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► **To cite this version:**

Cyril Martin de Lagarde. Promoting renewable energy : subsidies, diffusion, network pricing, and market impacts. Economics and Finance. Université Paris sciences et lettres, 2018. English. NNT : 2018PSLED076 . tel-03222707

HAL Id: tel-03222707

<https://theses.hal.science/tel-03222707>

Submitted on 10 May 2021

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THÈSE DE DOCTORAT

de l'Université de recherche Paris Sciences et Lettres
PSL Research University

Préparée à l'Université Paris-Dauphine

Promoting renewable energy: subsidies, diffusion, network pricing, and market impacts

École Doctorale de Dauphine — ED 543

Spécialité Sciences économiques

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Remerciements

Bien que ce doctorat fût une expérience éminemment personnelle, je n'aurais pas pu la vivre sans le concours d'un grand nombre de personnes et d'institutions. En premier lieu, je tiens à remercier Anna et Frédéric, qui m'ont fait confiance dès le début et m'ont aidé à bâtir mon projet de thèse. Puis ils m'ont accompagné tout au long de ce périple, en me laissant toujours très autonome dans mon travail et en intervenant lorsque cela était nécessaire. Leurs conseils avisés, leur bienveillance et leurs nombreuses relectures m'ont permis de ne pas perdre le cap et d'arriver à bon port.

En outre, je suis reconnaissant au corps des Ingénieurs des Ponts, des Eaux et des Forêts et au Ministère de la Transition Écologique et Solidaire, grâce auxquels j'ai eu la chance de bénéficier de trois ans pour faire ma thèse, avant de prendre un poste dans l'administration. Merci aussi à Vincent, qui m'a laissé prendre des vacances dès mon arrivée, après avoir passé l'été à rédiger !

Je souhaite également remercier les membres du jury, et en particulier Valérie Mignon et Stef Proost, qui ont accepté d'être rapporteurs et ont formulé de judicieuses remarques au moment de la présentation. Merci de même à Patrice Geoffron, que j'avais par ailleurs rencontré avant de me décider à faire un doctorat, et qui m'avait aidé dans ma réflexion.

Certains de mes travaux ont de plus bénéficié de relectures et de commentaires de la part de différentes personnes, auxquelles je suis reconnaissant. Je pense notamment à Patrick Criqui, membre du « jury » à ma présentation de mi-parcours à l'IFP ; à Cédric Clastres, Richard Green et Roland Ortt, qui ont chacun discuté un de mes articles en détail lors de séminaires étudiants ; et à Jan Keppler, pour son intérêt dans mes sujets de recherche et sa relecture de mes *working papers*. Mon troisième chapitre doit également beaucoup à des discussions fructueuses avec René Aïd.

Je tiens par ailleurs à remercier l'entreprise Enedis, qui fut un partenaire important de ma thèse. En particulier, merci à Christophe et Jean-Baptiste, qui ont accepté de m'accueillir dans leur équipe pour travailler sur les sujets de mon choix. Grâce à eux, j'ai pu obtenir des données très riches qui ont alimenté deux de mes articles. Je remercie de même Hervé et François, qui m'ont fourni ces données et

m'ont aidé à les interpréter. Un grand merci bien sûr à Mathieu et Laurent pour leur sympathie et pour toutes les discussions que nous avons eues, sur ma thèse comme sur bien d'autres sujets! De manière générale, je n'oublierai pas l'accueil chaleureux de la direction de la stratégie, pour lequel je remercie notamment Florent, Axel, Dominique, Thomas V., Thomas H., Olivier, et tous les autres.

Bien évidemment, ma thèse n'aurait pas été la même sans l'amitié de Clara, Charlotte et Sana, toujours là pour prendre des nouvelles et me soutenir. Un immense merci à toutes les trois! Je pense aussi à tous les autres doctorants et ex-doctorants de Dauphine pour leur contribution à l'ambiance de la C104 et pour les moments que nous avons pu partager : Geoffrey, Nina, Marion, Marine, Lexane, Antoine, Pierre, Mohammad, Manuel, Sandra, Charlie, Homero, Étienne B., Étienne G., Arnold, Amina, Dio, Leslie (vive le yoga!), Zied, Yeganeh, Alexis, Eugénie, Seungman, Michelle, Doriane (vive le yoga?), Sarah, Morgan, Maroua, Christian, Guilhem, Yuanjing, Marie, et tous ceux que j'ai pu oublier de citer (désolé si c'est le cas)! Toujours à Dauphine, un grand merci à Fatoumata pour son soutien et sa bienveillance, et à Chantal, Dominique et Igor pour leur support logistique et administratif.

Je n'oublie pas non plus les doctorants d'autres horizons, avec qui j'ai passé de bons moments, notamment à Bergen, Édimbourg, Vienne, etc. : merci à Déborah, Victor, Romain, Anthony, Quentin, Xavier, Martin, Telman, Ahmed, Audrey, Édouard, Ekaterina, Paul-Hervé; sans oublier Florian, Nicolas, et Büşra, qui ont de plus pris le temps de commenter mes travaux lors de séminaires étudiants.

Je garde de même de très bons souvenirs de mes passages à l'IFP, où j'ai eu plaisir à discuter avec Olivier, Arash, Sydney, Sébastien, Marie, Annick et Claude, sans oublier les répétitions de musique avec Pauline et Malik! Merci en outre à Benoît pour l'organisation des séminaires-lunch, où j'ai pu présenter mon travail, et à Chantal pour son efficacité et sa gentillesse.

Enfin, je souhaite remercier mes proches, qui m'ont soutenu durant ces trois années, et qui m'ont permis de m'évader de la thèse. Merci à ma famille, et en particulier ma mère, qui a eu le courage de relire l'intégralité de mon manuscrit en anglais; à mes amis, témoins, licornes, chanteurs, et tous les autres! Pour finir, merci infiniment à Emma, qui partage ma vie, m'encourage et me supporte, et surtout me donne envie de continuer à aller de l'avant.

Cyril

Résumé en français

Introduction

L'urgence du réchauffement climatique a poussé de nombreux États à prendre des engagements en faveur du climat, ce qui s'est traduit notamment par des objectifs de réduction des émissions de gaz à effet de serre. Dans le secteur de l'énergie, fortement émetteur de CO₂, le recours aux énergies renouvelables (EnR) a été l'une des pistes privilégiées pour « décarboner » le secteur, bien qu'elles ne fassent pas l'unanimité pour répondre aux défis du développement durable. L'Union européenne s'est par exemple engagée en 2008 dans ses objectifs pour 2020 (dits des « 20-20-20 ») à : réduire de 20% les émissions de gaz à effet de serre par rapport à 1990, porter à 20% la part des énergies renouvelables dans la consommation d'énergie finale, et d'augmenter de 20% l'efficacité énergétique par rapport à 1990. En 2014, ces cibles ont été étendues à respectivement 40%, 27% et 27% pour 2030. Dans le secteur électrique, les « nouvelles » EnR telles que le photovoltaïque (PV), l'éolien, la biomasse ou la géothermie ont été subventionnées pendant de nombreuses années. Elles le sont toujours pour la plupart, puisqu'elles ne sont en général pas aussi rentables que les moyens de production conventionnels (charbon, gaz, hydraulique, nucléaire historique, etc.). Ce soutien a le plus souvent pris la forme de tarifs d'obligation d'achat (*feed-in tariffs* en anglais), qui tendent à être remplacés par des compléments de rémunération (*feed-in premiums*) pour la plupart des nouvelles installations en Europe. Dans l'UE, ces aides sont désormais majoritairement attribuées à l'issue d'appels d'offres, bien qu'il existe encore des « guichets ouverts » pour les plus petites installations. Enfin, d'autres mécanismes de soutien existent également, tels que les quotas échangeables, ou « certificats verts »¹

Compte tenu du poids budgétaire qu'elle peuvent représenter (5,5 Md€ en France en 2018, d'après la Commission de régulation de l'énergie²), la double question de l'efficacité et de la possible amélioration de ces politiques de soutien se pose. Cette problématique est d'autant plus prégnante que l'on prévoit

¹ Contrairement aux subventions, qui sont des mécanismes de soutien par les prix, ces derniers sont basés sur la quantité. L'efficacité relative de ces deux formes a été étudiée notamment par WEITZMAN (1974).

² CRE (2018).

une accumulation d'installations subventionnées (sur des durées de l'ordre de la vingtaine d'années) dans les années à venir³.

Dans le premier chapitre, j'étudie donc la diffusion du PV chez les particuliers en France, et plus précisément l'impact des subventions nationales (tarifs d'achat) et locales (primes fixes ou variables, le plus souvent à l'installation) sur la dynamique de cette filière, première en nombre d'installations mais marginale en puissance installée.

Par ailleurs, le développement des EnR s'est accompagné de nouvelles réglementations et suscite encore des interrogations quant à la manière de les réguler tout en continuant à les promouvoir efficacement, et sans générer de distorsions économiques trop importantes. Par exemple, la question des coûts de raccordement et de renforcement du réseau, quoique relativement absente de la littérature, a potentiellement des implications sur les choix d'investissement dans les EnR. La France a ainsi proposé des schémas de raccordement innovants, dont l'étude dans le cas de l'éolien terrestre (*onshore*) fait l'objet du deuxième chapitre.

Si les deux premiers chapitres concernent l'évaluation a posteriori de politiques publiques, il est des situations dans lesquelles le manque de recul empêche une telle analyse, dite positive (ou descriptive). C'est en particulier le cas pour les tarifs de réseau qui, bien qu'existant depuis longtemps, sont confrontés à de nouveaux problèmes liés au développement des EnR, tels que l'autoconsommation⁴. Les outils de la théorie économique peuvent alors aider à dresser des recommandations d'ordre plus ou moins normatif. Dans le troisième chapitre, je m'intéresse donc à la pertinence de la tarification à l'énergie et à la puissance souscrite telle qu'elle existe notamment en France, et sur l'évolution qu'elle devrait prendre en présence d'autoconsommateurs.

Enfin, après avoir étudié des questions liées aux investissements dans les moyens de production renouvelable, il convient de s'interroger des possibles impacts de ces derniers sur les marchés de l'électricité, où l'on souhaiterait qu'ils deviennent un jour rentables. En effet, un tel niveau de compétitivité permettrait de se passer de politiques de soutien. Malheureusement, les aides dites « hors marché »⁵ telles que celles pratiquées actuellement ont pour effet pervers de créer un choc d'offre dont le coût marginal de production est quasi-nul, et dont la conséquence principale est de une baisse des prix. Ceci a pour effet de faire chuter la rentabilité des autres moyens de production, ce qui risque de créer des problèmes de sécurité d'approvisionnement. D'autre part, cela compromet à long terme la rentabilité

³ « Près de la moitié du montant des charges 2022 relève de dépenses engagées avant 2011 » (CRE, 2018).

⁴ C'est-à-dire le fait de consommer sa propre production, par exemple solaire, au lieu de la valoriser sur le marché ou via des tarifs d'achat.

⁵ Dont le contraire serait par exemple une taxe carbone.

des EnR en l'absence de subventions. Le quatrième et dernier chapitre est donc consacré à l'analyse de l'impact de la production renouvelable sur les prix de gros en Allemagne, où la capacité installée est très importante du fait d'un soutien aux EnR plus ancien, par rapport à d'autres pays européens. Ce dernier chapitre a été publié dans *Energy Policy* (MARTIN DE LAGARDE et LANTZ, 2018).

Chapitre I - Diffusion du photovoltaïque chez les particuliers et ses déterminants

Ce premier chapitre s'intéresse à l'impact des subventions aux installations photovoltaïques de moins de 3 kW (qui concernent majoritairement des particuliers installant un panneau solaire sur leur toit) en France, ainsi qu'à la dynamique de cette filière. En effet, ce segment a été subventionné pendant de nombreuses années, à la fois par l'État à travers des tarifs d'obligation d'achat et par différentes régions, départements et communes, le plus souvent via des primes à l'installation. Par ailleurs, le PV étant une technologie relativement nouvelle dans son utilisation à grande échelle, son développement est susceptible de suivre un processus dit de « diffusion » qui lui est propre. Aux niveaux national et régional, on observe en particulier une courbe en « S » pour la quantité installée cumulée, comme décrit pour la première fois par GRILICHES (1957) pour la diffusion du maïs hybride aux États-Unis. Cette caractéristique commune à de nombreux biens durables a été modélisée notamment par BASS (1969) dans un article fondateur, qui fut adapté maintes fois par la suite.

BASS (1969) décrit l'adoption d'un nouveau produit comme se faisant par des « innovateurs », qui réagissent à une communication externe (type publicité) et par des « imitateurs », qui sont influencés par le bouche à oreille (communication interne). Au début de la diffusion, seuls les innovateurs, en proportion fixe dans la population, achètent le produit, puis au fur et à mesure que la part de marché augmente, le bouche à oreille prend de l'ampleur, ce qui donne lieu à une accélération du nombre de ventes. Lorsque le marché arrive à saturation, une décélération se produit du fait du moindre nombre d'acheteurs potentiels restants. Cette modélisation relativement simple permet ainsi de paramétrer les courbes en « S », et dans sa version linéarisée d'ajouter des variables explicatives. La simplification la plus répandue consiste à utiliser la quantité cumulée de ventes passées (la « base installée ») comme covariable modélisant la « contagion ». Dans la version linéarisée originale de BASS (1969), le carré de cette variable est également utilisé, ce qui permet de donner la forme en « S » et modélise donc le ralentissement dû à l'accumulation du stock dans un marché de taille finie.

Données

L'analyse des subventions au niveau local requiert l'emploi de données très désagrégées. Ceci a été rendu possible par Enedis, gestionnaire de 95% du réseau de distribution d'électricité français, qui m'a fourni l'ensemble des demandes de raccordement de panneaux solaires de moins de 3 kW sur son réseau. Ces données révèlent que la grande majorité des installations font en réalité 3 kW, ce qui permet de modéliser le nombre d'installations en lieu et place de la puissance raccordée. À partir de mars 2011, on constate également un pic de demande à la fin de chaque trimestre, soit juste avant que le tarif d'achat ne soit réévalué (à la baisse), comme prévu par les arrêtés tarifaires à partir de cette date⁶. Ainsi, il est logique d'agréger ces données au pas de temps trimestriel. N'ayant pas d'information sur les individus ayant fait une demande de raccordement, j'agrège par ailleurs les demandes au niveau communal. Le jeu de données final comporte ainsi plus d'un million d'observations, dont 94% de zéros. Il s'ensuit une majorité de 1, tandis que le maximum est de 18 demandes dans un trimestre donné (Calais au quatrième trimestre 2010 et Niort au premier trimestre 2011, soit au moment de la « bulle » décrite précédemment).

Par ailleurs, j'utilise un ensemble de données publiques : coût d'une installation PV de moins de 3 kW (estimations de l'ADEME⁷), tarifs d'obligation d'achat pour le segment 0-3 kW, subventions locales (recensement Enerplan et personnel auprès des régions), ensoleillement (PVGIS - Joint Research Centre, Commission européenne). Ces données me permettent de calculer un taux de rentabilité interne (TRI) par commune et par trimestre, en utilisant des hypothèses simplificatrices sur l'efficacité, le coût de maintenance ou l'orientation des panneaux. Ces hypothèses « moyennes » sont nécessaires compte tenu de l'absence d'information sur les panneaux installés, mais ne semblent pas déraisonnables ni avoir une influence majeure sur les résultats. L'analyse des TRI met en lumière l'importance de certaines subventions locales dans la rentabilité des projets PV, avec des taux aussi voire plus élevés dans en Nord-Pas-de-Calais ou Lorraine qu'en Provence-Alpes-Côte d'Azur.

