the second period (P2). Moreover, the third period (P3) should comprise the night peak hours, i.e., from 5 p.m. to 12 p.m. In Germany, on summer weekends and holidays, the P3 should also include the hours between 7 a.m. and 9 a.m. to reduce consumption during this time. Please note that these price periods could be equally employed in Germany and France. However, the proposed algorithms must be applied to control the demand levels of a specific country so that tariffs are appropriately charged. For instance, it can be seen from Figure 4.8 that the P3 periods can be shorter in Germany (only between 5 p.m. and 9 p.m.) than those in France, except in summer season weekdays.

Considering the price differentiation between the three pricing periods, this thesis can provide some hints. For instance, the electricity price charged in P1 should be lower than that in P2 and P3. The electricity price in P1 should be as low as possible in the first few months (depending on the consumers' responsiveness) of application to encourage electricity consumption during these periods. Afterwards, as electricity consumption during P1 increases, the electricity price must also steadily increase. Meanwhile, the price charged in P3 should be higher than that levied in P2 in order to increase the predisposition of consumers to reduce their electricity consumption in P3. In the summer season working days, the price differentiation between P2 and P3 in Germany should be greater than in France, as German net demand in P2 is low (due to the high electricity generation from solar PV). The price differentiation between periods P2 and P3 is expected to decrease over time as electricity demand changes/shifts to other pricing periods. Lastly, and considering the price differentiation between seasons and days of the week: (a) the formation of electricity prices should weigh the season of the year – during the summer, tariff prices must be lower than in the winter, mainly at night peak; (b) on Saturdays and Sundays, electricity tariffs charged in P3 must be higher than in weekdays; and (c) on Saturdays and Sundays, the electricity tariff applied in P2 price must be lower than in weekdays.

Smart grids have allowed the applicability of dynamic pricing strategies, encouraging consumers to break up their demand patterns and adjust their demand to the availability of natural resources. So, why are flat-rate tariffs still at consumers' disposable? It is not reasonable to expect consumers to change their habits while the status quo is maintained. Flat-rate tariffs should be progressively substituted by dynamic pricing strategies and even abolished in the near future. This is a crucial solution to add the demand-side flexibility needed to leverage RES-I production into the energy mix. As this thesis reveals, the ToU tariff seems to have the potential to provide the required demand-side flexibility for electrical systems. ToU periods-block prices are set beforehand so that it gives consumers enough time to adjust their demand habits to the new prices, and the risk aversion of electricity consumption is likely to reduce. Therefore, in the first stage, flat-rate tariffs should be replaced by ToU tariffs in order to increase the willingness of consumers to accept changes in their demand habits. Their electricity consumption could then be synchronized with the availability of RES-I production. Additionally, the potential savings provided by ToU could reduce energy poverty, bringing more equity for society. To conclude, empowering citizens to fully exploit green energy sources to match their energy needs should be made with the right and appropriate tools; leaving things as they stand is not an option. It is crucial to share the economic benefits of RES-I with consumers to encourage them to perform the desired changes and reduce the threat of energy poverty.

8.2 Future research

During this thesis, other pertinent questions have arisen. These questions were raised by authors' questions, and peers' suggestions. However, the time to address all the questions and suggestions was actually short. However, the research questions that have arisen in the meanwhile deserves a note of description. This also allows us to note how future research can evolve. The most recommended suggestion is related to the methodologies applied in Chapters 4 and 5, which provide easy-to-read consumption patterns for consumers to understand their demand habits. Implementing such methodologies through mobile apps or web interfaces was also suggested. Additionally, the use of the proposed demand classification methods to forecast future demand patterns is recommended. It is noteworthy that additional research is needed to further develop mechanisms and services, such as mobile apps and interfaces, home automation, and energy sell/buy strategies into smart home systems. This technological advance would provide consumers with meaningful tools to understand price signals and adjust their electricity consumption. In fact, smart meters and their connection to smartphone/ web applications has already provoked an efficiency increase in ToU and CPP as these pricing strategies do not require an advanced meter for billing purposes.

Further research is needed to surpass the limitations of data availability and countries comparison and extend the research into the energy poverty issue. To go beyond these obstacles, the European Commission should define a single energy poverty definition and measure appropriate for all European countries. The US should recognize the existence of energy poverty and define it, outlining a single measure of energy poverty transversal across all its states. Accordingly, the construction of a data set about energy poverty should be followed by European countries and states of the US. In this way, researchers could compare energy poverty effects between countries and regions, providing more feasible outcomes. Surveys concerning residential consumption should be carried out annually to build a set of microdata on energy poverty, risk of poverty and social exclusion. In the future, residential inquiries should include questions about forms of energy consumption and their costs, as well as the number of appliances and consumption habits.

Lastly, a microeconomic approach, using the agency theory and game theory, should be pursued to provide evidence about the development of price differential strategies. These microeconomic theories are relatively close to the connection between electricity retailers and consumers. Besides, they are able to understand and reflect the existent conflict of interests and asymmetric information. This theoretical framework has the advantage of interpreting the behaviour of two parties with the same problem. On the supply side, the retailer maximizes their profit equation considering their variable and fixed costs. On the demand-side, the consumers maximize the utility derived from the electricity consumption subject to their budget constraints. It should be noted that budget constraints should be set with energy poverty assumptions. This theoretical framework of the microeconomic law of demand and supply, along with natural resources forecasting and microeconomic signalling theory, could provide insights into pricing strategies to leverage the integration of electricity production from endogenous and green resources.

Appendix

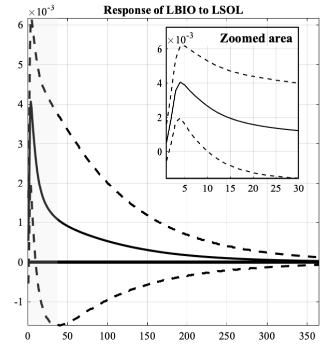
A.2 – Chapter 2 - Are renewables affecting income distribution and increasing the risk of household poverty?

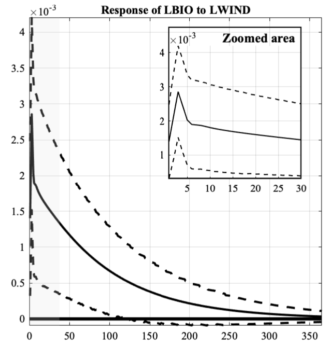
Table A.2.1. Distribution of population by household type (%)

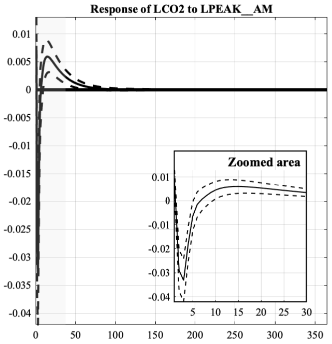
		BE	CZ	DK	DE	EL	ES	FR	IT	LU	NL	AT	PT	FI	SE	UK
Single person	g(05;15)	0.03	0.30	0.05	0.18	0.36	0.28	0.20	0.24	0.18	0.13	0.14	0.46	0.12	0.01	-0.13
	2015	15.20	11.70	22.70	20.60	10.10	10.10	16.40	13.60	13.80	17.10	16.70	8.60	20.10	20.40	12.30
Single person with dependent children	g(05;15)	0.15	0.02	0.01	-0.07	-0.06	1.07	0.15	0.40	0.45	0.26	0.03	0.73	-0.06	-0.14	-0.10
	2015	7.00	4.20	6.80	5.60	1.70	3.10	6.30	3.50	4.80	4.80	3.80	4.50	4.80	6.90	7.30
Two adults	g(05;15)	-0.01	0.06	0.01	0.06	0.08	0.20	0.03	0.03	-0.02	0.03	0.13	0.26	0.09	0.09	0.00
	2015	24.60	25.70	27.90	31.20	22.30	22.60	27.60	21.30	20.80	27.40	25.20	23.40	32.00	29.00	28.30
Two adults younger than 65 years	g(05;15)	-0.08	-0.07	-0.15	0.02	0.05	0.13	-0.03	-0.13	-0.01	-0.17	0.05	0.21	-0.02	-0.04	-0.08
	2015	13.20	13.80	15.50	16.70	9.60	11.60	15.10	8.20	12.50	14.60	13.80	10.30	18.90	15.80	15.80
Two adults, at least one aged 65 years or over	g(05;15)	0.09	0.25	0.33	0.12	0.10	0.28	0.13	0.15	-0.03	0.39	0.23	0.30	0.31	0.28	0.13
	2015	11.40	11.90	12.40	14.50	12.70	11.00	12.60	13.00	8.30	12.80	11.40	13.10	13.10	13.10	12.50
Two adults with one dependent children	g(05;15)	-0.06	0.03	-0.06	-0.12	-0.07	0.11	-0.11	0.05	-0.03	-0.01	0.03	-0.09	-0.08	0.06	0.12
	2015	10.40	12.10	10.20	11.30	10.60	13.10	11.60	12.90	11.80	10.50	11.70	15.40	10.70	11.00	11.50
Two adults with two dependent children	g(05;15)	0.17	-0.08	-0.05	-0.12	-0.34	0.15	-0.11	-0.05	0.13	-0.05	-0.07	-0.04	-0.03	-0.14	-0.02
	2015	17.60	19.40	18.00	14.40	17.20	17.90	19.20	17.10	21.50	19.00	14.20	15.30	15.70	16.10	15.30
Two adults with three or more dependent children	g(05;15)	-0.12	0.15	-0.10	-0.11	2.16	-0.21	0.04	0.00	-0.50	-0.17	-0.20	-0.22	-0.10	-0.22	-0.10
	2015	11.30	5.40	8.70	6.50	6.00	4.60	9.40	4.90	6.40	10.40	6.60	3.20	10.70	8.70	7.20
Three or more adults	g(05;15)	-0.06	-0.16	0.08	0.12	-0.08	-0.20	-0.11	-0.13	0.08	-0.05	-0.10	-0.07	-0.29	0.59	0.22
	2015	7.80	12.50	2.70	6.60	20.10	17.10	5.10	16.30	10.50	5.60	11.20	16.70	3.40	3.50	11.20
Three or more adults with dependent children	g(05;15)	-0.14	-0.11	0.38	-0.17	0.30	-0.34	-0.06	-0.12	0.01	-0.02	-0.10	-0.28	-0.16	0.55	0.03
	2015	6.10	9.10	2.90	3.90	12.00	11.50	4.50	10.40	10.20	5.20	10.50	12.90	2.70	4.50	6.80
Households without dependent children	g(05;15)	-0.01	0.04	0.03	0.11	0.05	0.04	0.07	0.01	0.06	0.05	0.07	0.15	0.07	0.08	0.00
	2015	47.50	49.90	53.30	58.40	52.40	49.80	49.10	51.10	45.20	50.20	53.10	48.80	55.40	52.80	51.80
Households with dependent children	g(05;15)	0.01	-0.03	-0.03	-0.12	-0.05	-0.03	-0.06	-0.01	-0.05	-0.05	-0.07	-0.11	-0.07	-0.08	0.00
	2015	52.50	50.10	46.70	41.60	47.60	50.20	50.90	48.90	54.80	49.80	46.90	51.20	44.60	47.20	48.20

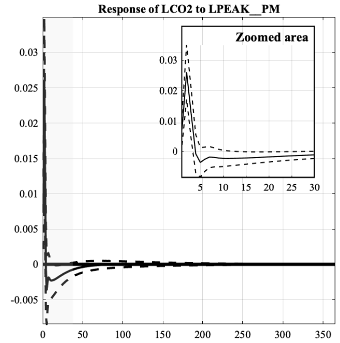
Notes: g(05;15) represents the growth rate between 2005 and 2015.

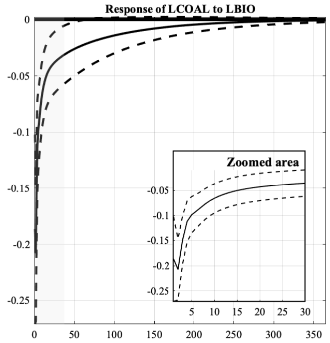
A.3 – Chapter 3 - Could electricity demand contribute to diversifying the mix and mitigating CO_2 emissions? A fresh daily analysis of the French electricity system

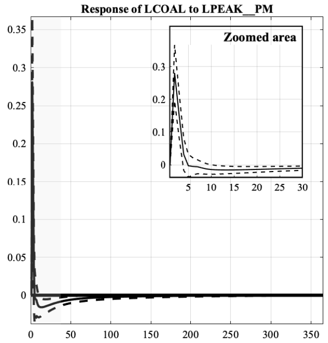


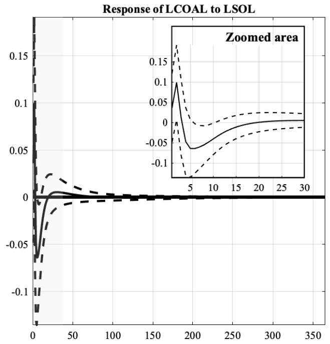


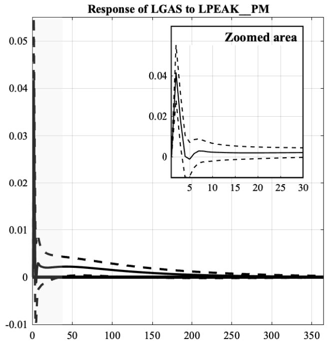


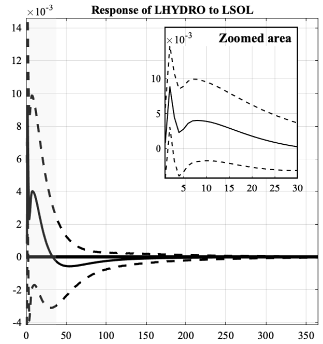


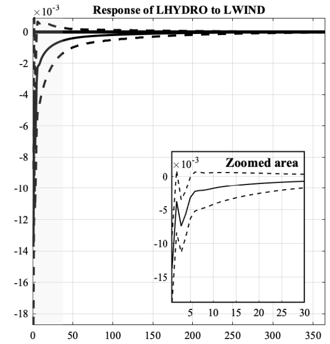


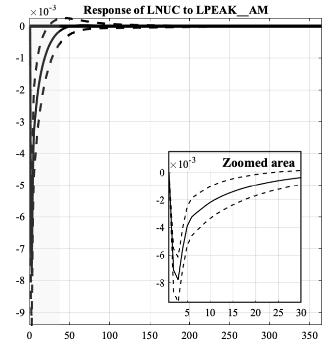


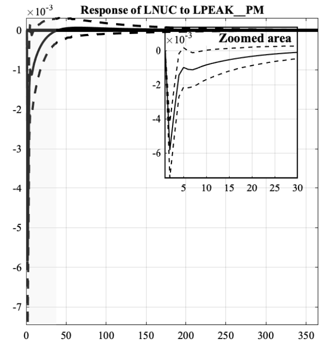












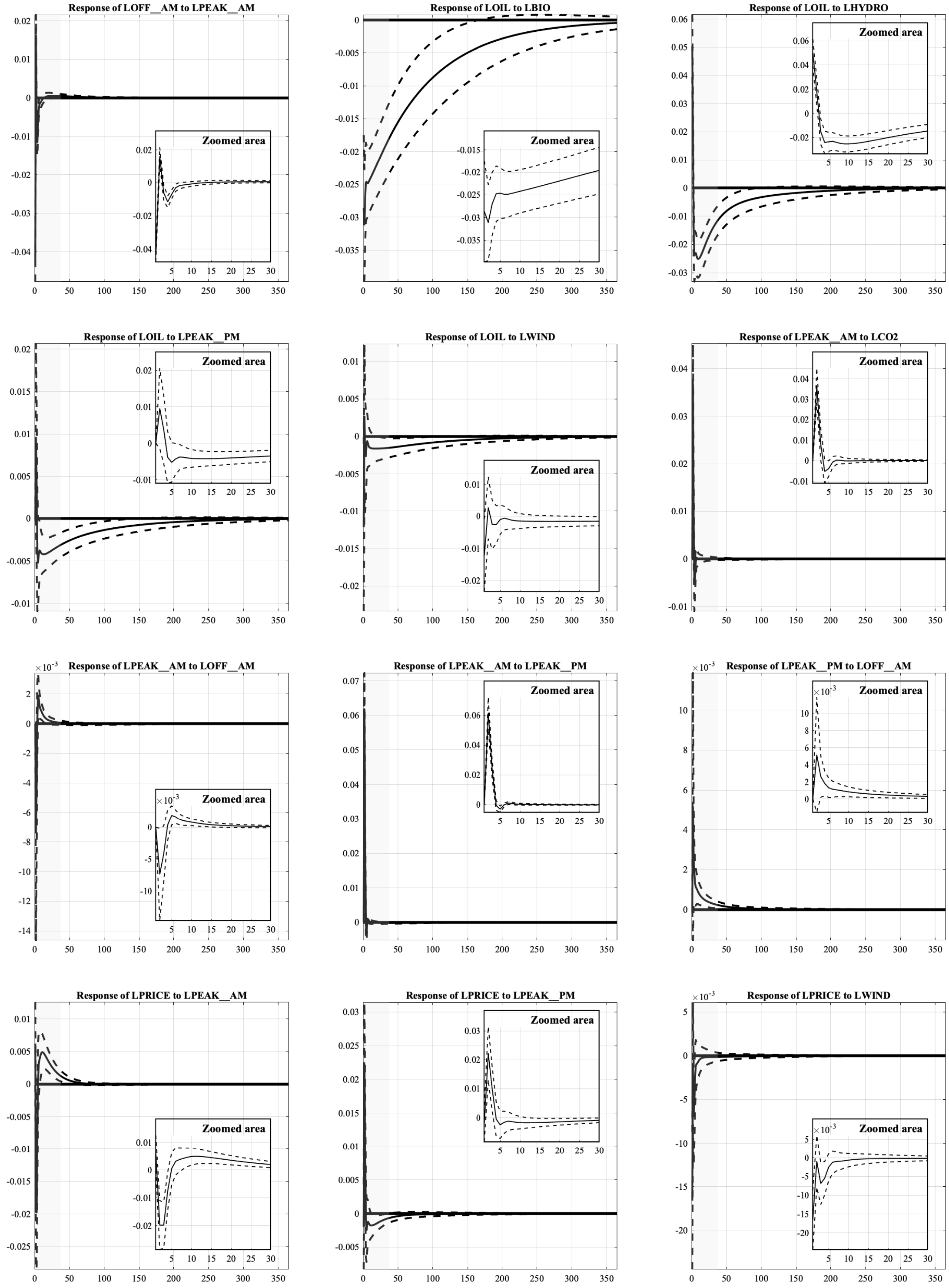


Figure A3.1. Impulse response functions

Table A.3.1. Correlation matrix

	LWIND	*LSOL*	*LBIO*	*LHYDRO*	*LCOAL*	*LNUC*	*LOIL*	*LGAS*	*LPUMP*	*LPEAK_AM*	*LPEAK_PM*	*LOFF_AM*	*LOFF_MI*	*LRXM*	*LCO2*	*LPRICE*	*GSHI*	*LTEMP*	*LPRCP*	*LVISIB*	*LWDSP*	*LGUST*
LWIND	1.00																					
LSOL	-0.22	1.00																				
LBIO	0.33	0.29	1.00																			
LHYDRO	0.01	-0.17	-0.17	1.00																		
LCOAL	-0.05	-0.22	-0.08	0.03	1.00																	
LNUC	0.22	-0.66	0.06	0.33	0.29	1.00																
LOIL	0.04	-0.55	-0.35	0.17	0.32	0.48	1.00															
LGAS	0.23	-0.37	0.37	0.01	0.47	0.54	0.38	1.00														
LPUMP	0.22	-0.13	0.08	-0.22	-0.39	-0.09	-0.16	-0.29	1.00													
LPEAK_AM	0.14	-0.35	0.02	0.39	0.50	0.62	0.43	0.59	-0.55	1.00												
LPEAK_PM	0.23	-0.46	0.09	0.13	0.22	0.53	0.34	0.48	0.02	0.23	1.00											
LOFF_PMAM	0.32	-0.58	0.23	0.12	0.30	0.71	0.40	0.67	0.06	0.37	0.54	1.00										
LOFF_MI	-0.04	-0.02	-0.15	0.35	0.07	0.13	0.21	-0.01	-0.08	0.11	-0.14	0.01	1.00									
LRXM	0.04	-0.18	0.19	0.00	0.31	0.20	0.35	0.56	-0.20	0.36	0.33	0.46	0.14	1.00								
LCO2	-0.02	-0.30	0.07	-0.09	0.74	0.32	0.45	0.78	-0.40	0.54	0.32	0.48	0.04	0.57	1.00							
LPRICE	-0.04	-0.21	0.00	0.00	0.56	0.29	0.48	0.51	-0.41	0.48	0.20	0.35	0.09	0.51	0.66	1.00						
GSHI	0.15	0.00	-0.06	0.09	0.12	0.01	0.10	0.14	-0.27	0.22	0.07	-0.14	-0.02	0.03	0.16	0.10	1.00					
LTEMP	-0.28	0.60	-0.10	-0.32	-0.30	-0.77	-0.54	-0.64	0.04	-0.52	-0.59	-0.76	-0.22	-0.55	-0.47	-0.35	-0.01	1.00				
LPRCP	0.27	-0.29	-0.04	0.15	-0.03	0.06	0.00	-0.02	0.17	-0.01	0.11	0.09	-0.10	-0.09	-0.07	-0.07	0.01	-0.10	1.00			
LVISIB	0.00	0.46	-0.12	-0.14	-0.25	-0.50	-0.34	-0.46	0.02	-0.35	-0.32	-0.50	-0.10	-0.36	-0.39	-0.30	0.00	0.55	0.01	1.00		
LWDSP	0.85	-0.31	-0.02	0.17	-0.07	0.20	0.12	0.04	0.20	0.11	0.20	0.21	0.04	-0.06	-0.12	-0.11	0.16	-0.24	0.37	0.13	1.00	
LGUST	0.54	-0.32	0.05	0.08	0.01	0.26	0.19	0.19	0.16	0.15	0.24	0.31	0.02	0.16	0.06	0.01	0.05	-0.34	0.19	-0.04	0.62	1.00