Enfin, j'utilise des données IRIS (Îlots regroupés pour l'information statistique) de l'INSEE⁸, comprenant notamment le nombre de logements et leur type (maison/appartement, résidence principale/secondaire), que j'ai également agrégées par commune. Ces données n'étant disponibles que sur peu d'années, j'ai choisi celles de 2013. L'utilisation de données en coupe (c'est-à-dire à date fixée) empêche *de facto* l'emploi d'effets fixes alors que les autres données sont longitudinales (panel). Néanmoins, le faible nombre

⁶À la fin des années 2000, les subventions étaient telles qu'une quasi « bulle » du photovoltaïque s'était formée, ce qui a donné lieu à un moratoire de trois mois sur les tarifs d'achat, de décembre 2010 à mars 2011. Ce moratoire n'a cependant pas concerné le PV de moins de 3 kW, qui nous intéresse ici. À son issue néanmoins, les tarifs ont largement diminués et ont commencé à être révisés tous les trimestres.

⁷Agence de l'environnement et de la maîtrise de l'énergie.

⁸Institut national de la statistique et des études économiques.

d'observations positives (62 909 pour 33 842 communes) risquerait de fausser les résultats par surapprentissage (*overfitting*) en présence d'effets fixes. De plus, le calcul d'une quantité aussi importante de paramètres est compliqué d'un point de vue numérique.

Modèle économétrique

En raison de l'abondance de zéros de la variable dépendante (ou à expliquer), il est nécessaire d'utiliser une modélisation adaptée à cette particularité. Si plusieurs alternatives sont possibles (MIN et AGRESTI, 2002), j'ai choisi de modéliser séparément la probabilité qu'il y ait une installation dans une commune durant un trimestre donné et le nombre d'installation(s) lorsque celui-ci est strictement positif. Cette approche en deux temps a été proposée initialement par MULLAHY (1986), et permet une interprétation plus simple que la plupart des alternatives. Concernant la probabilité d'adoption, j'ai choisi d'utiliser une régression logistique, qui fournit des queues de distribution plus épaisses qu'une régression de type probit, et dont les coefficients sont plus facilement interprétables. Pour ce qui est du nombre d'installations, j'utilise une loi négative binomiale tronquée, qui est une généralisation de la loi de Poisson tronquée.

Les variables explicatives choisies sont pour les deux régressions : le TRI, calculé uniquement avec le tarif d'achat ; la différence entre le TRI calculé en tenant compte des subventions locales et sans celles-ci ; le logarithme du nombre de logements ; la proportion de résidences principales ; la proportion de maisons. Par ailleurs, j'utilise le nombre cumulé de demandes passées et son carré dans le modèle de choix discret (logit) afin de modéliser la diffusion. Le choix du logarithme du nombre de logements s'explique par la quasi-proportionnalité attendue entre le nombre de logements pouvant disposer d'un panneau solaire et le nombre effectif d'installations. Cela se traduit dans un modèle de comptage de type Poisson (avec lien logarithmique) par l'utilisation d'une variable dite d'exposition, c'est-à-dire sous forme logarithmique et dont le coefficient est contraint d'être égal à 1. Dans notre cas, le modèle de comptage étant tronqué, ce lien est perdu et la valeur du coefficient n'est pas contrainte. Comme il est attendu que la plupart des installations se font sur des maisons, on utilise la proportion de celles-ci. De même, on suppose que les particuliers seront plus enclins à investir pour leur résidence principale que secondaire.

Résultats et interprétations

Concernant la régression logistique, tous les coefficients sont significatifs, et leur interprétation est usuelle en économétrie, à savoir que leur exponentielle est égale au rapport des cotes ou des chances (*odds ratio*).

Ainsi, au premier ordre le stock cumulé a un effet similaire au TRI (calculé uniquement sur la base des tarifs d'achat), c'est-à-dire que l'existence d'une installation supplémentaire par le passé impacte autant la probabilité d'adoption qu'un point de TRI. Ceci est loin d'être négligeable : en effet, un point de TRI supplémentaire augmente la chance qu'il y ait une installation de 10% en moyenne, ce qui entraînerait un passage de 94% à 93,5% de zéros. En revanche, les subventions locales ont un impact bien plus modéré, puisqu'une augmentation d'un point de TRI par le biais de subventions locales n'augmente la cote que de 1,4%. Par ailleurs, on observe le début d'un effet de stock (négatif), pour le moment très léger, mais qui montre que la dynamique de diffusion en « S » est également présente au niveau local.

Pour ce qui est du modèle de comptage, on peut s'appuyer sur le fait qu'il y a une majorité de 1 pour montrer qu'au premier ordre les coefficients sont des semi-élasticités (ou des élasticités si les covariables sont sous forme logarithmique) pour le nombre moyen de demandes moins un. Pour avoir un effet multiplicatif (sur la moyenne moins un), il suffit de regarder de nouveau l'exponentielle des coefficients.

Les résultats révèlent que contrairement à la régression logistique, les subventions locales ont un impact bien plus important que les tarifs d'achat sur le nombre d'installations (le TRI « simple » n'est d'ailleurs pas significatif au seuil des 22%). Une augmentation d'un point de TRI par des subventions locales fait ainsi passer la demande trimestrielle moyenne de 1,267 à 1,308 (+3.2%). Enfin, les variables de contrôle sont fortement significatives dans les deux parties du modèle, et ont un impact très fort sur la probabilité et le nombre d'adoptions.

Ainsi, il peut être tout aussi efficace et moins coûteux pour les finances publiques de développer les énergies renouvelables en informant mieux les individus, car le phénomène de diffusion est avant tout lié à la communication, aussi bien interne qu'externe. Pour des projets de plus grande envergure, cela peut par exemple passer par davantage de financement participatif, qui favorise l'acceptabilité des EnR au niveau local.

Chapitre II - Schémas de raccordement au réseau des énergies renouvelables : une analyse spatiale

En France, le calcul des frais de raccordement d'une centrale au réseau électrique prévoit que si un renforcement est nécessaire (nouvelle ligne ou transformateur, par exemple), le producteur qui en est à l'origine le paie intégralement. Or ces renforcements sont par nature « discrets » (au sens mathématique, c'est-à-dire par paliers), et sont donc a priori suffisants pour accueillir plusieurs raccordements successifs

si la centrale en question n'est pas trop importante. Les quelques producteurs suivants éventuels n'auront donc pas à le payer. Si cette approche n'est pas nécessairement gênante pour les « grosses » unités de production centralisées, pour lesquelles un tel coût est quasiment systématique tout en étant relativement modeste par rapport au coût total de la centrale, elle l'est beaucoup plus pour les EnR. En effet, celles-ci étant le plus souvent de petite taille et « décentralisées », c'est-à-dire (dans l'acception la plus courante) connectées au réseau de distribution⁹. Une alternative, qui existe par exemple en Allemagne, consiste à ne jamais faire payer les renforcements aux producteurs, qui ne paient alors que le coût de leur raccordement. Dans ce cas, ce sont les consommateurs qui paient les renforcements directement via le tarif d'utilisation du réseau. L'inconvénient principal de cette méthode est qu'elle n'incite pas les producteurs à se raccorder là où le réseau est moins contraint.

Afin de ne pas pénaliser les filières renouvelables en leur faisant payer les coûts complets des renforcements, tout en évitant l'écueil mentionné précédemment, la France a décidé de les mutualiser entre producteurs renouvelables de plus de 100 kW, et d'en exonérer les plus petits. Cette mesure a été prise dans la loi « Grenelle II »¹⁰, qui a introduit l'obligation pour les régions de se doter de Schémas Régionaux Climat Air Énergie (SRCAE), lesquels les objectifs « 20-20-20 » à l'échelle régionale, et auxquels sont adossés des Schémas Régionaux de Raccordement au Réseau des Énergies Renouvelables (S3REnR, ou SRRRER). Ces derniers, réalisés par les gestionnaires des réseaux de transport et de distribution, partent des objectifs des SRCAE et définissent par poste électrique la capacité renouvelable raccordable et le coût correspondant à l'échelle de la région. Il en résulte des capacités réservées aux énergies renouvelables par poste source (elle est potentiellement nulle), et un coût total qui, rapporté à la capacité, donne une quote-part (en €/kW) dont les producteurs EnR de plus de 100 kW doivent s'acquitter. Ainsi, en plus de mutualiser les coûts de réseau, ces schémas fournissent de fait un signal prix régionalisé, censé inciter les projets à se développer dans les régions où le réseau est moins contraint et donc la quote-part moins élevée, du fait d'un moindre besoin de renforcement. La question est donc de savoir si d'une part cet objectif de différenciation spatiale a été rempli, c'est-à-dire si les porteurs de projet sont effectivement sensibles à cette « taxe » régionalisée ; et si d'autre part cela a été bénéfique, ou tout du moins neutre, sur le développement des EnR.

⁹La définition de la distribution et du transport d'électricité varie entre les pays, mais la distribution concerne généralement la basse, moyenne, et parfois haute tension, alors que le transport concerne en général la très haute tension. Par exemple en France, la limite réglementaire est fixée à 50 kV, mais le réseau de transport opère généralement à 63, 90, 225 et 400 kV, tandis que la haute tension au sens de la distribution est généralement de 20 kV.

¹⁰LOI n° 2010-788 du 12 juillet 2010 portant engagement national pour l'environnement (2010).

Données

Je m'attache à répondre à cette question dans le cas de l'éolien, qui est avec le photovoltaïque la filière renouvelable la plus dynamique. Contrairement à cette dernière, il est possible d'appréhender la filière éolienne dans son ensemble, car les projets sont plus homogènes en termes de puissance. Pour réaliser cette étude, je m'appuie de nouveau sur les demandes de raccordement au réseau d'Enedis. Plus précisément, je choisis comme variable dépendante la puissance entrant en file d'attente (i.e. la somme des puissances des projets pour lesquels une convention de raccordement a été signée avec Enedis). Afin d'analyser les S3REnR, j'agrège ces données à l'échelle régionale et au pas de temps trimestriel. Si ce premier choix est plutôt évident, le second permet de prendre en compte des dates d'entrée en vigueur très différentes, tout en gardant un nombre suffisant d'observations non nulles. Malgré un fort taux d'abandon des projets (environ 35%), et donc de sortie de file d'attente, les demandes de raccordement fournissent tout de même un bon indicateur du dynamisme de la filière, et sont responsables de l'arrivée à saturation des schémas, et donc de leur révision. Par ailleurs, ne s'intéresser qu'aux demandes ayant abouti à un raccordement ne permettrait pas d'étudier l'impact des schémas, en raison du délai important entre l'entrée en file d'attente et le raccordement, et de l'incertitude concernant un possible abandon du projet éolien.

L'analyse descriptive de ces données est en elle-même intéressante et révèle que plusieurs projets font en réalité plus de 12 MW, qui est la puissance maximale autorisée pour les raccordements au réseau de distribution (il existe une dérogation possible jusqu'à 17 MW, mais les données montrent que cela reste marginal). En effet, de nombreux porteurs de projets de plus de 12 MW préfèrent effectuer plusieurs raccordements sur le réseau de distribution plutôt qu'un unique raccordement, souvent plus onéreux et plus compliqué, sur le réseau de transport. On distingue également clairement que la majorité des turbines font 2 MW, car la puissance des projets en est en général un multiple.

Les deux composantes des schémas de raccordement qui nous intéressent sont la quote-part et la date d'entrée en vigueur. Les S3REnR pouvant être approuvés et publiés à n'importe quelle date dans un trimestre donné, j'ai choisi d'utiliser deux variables explicatives pour quantifier l'effet de l'entrée en vigueur : une variable indicatrice (*dummy variable*) du trimestre en question, et une variable indicatrice pour tous les suivants. Par ailleurs, afin de tenir compte de la dynamique « intrinsèque » de la filière, j'utilise le nombre de raccordements effectivement réalisés par le passé afin de modéliser le processus de diffusion. Cela permet de juger de l'effet « épidémique » du développement, comme dans le cas du photovoltaïque étudié précédemment. En revanche, les courbes n'ont pas encore une forme de « S » et

ne laissent donc pas supposer l'existence d'un effet de « stock », à ce stade tout du moins. Ceci conduit à ne pas utiliser le carré du nombre de raccords passés, contrairement à l'étude précédente.

Modèle économétrique

En raison du caractère géographique des données, il convient de prêter attention aux possibles auto-corrélations spatiales, qui risquent de biaiser et rendre non-convergens les estimateurs « classiques » (ELHORST, 2014). Pour cela, j'estime le modèle d'économétrie spatiale le plus général, à savoir le *general nesting spatial (GNS) model*, dans lequel on considère l'autocorrélation spatiale de la variable dépendante, des variables indépendantes, et des résidus. Les données étant longitudinales (panel), j'utilise également des effets fixes temporels et individuels (régionaux) afin de capturer au maximum l'effet des variables inobservées telles que l'évolution du coût des turbines et des tarifs d'achat et l'hétérogénéité des régions (richesse, potentiel éolien, etc.).

Afin de modéliser les interactions spatiales, il est nécessaire de définir une relation de voisinage entre les entités observées (les régions dans notre cas). Compte tenu de la situation étudiée, une relation de type *rook* ou *queen* (c'est-à-dire la tour et la reine dans un jeu d'échec) semble la plus adaptée, car elle considère que deux entités sont voisines si et seulement si elles partagent une arête dans le premier cas, et une arête ou un coin dans le deuxième. En ce qui concerne les régions françaises, le résultat est le même pour ces deux définitions. Ceci donne une matrice de voisinage W de taille $N \times N$, dont les lignes et les colonnes représentent les N entités géographiques, et dont les coefficients sont égaux à 1 lorsque celles-ci sont voisines (au sens de la relation choisie), et 0 sinon (en particulier, les éléments diagonaux sont nuls car une région n'est pas considérée comme étant son propre voisin). Les coefficients de chaque ligne sont ensuite normalisés afin que leur somme soit égale à 1.

La matrice est ensuite appliquée aux variables souhaitées, en introduisant un coefficient d'autocorrélation pour la variable dépendante ainsi que pour les erreurs, de façon semblable à un modèle auto-régressif à moyenne mobile en séries temporelles. On l'applique également aux variables explicatives, similairement à un modèle auto-régressif à retards échelonnés en séries temporelles.

Le coefficient d'autocorrélation de la variable dépendante peut alors s'interpréter comme un taux de substitution entre les régions, qui peut être négatif si les demandes sont substituables ou positif si elles sont complémentaires, par exemple si elles font l'objet d'un phénomène de bouche à oreille spatialisé. Ce dernier cas est le plus fréquent en économétrie spatiale et correspond à un phénomène de *clustering* (regroupement) de la variable observée (taux de pauvreté ou de délinquance par exemple).

Résultats et interprétations

L'estimation du modèle révèle la présence d'autocorrélation spatiale négative et significative, ainsi qu'une autocorrélation résiduelle positive et significative, ce qui confirme le choix du modèle. Usuellement, les deux sont de même signe et sont donc difficilement discernables car ils ont des effets similaires, ce qui n'est pas le cas ici. Ainsi, les demandes de raccordement dans les différentes régions apparaissent comme étant assez fortement substituables l'une à l'autre, tandis qu'il existe une ou plusieurs variables inobservées corrélées positivement. Cela pourrait être lié en partie aux vitesses de vent, pour lesquelles c'est le cas (il y a plus vent sur les façades maritimes ainsi que le long du couloir rhodanien, donc bel et bien sur des régions contiguës) et qui ne sont pas prises en compte explicitement¹¹.

Les coefficients d'un modèle spatial autorégressif n'étant pas interprétables directement, il faut calculer les effets marginaux des variables explicatives. Ceux-ci s'écrivent sous la forme d'une matrice dont les coefficients s'interprètent comme l'impact d'un changement infinitésimal de la covariable considérée dans une région donnée sur la demande dans une autre région. En particulier, les termes diagonaux représentent les effets directs des variables explicatives, et les éléments non-diagonaux leurs effets indirects, i.e. sur les autres régions. Les résultats montrent qu'en moyenne, l'augmentation de la quote-part d'un euro par kilowatt entraîne dans la région concernée une baisse des demandes de raccordement de 300 kW et une hausse cumulée dans les régions voisines de 138 kW. L'effet total de la quote-part est donc légèrement négatif, mais cela est compensé par l'effet positif lié à l'entrée en vigueur des S3REnR. On peut en effet calculer qu'en moyenne au niveau national, les schémas ont entraîné une réallocation trimestrielle de 23,8 MW et une augmentation nette de 4,5 MW des demandes trimestrielles de raccordement.