Table A.3.2. Variance inflation factor statistics

Dependent series	*LWIND*	*LSOL*	*LBIO*	*LHYDRO*	*LCOAL*	*LNUC*	*LOIL*	*LGAS*	*LPUMP*	*LPEAK_AM*	*LPEAK_PM*	*LOFF_AM*	*LOFF_MI*	*LRXM*	*LCO2*	*LPRICE*	*GSHI*
Independent series																	
LWIND	-	7.21	5.80	6.83	7.21	7.10	7.19	7.18	7.12	7.05	7.21	7.10	7.20	7.12	7.13	7.18	7.11
LSOL	3.90	-	3.06	3.88	3.86	3.52	3.88	3.86	3.74	3.90	3.90	3.88	3.85	3.90	3.86	3.89	3.89
LBIO	2.81	2.74	-	3.49	3.45	3.37	3.03	3.04	3.46	3.47	3.49	3.49	3.47	3.44	3.48	3.49	3.47
LHYDRO	2.06	2.17	2.18	-	2.17	2.08	2.18	2.17	2.15	1.81	2.10	2.06	1.91	2.09	2.01	2.18	2.14
LCOAL	2.93	2.90	2.90	2.93	-	2.88	2.84	2.76	2.93	2.90	2.90	2.93	2.93	2.90	1.89	2.87	2.92
LNUC	7.82	7.18	7.68	7.60	7.81	-	7.88	7.95	7.95	5.31	7.39	6.24	7.53	5.65	6.93	7.90	7.85
LOIL	2.48	2.48	2.16	2.49	2.42	2.47	-	2.49	2.48	2.49	2.48	2.48	2.48	2.49	2.44	2.30	2.49
LGAS	6.38	6.35	5.59	6.39	6.05	6.41	6.41	-	6.33	6.16	6.26	6.16	6.41	6.41	4.55	6.38	6.36
LPUMP	2.28	2.22	2.29	2.28	2.31	2.31	2.31	2.28	-	2.03	2.31	2.31	2.31	2.31	2.31	2.25	2.28
LPEAK_AM	5.00	5.11	5.09	4.25	5.06	3.42	5.12	4.91	4.49	-	4.47	4.27	4.72	4.58	4.99	5.12	5.08
LPEAK_PM	2.13	2.13	2.13	2.06	2.11	1.98	2.13	2.08	2.13	1.86	-	2.10	1.85	2.05	2.13	2.12	2.13
LOFF_PMAM	4.97	5.02	5.05	4.78	5.05	3.96	5.03	4.85	5.04	4.21	4.97	-	4.72	4.68	4.88	5.03	4.50
LOFF_MI	1.58	1.57	1.58	1.39	1.59	1.50	1.58	1.59	1.59	1.47	1.38	1.49	-	1.53	1.57	1.59	1.57
LRXM	3.03	3.07	3.03	2.95	3.05	2.19	3.07	3.08	3.08	2.75	2.97	2.85	2.96	-	3.08	2.89	3.07
LCO2	7.88	7.89	7.95	7.36	5.14	6.95	7.83	5.66	7.95	7.77	7.97	7.70	7.88	7.97	-	7.75	7.82
LPRICE	2.31	2.32	2.32	2.32	2.28	2.31	2.15	2.31	2.26	2.32	2.32	2.32	2.32	2.19	2.26	-	2.32
GSHI	1.34	1.36	1.35	1.34	1.35	1.34	1.36	1.35	1.34	1.35	1.36	1.21	1.34	1.36	1.33	1.36	-
LTEMP	6.07	6.07	6.07	5.75	6.05	5.06	5.95	6.05	6.04	6.01	5.95	6.02	5.96	4.86	5.99	5.98	6.07
LPRCP	1.37	1.26	1.36	1.34	1.37	1.36	1.37	1.38	1.37	1.37	1.38	1.37	1.36	1.37	1.38	1.37	1.37
LVISIB	1.90	1.77	1.88	1.91	1.91	1.92	1.91	1.91	1.90	1.91	1.91	1.91	1.91	1.91	1.92	1.92	1.91
LWDSP	2.62	7.72	7.04	7.65	7.79	7.76	7.79	7.75	7.79	7.78	7.78	7.78	7.76	7.78	7.78	7.76	7.77
LGUST	1.83	1.84	1.83	1.84	1.84	1.84	1.84	1.84	1.83	1.84	1.84	1.84	1.83	1.81	1.84	1.83	1.83

A.4 - Chapter 4 – How should price-responsive electricity tariffs evolve? An analysis of the German net demand case

Table A.4.1. Heat map of electricity traditional demand levels

Year	Season	Day of the Weeks	0h	1h	2h	3h	4h	5h	6h	7h	8h	9h	10h	11h	12h	13h	14h	15h	16h	17h	18h	19h	20h	21h	22h	23h
2015	Winter	Weekdays	I	V	V	V	V	V	V	V	I	I	I	P	P	I	I	I	I	P	P	P	P	I	I	I
2015	Winter	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	I	I	I	I	P	I	I	I	I	I
2015	Winter	Sunday and Holidays	V	V	V	V	V	I	I	I	P	I	P	P	P	P	I	I	I	I	P	I	I	I	I	I
2015	Summer	Weekdays	I	V	V	V	V	V	V	V	I	I	I	P	P	P	I	I	I	I	P	I	I	I	I	I
2015	Summer	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	I	I	I	I	I	I	I	I	I	I
2015	Summer	Sunday and Holidays	V	V	V	V	V	V	I	I	I	P	P	P	P	P	P	P	I	I	I	I	I	I	I	I
2016	Winter	Weekdays	I	V	V	V	V	V	V	V	I	I	I	P	P	I	I	I	I	P	P	P	P	I	I	I
2016	Winter	Saturday	V	V	V	V	V	V	I	I	I	P	P	P	P	P	I	I	I	P	P	I	I	I	I	I
2016	Winter	Sunday and Holidays	V	V	V	V	V	V	I	I	I	P	P	P	P	P	I	I	I	I	P	P	I	I	I	I
2016	Summer	Weekdays	I	V	V	V	V	V	V	V	I	I	I	P	P	I	I	I	I	I	I	P	I	I	I	I
2016	Summer	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	P	I	I	I	I	I	I	I	I	I
2016	Summer	Sunday and Holidays	V	V	V	V	V	V	I	I	P	P	P	P	P	P	P	I	I	I	I	I	I	I	I	I
2017	Winter	Weekdays	I	V	V	V	V	V	V	V	I	I	I	P	P	I	I	I	I	P	P	P	I	I	I	I
2017	Winter	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	I	I	I	I	P	I	I	I	I	I
2017	Winter	Sunday and Holidays	V	V	V	V	V	I	I	I	I	P	P	P	P	P	P	I	I	P	P	P	I	I	I	I
2017	Summer	Weekdays	I	V	V	V	V	V	V	V	I	I	P	P	P	P	I	I	I	I	I	I	I	I	I	I
2017	Summer	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	P	I	I	I	I	I	I	I	I	I
2017	Summer	Sunday and Holidays	V	V	V	V	V	V	I	I	I	P	P	P	P	P	P	P	I	I	I	I	I	I	I	I
2018	Winter	Weekdays	I	V	V	V	V	V	V	V	I	I	I	P	P	I	I	I	I	P	P	P	P	I	I	I
2018	Winter	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	I	I	I	I	P	I	I	I	I	I
2018	Winter	Sunday and Holidays	V	V	V	V	V	I	I	I	I	P	P	P	P	P	I	I	I	P	P	P	I	I	I	I
2018	Summer	Weekdays	I	V	V	V	V	V	V	V	I	I	I	P	P	I	I	I	I	I	I	P	P	P	I	I
2018	Summer	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	P	I	I	I	I	I	I	I	I	I
2018	Summer	Sunday and Holidays	V	V	V	V	V	V	I	I	I	I	P	P	P	P	P	I	I	I	I	I	I	I	I	I
2019	Winter	Weekdays	I	V	V	V	V	V	V	V	I	I	I	I	I	I	I	I	I	P	P	P	I	I	I	I
2019	Winter	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	I	I	I	I	P	P	I	I	I	I
2019	Winter	Sunday and Holidays	V	V	V	V	V	V	I	I	I	I	P	P	P	P	I	I	I	I	P	I	I	I	I	I
2019	Summer	Weekdays	I	V	V	V	V	V	V	V	I	I	I	P	P	P	I	I	I	I	I	P	I	I	I	I
2019	Summer	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	P	I	I	I	I	I	I	I	I	I
2019	Summer	Sunday and Holidays	V	V	V	V	V	V	I	I	I	P	P	P	P	P	P	P	I	I	I	I	I	I	I	I
ALL	Winter	Weekdays	I	V	V	V	V	V	V	V	I	I	I	P	P	I	I	I	I	P	P	P	I	I	I	I
ALL	Winter	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	I	I	I	I	P	I	I	I	I	I
ALL	Winter	Sunday and Holidays	V	V	V	V	V	I	I	I	I	P	P	P	P	P	I	I	I	I	P	I	I	I	I	I
ALL	Summer	Weekdays	I	V	V	V	V	V	V	V	I	I	I	P	P	I	I	I	I	I	I	P	I	I	I	I
ALL	Summer	Saturday	V	V	V	V	V	V	I	I	I	I	P	P	P	P	P	I	I	I	I	I	I	I	I	I
ALL	Summer	Sunday and Holidays	V	V	V	V	V	V	I	I	I	P	P	P	P	P	P	P	I	I	I	I	I	I	I	I

Notes: ALL means all years (2015 to 2019), V denotes valley electricity demand level, I represents the intermediate electricity demand level, and P designates the Peak electricity demand level.

A.5 – Chapter 5 - An analysis of the interactions between daily electricity demand levels: the French case

Table A.5.1. Correlation Matrix

	LIEDL	*LPEDL_MRG*	*LPEDL_MDD*	*LPEDL_NGT*	*LVEDL_MRG*	*LVEDL_MDD*	*LVEDL_NGT*
LIEDL	1.0000						
LPEDL_MRG	-0.4173	1.0000					
LPEDL_MDD	-0.2575	-0.3398	1.0000				
LPEDL_NGT	0.2348	0.4436	-0.7308	1.0000			
LVEDL_MRG	0.6866	-0.5335	-0.0748	0.1629	1.0000		
LVEDL_MDD	0.1487	0.4100	-0.1944	0.1913	-0.3568	1.0000	
LVEDL_NGT	0.3714	-0.1365	0.0329	0.0261	0.2219	-0.0165	1.0000

Table A.5.2. Variance inflation factors

Model *Variables*	*Smooth demand*	*Peak in working hours*	*Peak at night*	*Valley at morning*
LIEDL	-	3.8877	4.2518	2.4859
LPEDL_MRG	2.4005	2.9103	2.3062	2.8693
LPEDL_MDD	2.1769	-	1.5405	2.2713
LPEDL_NGT	2.9629	1.9172	-	2.7043
LVEDL_MRG	2.0905	3.4111	3.2633	-
LVEDL_MDD	1.2761	2.1272	2.1687	1.5246
LVEDL_NGT	1.0639	1.2062	1.2434	1.2219

Table A.5.3. Traditional integration order tests

	ADF			**PP**			**KPSS**	
	a)	**b)**	**c)**	**a)**	**b)**	**c)**	**a)**	**b)**
LIEDL	-3.7802***	-3.7424**	-0.4132	-15.9591***	-16.2134***	-0.182	0.1671	0.0605
LPEDL_MRG	-6.0843***	-6.1603***	-1.9005*	-41.4533***	-41.4024***	-57.353***	0.0991	0.0341
LPEDL_MDD	-4.4397***	-4.4243***	-0.4216	-60.3205***	-60.4306***	-2.6419***	0.1483	0.0461
LPEDL_NGT	-3.9992	-3.9736***	-1.7104	-47.2677	-47.2978	-23.2713	0.0571**	0.0285*
LVEDL_MRG	-5.1036***	-5.082***	-0.3531	-41.8001***	-41.9387***	-0.2684	0.1838	0.07
LVEDL_MDD	-5.0238	-5.0307*	-3.7666*	-51.2748	-51.2713	-47.8926*	0.0368**	0.0308*
LVEDL_NGT	-8.7751***	-8.8105***	-7.0064***	-47.981***	-47.8933***	-52.2638***	0.1171	0.0493
First Differences								
DLIEDL	-13.1241***	-13.1325***	-13.1218***	-84.1294***	-84.1157***	-84.1217***	0.0174	0.0156
DLPEDL_MRG	-22.3561***	-22.3598***	-22.3599***	-228.0732***	-227.9321***	-228.1442***	0.0678	0.0273
DLPEDL_MDD	-23.8992***	-23.8983***	-23.9034***	-243.2661***	-243.3099***	-243.3039***	0.0783	0.0349
DLPEDL_NGT	-16.2255***	-16.2318***	-16.2286***	-197.6357***	-197.8279***	-197.693***	0.0323	0.0179
DLVEDL_MRG	-18.8062***	-18.8101***	-18.8075***	-149.0416***	-149.0155***	-149.0627***	0.0094	0.0093
DLVEDL_MDD	-18.4555***	-18.4529***	-18.4586***	-206.9618***	-206.8854***	-207.0152***	0.0164	0.0137
DLVEDL_NGT	-20.4793***	-20.4756***	-20.4829***	-160.2278***	-160.1884***	-160.2666***	0.0104	0.0096

Notes: a), b), and c) denotes that tests were performed with constant, with constant and trend, and without constant and trend, respectively. ***, **, * indicates that the statistic is significant at 1%, 5%, and 10% level, respectively.

Table A.5.4. Seasonal integration order tests

	Traditional HEGY			Likelihood-Ratio HEGY		
	a)	b)	c)	a)	b)	c)
LIEDL	***	***	***	***	***	***
LPEDL_MRG	***	***	***	***	***	***
LPEDL_MDD	***	***	**	**	NS	*
LPEDL_NGT	NS	*	NS	NS	**	NS
LVEDL_MRG	**	***	**	***	**	**
LVEDL_MDD	NS	NS	*	NS	*	NS
LVEDL_NGT	***	***	***	***	***	***
First differences						
DLIEDL	***	***	***	***	***	***
DLPEDL_MRG	***	***	***	***	***	***
DLPEDL_MDD	***	***	***	***	***	***
DLPEDL_NGT	***	***	***	***	***	***
DLVEDL_MRG	***	***	***	***	***	***
DLVEDL_MDD	***	***	***	***	***	***
DLVEDL_NGT	***	***	***	***	***	***

Notes: a), b), and c) denotes that tests were performed with constant, with constant and trend, and without constant and trend, respectively. ***, **, * indicates that the statistic is significant at 1%, 5%, and 10% level, respectively. NS indicates that the statistics are not significant.

Table A.5.5. Diagnostic and ARDL bounds test

Models	**Smooth demand**	**Peak in working hours**	**Peak at night**	**Valley in the morning**
LM				
Lag 1	2.5049	0.4982	0.0016	0.006
Lag 2	1.2556	1.2585	0.7625	0.996
Lag 7	1.6552	1.4552	1.9135*	2.1472*
Lag 15	1.0145	1.6056*	1.4377	1.7747*
Lag 31	1.0389	0.9722	0.9333	1.2383
ARCH				
Lag 1	145.0729***	22.9852***	13.3446***	452.1687***
Lag 2	77.141***	13.7519***	10.2282***	37.5133***
Lag 7	34.5631***	23.5749***	8.9929***	30.5756***
Lag 15	16.9743***	11.5939***	4.8124***	14.8881***
Lag 31	9.3548***	6.4405***	2.7145***	3.2761***
JB	294.8126***	129.6274***	151.6274***	779.61***
RESET	0.5302	1.5371	0.0192	0.0166
CUSUM	Approved	Approved	Approved	Approved
ARDL Bounds	51.43133***	55.9249***	263.7633***	662.8645***
ARS	0.9098	0.7675	0.8761	0.8054
SER	0.0259	0.7502	0.7572	0.1013
SIC	4.1072	1.7465	2.7775	-0.9745

Notes: JB means Jarque-Bera normality test, LM means Breusch-Godfrey test, ARCH means ARCH test, RESET means Ramsey RESET test, ARS means adjusted R-square, SER means standard error of regression, and SIC means Schwarz information criterion. The diagnostic tests are based on the F-statistic. *,*** denotes the statistical significance at 10%, and 1% level, respectively.

Table A.5.6. *Smooth demand* model results

Speed of adjustment	
ECM	-0.0973***
Equilibrium (long-run)	
LPEDL_MRG(-01)	-0.0073***
LPEDL_MDD(-01)	-0.006***
LPEDL_NGT(-01)	0.0034***
LVEDL_MRG(-01)	0.0735***
LVEDL_MDD(-01)	0.0017***
LVEDL_NGT(-01)	-0.0056***
Constant	0.381***
Dynamic effects (short-run)	
DLIEDL(-01)	-0.0463***
DLIEDL(-02)	-0.0423**
DLIEDL(-03)	-0.0454***
DLIEDL(-04)	-0.0702***
DLIEDL(-06)	-0.0488***
DLIEDL(-07)	0.2764***
DLIEDL(-12)	-0.0417**
DLIEDL(-14)	0.0489***
DLIEDL(-15)	-0.032**
DLIEDL(-17)	-0.0387**
DLIEDL(-18)	-0.0262**
DLIEDL(-21)	0.0348**
DLIEDL(-24)	0.029**
DLIEDL(-26)	-0.038**
DLIEDL(-29)	-0.026*
DLIEDL(-31)	-0.0345**
DLIEDL(-32)	-0.0346**
DLIEDL(-33)	-0.0288*
DLIEDL(-36)	-0.0383**
DLIEDL(-37)	-0.0334**
DLIEDL(-39)	-0.0454***
DLIEDL(-42)	0.0373***
DLIEDL(-44)	-0.0349**
DLPEDL_MRG	-0.0184***
DLPEDL_MRG(-01)	-0.0081***
DLPEDL_MRG(-02)	-0.0042***
DLPEDL_MRG(-03)	-0.0028**
DLPEDL_MRG(-04)	-0.0028**
DLPEDL_MRG(-05)	-0.0032***
DLPEDL_MRG(-06)	-0.0034***
DLPEDL_MRG(-11)	-0.001*
DLPEDL_MRG(-12)	-0.0015**
DLPEDL_MRG(-15)	-0.0018***
DLPEDL_MRG(-19)	-0.0011**
DLPEDL_MRG(-22)	-0.0009*
DLPEDL_MRG(-23)	-0.0016***
DLPEDL_MRG(-34)	-0.0015**
DLPEDL_MRG(-35)	-0.0014*
DLPEDL_MRG(-36)	-0.0038***
DLPEDL_MRG(-37)	-0.0039***
DLPEDL_MRG(-38)	-0.0035***
DLPEDL_MRG(-39)	-0.0038***
DLPEDL_MRG(-40)	-0.0034***
DLPEDL_MRG(-41)	-0.0019***
DLPEDL_MRG(-44)	-0.0012**
DLPEDL_MDD	-0.0061***
DLPEDL_MDD(-01)	-0.007***
DLPEDL_MDD(-02)	-0.0028***
DLPEDL_MDD(-15)	0.0033***
DLPEDL_MDD(-16)	0.004***
DLPEDL_MDD(-17)	0.004***
DLPEDL_MDD(-18)	0.0024*
DLPEDL_MDD(-19)	0.0023*
DLPEDL_MDD(-20)	0.0034***
DLPEDL_MDD(-21)	0.0021**
DLPEDL_MDD(-28)	-0.0025***
DLPEDL_MDD(-29)	-0.0016*
DLPEDL_MDD(-42)	0.0027***
DLPEDL_MDD(-43)	0.0026***
DLPEDL_MDD(-44)	0.0026***
DLPEDL_NGT	-0.0123***
DLPEDL_NGT(-03)	-0.0016***
DLPEDL_NGT(-07)	0.003***
DLPEDL_NGT(-08)	-0.0015**
DLPEDL_NGT(-09)	-0.0013**
DLPEDL_NGT(-10)	-0.0021***
DLPEDL_NGT(-11)	-0.002***
DLPEDL_NGT(-12)	-0.002***
DLPEDL_NGT(-13)	-0.0013***
DLPEDL_NGT(-17)	-0.001*
DLPEDL_NGT(-26)	-0.0012**
DLPEDL_NGT(-28)	-0.0017***
DLPEDL_NGT(-29)	-0.0014***
DLPEDL_NGT(-31)	-0.0012**
DLPEDL_NGT(-32)	-0.0014***
DLPEDL_NGT(-33)	-0.0015***
DLPEDL_NGT(-35)	-0.0014***
DLVEDL_MRG	0.0337***
DLVEDL_MRG(-01)	-0.0308***
DLVEDL_MRG(-02)	-0.0228***
DLVEDL_MRG(-03)	-0.0262***
DLVEDL_MRG(-04)	-0.024***
DLVEDL_MRG(-05)	-0.0218***
DLVEDL_MRG(-06)	-0.026***
DLVEDL_MRG(-07)	-0.0347***
DLVEDL_MRG(-08)	-0.0304***
DLVEDL_MRG(-09)	-0.0291***
DLVEDL_MRG(-10)	-0.0231***
DLVEDL_MRG(-11)	-0.0248***
DLVEDL_MRG(-12)	-0.0229***
DLVEDL_MRG(-13)	-0.02***
DLVEDL_MRG(-14)	-0.0238***
DLVEDL_MRG(-15)	-0.0237***
DLVEDL_MRG(-16)	-0.023***
DLVEDL_MRG(-17)	-0.0216***
DLVEDL_MRG(-18)	-0.0142**
DLVEDL_MRG(-19)	-0.0111**
DLVEDL_MRG(-20)	-0.0155***
DLVEDL_MRG(-21)	-0.0107**
DLVEDL_MRG(-22)	-0.0095**
DLVEDL_MRG(-23)	-0.0072*
DLVEDL_MRG(-34)	0.008***
DLVEDL_MRG(-42)	-0.0064**
DLVEDL_MRG(-44)	-0.0062**
DLVEDL_MDD	-0.0006**
DLVEDL_MDD(-01)	-0.0005*
DLVEDL_MDD(-03)	-0.001***
DLVEDL_MDD(-04)	-0.0008***
DLVEDL_MDD(-05)	-0.0009***
DLVEDL_MDD(-06)	-0.0012***
DLVEDL_MDD(-07)	-0.0006**
DLVEDL_MDD(-08)	-0.0005**
DLVEDL_MDD(-16)	-0.0006***
DLVEDL_MDD(-17)	-0.0005*
DLVEDL_MDD(-18)	-0.0005**
DLVEDL_MDD(-20)	-0.0006***
DLVEDL_MDD(-23)	0.0007***
DLVEDL_MDD(-24)	0.0005**
DLVEDL_MDD(-25)	0.0004**
DLVEDL_MDD(-28)	0.0005***
DLVEDL_MDD(-30)	0.0003*
DLVEDL_MDD(-33)	-0.0004**
DLVEDL_MDD(-36)	0.0004*
DLVEDL_NGT	-0.0037***
DLVEDL_NGT(-01)	0.0007**
DLVEDL_NGT(-03)	-0.0006**
DLVEDL_NGT(-04)	-0.0015***
DLVEDL_NGT(-05)	-0.0016***
DLVEDL_NGT(-06)	-0.0015***
DLVEDL_NGT(-07)	-0.001***
DLVEDL_NGT(-08)	-0.0009**
DLVEDL_NGT(-09)	-0.0008***
DLVEDL_NGT(-11)	-0.0009***
DLVEDL_NGT(-12)	-0.0008***
DLVEDL_NGT(-33)	-0.0008***
DLVEDL_NGT(-37)	0.0004*
DLVEDL_NGT(-40)	-0.0006**