Par ailleurs, les raccordements passés ont un impact positif et significatif sur la demande, ce qui confirme le caractère « épidémique » de la diffusion. En moyenne, chaque mégawatt supplémentaire par région induit une hausse de la demande trimestrielle de 30,2 kW. Cela peut sembler peu, mais il ne faut pas oublier le caractère exponentiel d'une telle dynamique. En définitive, le bilan de ces schémas incitatifs apparaît donc comme positif, aussi bien en termes de réallocation spatiale des raccordements qu'en termes de demande globale.

¹¹L'utilisation de la vitesse du vent comme variable explicative est compliquée compte tenu de son hétérogénéité au sein même des régions (qui sont assez étendues), de la relation non-linéaire inconnue (car dépendante de la technologie notamment) entre vitesse et productible, et du fait que cela empêcherait de fait d'utiliser des effets fixes pour contrôler les autres variables inobservables.

Chapitre III - La puissance souscrite revisitée : extensions et application à l'autoconsommation

Bien que la majorité des pays européens aient adopté un système de tarification du réseau électrique basé uniquement sur l'énergie consommée (parfois avec une part fixe), certains pays (dont la France) ont également une composante liée à la puissance souscrite par l'utilisateur du réseau. Chez les consommateurs particuliers, celle-ci ne peut en général pas être dépassée en raison de la présence d'un disjoncteur, et l'on peut alors parler d'auto-rationnement (*self-rationing*).

Par ailleurs, si les tarifs de réseaux semblent partager des objectifs communs (recouvrement des coûts, utilisation efficace du réseau, etc.), aucune structure ne semble faire l'unanimité. En effet, on observe une assez forte hétérogénéité dans les proportions que les parts énergie et puissance prennent dans la facture finale du consommateur, dans les pays qui disposent de ces deux outils de tarification.

La tarification à l'énergie en temps réel (*real-time pricing*), et en particulier en pointe (*peak-load pricing*) est quant à elle considérée comme la solution théorique optimale, et a fait l'objet de nombreux traitements théoriques depuis les premières contributions de BOITEUX (1951), STEINER (1957) et WILLIAMSON (1966) notamment. Elle pose cependant des problèmes d'implémentation (il faut des compteurs « intelligents », tels que les compteurs Linky en cours de déploiement en France), mais également de coûts de transaction pour les consommateurs, dont on imagine mal qu'ils soient prêts à ajuster leur consommation en continu en fonction du prix. Une variante moins contraignante mais moins efficace consiste à avoir des tarifs horosaisonnalisés (heures pleines/heures creuses par exemple), qui existent en France, combinés à une tarification à la puissance souscrite.

D'autre part, le développement de l'autoconsommation, c'est-à-dire le fait de consommer sa propre production (le plus souvent celle d'un panneau solaire) complique la tâche de l'élaboration du tarif. En effet, une tarification à l'énergie consommée nette (ce qui équivaut à valoriser la vente du surplus au prix de détail, qui contient notamment des taxes et la part variable du tarif de réseau) diminue l'assiette disponible pour recouvrir les coûts fixes du réseau, lorsqu'ils sont présents. On peut considérer que c'est le cas à court terme, car le réseau a déjà été construit et ne peut pas s'adapter instantanément à une nouvelle situation. De même, avec une tarification de la puissance souscrite, la possible diminution de cette dernière par des autoconsommateurs engendre le même problème, mais a priori dans une moindre mesure.

La présence de coûts fixes est un cas particulier d'économies d'échelles, qui justifie l'existence d'un

monopole, dit « naturel »¹². Si le recouvrement des coûts fixes via une somme forfaitaire est la solution optimale d'un point de vue économique (car ne créant pas de distorsion de consommation), elle ne paraît pas toujours « équitable » aux yeux de tous. Une alternative consiste à rechercher l'écart optimal du prix par rapport au coût marginal, ce qui conduit à un optimum économique dit de second rang (*second best*). Ce problème a été formulé pour la première fois par RAMSEY (1927) pour la taxation optimale, et indépendamment par BOITEUX (1956) pour les monopoles naturels, ce qui fait que l'on parle également de tarification à la « Ramsey-Boiteux ». Un des objectifs de ce papier est de déterminer ces prix avec et sans autoconsommateurs.

Cas général

La question de l'auto-rationnement a été traitée en premier lieu par PANZAR et SIBLEY (1978), dont le travail a été complété notamment par SCHWARZ et TAYLOR (1987). Selon leurs hypothèses, qui sont standard en économie industrielle, les consommateurs maximisent leur surplus espéré¹³ par rapport à leur puissance souscrite, lorsque leur demande et les prix auxquels ils font face sont stochastiques. Cela les conduit à égaliser en espérance le prix de la puissance souscrite à l'utilité marginale qu'ils peuvent dégager d'une unité additionnelle de cette puissance.

Dans le cas de coûts marginaux de fourniture et de capacité réseau constants, si les consommateurs ont des préférences faiblement séparables en consommation et « goût » (qui caractérise l'hétérogénéité des consommateurs), alors ils atteignent leur puissance souscrite simultanément et il est optimal de tarifier l'énergie et la puissance à leurs coûts marginaux respectifs. De plus, cela conduit à l'optimum économique de premier rang. Sous cette hypothèse, il suffit donc de considérer un consommateur représentatif, ce que nous ferons par la suite. Par ailleurs, on considère pour simplifier que la consommation peut être haute ou basse avec des probabilités fixes (et bien évidemment complémentaires). On fait de plus l'hypothèse que la puissance souscrite n'est atteinte qu'en période haute, et est donc strictement supérieure à la consommation en période basse.

Application à l'autoconsommation

Afin de traiter le cas de l'autoconsommation, on introduit de l'hétérogénéité entre les consommateurs à la manière de GAUTIER et al. (2018), en considérant que le coût marginal d'un moyen de production

¹²En réalité, il faut que la fonction de coût soit sous-additive, ce qui est moins restrictif lorsque celle-ci a plusieurs arguments (BAUMOL, 1977).

¹³Dans ces modèles, les consommateurs ont une fonction d'utilité quasi-linéaire par rapport à leur revenu, ce qui rend la maximisation de l'utilité équivalente à la maximisation du surplus.

décentralisé (comme un panneau solaire) est constant jusqu'à une certaine capacité (par exemple 3 kW) et infini au-delà (par exemple car il n'y a plus de place sur le toit). De plus, on suppose que ce coût est distribué dans la population selon une loi de probabilité connue de tous. En supposant que la production décentralisée est maximale en période basse et infinitésimale en période haute, et que les autoconsommateurs sont uniquement facturés en fonction de leur consommation nette, ils diminuent leur puissance souscrite de cette quantité infinitésimale dès lors que leur coût marginal de capacité décentralisée est inférieur à un certain seuil. Ce seuil correspond à l'économie marginale liée à la non-consommation depuis le réseau et à la réduction de la puissance souscrite permise par le moyen de production décentralisé. La proportion d'autoconsommateurs est alors endogène et donnée par la valeur de la fonction de répartition du coût marginal de production au seuil considéré.

Long terme

À long terme, la capacité du réseau est variable, et en l'absence d'économies d'échelles il est optimal de tarifier l'énergie et la capacité au coût marginal. Dans le cas contraire, par exemple s'il y a des coûts fixes, alors il est facile de montrer qu'en l'absence d'autoconsommateurs le prix *second best* de l'énergie suit la règle usuelle de l'inverse de l'élasticité (aussi dite de Ramsey-Boiteux), c'est-à-dire que l'écart du prix au coût marginal de production (et d'acheminement dans notre cas) est inversement proportionnel à l'élasticité de la demande en période basse. En présence d'autoconsommateurs, on a toujours un prix supérieur au coût marginal, et la proportion d'autoconsommateurs est également supérieure au niveau optimal. De plus, lorsqu'ils sont très peu nombreux, alors le prix à l'optimum de second rang baisse.

Quant au prix Ramsey-Boiteux de la capacité, il ne suit pas la règle de l'inverse de l'élasticité, et peut être supérieur ou inférieur au coût marginal. Cependant, si l'élasticité de la demande est plus élevée en heures creuses qu'en heures pleines, le prix est bien supérieur au coût marginal, et cela reste vrai en présence d'autoconsommateurs. En revanche, savoir s'il est plus élevé avec ou sans ces derniers est plus compliqué et dépend notamment des élasticités et de la proportion d'autoconsommateurs. Si celle-ci est élevée et si le prix en leur absence est supérieur au coût marginal, il est probable qu'il augmente par rapport à ce dernier, une condition suffisante étant que la densité du coût marginal de la capacité décentralisée tende vers 0 quand la proportion d'autoconsommateurs tend vers 1.

Court terme

À court terme, la capacité du réseau est fixe et son coût peut donc être considéré comme échoué. Dans ce cas, les résultats obtenus pour le long terme s'étendent en considérant simplement un coût marginal de la capacité réseau égal à zéro. Une alternative peut être de tarifer énergie et puissance au coût marginal, en empêchant les consommateurs de choisir leur puissance souscrite. Dans ce cas, ils remboursent tous intégralement le coût de leur connexion au réseau. Le problème est qu'une telle solution n'est pas optimale à long terme car elle conduirait à un nombre insuffisant d'autoconsommateurs et donc à trop de capacité réseau.

Ce chapitre théorique a donc montré qu'il était possible d'appliquer la théorie de l'optimum économique de second rang à la tarification du réseau de distribution lorsque les (auto)consommateurs peuvent choisir leur puissance souscrite. Si les résultats obtenus ne sont pas forcément évidents et requièrent une analyse détaillée de la situation, certaines grandes tendances ont pu être dégagées.

Chapitre IV - Comment la production renouvelable impacte les prix de l'électricité : le cas de l'Allemagne

La production d'électricité à partir de sources d'énergie renouvelable n'est également pas sans conséquence sur les prix de gros de l'électricité. En effet, si les coûts d'investissement des EnR peuvent être relativement importants, le coût marginal de production d'une éolienne ou d'un panneau solaire est en revanche presque nul. Leur utilisation à court terme est donc prioritaire, dans le respect de l'ordre de préséance économique (*merit order*) des moyens de production, i.e. du coût marginal le plus faible au plus élevé. En situation (idéalisée) de concurrence parfaite, la courbe d'offre sur le marché de gros respecte cet ordre et est donc constituée des couples volume/coût marginal de production ordonnés par ordre croissant des coûts marginaux. Ainsi, les productions solaire et éolienne viennent « décaler » cette courbe vers la droite, ce qui se traduit par une baisse des prix. Ce *merit order effect* (MOE) a déjà fait l'objet de nombreuses études, qui ont aussi souvent mis en évidence l'impact de la production renouvelable sur la volatilité des prix (KETTERER, 2014).

Par ailleurs, les coûts marginaux de production étant généralement de plus en plus élevés pour des capacités de plus en plus faibles, la courbe d'offre est le plus souvent convexe. Par conséquent, le MOE est a priori plus important lorsque les prix sont élevés : une baisse de la demande résiduelle correspondant alors à une baisse plus importante des prix que lorsque ceux-ci sont faibles. Pourtant, il n'existe pas

d'étude prenant en compte ce phénomène, qui est donc l'objet de cet article.

Données

Afin d'analyser le MOE, il convient d'utiliser des données de prix *spot* telles que celles du *day-ahead market*, qui sont calculés la veille pour le lendemain sur la base des courbes d'offre et de demande fournies par les participants au marché. Le cas de l'Allemagne est particulièrement intéressant, car la production renouvelable y est conséquente et son marché spot est relativement liquide. Nous avons donc décidé de modéliser son prix day-ahead sur les années 2014 et 2015. En raison de la forte saisonnalité des prix, qui est essentiellement due à la demande, nous utilisons cette dernière dans notre modélisation, en partant de données fournies par ENTSO-E¹⁴. Afin de quantifier l'impact de la production éolienne et photovoltaïque sur les prix, nous nous basons sur les données des quatre gestionnaires du réseau de transport d'électricité allemand¹⁵, que nous ramenons à la demande. En effet, ces variables ont un meilleur pouvoir explicatif que leur équivalent « brut », de même que la demande résiduelle (c'est-à-dire la demande moins la production renouvelable), que nous pouvons donc utiliser. Malgré le risque de multicollinéarité entre ces variables, nous verrons qu'il n'y a pas de problème de significativité des coefficients.

Modèle économétrique

Une des difficultés liées à la modélisation des prix de l'électricité est la dépendance temporelle de ceux-ci. Si une partie est due à leur saisonnalité et est donc capturée par la demande (résiduelle), il convient néanmoins de garder une continuité dans l'échantillon de données, alors qu'il serait tentant de le diviser suivant différents niveaux de prix pour étudier le MOE séparément. Afin de palier ce problème, nous utilisons une transformation non-linéaire du prix à l'aide de la fonction sinus hyperbolique réciproque, centrée sur la moyenne des prix. Cette fonction a un comportement logarithmique à l'infini, aussi bien dans les valeurs positives que négatives¹⁶, et linéaire entre les deux. Cela permet de limiter le poids des valeurs extrêmes, comme c'est le cas pour une transformation logarithmique usuelle. La distribution résultante est bimodale, ce qui la rend particulièrement adaptée à un modèle à changement de régime.

Nous choisissons donc de modéliser ce prix transformé à l'aide d'un modèle à changement de régime markovien à deux états (ou régimes), tel que développé par HAMILTON (1989). Cela permet d'estimer

¹⁴European Network of Transmission System Operators for Electricity, ou Réseau européen des gestionnaires de réseau de transport d'électricité.

¹⁵50Hertz, Amprion, TenneT, et TransnetBW.

¹⁶Les prix de l'électricité ont la particularité de pouvoir être négatifs, notamment en raison de contraintes de gradient de production et de la priorité à l'injection des EnR.

des coefficients et des variances résiduelles différents en fonction des régime, qui sont déterminés automatiquement lors de la procédure d'estimation. Comme indiqué précédemment, les variables explicatives choisies sont : les parts des productions solaire et éolienne dans la demande, et la demande résiduelle.

La structure choisie est markovienne de rang un, c'est-à-dire que la probabilité d'être dans un état à un instant donné ne dépend que de l'état précédent. Par ailleurs, on autorise les probabilités de transition (i.e. les probabilités de changer de régime ou non) à dépendre du temps suivant une loi logistique, dont les paramètres sont les parts des productions solaire et éolienne dans la demande d'électricité. En effet, l'utilisation de la demande résiduelle empêchait l'estimation de converger.

Résultats et interprétations

Les deux régimes de prix sont bien identifiés lors de l'estimation, avec des probabilités d'être dans un régime ou l'autre très proches de 1 ou 0, suivant le cas. Si les coefficients de l'équation de la moyenne ne sont pas directement interprétables, il est néanmoins possible de calculer les effets marginaux moyens dans chaque état. On montre ainsi qu'en moyenne, un gigawatt additionnel de production éolienne diminue le prix spot de 0,77€/MWh lorsque les prix sont faibles, et de 1€/MWh lorsqu'ils sont élevés. De façon similaire, ces effets marginaux sont de 0,73€/MWh et 0,96€/MWh pour le solaire. Ces résultats valident donc l'hypothèse d'un MOE croissant avec le niveau des prix.

De plus, l'analyse met en lumière l'impact de la production renouvelable sur les changements de régime. En effet, en l'absence d'EnR les prix sont relativement proportionnels à la demande, tandis qu'en leur présence on observe des épisodes de prix faibles lorsque la demande est élevée. Ce phénomène est quantifié par les coefficients de la régression logistique sur les probabilités de transition, dont on montre qu'à un coefficient près ils peuvent s'interpréter de façon approximative comme des semi-élasticités pour la durée résiduelle moyenne des régimes (i.e. le temps moyen restant sachant que l'on est déjà dans le régime considéré). En particulier, on montre que la production éolienne a un impact bien plus important que la production solaire sur les changements d'état. Ceci est probablement dû au fait que les prix élevés ont lieu en matinée et en soirée, lorsque la production solaire est faible (voire nulle en hiver).

Ainsi, la production renouvelable modifie la distribution des prix de manière globale, et pas seulement à la marge à travers le MOE. En plus de l'effet sur la durée des régimes mentionné ci-dessus, leur fréquence est également impactée, car la production renouvelable, par nature intermittente, induit des épisodes de prix bas de plus en plus nombreux. Ceci, en plus du MOE plus important en période de prix élevés, pénalise la rentabilité des centrales dites de pointe (turbines à combustion et centrales

au fioul notamment), qui sont nécessaires à la sécurité d’approvisionnement. En ne considérant qu’un MOE moyen, on risque de sous-estimer le risque financier que font peser les EnR sur ces moyens de production. En ne considérant que le MOE, on néglige également les variations plus soudaines du prix, qui peuvent être problématiques pour certaines centrales électriques, notamment si elles sont soumises à des contraintes de *ramping*, c’est-à-dire de gradient temporel de production.

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Introduction

The emergency of climate change has pushed several governments to invest more or less massively in renewable energy sources (RES), convinced that they would be the key to reduce greenhouse gas emissions, and simultaneously energy dependence towards fossil fuels and the countries producing them. Whether this strategy is justified ecologically and economically or not has been subject to intense debate, even among scientific experts. Nevertheless, it is clear that it is an ongoing path for many developed economies. In the European Union for instance, the last two “energy packages” have set renewable energy targets for 2020 and 2030, among other goals.

In such countries, the promotion of RES has given rise to a number of subsidies and other regulations. This has been particularly true in the electricity sector, where off-market support mechanisms using prices (such as feed-in tariffs - FIT, or premiums - FIP), or quantities (e.g., tradable certificates) have been widely used for more than a decade. In addition, other forms of regulation exist or are being discussed. In particular, most RES being “decentralised” (i.e. connected to the distribution instead of the transmission network¹⁷), their interaction with the electricity network is subject to sharp discussions. More precisely, the question of connection charges and network tariffs are crucial, as both have an impact on investment choices in decentralised generation (DG) and, in the case of tariffs, on network use (Brandstätt et al., 2011). For example, network tariffs may incentivise the adoption of decentralised production units (DPU), even in the absence of subsidies. Indeed, depending on the structure and level of the tariff components, installing a DPU may become profitable. This is the case of so-called “prosumers” (i.e. producers-consumers) who install for instance a solar panel on their roof.

Unfortunately, subsidies and other regulations are usually not free of perverse effects, as they may cause distortions and hence indirect costs in addition to the obviously direct ones (e.g. public spending in the case of subsidies, network investment costs, etc.), which should be controlled as well. Upstream, i.e.

¹⁷The definition of the limit between both networks varies between countries, but electricity distribution is often considered as covering low to medium/high voltage levels, whereas electricity transport deals with high and very high voltage levels. For example in France, the limit is set at 50 kV, although the distribution network mainly operates at 20 kV and below, and the transmission one between 63 and 400 kV.

on the production side, off-market subsidies create a positive supply shock with (almost) zero marginal cost. This results in particular in a decrease in electricity wholesale prices on the spot market (Cludius et al., 2014;Ketterer, 2014), which reduces the profitability of all power plants, including RES themselves. As a consequence, there may be less investment in other technologies of production such peak power plants, that are essential to the security of supply. Downstream, the development of DG is likely to lead to a revenue shortfall for distribution system operators (DSOs) or public utilities, and may also create cross-subsidies from regular consumers to prosumers, depending on the structure of network tariffs (Eid et al., 2014). In-between, additional management and reinforcement costs of electricity networks can also be a consequence of the expansion of DG, although it may also be beneficial to the system (Picciariello et al., 2015).

A first natural question thus concerns the efficacy and efficiency of such policies, i.e. whether they effectively reach their objectives, and at what cost. Policy analysis has become a frequent task for economists and scientists in public administrations as well as a subject of research among scholars. This positive (or descriptive) approach relies especially on data analysis which often aims at measuring causal relationships using e.g. econometrics. Such tools can also be used to quantify impacts of public policies more widely, i.e. effects other than the desired ones, such as spillovers (which can be positive or negative, such as perverse effects).

Another question relates to what ought to be done in an economy. This approach, which is said to be normative, can be useful in situations in which no or very little feedback is available, but can apply to other situations as well. Although it is sometimes based on ideas and opinions, it also uses theoretical frameworks to describe the problem in a simplified manner in order to draw conclusions. In particular, mathematics can be used as a powerful tool in this field as they can help derive optimal allocation rules.

This thesis deals with several economic aspects of renewable electricity, from downstream investment decisions in renewable production to upstream impacts on wholesale markets, and is thus organised in this order, as detailed below. Although most of the work is empirical and is based econometrics, I also use theoretical modelling in the study of electricity network tariffs.

In the first chapter, I model the pattern of adoption of individual solar photovoltaic (PV) panels by residential consumers in France. More precisely, I focus on the impact of national and local subsidies on the probability and number of quarterly installations from the end of 2008 to mid-2016, for the 33,842 municipalities (cities) served by Enedis, which is the DSO for 95% of the French population and who provided this unique data of more than a million observations. Due to the very high number of

zeros, I use the two-part “hurdle” model of Mullahy (1986), which deals with zeros and positive values separately. I show that whereas the probability of adoption has mainly been the result of FITs, local subsidies have had a weaker effect on the probability but a stronger one on the number of connection requests. Building on the common linearisation of the Bass (1969) model, I find that the probability is positively impacted by the number of past installations. This supports the hypothesis of an “epidemic” diffusion process, as is frequently observed for new durable goods and for RES in particular. A “stock” effect, i.e. a decrease in the epidemic effect, is also observed, which is consistent with the observation of “S” curves (Griliches, 1957) at the national and regional levels. The analysis reveals that an additional past installation in a city has relatively the same impact on the probability of adoption as a one-point increase of the internal rate of return. This results calls for more communication on RES projects, which can be done for example through local ownership.

In chapter II, I assess the effectiveness of the 21 French regional network connection schemes on the development of wind energy, from 1998 to mid-2016 (1554 observations over 74 quarters). These schemes are a relatively unique and original regulation and aim at sharing network reinforcement costs between RES producers, while providing a regionally differentiated price signal that should incentivise connections in regions where the network is less constrained. I analyse this phenomenon thanks to a general nesting spatial (GNS) panel model, that enables to take spatial autocorrelations of variables and residuals into account as well as spatial interactions of the covariates. Omitting these would result in biased and inconsistent estimates (Elhorst, 2014). Using the quarterly capacity of connection requests on Enedis’ network as dependent variable, I show that the schemes have reached their goal in reallocating connection requests more efficiently, without altering the dynamic. As for solar panels, I find evidence of an epidemic effect, but no stock effect, due to the relatively early development of wind compared to PV. In addition, I show that regions are substitutes to one another in the sense that connection requests in a region impact negatively those in the neighbouring ones.

In the third chapter, I study electricity distribution tariffs in the presence of prosumers. Contrarily to the other chapters, I address the subject from a theoretical point of view, which enables to provide rather normative results. Starting from the literature on self-rationing (i.e. capacity subscription by electricity consumers) initiated by Panzar and Sibley (1978) and Schwarz and Taylor (1987), I introduce prosumers in a simplified but standard framework, following in particular the endogenous specification of Gautier et al. (2018). Then, I derive optimal departures from marginal-cost pricing, i.e. so-called second-best, or Ramsey (1927)-Boiteux (1956) prices. These give indications on how energy and capacity prices

should be balanced with respect to each other and to marginal costs, and how they are modified by prosumption. In particular, I show that they are highly dependent on peak and off-peak elasticities, as well as on the level of prosumers.

In the fourth and last chapter, which is co-authored by Frédéric Lantz and has been published in *Energy Policy* (Martin de Lagarde and Lantz, 2018), we analyse the impact of wind and solar productions on electricity spot prices in Germany, that has invested early and massively in RES. We use the Markov regime-switching model of Hamilton (1989), which we estimate on hourly price and RES production data over the years 2014 and 2016. Thanks to an appropriate inverse-hyperbolic sine transformation (Johnson, 1949) of electricity prices, we show that the merit order effect (i.e. the decrease in electricity prices) is stronger during high-price regimes than in low-price ones, as expected from the theory on wholesale electricity markets. Furthermore, we highlight how the distribution of prices can be more globally affected by renewable production, which is found to have a significant impact on the frequency and mean duration of high- and low-price regimes.

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Chapter I

Drivers and diffusion of residential photovoltaics in France

About this chapter

This chapter was realised thanks to data provided by Enedis under a non-disclosure argument. I wish to thank Christophe Bonnery, François Dispot and Hervé Lextrait for allowing me access this data. This work was presented internally at IFPEN in December 2017 and at Enedis in January 2018. I also had the opportunity to present it twice externally: in April 2018 at the 24th Young Energy Economists and Engineers Seminar (YEEES) in Delft (Netherlands), and in June 2018 at the 41st International conference of the International Association for Energy Economics (IAEE) in Groningen (Netherlands). I am grateful to all participants of these seminars, and in particular to Roland Ortt from TU Delft for reviewing my paper thoroughly. Finally, I thank Jan Keppler for reviewing the related working paper.

Abstract

This paper analyses the diffusion of residential solar panels in France and the impact of financial incentives on this dynamic. We use a unique database provided by Enedis, the main French DSO, giving the number of connection requests for 33,842 municipalities and 31 quarters, from the end of 2008 to mid-2016. Using solar irradiance, panel costs, national feed-in tariffs (FIT) and local subsidies, we compute an internal rate of return (IRR) per municipality and per quarter. In order to disentangle the effect of FIT and local subsidies, we compute an IRR with and without the latter. Due to the high number of zero-installation data points, we adopt a two-stage (“hurdle”) methodology: we first model the probability of having at least one installation, and then their number (the vast majority being 3-kW panels). Controlling for individual characteristics of the municipalities, we find that whereas FIT had a positive and significant impact on the probability of adoption, local subsidies mostly impacted the number of connection requests. Furthermore, we show that the diffusion process exhibits “epidemic” and “stock” effects, which are consistent with the “S”-shaped diffusion curve observed at the national and regional levels. Considering only epidemic effects, we show that an additional past installation in a city has the same effect as a one-point increase of the IRR, that is, an increase of the odds of installing at least one solar panel by roughly 10%. Hence, informing households more thoroughly could help promote renewables at a lower cost. This could be done for example through more implication of citizens at the local level.

1 Introduction

In the fight against global warming, many governments have chosen to develop renewable energy sources (RES). Indeed, these should hopefully help reduce greenhouse gas emissions associated with energy production, if they can be substituted to fossil fuels. In the electricity sector, renewables have been developing at high pace in many developed countries, mainly thanks to public subsidies. If these are often justified by the necessity to reduce CO₂ emissions, they also aim at internalising the learning effect (or “learning-by-doing”), i.e. the decrease in costs associated with the development of the technology. Indeed, without subsidies, RES would be installed in meager quantities as their cost would be too high compared to conventional power plants. In the long run, RES supporters expect that they will be competitive with other means of production.

A rather common way of subsidising electric renewables has been to use feed-in tariffs (FITs), that guarantee a price ex-ante for each unit of energy (e.g. kilowatt-hour - kWh) produced over the duration of the contract (usually fifteen to twenty years). This remuneration does not depend on the time at which the electricity is produced, and hence on the spot market price. As many other European countries such as Germany (who was a pioneer for RES in Europe), France has had such FIT for over a decade, before switching to ex-post feed-in premiums (FIPs) in 2015 for most of the new installations¹. However, the cost of these subsidies is sometimes passed on to consumers through taxes in the electricity bill². Furthermore, residential solar panels have been subsidised at the national level through other instruments such as reduced VAT or tax credits, and several regions, departments, or cities have decided to subsidise them as well. These other subsidies are on the contrary borne by taxpayers.

Distributed³ production units such as small-scale residential photovoltaic (PV) solar panels play an increasing role in this energy transition. Indeed, in France more than 95% of newly installed renewable production is connected to the distribution grid, and household solar panels represent the most widespread technology in number of installations (but not in capacity). However, the distribution network was originally designed to deliver electricity to end-users, which were almost only consumers. Now that decentralised producers and “prosumers” (i.e. producing consumers) massively invest in RES, many reinforcements need to be made at the distribution level in order to adapt to this whole new envi-

¹ *LOI n° 2015-992 du 17 août 2015 relative à la transition énergétique pour la croissance verte* (2015).

² The electricity bill of a French residential customer is almost equally divided between the cost of energy, the network tariff, and taxes, according to the French ministry in charge of energy (MTES, 2016). In 2016, support mechanisms for electric renewables accounted for approximately a quarter of the taxes, according to the French energy regulator (CRE, 2016). Afterwards, the funding of RES have been separated from the taxes on electricity consumption.

³ There are several definitions of distributed (or decentralised), but the most widespread is to call distributed all devices (panels, batteries...) that are connected to the distribution network. In France, the limit between electricity transmission and distribution is set at 50 kV, but this limit can differ between countries.

ronment. The transmission network also needs to be reinforced as RES generation is variable, which calls for more global system integration and balancing. The cost of these investments is also borne by consumers, through the network tariff. It is therefore crucial for both policy makers, distribution and transmission system operators (DSO and TSO) to understand the dynamic of adoption of RES, and in particular solar panels, in order to limit unnecessary costs and inefficiencies. This can be done by conceiving efficient subsidies, network tariffs and electricity pricing methodologies.

Although electric renewables would probably not have emerged quite so swiftly without subsidies, financial issues are not expected to be the only drivers of renewable development. Indeed, considering them as relatively new products, their diffusion pattern is also likely to follow an “S”-shaped curve at the aggregate level, as famously modelled by Bass (1969) for durable consumer goods. Accordingly, the diffusion process is expected to benefit from an “epidemic” or “contagion” effect (word-of-mouth): the more the technology spreads, the more it becomes known and accepted, and adopted in return. It might also exhibit a “stock” effect, i.e. a decrease of the epidemic effect in the long run, due to the finite size of the market⁴. However, to the best of our knowledge, the impact of financial incentives (and especially local ones) on the diffusion of solar panels (or other products) has not yet been studied at a very small scale.

Thus, we model the demand for solar panels by households, using a unique data set of all connection requests for small (< 3 kW) solar panels received by Enedis, the DSO for 95% of distributed customers and more than 95% of installed PV projects in France.

The contribution of this article is then threefold. First, we show that households act in a rather rational way. Indeed, they tend to maximise their installed capacity, and they strongly react to quarterly changes in the FIT. Second, using public data for national and local subsidies, solar irradiance and panel costs, we are able to compute an internal rate of return (IRR) for each city whose distribution network is managed by Enedis (33,842) over 31 quarters, from the end of 2008 to mid-2016. We use this variable to measure the impact of financial incentives on the probability and number of installations, and we disentangle the effect of national and local subsidies. In addition, we control for individual (municipal) characteristics such as population or the proportion of houses, which also affect the number of installations in a given city. Therefore, we are able to measure the effect of variables that are often omitted or averaged in large-scale studies, despite their strong heterogeneity. Third, we are able to analyse the “intrinsic” diffusion process by adapting the famous Bass (1969) model at a very fine scale,

⁴A more detailed description of the different diffusion effects can be found in Karshenas and Stoneman (1993), along with an empirical application to the computer numerically controlled control machine tools market

using data at the municipality and quarterly levels. This requires taking into account the very important number of zeros in the data set. We manage to do this using the two-part “hurdle” model of Mullahy (1986), which we apply to the number of connection requests, as most PV systems have the same nominal capacity of 3 kW. In the end, we show that an additional past installation and a one-percentage point increase of the IRR have a similar effect, which is an increase the odds of having a connection request by almost 10%. In addition, the IRR also has a positive effect on the number of installed panels in a given city during a quarter. This result calls for more “advertising” on RES at the local level, as information is essential in a diffusion process. Given the very high value of the observed subsidies and IRR, increased information is likely to help promote renewables at a lower cost. This may be encouraged by a better implication of local residents in RES projects, for example through shared ownership.