Table A.5.7. *Peak in working hours* model results

Speed of adjustment		*DLPEDL_MRG(-73)*	0.0195***	*DLVEDL_MRG(-15)*	0.6297***
ECM	-0.4119***	*DLPEDL_MRG(-75)*	0.0181***	*DLVEDL_MRG(-16)*	0.6574***
Equilibrium (long-run)		*DLPEDL_MDD(-1)*	-0.4662***	*DLVEDL_MRG(-17)*	0.621***
LIEDL(-1)	0.6273***	*DLPEDL_MDD(-2)*	-0.3798***	*DLVEDL_MRG(-18)*	0.5322***
LPEDL_MRG(-1)	-0.0275	*DLPEDL_MDD(-3)*	-0.367***	*DLVEDL_MRG(-19)*	0.5011***
LPEDL_NGT(-1)	-0.1389***	*DLPEDL_MDD(-4)*	-0.3051***	*DLVEDL_MRG(-20)*	0.3821***
LVEDL_MRG(-1)	-0.4932***	*DLPEDL_MDD(-5)*	-0.2986***	*DLVEDL_MRG(-21)*	0.2946***
LVEDL_MDD(-1)	-0.0264***	*DLPEDL_MDD(-6)*	-0.2357***	*DLVEDL_MRG(-22)*	0.2897***
LVEDL_NGT(-1)	0.0249***	*DLPEDL_MDD(-8)*	-0.0548***	*DLVEDL_MRG(-23)*	0.3166***
Constant	0.5363	*DLPEDL_MDD(-9)*	-0.0633***	*DLVEDL_MRG(-24)*	0.1822***
Dynamic effects (short-run)		*DLPEDL_MDD(-11)*	-0.0254*	*DLVEDL_MRG(-25)*	0.1446**
DLIEDL	-2.0175***	*DLPEDL_MDD(-20)*	-0.0332**	*DLVEDL_MRG(-30)*	0.0883*
DLIEDL(-3)	-1.4545***	*DLPEDL_MDD(-35)*	-0.0324**	*DLVEDL_MRG(-31)*	0.0919*
DLIEDL(-4)	-0.5366*	*DLPEDL_MDD(-36)*	-0.0481***	*DLVEDL_MRG(-33)*	0.1305**
DLIEDL(-6)	-1.9729***	*DLPEDL_MDD(-37)*	-0.0373**	*DLVEDL_MRG(-70)*	-0.1397***
DLIEDL(-7)	-0.5919**	*DLPEDL_MDD(-41)*	0.0375***	*DLVEDL_MDD*	0.0133***
DLIEDL(-8)	-1.6649***	*DLPEDL_MDD(-46)*	0.08***	*DLVEDL_MDD(-1)*	0.0581***
DLIEDL(-9)	-0.9956***	*DLPEDL_MDD(-47)*	0.0971***	*DLVEDL_MDD(-2)*	0.064***
DLIEDL(-10)	-1.0039***	*DLPEDL_MDD(-48)*	0.0796***	*DLVEDL_MDD(-3)*	0.0535***
DLIEDL(-11)	-0.9862***	*DLPEDL_MDD(-49)*	0.1501***	*DLVEDL_MDD(-4)*	0.0584***
DLIEDL(-12)	-0.9313***	*DLPEDL_MDD(-50)*	0.156***	*DLVEDL_MDD(-5)*	0.0606***
DLIEDL(-13)	-1.4025***	*DLPEDL_MDD(-51)*	0.1309***	*DLVEDL_MDD(-6)*	0.0616***
DLIEDL(-14)	-1.3048***	*DLPEDL_MDD(-52)*	0.1681***	*DLVEDL_MDD(-7)*	0.057***
DLIEDL(-15)	-1.5319***	*DLPEDL_MDD(-53)*	0.1933***	*DLVEDL_MDD(-8)*	0.0541***
DLIEDL(-16)	-1.078***	*DLPEDL_MDD(-54)*	0.138***	*DLVEDL_MDD(-9)*	0.0671***
DLIEDL(-17)	-1.3765***	*DLPEDL_MDD(-55)*	0.1368***	*DLVEDL_MDD(-10)*	0.0532***
DLIEDL(-18)	-0.8669***	*DLPEDL_MDD(-56)*	0.1676***	*DLVEDL_MDD(-11)*	0.0512***
DLIEDL(-20)	-0.7487***	*DLPEDL_MDD(-57)*	0.1698***	*DLVEDL_MDD(-12)*	0.0471***
DLIEDL(-26)	-0.5389**	*DLPEDL_MDD(-58)*	0.1781***	*DLVEDL_MDD(-13)*	0.0326***
DLIEDL(-30)	-0.8005***	*DLPEDL_MDD(-59)*	0.1703***	*DLVEDL_MDD(-14)*	0.0419***
DLIEDL(-33)	-0.7736***	*DLPEDL_MDD(-60)*	0.1362***	*DLVEDL_MDD(-15)*	0.0244***
DLIEDL(-38)	0.6115***	*DLPEDL_MDD(-61)*	0.1553***	*DLVEDL_MDD(-16)*	0.021***
DLIEDL(-54)	-0.8577***	*DLPEDL_MDD(-62)*	0.1132***	*DLVEDL_MDD(-17)*	0.0245***
DLIEDL(-57)	-0.4762**	*DLPEDL_MDD(-63)*	0.07**	*DLVEDL_MDD(-18)*	0.0118**
DLIEDL(-60)	-0.8569***	*DLPEDL_MDD(-64)*	0.05*	*DLVEDL_MDD(-19)*	0.0118**
DLIEDL(-64)	-0.6958***	*DLPEDL_MDD(-65)*	0.0469*	*DLVEDL_MDD(-39)*	0.0057*
DLIEDL(-69)	-0.4935**	*DLPEDL_MDD(-66)*	0.0703***	*DLVEDL_MDD(-51)*	0.0081**
DLIEDL(-72)	-0.726***	*DLPEDL_MDD(-67)*	0.0712***	*DLVEDL_MDD(-52)*	0.0073*
DLPEDL_MRG	-0.0802***	*DLPEDL_MDD(-69)*	0.028**	*DLVEDL_MDD(-53)*	0.0072**
DLPEDL_MRG(-1)	-0.0252**	*DLPEDL_NGT*	-0.2224***	*DLVEDL_MDD(-68)*	0.009***
DLPEDL_MRG(-8)	-0.0511***	*DLPEDL_NGT(-3)*	-0.0607***	*DLVEDL_MDD(-69)*	0.0091***
DLPEDL_MRG(-9)	-0.0504***	*DLPEDL_NGT(-4)*	-0.024**	*DLVEDL_MDD(-71)*	0.0069**
DLPEDL_MRG(-10)	-0.0498**	*DLPEDL_NGT(-5)*	-0.0497***	*DLVEDL_NGT*	0.0432***
DLPEDL_MRG(-11)	-0.0529**	*DLPEDL_NGT(-6)*	-0.0766***	*DLVEDL_NGT(-7)*	-0.0073*
DLPEDL_MRG(-12)	-0.0467**	*DLPEDL_NGT(-20)*	-0.0184**	*DLVEDL_NGT(-10)*	-0.0073*
DLPEDL_MRG(-13)	-0.0527**	*DLPEDL_NGT(-33)*	-0.0318***	*DLVEDL_NGT(-17)*	-0.0106**
DLPEDL_MRG(-14)	-0.0463**	*DLPEDL_NGT(-54)*	-0.0211**	*DLVEDL_NGT(-18)*	-0.0174***
DLPEDL_MRG(-15)	-0.0449**	*DLPEDL_NGT(-60)*	-0.0265***	*DLVEDL_NGT(-19)*	-0.0348***
DLPEDL_MRG(-16)	-0.0387**	*DLPEDL_NGT(-64)*	-0.0274***	*DLVEDL_NGT(-20)*	-0.0424***
DLPEDL_MRG(-17)	-0.0407**	*DLPEDL_NGT(-72)*	-0.0177**	*DLVEDL_NGT(-21)*	-0.0388***
DLPEDL_MRG(-18)	-0.0274**	*DLVEDL_MRG*	0.7792***	*DLVEDL_NGT(-22)*	-0.0251***
DLPEDL_MRG(-26)	-0.0268***	*DLVEDL_MRG(-1)*	1.2838***	*DLVEDL_NGT(-23)*	-0.0117**
DLPEDL_MRG(-34)	-0.0175**	*DLVEDL_MRG(-2)*	1.2328***	*DLVEDL_NGT(-27)*	-0.0088**
DLPEDL_MRG(-35)	-0.027**	*DLVEDL_MRG(-3)*	1.1321***	*DLVEDL_NGT(-28)*	-0.0122***
DLPEDL_MRG(-36)	-0.0391***	*DLVEDL_MRG(-4)*	1.0357***	*DLVEDL_NGT(-30)*	-0.0109**
DLPEDL_MRG(-37)	-0.052***	*DLVEDL_MRG(-5)*	0.881***	*DLVEDL_NGT(-31)*	-0.0154***
DLPEDL_MRG(-47)	0.013*	*DLVEDL_MRG(-6)*	0.9249***	*DLVEDL_NGT(-33)*	-0.016***
DLPEDL_MRG(-49)	0.0204**	*DLVEDL_MRG(-7)*	0.8233***	*DLVEDL_NGT(-34)*	-0.0101**
DLPEDL_MRG(-50)	0.0282***	*DLVEDL_MRG(-8)*	0.8934***	*DLVEDL_NGT(-41)*	-0.0194***
DLPEDL_MRG(-53)	0.0317***	*DLVEDL_MRG(-9)*	0.9254***	*DLVEDL_NGT(-42)*	-0.0119**
DLPEDL_MRG(-56)	0.0175**	*DLVEDL_MRG(-10)*	0.8074***	*DLVEDL_NGT(-43)*	-0.0115***
DLPEDL_MRG(-58)	0.03***	*DLVEDL_MRG(-11)*	0.8073***	*DLVEDL_NGT(-48)*	-0.0082**
DLPEDL_MRG(-59)	0.0258***	*DLVEDL_MRG(-12)*	0.7289***	*DLVEDL_NGT(-54)*	-0.0094**
DLPEDL_MRG(-67)	0.0193***	*DLVEDL_MRG(-13)*	0.5585***	*DLVEDL_NGT(-65)*	0.0104***
DLPEDL_MRG(-71)	0.0133*	*DLVEDL_MRG(-14)*	0.7684***	*DLVEDL_NGT(-68)*	0.009**