The remainder of the paper is organised as follows. Section 2 first presents a literature review on the subject. In section 3, we describe the data on connection requests, before presenting the rest of the data and the computation of the IRR in section 4. In section 5, we detail our modelling strategy of the diffusion process and the hurdle model. The results are then shown and discussed in section 6. Section 7 concludes and presents future research avenues.

2 Literature review

Many articles have analysed the development of RES in several countries or regions. Although support schemes have been studied and compared theoretically (Marschinski and Quirion, 2014; Mir-Artigues and R  o, 2014; Boomsma and Linnerud, 2015; Bauner and Crago, 2015) and empirically (Kilinc-Ata, 2016; Aguirre and Ibikunle, 2014), we will focus on empirical studies in the rest of the review. In particular, the impact of support schemes on the development of RES has been widely discussed: feed-in tariffs, as one of the most widespread support schemes, but other mechanisms such as renewable portfolio standards, green certificates or carbon taxes have also been analysed. Most studies find a positive and significant effect of these on the development of solar PV, whilst there is less evidence concerning wind power. For example, Zhang et al. (2011) investigate the impact of regional subsidies on the diffusion of solar PV in Japan using panel data at the municipal level. Their results indicate that regional policies tend to promote the adoption of solar panels, while installation costs have a negative impact, and housing investment and environmental awareness a positive one. Jenner et al. (2013) use panel data in 26 European countries for the period 1992-2008 and construct a return-on-investment indicator for FIT strength in order to take into account in particular variability in tariff level and

contact duration between countries. They conclude that FITs have driven solar PV but find no evidence concerning wind energy, and also argue that the influence of FITs highly depends on several factors such as production costs or electricity prices. Dijkgraaf et al. (2018) perform a similar analysis in 30 OECD countries for the period 1990-2011 and find a positive effect of FITs on the adoption of solar panels per capita. They also show that some features of the contract, such as the duration of the absence or presence of a cap have an impact on the adoption as well. Many authors have also studied other factors such as political ones (Cadoret and Padovano, 2016; Strunz et al., 2016), location, socio-economic drivers, local subsidies and spatial spillovers (Schmidt et al., 2013; Ek et al., 2013; Müller and Rode, 2013; Graziano and Gillingham, 2015; Schaffer and Brun, 2015; Balta-Ozkan et al., 2015; Schaffer and Düvelmeyer, 2016; Carfora et al., 2017; Allan and McIntyre, 2017).

Furthermore, several authors have modelled the pattern of adoption of electric renewables using “S-curves”, as first introduced by Griliches (1957): see for example Schilling and Esmundo (2009) for solar PV. These curves can also be fitted using a diffusion model in the line of Bass (1969), such as in the work of Guidolin and Mortarino (2010). In addition, several diffusion models have been developed to incorporate external influence such as price or advertising. A review of such models is provided by Radas (2006). However, these are often highly non-linear, such as the Generalised Bass Model (Bass et al., 1994), which makes them less flexible and complicates their estimation. As a consequence, some authors have used linear(ised) diffusion models when studying RES development. For example, Liu and Wei (2016) derive a linear regression equation from a logistic growth function, following the work of Benthem et al. (2008) for solar PV. They show that the development of wind power in China has been driven by financial incentives as well as by epidemic effects, using panel data from clean development mechanism projects in China. Similarly, using data at the zip code and street levels and a linear probability panel model, Bollinger and Gillingham (2012) show that diffusion has had a strong impact on PV adoption in California by the means of peer effects.

A drawback of these studies, and of diffusion models in general, is that they require relatively “smooth” data to be fit, as they predict a strictly positive number of sales (except in the long run: when the market is fully reached, sales drop to zero). This issue challenges their applicability to low-level data such as ours, where the number of installations is very low and often equal to zero. Indeed, we want to study the impact of both national and local subsidies, at a quarterly time step. Therefore, our data contains many zeros (it is said to be “zero-inflated”). This peculiarity automatically rules out the use of a linear regression model, which would predict many negative values, and in particular not enough

zeros. Fortunately, there exist several possibilities to deal with this kind of data, and the interested reader can have a look for example at Min and Agresti (2002) for a quick survey. Such models can be decomposed in several categories, depending on the data being (semi-)continuous or discrete, on the model proposing a single underlying mechanism for the creation of zeros or two separate mechanisms for zero and non-zero values, on the type of distribution (single, compound, finite mixture...), etc.

One of the first and most famous of these is the Tobit model (Tobin, 1958), which assumes a unique Gaussian data generating process for semi-continuous data. It has been used for example by Hitaj (2013) to analyse the drivers of wind development in the United States. However, the Tobit model is more adapted to censored data, as the same process determines whether the dependent variable is zero or is value when it is positive. Furthermore, it assumes (semi-)continuous data, which would not be adapted to small-scale PV projects. Indeed, we we will see in section 3 why using count data (i.e. the number of installations) is more adequate. For instance, Kwan (2012) use a zero-inflated negative binomial (ZINB) model to analyse the number of PV installations at the ZIP code level in the United States. Although this enables to model accurately to large number of zeros, the interpretation can be difficult, as zeros are produced twice: first by a binomial regression, and then by a count model. Thus, De Groote et al. (2016) prefer using a Poisson regression, although their data is zero-inflated, but not as much as ours. In our case, we apply the two-part “hurdle” model of Mullahy (1986) to the number of installations. Unlike zero-inflated models, hurdle models deal separately with zeros and non-zero values, hence leading to an easier interpretation. We will further motivate this choice in section 5, as it is due to some characteristics of the data that will be presented in the following section.

3 Data

3.1 Connection requests

In order to study the dynamic of household PV adoptions, we use a unique database provided by Enedis, which is the distribution system operator (DSO) for 95% of French clients. We have received from Enedis the register of all received connection requests for PV projects until mid-2016⁵. We restricted ourselves to the small-scale (< 3 kW) segment, as it mostly corresponds to connection requests from households. It also has the advantage of having benefited from relatively stable subsidies, compared to other segments. Indeed, other categories have seen their capacity boundaries changed several times and tariffs have sometimes been dependent on the type of building or building integration, for which

⁵In France, all generating capacity under 17 MW must be connected to the distribution network.

we have no information. In particular, this segment was the only one that was not concerned by the three-month moratorium on feed-in tariffs from December 9 2010 to March 9 2011.

The original data being at the municipal and daily levels, we had to aggregate it in order to avoid having too many zeros (we still have a lot of zeros at the end of the aggregation process). Due to the high heterogeneity between municipalities in terms of solar irradiance, local subsidies, but also population characteristics, we find preferable to keep the data at this scale. Unfortunately, we are not able to consider household heterogeneity within a given city, due to the absence of personal data. In particular, the data set has been anonymised. Hence, our “individuals” will be municipalities rather than households. In the time range, quarterly aggregation appears as a rather natural choice for small-scale solar PV, as FITs have been changing quarterly since 2011.

Thus, we end up with 31 quarters of observations for 33,842 municipalities, which represents 1,049,102 observations, only 62,909 (6%) of which are non-zeros, as can be seen from table I.1. Then, most of non-zero values are ones (83%). Mid-2016, there are still 13,011 municipalities (38%) with no domestic solar panel at all. Table I.2 below displays some descriptive statistics for the demand of connection requests, in count and in capacity (kW), as well as for the cumulative data for the last quarter of the sample. Due to the very high number of zeros, we present statistics for the non-truncated data and for the strictly positive one, as these will be modelled separately. These statistics show that the demand and count data are overdispersed (i.e. the variance is bigger than the mean), while the strictly positive count data is underdispersed. However, although most of the time there is only one connection request, this number can rise up to 18. Interestingly, this maximum happened in Q4 2010 in Calais, which is one of the northernmost cities in France, and in 2011 Q1 in Niort (centre-west).

Number of requests	0	1	2	3	4	5	6	7	8
Occurrences	986193	51948	7828	1930	608	274	119	62	55
Number of requests	9	10	11	13	12	14	16	15	18
Occurrences	26	22	11	11	5	3	3	2	2

Table I.1 – Occurrences of the number of connection requests

To get an idea of the diffusion process and its heterogeneity, figures I.7 and I.8 in appendix A and B show the quarterly demand and cumulative demand for PV projects per region⁶. These graphs show that the dynamic is already highly heterogeneous between regions, but the "S"-shaped curve can still

⁶Although there has been a change in the number of regions in January 2016 (from 20 to 12 in metropolitan France, Corsica excluded - Enedis is not the DSO there), we have decided to keep the initial regions as there have been several regional subsidies before this reform.

Statistic	N	Mean	St. Dev.	Min	Median	Max
Demand (kW)	1,049,102	0.213	0.999	0	0	51.6
Demand >0 (kW)	62,909	3.557	2.178	0.100	3	51.6
Cumulative demand (2016 Q2)	33,842	6.611	12.605	0	3	456
Count	1,049,102	0.076	0.356	0	0	18
Count >0	62,909	1.267	0.774	1	1	18
Cumulative count (2016 Q2)	33,842	2.356	4.516	0	1	162

Table I.2 – Descriptive statistics of connection requests

be observed for all of them. It would also be observed at the national scale, but not at the scale of most municipalities, as there are usually very few installations, or none at all. Finally, the left map in figure I.1 shows the regional cumulative capacity at the end of June 2016, while the right map presents the mean annual optimal irradiance (i.e. for the best possible angle). Quite interestingly, these two maps seem almost uncorrelated, or even negatively correlated. For example, Nord-Pas-de-Calais, which is the northernmost region, and Lorraine, a northeastern region, have very high installed capacities compared to their received irradiance.

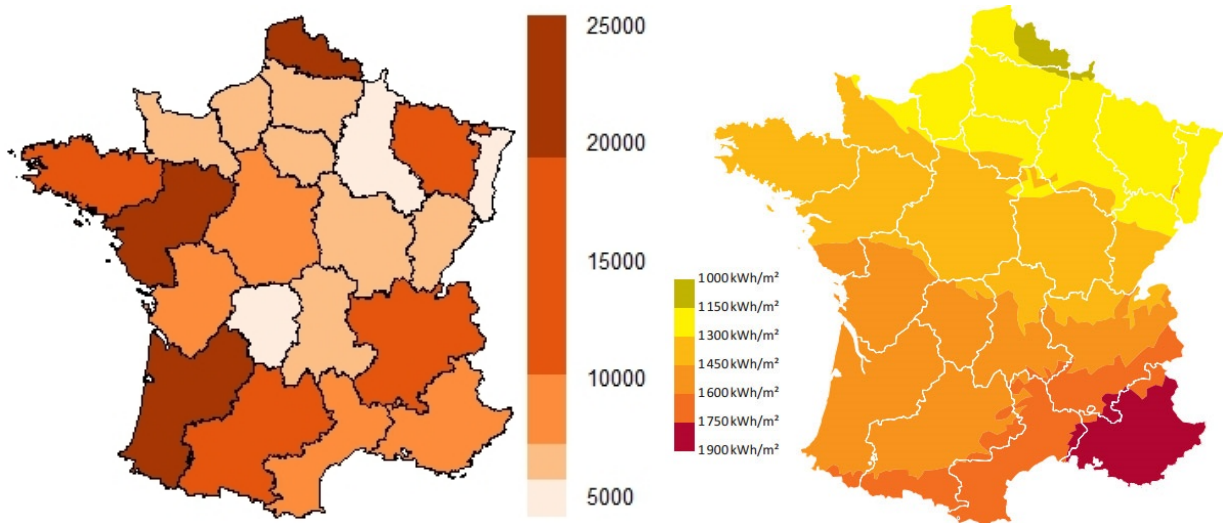


Figure I.1 – Left: Regional cumulative PV capacity (kW) of projects of less than 3 kW, mid-2016. Right: Annual optimal irradiance (source: PVGIS, JRC).

3.2 Analysis of households behaviour

When studying the effect of financial incentives on the adoption of solar panels by households, we hope to find that these latter are rather rational, in that they react positively to subsidies. Without any modelling, the raw data can already give some confirmation that the behaviour of the households is

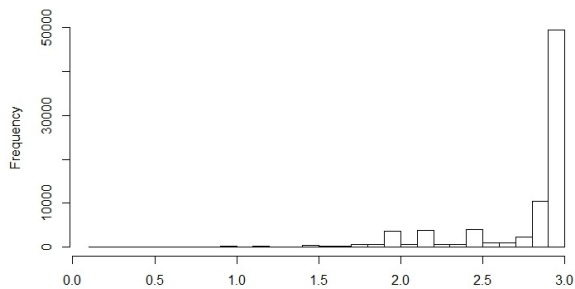


Figure I.2 – Histogram of individual capacity demands (kW)

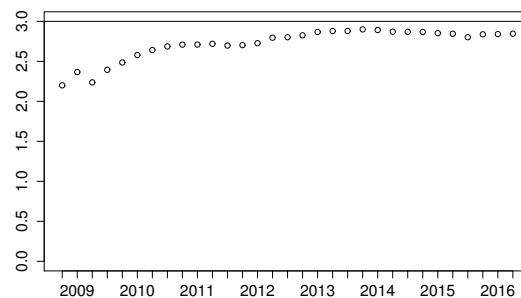


Figure I.3 – Average capacity per connection request (kW)

indeed quite rational.

First, assuming that a PV project is profitable for the investor, and considering the fact that FITs are designed by segments of power, agents should maximise their installed capacity while staying under the tariff change power threshold. We expect only physical constraints such as the available area on the roof to limit the installed capacity. As a matter of fact, most roofs are large enough for 3-kW panels (approximately 10 m^2 per kW are required). Figure I.2 shows that most installations are indeed 3-kW ones. Furthermore, figure I.3 illustrates that the average capacity per connection request has slightly increased towards 3 kW over time. This could be the sign of a “learning” process, of more confidence of investors, or maybe of a standardisation of panels. Besides, this characteristic of the installations will allow us to use the number of installations rather than the demand in kW, as we will explain in section 5.

Another feature of FITs for solar PV is that they have been revised quarterly since the end of the moratorium on March 10, 2011 (which coincides with the first observed peak in figure I.4)⁷. Indeed, at the end of each quarter the tariff is adjusted by a coefficient decreasing with the accumulated capacity. As a consequence, we expect connection requests to rise at the end of each quarter, in what we could call a “deadline effect”, as agents would rather hurry in order to benefit from the highest possible FIT before it decreases. Figure I.4 shows that this is indeed the case, as the spikes correspond to the end of each quarter. Thus, it is preferable that the minimum temporal aggregation be at least at the quarterly level, to avoid the difficulty of modelling this behaviour. This also comforts us in thinking that agents are price-sensitive, hence legitimating the question of quantifying the role of incentives in the diffusion process.

⁷There has also been a change at the beginning of February 2013, with a huge decrease in the number of FIT categories, but it did not concern small PV installations.