Table A.5.8. *Peak at night* model results

Speed of adjustment		DLPEDL_MDD(-08)	0.1479***	DLVEDL_MRG(-34)	0.3438***
ECM	-0.2216***	DLPEDL_MDD(-09)	0.1514***	DLVEDL_MRG(-39)	0.2343**
Equilibrium (long-run)		DLPEDL_MDD(-10)	0.0569**	DLVEDL_MRG(-40)	0.2394**
LIEDL(-01)	-1.3215***	DLPEDL_MDD(-17)	0.0818***	DLVEDL_MRG(-41)	0.2362**
LPEDL_MRG(-01)	-0.1007**	DLPEDL_MDD(-18)	0.0892***	DLVEDL_MRG(-54)	0.1929**
LPEDL_MDD(-01)	-0.6969***	DLPEDL_MDD(-19)	0.0465*	DLVEDL_MRG(-62)	0.1692*
LVEDL_MRG(-01)	1.1225***	DLPEDL_MDD(-25)	-0.0558**	DLVEDL_MRG(-63)	0.2677**
LVEDL_MDD(-01)	0.0125	DLPEDL_MDD(-32)	0.0582**	DLVEDL_MRG(-64)	0.4073***
LVEDL_NGT(-01)	-0.0955***	DLPEDL_MDD(-46)	0.0877***	DLVEDL_MRG(-65)	0.3031***
Constant	8.0919***	DLPEDL_MDD(-47)	0.1006***	DLVEDL_MRG(-66)	0.4281***
Dynamic effects (short-run)		DLPEDL_MDD(-48)	0.1232***	DLVEDL_MRG(-67)	0.5172***
DLIEDL	-10.8007***	DLPEDL_MDD(-49)	0.0865**	DLVEDL_MRG(-68)	0.4931***
DLIEDL(-01)	-1.6308***	DLPEDL_MDD(-50)	0.1214***	DLVEDL_MRG(-69)	0.2809***
DLIEDL(-02)	-2.1888***	DLPEDL_MDD(-51)	0.1349***	DLVEDL_MRG(-72)	0.2755***
DLIEDL(-03)	-1.8999***	DLPEDL_MDD(-52)	0.1433***	DLVEDL_MRG(-73)	0.1809**
DLIEDL(-04)	-3.7185***	DLPEDL_MDD(-53)	0.1843***	DLVEDL_MRG(-74)	0.3048***
DLIEDL(-05)	-2.8182***	DLPEDL_MDD(-54)	0.1084**	DLVEDL_MDD	-0.0247***
DLIEDL(-06)	-3.3652***	DLPEDL_MDD(-55)	0.1393***	DLVEDL_MDD(-02)	0.0276***
DLIEDL(-09)	-1.2198***	DLPEDL_MDD(-56)	0.1794***	DLVEDL_MDD(-03)	0.0164*
DLIEDL(-11)	-1.9116***	DLPEDL_MDD(-57)	0.1597***	DLVEDL_MDD(-04)	0.0366***
DLIEDL(-13)	-1.2778***	DLPEDL_MDD(-58)	0.1347***	DLVEDL_MDD(-05)	0.0461***
DLIEDL(-17)	-1.4609***	DLPEDL_MDD(-59)	0.1142***	DLVEDL_MDD(-06)	0.0429***
DLIEDL(-21)	1.7982***	DLPEDL_MDD(-66)	-0.0492*	DLVEDL_MDD(-07)	0.0356***
DLIEDL(-27)	1.8713***	DLPEDL_MDD(-67)	-0.0861***	DLVEDL_MDD(-08)	0.0345***
DLIEDL(-28)	1.273***	DLPEDL_MDD(-68)	-0.0768***	DLVEDL_MDD(-09)	0.0418***
DLIEDL(-35)	1.6494***	DLPEDL_MDD(-72)	-0.0551**	DLVEDL_MDD(-10)	0.0259***
DLIEDL(-37)	0.7479**	DLPEDL_MDD(-73)	-0.0561**	DLVEDL_MDD(-11)	0.0221***
DLIEDL(-38)	0.9446**	DLPEDL_MDD(-78)	-0.058***	DLVEDL_MDD(-12)	0.0209***
DLIEDL(-43)	0.8947**	DLPEDL_MDD(-79)	-0.0823***	DLVEDL_MDD(-23)	0.0221***
DLIEDL(-45)	1.2119***	DLPEDL_NGT(-01)	-0.2888***	DLVEDL_MDD(-34)	0.021***
DLIEDL(-57)	-0.7129**	DLPEDL_NGT(-02)	-0.2745***	DLVEDL_MDD(-35)	0.0207***
DLIEDL(-61)	1.1719***	DLPEDL_NGT(-03)	-0.2542***	DLVEDL_MDD(-36)	0.0242***
DLIEDL(-64)	-1.4429***	DLPEDL_NGT(-04)	-0.2364***	DLVEDL_MDD(-37)	0.0251***
DLIEDL(-66)	-0.8136**	DLPEDL_NGT(-05)	-0.2462***	DLVEDL_MDD(-38)	0.0238***
DLIEDL(-68)	0.778**	DLPEDL_NGT(-06)	-0.1785***	DLVEDL_MDD(-39)	0.0239***
DLIEDL(-76)	0.5561*	DLPEDL_NGT(-07)	0.1065***	DLVEDL_MDD(-40)	0.0296***
DLPEDL_MRG	0.2345***	DLPEDL_NGT(-08)	0.0801***	DLVEDL_MDD(-41)	0.0168**
DLPEDL_MRG(-01)	0.261***	DLPEDL_NGT(-11)	-0.0305*	DLVEDL_MDD(-63)	0.0157***
DLPEDL_MRG(-02)	0.1961***	DLPEDL_NGT(-14)	0.0829***	DLVEDL_MDD(-68)	0.0151**
DLPEDL_MRG(-03)	0.1903***	DLPEDL_NGT(-15)	0.0502***	DLVEDL_MDD(-69)	0.0164***
DLPEDL_MRG(-04)	0.0899***	DLPEDL_NGT(-16)	0.0435***	DLVEDL_MDD(-85)	0.0095*
DLPEDL_MRG(-05)	0.0397*	DLPEDL_NGT(-21)	0.0587***	DLVEDL_NGT	-0.0862***
DLPEDL_MRG(-24)	0.0604***	DLPEDL_NGT(-25)	0.0402***	DLVEDL_NGT(-05)	-0.02**
DLPEDL_MRG(-26)	0.0474***	DLPEDL_NGT(-27)	0.0561***	DLVEDL_NGT(-06)	-0.0169**
DLPEDL_MRG(-27)	0.0667***	DLPEDL_NGT(-33)	-0.0396***	DLVEDL_NGT(-11)	-0.0214***
DLPEDL_MRG(-28)	0.1088***	DLPEDL_NGT(-34)	-0.0447***	DLVEDL_NGT(-12)	-0.014*
DLPEDL_MRG(-29)	0.0736***	DLPEDL_NGT(-36)	-0.0401***	DLVEDL_NGT(-17)	-0.0157**
DLPEDL_MRG(-30)	0.0431***	DLPEDL_NGT(-41)	-0.032**	DLVEDL_NGT(-18)	-0.0164*
DLPEDL_MRG(-32)	0.0327**	DLPEDL_NGT(-46)	-0.0318**	DLVEDL_NGT(-19)	-0.0175*
DLPEDL_MRG(-33)	0.0463***	DLPEDL_NGT(-60)	-0.0588***	DLVEDL_NGT(-20)	-0.0306***
DLPEDL_MRG(-38)	0.0616***	DLPEDL_NGT(-62)	-0.0368***	DLVEDL_NGT(-30)	-0.0225***
DLPEDL_MRG(-39)	0.0499**	DLPEDL_NGT(-63)	-0.0337**	DLVEDL_NGT(-31)	-0.0179*
DLPEDL_MRG(-40)	0.0724***	DLPEDL_NGT(-64)	-0.0477***	DLVEDL_NGT(-32)	-0.0163*
DLPEDL_MRG(-41)	0.0888***	DLPEDL_NGT(-65)	-0.0311**	DLVEDL_NGT(-33)	-0.0304***
DLPEDL_MRG(-42)	0.0767***	DLPEDL_NGT(-91)	-0.0328***	DLVEDL_NGT(-34)	-0.0188**
DLPEDL_MRG(-43)	0.0491***	DLPEDL_NGT(-93)	-0.0212**	DLVEDL_NGT(-41)	-0.0217***
DLPEDL_MRG(-75)	0.0292**	DLVEDL_MRG	1.627***	DLVEDL_NGT(-42)	-0.0213**
DLPEDL_MRG(-79)	0.0279*	DLVEDL_MRG(-01)	0.5532***	DLVEDL_NGT(-43)	-0.0259***
DLPEDL_MRG(-80)	0.042**	DLVEDL_MRG(-02)	0.7483***	DLVEDL_NGT(-47)	-0.0131*
DLPEDL_MRG(-81)	0.0797***	DLVEDL_MRG(-03)	0.7248***	DLVEDL_NGT(-51)	-0.0186**
DLPEDL_MRG(-82)	0.0643***	DLVEDL_MRG(-04)	0.6437***	DLVEDL_NGT(-52)	-0.0147*
DLPEDL_MRG(-83)	0.0595***	DLVEDL_MRG(-05)	0.5561***	DLVEDL_NGT(-53)	-0.0164**
DLPEDL_MRG(-84)	0.0716***	DLVEDL_MRG(-06)	0.2832**	DLVEDL_NGT(-60)	-0.0124*
DLPEDL_MRG(-85)	0.045**	DLVEDL_MRG(-08)	0.286***	DLVEDL_NGT(-80)	-0.0194***
DLPEDL_MRG(-86)	0.056***	DLVEDL_MRG(-23)	0.2858***	DLVEDL_NGT(-86)	-0.025***
DLPEDL_MDD	-0.6173***	DLVEDL_MRG(-24)	0.2834***	DLVEDL_NGT(-87)	-0.0226***
DLPEDL_MDD(-07)	0.1686***	DLVEDL_MRG(-33)	0.3278***	DLVEDL_NGT(-91)	-0.015**