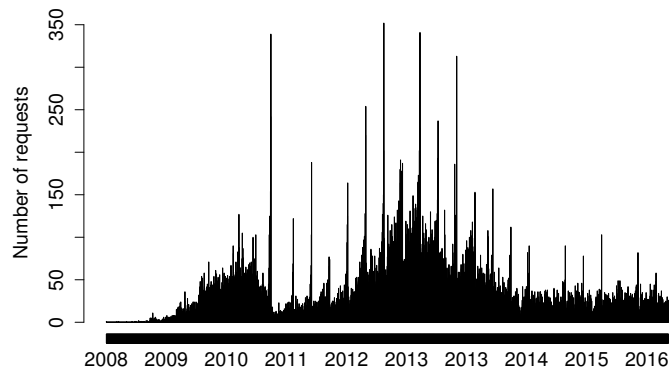


Figure I.4 – Illustration of the “deadline effect”

4 Other data

In order to analyse the diffusion of residential PV, we need data on costs and subsidies for such installations, but also control variables, as the number of installations is likely to depend on socio-economic factors.

4.1 Costs and feed-in tariffs

While FIT data is publicly published on official websites, data for system costs (panels, power inverter⁸, installation...) can be more difficult to find. Given the heterogeneity of sources, we have chosen annual data⁹ provided by the French Environment and Energy Management Agency (ADEME). Figure I.5 below shows the evolution of FITs and gross system costs from the end of 2008 to mid-2016. The graph shows that despite an overall decreasing trend for both costs and FITs, the latter have remained relatively constant until the end of 2010, whilst costs were declining. This explains at least partly the “bubble” observed at the end of 2010, which led to the three-month moratorium, and later an important decrease and a quarterly revision of FITs.

In addition to the FIT, the State has also decided to subsidise RES in several ways. Indeed, some installations entitle their owner to tax credits under certain conditions (e.g. income, type of installation, etc.). Also, VAT is reduced to 10% (instead of 20%) for solar panels, and to 5% for projects eligible to tax credits. Finally, the National agency for housing (Agence nationale de l’habitat) can also subsidise RES installations in case of renovation works for low-income households. Unfortunately, we are not able to determine whether projects were eligible to some of these subsidies or not, so we will not consider them. However, we believe they have had a smaller impact on the diffusion than FITs and local subsidies.

⁸Electric device used to change direct current (DC) produced by the panel, to alternative current (AC).

⁹In order to get quarterly data, we used linear interpolation.

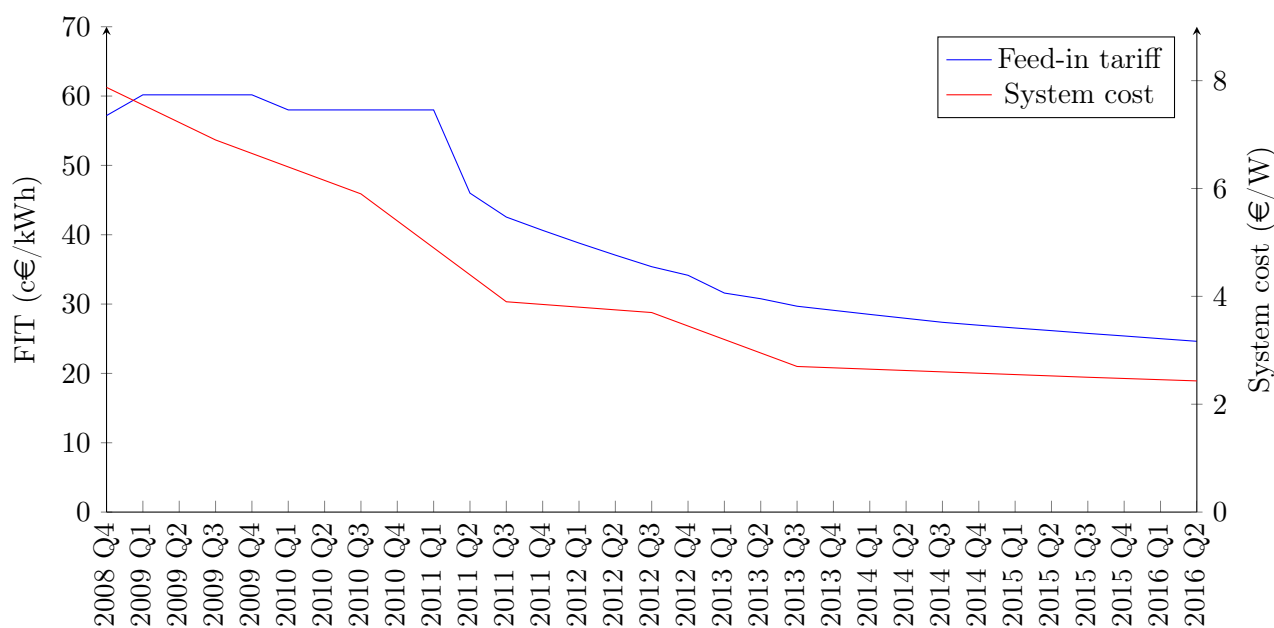


Figure I.5 – Evolution of feed-in tariffs and system costs for small-scale PV (< 3 kW). Sources: ADEME (costs) and Photovoltaïque.info (tariffs).

4.2 Local subsidies

As already mentioned, many local entities have chosen to subsidise RES, and in particular small-scale PV, in addition to the existing national subsidies. In France, the main sub-national administrative entities are the 21 regions, 94 departments and roughly 36,000 communes (municipalities) of Metropolitan France (Corsica excluded). Several of them have decided to subsidise RES in their various ways, for example through a fixed or proportional subsidy for the entire system or for the installation only (usually with a certified installer only); a subsidy per kilowatt-peak (sometimes with an upper limit); a premium on the FIT for a few years; etc. Due to the heterogeneity of local subsidies, and as most of panels have a capacity of 3 kW, we consider for simplicity reasons that all projects have this capacity, so that we can compare them. A summary of these subsidies is displayed in table I.3 below.

As can be seen from the table, positive regional subsidies concern 17.5% of all observations, with relatively high mean and maximum values (recall that the price of 3-kW modules have varied between roughly 24,000€ and 7,300€). Subsidies at the department and municipality levels concern much less observations (3.4% and 0.66%, respectively), but attained values are rather high as well.

Entity	N. obs. (entity level)	N. obs. (municipality level)	Mean	St. Dev.	Min	Max
Regions	651	1,049,102	368	970	0	6,000
Regions (>0)	120	183,578	1,998	1,364	300	6,000
Departments	2,914	1,049,102	53.9	384	0	6,396
Departments (>0)	97	36,016	1,619	1,384	300	6,396
Municipalities	1,049,102	1,049,102	5.78	92.1	0	3,690
Municipalities (>0)	6,935	6,935	874	723	75	3,690

Table I.3 – Descriptive statistics of local subsidies (in euros) for a 3-kW PV project, from 2008 Q1 to 2016 Q2, for several administrative levels.

4.3 Internal rate of return

Motivation

To analyse the influence of subsidies on the demand for solar panels, we need in fact to assess the profitability of PV projects, taking into account costs and subsidies in this profitability measure. Using these directly as covariates would be inappropriate: first, they are likely to evolve simultaneously over time (see figure I.5) and hence be somewhat correlated; second, they would not entirely capture the profitability of a project, as they would ignore key local factors such as sun irradiation. The latter could be used as a proxy for profitability, but only in a cross-section analysis, as in Davidson et al. (2014). Knowing these local factors, an alternative would be to use the net present value (NPV), as in Liu and Wei (2016). For a given FIT (possibly enhanced by a premium), discount rate i , investment cost I (possibly reduced through various subsidies) and annual electricity output q , the NPV is defined as follow¹⁰:

$$\text{NPV} = -I + \sum_{t=1}^T \frac{\text{FIT} \times q}{(1+i)^t} \quad (\text{I.1})$$

Despite its simplicity of use, we think that a NPV can be difficult to interpret, in particular for people who are not familiar with the currency (whereas the euro is relatively well-known, the use of the same methodology elsewhere could lead to a more difficult interpretation for foreigners). In addition, its computation requires making an assumption regarding the discount rate. Other authors have used a return-on-investment (ROI) variable, but then an discount rate is either needed (as in Dharshing, 2017), or ignored (as in Jenner et al., 2013). Therefore, we find it more convenient to compute the rate which

¹⁰The choice of having the payments made at the end of each year is arbitrary, and another choice might be more appropriate, but would have a rather small impact on the computed value.

sets the NPV to zero, namely the internal rate of return (IRR). Furthermore, the IRR enables to compare projects independently of the initial investment, while higher investments will give higher NPVs for the same IRR. On that account, we believe that it is a more adequate tool to make an investment decision. Finally, note that some authors use several profitability metrics such as NPV, IRR, payback period or discounted cash flows (e.g. Campoccia et al., 2014; De Boeck et al., 2016; Dusonchet and Telaretti, 2015; Dusonchet and Telaretti, 2010), but these studies aim more at comparing policy instruments in different countries than explaining the installation rates quantitatively.

Assumptions

In order to compute the IRR for each city, we need to make several assumptions concerning the characteristics of the PV systems. First of all, the efficiency of a solar panel decreases with age. In practice, solar panel manufacturers guarantee a minimum performance, usually 90% for the 10 first years, and 80% up to 25 years (Energy Informative, 2013). This is relatively consistent with an annual decrease of 1% (assumption H1), which yields 83% efficiency on the 20th year and 79% on the 25th. This assumption decreases the IRR by roughly 1 percentage point with respect to a constant efficiency.

In addition, we have to make assumptions concerning operation and maintenance (O&M) costs. Whereas panels are usually guaranteed for a certain duration (e.g. 25 years) and do not necessitate any particular maintenance, the inverter usually needs to be replaced every 8-10 years, with a cost varying between 0.3€/kW and 0.6€/kW, i.e. between 900€ and 1800€ for a 3-kW panel (photovoltaïque.info, 2018). For simplicity, we consider an additional cost of 1000€ after 10 years, but this only decreases the IRR by 0.3 percentage point. Furthermore, the producer has to pay the distribution network for managing its production contract and for the metering of the electricity production. These cost respectively 14.88€ and 19.8€ (plus VAT) in 2018 (photovoltaïque.info, 2018). The latter being very small, we neglect them for simplicity, and only consider the cost 1000€ after ten years (H2).

In France, FIT contracts for small-scale PV have a duration of 20 years. However, solar panels usually have a longer lifetime, so that their production becomes a substitute to the electricity sold by the retailer. The profitability of a panel which is no longer subsidised by FIT will depend on the future retail prices and cost of inverter (if it needs to be replaced). It will also depend on how synchronised production and consumption are. It may also be possible to sell the produced output on the wholesale market, for example via an aggregator. Given these uncertainties, we assume that the solar panels have no residual value at the end of the contract (H3). This probably underestimates their profitability, but only moderately as it concerns a potential benefit after 20 years.

Then, in order to compute the annual production q of a solar panel, we have to make additional hypotheses. Indeed, this output depends on several factors, such as solar irradiance, panel efficiency and orientation, temperature, etc. Solar irradiance (or irradiation) is the power per unit area which is received from the sun by a surface at a particular location. It can be given for example in kW/m^2 or in $\text{kWh}/\text{m}^2\cdot\text{year}$, depending on the use we make of it. Although the orientation of the panel changes its received irradiance, we do not have this information and thus we use irradiance data for horizontal panels (H4). This assumption may lead to an underestimation of the IRR, as panels are usually set on the “best” (i.e. south, if possible) side of an inclined roof, or face the optimal direction when on a horizontal roof. In some cases however it could lead to an overestimation of the IRR, if the orientation is constrained, or if the panel is partly shaded by trees.^t

We downloaded irradiance data from the Photovoltaic Geographical Information System (PVGIS) of the Joint Research Centre (JRC) the European Commission¹¹. It consists in the yearly sum of global irradiance (in $\text{kWh}/\text{m}^2\cdot\text{year}$) on a horizontal surface, averaged over ten years (1981-1990), with a grid cell size of 1000 meters, for all Europe. Using a Geographical Information System software, we managed to average this solar irradiation for each French municipality.

Knowing the irradiance, the efficiency characterises how much of the received energy is converted to electricity by the panel. For simplicity, we assume that panels have an efficiency of 15% (H5), which is a frequently encountered value (construction21.org, 2012; solarpanelsphotovoltaic.net, 2014). Another characteristic of the panel is its size. As a matter of fact, the power produced by a panel depends on the received irradiance, on its efficiency and on its area. The output is then just a product of these three variables. However, solar panels have a nominal power output (or nameplate capacity), sometimes given in kilowatt-peak (kWp), which corresponds to the maximum measured power output of the panel under some Standard Test Conditions (STC)¹². The ratio between the nominal and the real power output is the well-known capacity factor. The nameplate capacity is the information requested by the DSO to anyone asking to connect its panel to the grid, and so it is what we have in our data. To simplify the reasoning, we assume that the area of all solar panels is $10 \text{ m}^2/\text{kWp}$ (H6), which is also a common value (Engie, 2017).

Unfortunately, we do not have precise information on the characteristics of the installed panels, apart from their nameplate capacity. Hence, H4-H6 may lead to an under- or overestimation of the IRR, depending on the situation, so that their impact on the IRR is ambiguous. In any case, we think

¹¹Data available at http://re.jrc.ec.europa.eu/pvgis/download/solar_radiation_classic_laea_download.html

¹²STCs are usually defined by a particular irradiance, temperature, and light spectrum.

that our assumptions (summarised in table I.4 below) will not change the results dramatically, and that the heterogeneity of the IRR across municipalities will still be captured.

	H1	H2	H3	H4	H5	H6
Category	Efficiency loss	O&M costs	Residual value	Panel orientation	Initial efficiency	Panel area
Assumption	1% per year	1000€ 11 th year	none	horizontal	15%	10m ² /kWp

Table I.4 – Assumptions made for the computation of the IRR

Given assumptions H1-H6, we are able to compute an IRR per municipality and per quarter, with and without local subsidies. Although the values are not to be taken with certainty given these assumptions, we believe they are still quite reasonable. In any case, they are a good indicator of the heterogeneity of the profitability of a PV project, and we have discussed how they may influence the IRR. Table I.5 below presents some descriptive statistics of the computed IRR, with and without local subsidies. Although on average their impact may seem rather limited because they have not always been in place, figure I.6 illustrates their effect in the fourth quarter of 2010. We clearly see on these maps that local subsidies can strongly influence the IRR, which can become as high in northern regions as in southern ones.

Statistic	Mean	St. Dev.	Min	Q1	Median	Q3	Max
Without local subsidies	14.273	2.665	6.339	12.524	14.111	16.094	24.916
With local subsidies	14.725	2.560	6.362	12.893	14.493	16.489	24.925

Table I.5 – Descriptive statistics of the computed IRR

4.4 Cities characteristics

In order to control for the heterogeneity of the municipalities, we use publicly available data on socio-economic characteristics. These are available at an infra-municipal level called IRIS¹³, and are provided by the National Institute of Statistics and Economic Studies (INSEE - Institut national de la statistique et des études économiques). Unfortunately, this data is not available for the most recent years, so we will only use the 2013 data set to control for these characteristics. This will *de facto* prevent us from using individual fixed effects in our model, but with only 62,909 positive counts for 33,842 cities, the risk of overfitting the data with as many fixed effects would be relatively high. In the end, we believe that most of the heterogeneity can be captured by the chosen explanatory variables. The 2013 IRIS

¹³Îlots Regroupés pour l'Information Statistique, or "aggregated units for statistical information"

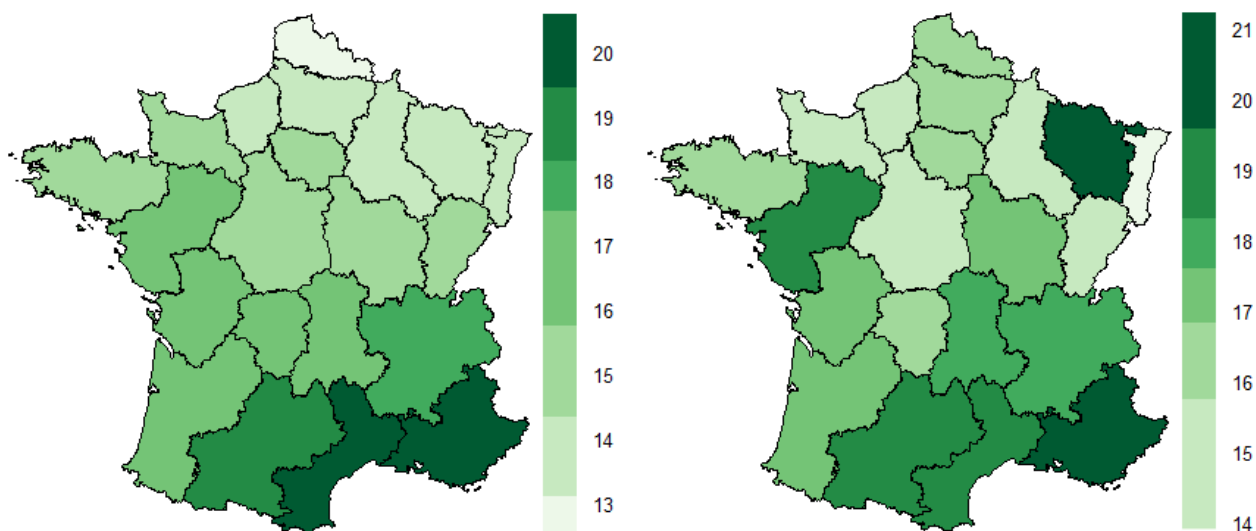


Figure I.6 – Left: average IRR without local subsidies for a project of less than 3 kW, Q4 2010. Right: average IRR with local subsidies for a project of less than 3 kW, Q4 2010.

data set consists of more than a hundred variables, but we will only need a few of them. Indeed, we have tested several specifications using several variables or combinations of them, but we are only going to present the ones that we finally kept in the model.

Ceteris paribus, the number of installations in a city should be proportional to the number of available sites, i.e. essentially the number houses and residential buildings roofs. Unfortunately, this data is not publicly available, but we can use proxies. To this end, we use the number of dwellings, which does not differentiate between apartments and houses and that can hence capture installations on houses and on buildings. To add another degree of control, we use the proportion of houses (the number of houses would be too collinear with the number of dwellings). We also tried using only the number of houses, but the fit was not as good.

Statistic	Mean	St. Dev.	Min	Median	Max
Number of dwellings	918	4,566	0	234	273,699
Number of primary residences	760	3,956	0	179	244,352
Proportion of primary residences	0.784	0.158	0.000	0.831	1.000
Number of houses	512	1,137	0	219	46,443
Proportion of houses	0.902	0.144	0.003	0.955	1.000

Table I.6 – Descriptive statistics of the control variables

Additionally, We use the proportion of primary residences, which we expect to have a positive effect for at least four reasons (that are debatable). First, we think that people are more likely to get more information about local subsidies where they live than where they go on vacation. Second, even though

self-consumption (or “prosumption”) is still little developed in France, some people might value the fact of consuming their own electricity, or at least electricity produced locally. As a consequence, it may make more sense for people to invest in a solar panel where they consume the most, i.e. their primary residence. Third, we could argue that people are more likely to invest in something that brings value to their principal residence rather than to a secondary one. Finally, we can expect people to want to be able to be present if there is a problem with the installation. Some descriptive statistics for these variables are shown in table I.6.

5 Modelling strategy

5.1 Diffusion

The original work of Bass (1969) models the diffusion of innovations by considering that purchases (or sales) S of a new durable good come from “innovators”, in fixed proportion p in the remaining market of size $m - Y$ (m is the market size and Y is the stock of cumulative sales), and from “imitators”, whose number is a fixed proportion q of the attained market share Y/m . In continuous time, the model then writes:

$$\forall t > 0 \quad S(t) = \text{Max} \left(0, p(m - Y(t)) + q \frac{Y(t)}{m} (m - Y(t)) = pm + (q - p)Y(t) - \frac{q}{m}[Y(t)]^2 \right) \quad (\text{I.2})$$

In discrete time, assuming $S > 0$ for the sake of simplicity, we obtain:

$$\forall t \in \mathbb{N} \setminus \{0\} \quad S_t = a + bY_{t-1} + cY_{t-1}^2 \quad (\text{I.3})$$

where it is possible to identify coefficients a , b and c to m , p and q :

$$m = \frac{-b \pm \sqrt{b^2 - 4ca}}{2c}, \quad p = \frac{a}{m}, \quad q = -mc \quad (\text{I.4})$$

In practice, b and c must be of opposite sign in order to have $m > 0$, and more precisely we expect to have $b > 0$ (epidemic effect) and $c < 0$ (stock effect): the influence of past sales is positive and decreasing with time. Equation I.3 has the advantage of being linear, while equation I.2 can be solved analytically and estimated by non-linear least squares. As we will use a non-linear model for which convergence can be difficult to achieve, we will add the Y_{t-1} and Y_{t-1}^2 terms of the linearised equation I.3 to our set of covariates and keep a linear combination of covariates.

Although the Bass (1969) model does not originally included additional covariates, we keep the assumption of “additivity” of the terms in the equation, in order to keep it linear. Such a modelling of RES diffusion has been done for example by Bollinger and Gillingham (2012) (only for the epidemic effect).

5.2 Model

As seen before, we are dealing with “zero-inflated” data, which requires the use of an appropriate model to take into account the non-negativity and the important proportion of zeros in the data. In our case, as almost all non-negative requests are for projects of 3 kW, it would be rather difficult to directly use demand as dependent variable, because its distribution is multimodal, with peaks at 3 kW, 6 kW, etc. For this reason, we prefer to model instead the number of connection requests as zero-inflated count data rather than demand as semi-continuous data. Furthermore, the observed zeros are “real” ones, i.e. are the result of a choice of non-installation, or of non-awareness of the technology (which is linked to the idea of diffusion and adoption of the technology). For this reason, we find it more realistic to model separately the number of zeros.

Hence, we use the “hurdle” model of Mullahy (1986), which consists in two parts: a discrete choice regression first models the proportion of zeros based on the distribution f_{zero} with covariates z ; the proportion of strictly positive values is then estimated using a truncated count model. The non-truncated density probability of the count model is f_{count} and depends on covariates x , which need not be the same as z . Hence, the number of installation requests in municipality i during quarter t , S_{it} , follows the following “hurdle” distribution:

$$f_{hurdle}(S_{it}|z_{it}, x_{it}) = \begin{cases} f_{zero}(0|z_{it}) & \text{if } S_{it} = 0 \\ (1 - f_{zero}(0|z_{it})) \frac{f_{count}(S_{it}|x_{it})}{1 - f_{count}(0|x_{it})} & \text{if } S_{it} > 0 \end{cases} \quad (\text{I.5})$$

We choose a logistic distribution for the first part of the model, and a negative binomial for the second part. The choice of a logit specification instead of e.g. a probit one is more consistent with the presence of heavy tails (recall that we have a large amount of zeros), and leads to more interpretable coefficients (logarithm of odds ratios). Furthermore, the results of a discrete choice regression are usually little affected by the choice of the distribution. The negative binomial distribution is on the other hand a common generalisation of the Poisson distribution which gives more flexibility as it allows the variance to be different from the mean.

Hence, we first assume that $S_{it} > 0$ with probability $p_{it} = \mathbb{P}[S_{it} > 0 | z_{it}]$ such that:

$$\text{logit}(p_{it}) = \ln\left(\frac{p_{it}}{1-p_{it}}\right) = z'_{it}\gamma \quad (\text{I.6})$$

and then that $f_{count}(S_{it}|x_{it}) \rightsquigarrow \text{NegBin}(\theta, \mu_{it})$, such that:

$$\begin{cases} f_{count}(S_{it}|x_{it}) = \frac{\Gamma(S_{it} + \theta)}{S_{it}!\Gamma(\theta)} \left(\frac{\theta}{\theta + \mu_{it}}\right)^\theta \left(\frac{\mu_{it}}{\theta + \mu_{it}}\right)^{S_{it}} \\ \ln(\mu_{it}) = x'_{it}\beta \end{cases} \quad (\text{I.7})$$

where Γ is the gamma function. Concerning the covariates, we used for both parts of the model:

- the IRR in the absence of local subsidies;
- ΔIRR , i.e. the difference between the IRR with and without local subsidies;
- the logarithm of the number of dwellings;
- the proportion of primary residences;
- the proportion of houses.

What should really drive the investment decision of a rational agent is the difference between the IRR and a reference rate of return, for example a risk-free one. However, this is captured by the constant. The use of both IRR and ΔIRR enables to disentangle the effect of national and local subsidies. The characteristics of the cities have been chosen in order to have the lowest information criterion.

For the logistic regression, we also added the diffusion variables Y_{t-1} and Y_{t-1}^2 , to take into account epidemic and stock effects. This is similar to El Zarwi et al. (2017), who use the cumulative number of adopters at the previous period and other explanatory variables to study the diffusion of new transportation services, using a discrete choice model. However their model differs from ours in that they use three latent classes, namely “imitators”, “innovators” and “non-adopters”, and use the cumulative number of adopters as a covariate only for the first class, which is consistent with the idea of contagion. Note that we did not use these variables in the count model, as the estimation produces *NA* coefficients for these variables.

The negative binomial distribution has the advantage of generalising the Poisson distribution for over-dispersed data, while keeping the same interpretation for the coefficients in case of a log link. Indeed, the conditional mean is then equal to the distribution parameter μ , whose logarithmic dependence with

respect to the covariates enables to interpret the coefficients as semi-elasticities (if the covariates are in level) or elasticities (if the covariates are in logarithmic form). Then, whereas the variance of the Poisson distribution is also equal to μ , it is equal to $\mu(1 + \mu/\theta) > \mu$ for the negative binomial distribution.

In our case, the non-truncated count data is over-dispersed (as it is usually the case with zero-inflated data), while the strictly positive count data is under-dispersed. Concerning the zero-truncated distributions, the Poisson distribution leads to under-dispersion while the negative binomial can give both under and over-dispersion, depending on the value of θ , which makes it more flexible and adapted to our case. Although the interpretation of the coefficients is not as straightforward as in the non-truncated case, we will show in the next section how we can still interpret them in our case.

Finally, the use of the logarithm of the number of housing units is justified by the fact that we would expect the number of installations to be rather proportional to the number of dwellings. In a non-truncated model with log link, this is called an exposure variable, whose logarithm is used as an offset, i.e. a covariate with coefficient (elasticity) equal to one. In a zero-truncated negative binomial model however, the expected count is not equal to μ anymore, so that the coefficient of the exposure variable should not be constrained to one.

6 Results and interpretation

Equations I.6 and I.7 are estimated for the whole sample using the R package **pscl** developed by Jackman (2017). We kept the model with the highest Akaike information criterion (AIC), but the results are robust when changing control variables for others (e.g. number of houses instead of number of dwellings).

6.1 Binomial model (hurdle part)

The estimation results of the hurdle part are presented in table I.7 below. We see that all coefficients are significant and have the expected sign. Although they cannot be interpreted directly, it is well known that in a logistic regression the exponential of a coefficient can be interpreted as an odds ratio:

$$e^{\gamma_j} = OR_j = \frac{\frac{\mathbb{P}[S > 0|x_j + 1]}{1 - \mathbb{P}[S > 0|x_j + 1]}}{\frac{\mathbb{P}[S > 0|x_j]}{1 - \mathbb{P}[S > 0|x_j]}} \quad (\text{I.8})$$

Hence, table I.8 shows the exponential of the coefficients (we have omitted the intercept). From this, we can determine that a one-point increase of the IRR (without local subsidies) increases the

odd of having at least one installation by 10%. The mean odds of installation would then increase from $6/94 \simeq 0.064$ on average to 0.070, i.e. there would be 93.5% of zeros instead of 94%. This is not negligible, as it represents an 8% increase of the probability of adoption. However, we see that the additional profitability due to local subsidies has a much more moderate (and slightly less significant) impact (seven times lower). This result show that the probability of adoption has been mainly driven by national subsidies, and less by local ones.

Furthermore, we observe epidemic and stock effects. In particular, at the first order (i.e. considering only Y_{t-1}) we find that an additional installation in the past periods increases the chance of adoption by 9.1%, which is almost the same impact as an additional point of IRR. This highlights the importance of word-of-mouth in the diffusion mechanism. Also, although residential solar panels are not widespread in France yet, we do find a stock effect, i.e. a decrease in the epidemic effect with the number of installations. This effect is very small and plays a minor role in the diffusion at this stage, but it is likely to become more important in the future. Finally, the proportions of primary residences and houses have a much stronger influence. However, recall that these are only control variables, on which public policies have little to no impact in the short run.

	Estimate	Std. Error	z value	p-value
(Intercept)	-12.0227	0.0706	-170.38	< 2e-16
IRR	0.0957	0.0018	53.90	< 2e-16
Δ IRR	0.0142	0.0046	3.04	0.0023
ln(Dwellings)	0.7320	0.0053	137.08	< 2e-16
Proportion of primary residences	1.7260	0.0355	48.65	< 2e-16
Proportion of houses	2.1164	0.0362	58.44	< 2e-16
Y_{t-1}	0.0874	0.0016	53.53	< 2e-16
Y_{t-1}^2	-0.0012	0.0000	-29.03	< 2e-16

Table I.7 – Estimation results of the hurdle part

IRR	Δ IRR	ln(Dwellings)	Prop. of prim. res.	Prop. of houses	Y_{t-1}	Y_{t-1}^2
1.100	1.014	2.079	5.618	8.301	1.091	0.9988

Table I.8 – Exponentiated coefficients of the hurdle part

Concerning the explanatory power of the covariates, we use the AIC as means of comparison. Table I.11 in appendix C shows the value of the AIC for several specifications of the binomial model. We see that the IRR improves the AIC almost as well as the diffusion variables. We can thereupon consider that their explanatory power is quite similar.

6.2 Count model

The estimation results of the count part are shown in table I.9 below. As for the logistic regression, all coefficients are highly significant (except for the IRR) and have the expected sign. Unfortunately, convergence could not be achieved using diffusion variables Y_{t-1} and Y_{t-1}^2 . However, as the main outcome is one, the first part of the model explains most of the adoptions, while the second part can be seen as a second-order refinement. Nevertheless the count model is expected to have an increasing explanatory power as the diffusion progresses, and to become influenced by the diffusion variables as well.