Table A.5.9. *Valley at morning* model results

Speed of adjustment	
ECM	-0.5963***
Equilibrium (long-run)	
LIEDL(-01)	0.6631***
LPEDL_MRG(-01)	0.0144**
LPEDL_MDD(-01)	0.0008
LPEDL_NGT(-01)	0.0054***
LVEDL_MDD(-01)	-0.0244***
LVEDL_NGT(-01)	-0.0051***
Constant	-1.5095***
Dynamic effects (short-run)	
DLIEDL	0.7443***
DLIEDL(-10)	-0.1138**
DLIEDL(-11)	-0.2108***
DLIEDL(-14)	-0.1825***
DLIEDL(-29)	-0.2018***
DLIEDL(-31)	-0.2817***
DLIEDL(-35)	-0.2572***
DLIEDL(-51)	-0.131**
DLIEDL(-52)	-0.1642**
DLIEDL(-77)	0.1682***
DLIEDL(-85)	-0.1712**
DLIEDL(-94)	-0.1469**
DLIEDL(-112)	-0.1378**
DLIEDL(-149)	-0.2089***
DLIEDL(-174)	-0.1049*
DLIEDL(-186)	-0.0724*
DLIEDL(-202)	0.0971**
DLIEDL(-238)	-0.181***
DLIEDL(-248)	-0.0871**
DLPEDL_MRG	-0.0313***
DLPEDL_MRG(-01)	-0.025***
DLPEDL_MRG(-02)	-0.017***
DLPEDL_MRG(-03)	-0.0191***
DLPEDL_MRG(-04)	-0.0175***
DLPEDL_MRG(-05)	-0.0191***
DLPEDL_MRG(-06)	-0.0078***
DLPEDL_MRG(-28)	-0.0042*
DLPEDL_MRG(-29)	-0.0061**
DLPEDL_MRG(-31)	-0.0066**
DLPEDL_MRG(-32)	-0.0063**
DLPEDL_MRG(-33)	-0.0059***
DLPEDL_MRG(-35)	-0.0088***
DLPEDL_MRG(-36)	-0.0057***
DLPEDL_MRG(-52)	-0.0078***
DLPEDL_MRG(-53)	-0.0071***
DLPEDL_MRG(-59)	-0.0059***
DLPEDL_MRG(-62)	-0.0137***
DLPEDL_MRG(-63)	-0.015***
DLPEDL_MRG(-64)	-0.0117***
DLPEDL_MRG(-65)	-0.0145***
DLPEDL_MRG(-66)	-0.0136***
DLPEDL_MRG(-67)	-0.0089***
DLPEDL_MRG(-68)	-0.0064***
DLPEDL_MRG(-71)	-0.0037*
DLPEDL_MRG(-76)	-0.0079***
DLPEDL_MRG(-79)	-0.0052***
DLPEDL_MRG(-85)	-0.0055**
DLPEDL_MRG(-86)	-0.0043**
DLPEDL_MRG(-91)	-0.0057***
DLPEDL_MRG(-92)	-0.0051***
DLPEDL_MRG(-94)	-0.0073***
DLPEDL_MRG(-102)	-0.0073***
DLPEDL_MRG(-103)	-0.006***
DLPEDL_MRG(-105)	-0.0051**
DLPEDL_MRG(-112)	-0.0061***
DLPEDL_MRG(-133)	-0.0039**
DLPEDL_MRG(-151)	-0.0047***
DLPEDL_MRG(-162)	-0.0044**
DLPEDL_MRG(-165)	-0.0046***
DLPEDL_MDD(-64)	-0.0127***
DLPEDL_MDD(-67)	-0.0057*
DLPEDL_MDD(-70)	-0.01***
DLPEDL_MDD(-72)	-0.0092***
DLPEDL_MDD(-74)	-0.0117***
DLPEDL_MDD(-75)	-0.0175***
DLPEDL_MDD(-79)	-0.0134***
DLPEDL_MDD(-80)	-0.0143***
DLPEDL_MDD(-82)	-0.0121***
DLPEDL_MDD(-83)	-0.0138***
DLPEDL_MDD(-85)	-0.0132***
DLPEDL_MDD(-88)	-0.0189***
DLPEDL_MDD(-101)	0.017***
DLPEDL_MDD(-102)	0.0193***
DLPEDL_MDD(-103)	0.0157***
DLPEDL_MDD(-104)	0.0125**
DLPEDL_MDD(-105)	0.0121**
DLPEDL_MDD(-106)	0.0147***
DLPEDL_MDD(-107)	0.014***
DLPEDL_MDD(-113)	0.0087***
DLPEDL_MDD(-118)	0.0087***
DLPEDL_MDD(-122)	0.0057**
DLPEDL_MDD(-124)	0.0059**
DLPEDL_MDD(-131)	0.0117***
DLPEDL_MDD(-132)	0.0085***
DLPEDL_MDD(-134)	0.0093***
DLPEDL_MDD(-135)	0.0111***
DLPEDL_MDD(-136)	0.0064**
DLPEDL_MDD(-140)	0.0081**
DLPEDL_MDD(-147)	0.0065**
DLPEDL_MDD(-150)	-0.0086***
DLPEDL_MDD(-151)	-0.0106***
DLPEDL_MDD(-222)	0.0048*
DLPEDL_MDD(-239)	-0.0059**
DLPEDL_MDD(-242)	-0.0062**
DLPEDL_NGT	0.0286***
DLPEDL_NGT(-07)	-0.0036*
DLPEDL_NGT(-18)	-0.0031*
DLPEDL_NGT(-20)	-0.005***
DLPEDL_NGT(-25)	-0.0032*
DLPEDL_NGT(-30)	-0.0054***
DLPEDL_NGT(-31)	-0.0068***
DLPEDL_NGT(-34)	-0.0053***
DLPEDL_NGT(-50)	-0.0038**
DLPEDL_NGT(-51)	-0.008***
DLPEDL_NGT(-60)	-0.0058***
DLPEDL_NGT(-61)	-0.0035*
DLPEDL_NGT(-63)	-0.0048**
DLPEDL_NGT(-64)	-0.0075***
DLPEDL_NGT(-72)	-0.0048***
DLPEDL_NGT(-75)	-0.0078***
DLPEDL_NGT(-80)	-0.0031*
DLPEDL_NGT(-85)	-0.0065***
DLPEDL_NGT(-88)	-0.0074***
DLPEDL_NGT(-89)	-0.0051***
DLPEDL_NGT(-90)	-0.0044**
DLPEDL_NGT(-94)	-0.0049**
DLPEDL_NGT(-102)	0.0059***
DLPEDL_NGT(-103)	0.0057***
DLPEDL_NGT(-104)	0.0052***
DLPEDL_NGT(-105)	0.0053***
DLPEDL_NGT(-121)	0.0029*
DLPEDL_NGT(-139)	0.0038**
DLPEDL_NGT(-140)	0.007***
DLPEDL_NGT(-141)	0.0029*
DLPEDL_NGT(-149)	-0.0052***
DLPEDL_NGT(-158)	0.0048***
DLPEDL_NGT(-162)	0.0053***
DLPEDL_NGT(-170)	-0.003**
DLPEDL_NGT(-180)	0.0028**
DLVEDL_MRG(-32)	0.0401**
DLVEDL_MRG(-41)	-0.0532***
DLVEDL_MRG(-55)	-0.0344**
DLVEDL_MRG(-56)	-0.0533***
DLVEDL_MRG(-62)	-0.0554***
DLVEDL_MRG(-63)	-0.0588***
DLVEDL_MRG(-66)	-0.0398***
DLVEDL_MRG(-68)	-0.0286**
DLVEDL_MRG(-71)	-0.0328**
DLVEDL_MRG(-98)	-0.0297**
DLVEDL_MRG(-119)	-0.0284**
DLVEDL_MRG(-255)	0.0276**
DLVEDL_MDD	-0.0258***
DLVEDL_MDD(-02)	-0.0024***
DLVEDL_MDD(-04)	-0.004***
DLVEDL_MDD(-05)	-0.0039***
DLVEDL_MDD(-06)	-0.0025***
DLVEDL_MDD(-08)	-0.0018**
DLVEDL_MDD(-14)	-0.0024***
DLVEDL_MDD(-17)	-0.0019**
DLVEDL_MDD(-25)	-0.0018**
DLVEDL_MDD(-26)	-0.0018*
DLVEDL_MDD(-27)	-0.0024***
DLVEDL_MDD(-29)	0.0038***
DLVEDL_MDD(-31)	0.0023**
DLVEDL_MDD(-32)	0.0018*
DLVEDL_MDD(-35)	-0.0017**
DLVEDL_MDD(-38)	-0.0015*
DLVEDL_MDD(-42)	-0.0015*
DLVEDL_MDD(-55)	-0.0032***
DLVEDL_MDD(-56)	-0.0021*
DLVEDL_MDD(-57)	-0.0021**
DLVEDL_MDD(-58)	-0.003***
DLVEDL_MDD(-60)	-0.0018**
DLVEDL_MDD(-63)	-0.0023**
DLVEDL_MDD(-66)	-0.0016*
DLVEDL_MDD(-76)	-0.0024***
DLVEDL_MDD(-77)	-0.0019**
DLVEDL_MDD(-81)	-0.0019**
DLVEDL_MDD(-98)	-0.0014*
DLVEDL_MDD(-120)	-0.0013*
DLVEDL_MDD(-135)	-0.0019***
DLVEDL_MDD(-164)	-0.0019***
DLVEDL_MDD(-231)	-0.0012*
DLVEDL_MDD(-254)	-0.0013*
DLVEDL_NGT	-0.0121***
DLVEDL_NGT(-04)	0.0018*
DLVEDL_NGT(-19)	0.0022**
DLVEDL_NGT(-28)	0.0021*
DLVEDL_NGT(-29)	0.0034***
DLVEDL_NGT(-33)	0.0025***
DLVEDL_NGT(-41)	0.0018*
DLVEDL_NGT(-43)	0.0022**
DLVEDL_NGT(-44)	0.0024**
DLVEDL_NGT(-47)	0.0026**
DLVEDL_NGT(-48)	0.0059***
DLVEDL_NGT(-49)	0.006***
DLVEDL_NGT(-50)	0.0063***
DLVEDL_NGT(-51)	0.0051***
DLVEDL_NGT(-52)	0.0052***
DLVEDL_NGT(-53)	0.0024*
DLVEDL_NGT(-54)	0.0039***
DLVEDL_NGT(-57)	0.0025**
DLVEDL_NGT(-60)	0.0038***
DLVEDL_NGT(-61)	0.0032**
DLVEDL_NGT(-62)	0.0053***
DLVEDL_NGT(-63)	0.0043***
DLVEDL_NGT(-64)	0.0033**
DLVEDL_NGT(-65)	0.0021*
DLVEDL_NGT(-67)	0.003***

DLPEDL_MRG(-166)	-0.0049***	*DLPEDL_NGT(-202)*	0.0033*	*DLVEDL_NGT(-70)*	0.0032***
DLPEDL_MRG(-174)	-0.0038*	*DLPEDL_NGT(-214)*	0.0034**	*DLVEDL_NGT(-79)*	0.002**
DLPEDL_MRG(-207)	-0.0028*	*DLPEDL_NGT(-219)*	0.0071***	*DLVEDL_NGT(-82)*	0.0019*
DLPEDL_MRG(-219)	-0.0044***	*DLPEDL_NGT(-221)*	0.0049***	*DLVEDL_NGT(-99)*	0.0035***
DLPEDL_MRG(-228)	-0.003*	*DLPEDL_NGT(-222)*	0.0041***	*DLVEDL_NGT(-100)*	0.0026***
DLPEDL_MRG(-234)	-0.0031**	*DLPEDL_NGT(-235)*	-0.0048***	*DLVEDL_NGT(-103)*	0.0027***
DLPEDL_MRG(-238)	-0.0068***	*DLPEDL_NGT(-242)*	-0.0036**	*DLVEDL_NGT(-109)*	0.0031***
DLPEDL_MRG(-239)	-0.0068***	*DLPEDL_NGT(-244)*	-0.003**	*DLVEDL_NGT(-110)*	0.0042***
DLPEDL_MDD	0.0356***	*DLVEDL_MRG(-04)*	0.0308**	*DLVEDL_NGT(-111)*	0.0046***
DLPEDL_MDD(-02)	-0.0092**	*DLVEDL_MRG(-07)*	0.1168***	*DLVEDL_NGT(-112)*	0.0053***
DLPEDL_MDD(-03)	-0.0095**	*DLVEDL_MRG(-08)*	0.0732***	*DLVEDL_NGT(-116)*	0.0023**
DLPEDL_MDD(-04)	-0.0202***	*DLVEDL_MRG(-09)*	0.1138***	*DLVEDL_NGT(-125)*	0.0019**
DLPEDL_MDD(-05)	-0.0127***	*DLVEDL_MRG(-10)*	0.1317***	*DLVEDL_NGT(-128)*	0.0028***
DLPEDL_MDD(-21)	0.0091***	*DLVEDL_MRG(-11)*	0.1261***	*DLVEDL_NGT(-129)*	0.0046***
DLPEDL_MDD(-28)	-0.0055*	*DLVEDL_MRG(-12)*	0.0909***	*DLVEDL_NGT(-130)*	0.0024**
DLPEDL_MDD(-30)	-0.0081**	*DLVEDL_MRG(-13)*	0.115***	*DLVEDL_NGT(-132)*	0.0023**
DLPEDL_MDD(-42)	-0.0143***	*DLVEDL_MRG(-14)*	0.1192***	*DLVEDL_NGT(-133)*	0.0048***
DLPEDL_MDD(-43)	-0.0098**	*DLVEDL_MRG(-15)*	0.1104***	*DLVEDL_NGT(-134)*	0.0021*
DLPEDL_MDD(-44)	-0.0088**	*DLVEDL_MRG(-16)*	0.0758***	*DLVEDL_NGT(-146)*	0.0019**
DLPEDL_MDD(-48)	-0.0058**	*DLVEDL_MRG(-17)*	0.0566***	*DLVEDL_NGT(-162)*	0.0028**
DLPEDL_MDD(-50)	-0.0078**	*DLVEDL_MRG(-18)*	0.066***	*DLVEDL_NGT(-163)*	0.0036***
DLPEDL_MDD(-51)	-0.0148***	*DLVEDL_MRG(-19)*	0.0566***	*DLVEDL_NGT(-164)*	0.0031**
DLPEDL_MDD(-52)	-0.0145***	*DLVEDL_MRG(-20)*	0.0369**	*DLVEDL_NGT(-165)*	0.0033**
DLPEDL_MDD(-53)	-0.0136***	*DLVEDL_MRG(-23)*	0.0492***	*DLVEDL_NGT(-166)*	0.0049***
DLPEDL_MDD(-57)	-0.0076**	*DLVEDL_MRG(-24)*	0.035***	*DLVEDL_NGT(-167)*	0.004***
DLPEDL_MDD(-58)	-0.0118***	*DLVEDL_MRG(-28)*	0.0835***	*DLVEDL_NGT(-168)*	0.0022**
DLPEDL_MDD(-59)	-0.009**	*DLVEDL_MRG(-29)*	0.0864***	*DLVEDL_NGT(-230)*	0.0015*
DLPEDL_MDD(-62)	-0.0076**	*DLVEDL_MRG(-30)*	0.0598***		
DLPEDL_MDD(-63)	-0.0223***	*DLVEDL_MRG(-31)*	0.0733***		

Table A.5.10. Summary of models results

Models	***Smooth demand***	***Peak in working hours***	***Peak at night***	***Valley in the morning***
Dynamic effects (short-run)				
DLIEDL	-	-2.0175***	-10.8007***	0.7443***
DLIEDL(-1)	-0.0463***		-1.6308***	
DLIEDL(-8)		-1.6649***		
DLPEDL_MRG	-0.0184***	-0.0802***	0.2345***	-0.0313***
DLPEDL_MRG(-1)	-0.0081***	-0.0252**	0.261***	-0.025***
DLPEDL_MRG(-8)		-0.0511***		
DLPEDL_MDD	-0.0061***	-	-0.6173***	0.0356***
DLPEDL_MDD(-1)	-0.007***	-0.4662***		
DLPEDL_MDD(-8)		-0.0548***	0.1479***	
DLPEDL_NGT	-0.0123***	-0.2224***	-	0.0286***
DLPEDL_NGT(-1)			-0.2888***	
DLPEDL_NGT(-8)	-0.0015**		0.0801***	-
DLVEDL_MRG	0.0337***	0.7792***	1.627***	
DLVEDL_MRG(-1)	-0.0308***	1.2838***	0.5532***	
DLVEDL_MRG(-8)	-0.0304***	0.8934***	0.286***	0.0732***
DLVEDL_MDD	-0.0006**	0.0133***	-0.0247***	-0.0258***
DLVEDL_MDD(-1)	-0.0005*	0.0581***		
DLVEDL_MDD(-8)	-0.0005**	0.0541***	0.0345***	-0.0018**
DLVEDL_NGT	-0.0037***	0.0432***	-0.0862***	-0.0121***
DLVEDL_NGT(-1)	0.0007**			
DLVEDL_NGT(-8)	-0.0009**			
Speed of adjustment				
ECM	-0.0973***	-0.4119***	-0.2216***	-0.5963***
Equilibrium (long-run)				
LIEDL(-1)	-	0.6273***	-1.3215***	0.6631***
LPEDL_MRG(-1)	-0.0073***	-0.0275	-0.1007**	0.0144**
LPEDL_MDD(-1)	-0.006***	-	-0.6969***	0.0008
LPEDL_NGT(-1)	0.0034***	-0.1389***	-	0.0054***
LVEDL_MRG(-1)	0.0735***	-0.4932***	1.1225***	-
LVEDL_MDD(-1)	0.0017***	-0.0264***	0.0125	-0.0244***
LVEDL_NGT(-1)	-0.0056***	0.0249***	-0.0955***	-0.0051***
Constant	0.381***	0.5363	8.0919***	-1.5095***

Notes: *, **, *** denotes the statistical significances at 10%, 5%, and 1% level, respectively. ECM means error correction mechanism.

Table A.5.11. Summary statis of daily data

	Equation	Mean	Median	Maximum	Minimum	Std. Dev.
IEDL	(11)	41379.11	38972.64	67574.09	27067.43	8143.993
PEDL_MRG	(8)	13.74391	0.000000	348.4167	0.000000	30.49707
PEDL_MDD	(9)	235.9009	213.0677	1070.115	0.000000	147.1594
PEDL_NGT	(10)	102.8748	57.95833	690.9583	0.000000	121.4647
VEDL_MRG	(12)	10767.77	10084.56	19469.16	925.3750	2635.432
VEDL_MDD	(13)	731.6984	0.000000	11881.23	0.000000	1805.176
VEDL_NGT	(14)	130.0233	0.000000	8419.656	0.000000	532.6797

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Table A.6.1. Cross-section dependence tests

	Level				**First differences**			
Variables	**Breusch-Pagan LM**	**Pesaran scaled LM**	**Bias-corrected scaled LM**	**Pesaran CD**	**Breusch-Pagan LM**	**Pesaran scaled LM**	**Bias-corrected scaled LM**	**Pesaran CD**
LARP-C	250.29***	16.04***	15.58***	5.93***	66.19	0.02	-0.48	0.52
LARP-TS	125.8***	5.21***	4.74***	-0.12	93.28**	2.37**	1.87**	0.99
LARP-RA	148.05***	7.14***	6.68***	3.9***	68.27	0.2	-0.3	-0.81
LPARPSE-C	318.32***	21.96***	21.5***	7.77***	91**	2.18**	1.68**	4.91***
LPARPSE-TS	179.85***	9.91***	9.45***	1.36	74.84	0.77	0.27	1.24
LPARPSE-RA	188.33***	10.65***	10.19***	2.26**	70.12	0.36	-0.14	0.35
LARP_DHC-C	198.98***	11.57***	11.11***	4.25***	64.65	-0.12	-0.62	1.23
LARP_DHC-TS	229.41***	14.22***	13.76***	-0.47	100.8***	3.03***	2.53**	1.66**
LARP_DHC-RA	210.33***	12.56***	12.1***	2.47**	88.99**	2**	1.5	0.56
LHCO-C	198.95***	11.57***	11.11***	0.22	76.81	0.94	0.44	0.11
LHCO-TS	131.92***	5.74***	5.28***	-0.52	58.92	-0.62	-1.12	0.02
LHCO-RA	138.52***	6.31***	5.85***	0.17	70.27	0.37	-0.13	1.37
LRPP-C	163.54***	8.49***	8.03***	0.58	108.02***	3.66***	3.16***	2.05**
LRPP-TS	193.71***	11.12***	10.65***	1.32	60.63	-0.47	-0.97	-0.61
LRPP-RA	215.62***	13.02***	12.56***	5.57***	61.59	-0.38	-0.88	-1.44
LINC-C	435.59***	32.17***	31.71***	13.94***	130.08***	5.58***	5.08***	8.29***
LINC-TS	504.75***	38.19***	37.73***	12.32***	124.71***	5.11***	4.61***	6.4***
LINC-RA	489.33***	36.85***	36.38***	12.8***	112.14***	4.02***	3.52***	5.66***
LHLWI-C	245.63***	15.64***	15.17***	1.31	90.83**	2.16**	1.66**	3.84***
LHLWI-TS	255***	16.45***	15.99***	9.67***	91.27**	2.2**	1.7**	4.52***
LHLWI-RA	293.37***	19.79***	19.33***	5.92***	74.27	0.72	0.22	3.25***
LOIL	605.92***	46.99***	46.53***	24.4***	155.09***	7.75***	7.25***	6.63***
LGAS	291.45***	19.62***	19.16***	9.99***	288.35***	19.35***	18.85***	12.92***
LWOOD	391.29***	28.31***	27.85***	10.54***	108.22***	3.68***	3.18***	3.87***
LELEC	206.69***	12.25***	11.78***	7.53***	185.23***	10.38***	9.88***	11.64***
LSPACE	167.03***	8.79***	8.33***	2.44**	82.96**	1.48	0.98	2.44**
LWATER	293.18***	19.77***	19.31***	-1.29	90.79**	2.16**	1.66**	-0.5
LCOOK	215.59***	13.02***	12.56***	0.47	67.36	0.12	-0.38	2.64***
LAPP_LIGH	194.89***	11.22***	10.76***	3.92***	93.88**	2.43**	1.93**	5.8***

Notes: *, **, *** denotes the statistical significance at 10%, 5%, and 1% levels, respectively. The null hypothesis of the cross-sectional dependence tests is the non-existence of cross-section.

Table A.6.2. Mean consumption by energy form

Country	Coal	Electricity	Wood/biomass	Gas	Oil
Austria	0.048407143	1.48095	1.765171429	1.436414286	1.175742857
Belgium	0.104821429	1.6554	0.440271429	3.3962	2.815178571
Bulgaria	0.201528571	0.890314286	0.705907143	0.0476	0.025857143
Cyprus	0	0.1377	0.057578571	0.0068072	0.122535714
Czechia	0.811292857	1.2663	1.57065	2.034164286	0.034442857
Denmark	0.000271429	0.876778571	1.0222	0.638585714	0.396257143
Estonia	0.00015	0.158178571	0.372478571	0.052207143	0.009021429
Finland	0.006707143	1.851842857	1.111264286	0.0313	0.464007143
France	0.113571429	12.98814286	7.757792857	12.62122143	6.8501
Germany	0.863521429	11.65151429	6.065571429	21.91882857	13.12380714
Greece	0.003135714	1.548357143	0.980007143	0.257585714	1.935264286
Hungary	0.14815	0.952335714	1.497807143	3.017457143	0.103178571
Ireland	0.454657143	0.692878571	0.045721429	0.601742857	1.0502
Italy	0.00265	5.777128571	6.276057143	17.17221429	3.200507143
Latvia	0.0163	0.153735714	0.625021429	0.10765	0.030457143
Lithuania	0.054621429	0.226292857	0.535028571	0.141542857	0.049978571
Luxembourg	0.000714286	0.077714286	0.019571429	0.214	0.191142857
Malta	0	0.055164286	0.003535714	0.0005648	0.014978571
Netherlands	0.0012	1.951014286	0.397857143	7.752764286	0.0406
Norway	0.000171429	3.183614286	0.572164286	0.003535714	0.138264286
Poland	6.723121429	2.39595	2.617457143	3.330028571	0.73745
Portugal	0	1.132892857	0.923528571	0.252192857	0.534257143
Slovakia	0.039292857	0.408142857	0.039135714	1.167635714	0.009821429
Slovenia	0.000464286	0.273114286	0.455892857	0.105757143	0.237928571
Spain	0.134314286	6.106714286	2.538907143	3.390514286	3.203278571
Sweden	NA	3.672742857	1.035021429	0.0486	0.212785714
United Kingdom	0.629321429	9.855192857	1.239414286	25.89085	2.673457143

Notes: National mean consumption during the entire time-span under analysis, the values are expressed in annual million tonnes of oil equivalent. NA means not available data.