	Estimate	Std. Error	z value	p-value
(Intercept)	-10.63159	0.201990	-52.634	< 2e-16
IRR	0.005505	0.004524	1.217	0.224
Δ IRR	0.142033	0.009593	14.806	< 2e-16
ln(Dwellings)	0.803501	0.012278	65.442	< 2e-16
Proportion of primary residences	1.082461	0.091995	11.767	< 2e-16
Proportion of houses	2.143338	0.079656	26.908	< 2e-16
ln(θ)	-0.997328	0.117984	-8.453	< 2e-16

Table I.9 – Estimation results of the count part

For a standard Poisson or negative binomial regression with logarithmic link (i.e. $\ln(\mu_{it}) = x'_{it}\beta$), coefficients are semi-elasticities of the conditional mean (an increase of x_j by one unit leads to an increase of the dependent variable Y by $100 \times \beta_j$ percent):

$$\mathbb{E}[Y|X] = \lambda = e^{X'\beta} \Rightarrow \frac{1}{\mathbb{E}[Y|X]} \frac{\partial \mathbb{E}[Y|X]}{\partial x_j} = \beta_j \quad (\text{I.9})$$

Alternatively, exponential of coefficients have a multiplicative impact when there is a one-unit increase:

$$\mathbb{E}[Y|x_j + 1] = e^{\beta_j} \mathbb{E}[Y|x_j] \quad (\text{I.10})$$

At the difference of the non-truncated distribution, the zero-truncated negative binomial of parameters μ and θ have a mean equal to $\mathbb{E}[S|X, S > 0] \stackrel{\text{not.}}{=} \nu = \frac{\mu}{1 - (1 + \mu/\theta)^{-\theta}} > \mu$, so that the exponential of the coefficients cannot longer be interpreted as multiplicative incremental effects on the conditional mean. However, when $\mu \rightarrow 0$ i.e. when the main outcome is $S = 1$ (which is our case), we have:

$$\nu \underset{\mu \rightarrow 0}{\sim} 1 + \frac{\theta + 1}{2\theta} \mu \quad (\text{I.11})$$

This enables to compute the following partial derivatives:

$$\frac{1}{\nu - 1} \frac{\partial(\nu - 1)}{\partial x_j} \simeq \beta_j \quad (\text{I.12})$$

or alternatively:

$$(\mathbb{E}[S|x_j + 1, S > 0] - 1) \simeq e^{\beta_j} (\mathbb{E}[S|x_j, S > 0] - 1) \quad (\text{I.13})$$

Coefficients are hence semi-elasticities (or elasticities when covariates are in logarithmic form) for the conditional mean minus one. Although these is not as easily interpretable as a “real” (semi-)elasticities, they nevertheless help to compute the effect of a given variable, as we will see now. Exponentiated coefficients are even more easily interpretable because they act in a multiplicative way on the conditional mean minus one. In our case, the main strictly positive outcome is 1, and the expected number of strictly positive counts is 1.267. Thus, we are in the case described above and we can interpret exponentiated coefficients presented in table I.10 (we have removed the intercept).

IRR	Δ IRR	ln(Dwellings)	Prop. of prim. res.	Prop. of houses	θ
1.006	1.153	2.233	2.952	8.528	0.369

Table I.10 – Exponentiated coefficients of the zero-truncated count model

For example, starting from the mean (1.267), a one-point increase of the proportion of primary residences will drive the average strictly positive count up to $2.952 \times 0.267 + 1 = 1.788$ (+41%). More generally, as for the hurdle part, the impact of the control variables is much stronger. In particular, the coefficient associated with the number of dwellings is relatively close to one (this would indicate proportionality in the case of a non-truncated model, as explained in section 5). Then, whereas the IRR is non-significant, Δ IRR is highly significant and has a rather non-negligible impact on the number of adoptions. Indeed, a one-point increase leads to an average positive count of $1.153 \times 0.267 + 1 = 1.308$ (+3.2%). Interestingly, we observe an “inversion” of the roles of national and local subsidies with respect to the probability of adoption. In particular, it helps explain the very high adoption rates.

7 Conclusions

This paper has investigated the diffusion of domestic solar panels in France. Thanks to a novel modelling methodology, we are able to exhibit “epidemic” and “stock” effects down to the local (municipal) level, even though the data is highly disaggregated and presents a vast majority of zeros. Furthermore, we

manage to disentangle the effect of national feed-in tariffs (FIT) and local subsidies by computing an internal rate of return per quarter, for all 33,842 municipalities whose distribution network is managed by Enedis. We have shown that local subsidies can deeply influence the IRR, which has reached values in the north of France as high as in the south. However, their impact on the probability of installing a solar panel is much more limited compared to the effect of national FIT. Conversely, they have a stronger impact on the number of connection requests than the FIT, whose influence was found to be non-significant.

This, along with other evidence from the data, indicates that households act in a rather rational way. It is thus the combination of financial incentives and an intrinsic diffusion process that enabled the development of residential solar panels in France. In particular, we show that an additional past installation in a city has the same impact as a one-point increase of the IRR. This result calls for more information and “advertising” of RES projects, as it can help promote RES at a lower cost than direct public subsidies. This could be done for example by better informing people, but also by encouraging local ownership and funding of such projects (this is still underdeveloped in France, whereas it is much more common in Germany for example). Thence, our conclusions support the findings of other authors, who have pointed out the important role of neighbours and installers (Rai et al., 2016) as well as local organisations promoting PV and local utilities (Palm, 2016).

Future avenues of research could aim at analysing the spatial dependence in the diffusion of residential solar panels. Indeed, several authors have found positive spatial correlation (Müller and Rode, 2013; Balta-Ozkan et al., 2015) or spatial clustering (Bollinger and Gillingham, 2012) of PV deployment. Although these authors have highlighted the presence of local peer effects, they did not analyse stock effects or looked into local subsidies. To the best of our knowledge, no study analyses both diffusion and the impact of all applicable subsidies at a fine spatio-temporal scale. Nevertheless, we might need higher resolution data to be able to perform such an analysis, as in Müller and Rode (2013), who used building-level data in the city of Wiesbaden, Germany. Also, the French market might not be mature enough, with an insufficient number of installations.

Another continuation of this work could include forecasts based on our model, in order to compare the trajectories with national and regional targets. Such a study could also help answer the question of the end of subsidies, as policy makers would like RES to be competitive with other means of production as soon as possible. When a technology reaches the grid parity (i.e. a levelised cost of electricity - LCOE - equal to the retail price), it becomes interesting for a consumer to invest in order to consume

its own production. However, this behaviour might create cross-subsidies from “regular” consumers to “prosumers” through the variable energy-related component of the network tariff. In turn the latter tends to increase, in order to compensate for the incurred loss in revenue. This might lead to the so-called “death spiral”, i.e. disconnection of most consumers, due to very high network charges. Thus, the incorporation of retail electricity prices and network tariff in a diffusion model of “prosumption” could help forecast future revenues for the DSO, and hence design efficient tariffs and electricity pricing methodologies that enable the DSO to recover its costs while ensuring an efficient use of the network. This may also be done using for example system dynamics, which has proven to be adapted to describe the diffusion of RES (e.g. Bildik et al., 2015), but could still use our model as a valuable input. Finally, our methodology could also be used to describe the diffusion of other relatively new technologies, such as alternative-fuel vehicles or batteries, at a high spatio-temporal resolution.

Appendices

A Demand for 3-kW PV projects per region

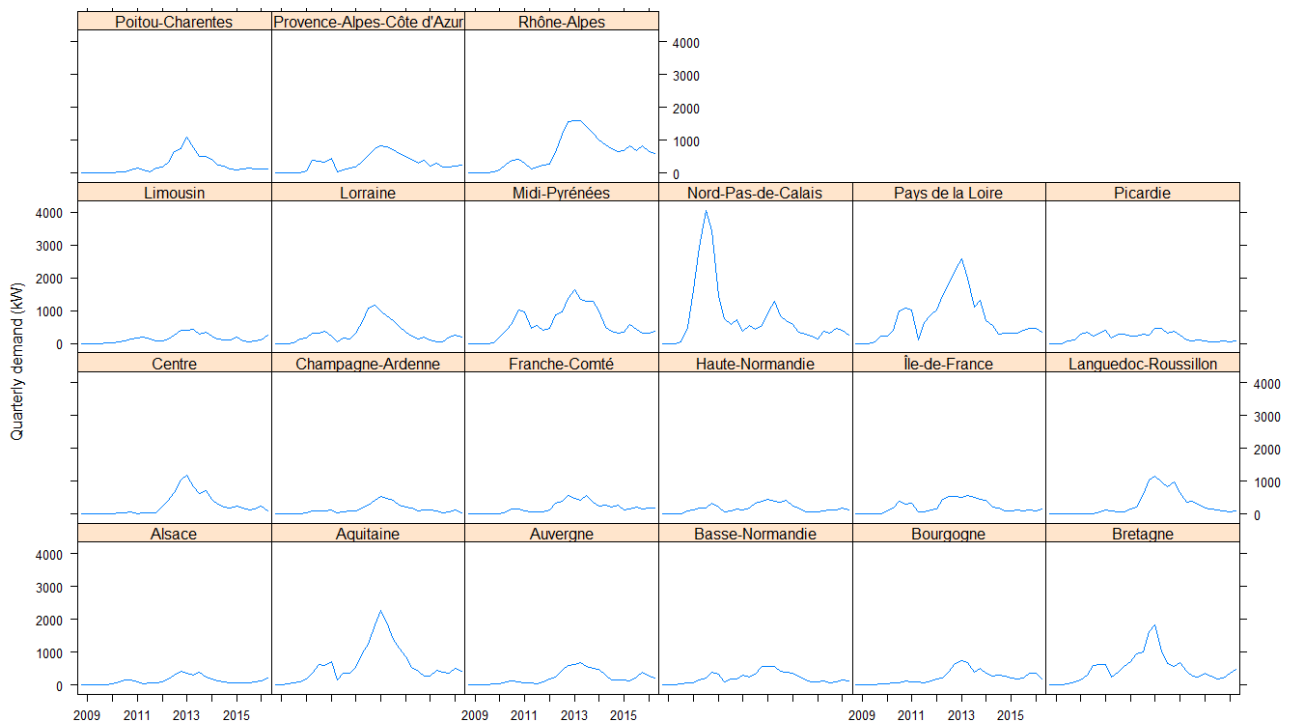


Figure I.7 – Quarterly demand for PV projects of less than 3 kW

B Cumulative demand for 3-kW PV projects per region

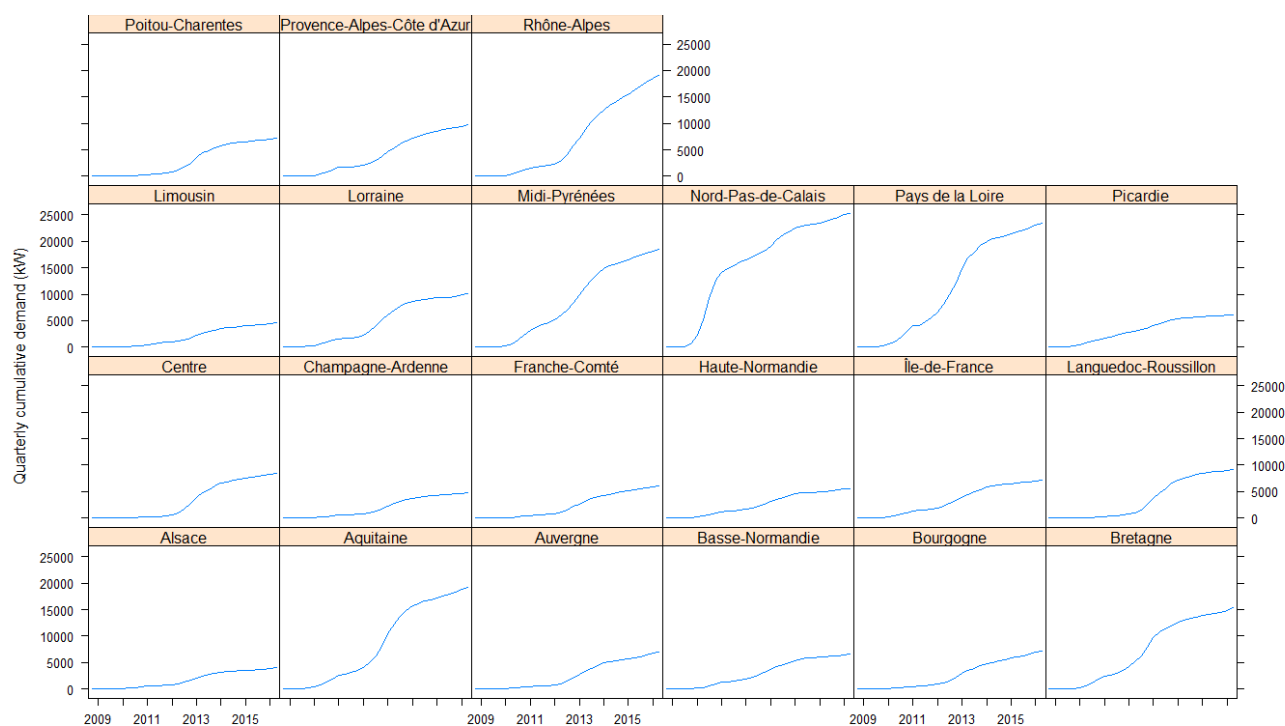


Figure I.8 – Quarterly cumulative demand for PV projects of less than 3 kW

C AIC of several binomial models

Constant Only	Control variables only	Diffusion and control variables	IRR and control variables	All variables
474,579	416,033	411,995	412,947	409,171

Table I.11 – AIC for several binomial model specifications

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Chapter II

Network connection schemes for renewable energy: a spatial analysis

About this chapter

This chapter was realised thanks to data provided by Enedis under a non-disclosure argument. I wish to thank Christophe Bonnery, François Dispot and Hervé Lextrait for allowing me access this data. I had the chance to present this work in September 2017 at the 15th European Conference of the International Association for Energy Economics (IAEE) in Vienna (Austria), and internally at IFPEN in December 2017 and at Enedis in January 2018. I wish to thank all participants of these seminars, and especially Richard Green for his review at the PhD day in Vienna.

Abstract

This paper aims at assessing the impact of regional network connection schemes for renewable energy sources (RES). These have been set in France in order to avoid “large” (i.e. > 100 kW) RES producers to pay deep-cost connection charges, that were seen as a brake on the development of renewable energy, and to give locational price signals. The schemes have been designed by transmission and distribution system operators and are based on regional targets of renewable capacity. These will require network reinforcements, the costs of which have been determined by network operators. Divided by the regional targets, they give a per-kW charge that varies between regions. Using a unique database of connection applications by wind producers to the main French DSO’s (Enedis) network, we develop a spatial panel model that captures the effect of this innovative regulation as well as spatial dependences of the variables. Thus, we show that the schemes have managed to redirect connection requests towards less constrained regions without altering the global level of connections, and that spatial substitution occurred between regions. On average, an increase of the network charge of €/kW in a region reduces quarterly connection requests by 300 kW in the region while increasing them by 138 kW in the neighbouring ones. Finally, we show that the diffusion of wind energy exhibits an “epidemic” effect, i.e. there is a positive impact of the number of past installations on the number of connection requests.

1 Introduction

Following the third European energy package, the 2020 “20-20-20” objectives¹ were transposed into French law in August 2009, setting i.a. a target of 23% of renewable energy sources (RES) in the final energy consumption in 2020². This law was completed in July 2010 and an obligation was made for each region to work out a scheme for climate, air and energy (SRCAE³), setting regional targets for RES for 2020⁴. Along with these schemes, the transmission and distribution system operators (the TSO - RTE, and DSOs such as Enedis, the DSO for 95% of the population) also had to design a network connection scheme for renewable energy sources for each region. These are named S3REnR or SRRER⁵.

The idea behind this planning tool is to make RES producers share network reinforcement charges, instead of applying the so-called “deep cost” methodology which otherwise prevails in France for electricity production units. This approach charges all network reinforcement costs to the first producer that triggers the reinforcement in question. The resulting uncertainty was considered a barrier to investments in renewable energy projects, which are usually decentralised. They are therefore relatively small compared to centralised units, for which such additional charges weigh less in the total installation cost. On the contrary, RES developers may not afford important network reinforcement charges, so it was decided that they would instead share these costs. Each plant with capacity higher than 100 kW would thus be charged proportionally to its capacity. Note that renewable producers with capacity lower than 100 kW do not pay reinforcement charges at all, and it was even decided that the smallest ones would have their connection subsidised up to 40%. Moreover, regionally differentiated network connection charges were expected to give a locational price signal to RES producers, and hence lead to a more efficient use of the existing network. Higher charges actually mean more network constraints, which should make additional renewable energy production less desirable.

Following the publication of the SRCAE schemes, S3REnRs have been designed by RTE and the DSOs, based on the 2020 targets. In order to meet these targets, they identified a potential RES capacity per electrical substation and computed the associated reinforcement costs. Furthermore, each substation has some capacity (which can be zero) reserved for RES projects, that can be publicly monitored on a dedicated website⁶. When all reserved capacities have been allocated, the scheme is said to be saturated,

¹Reduction of 20% of greenhouse gas emissions with respect to 1990, 20% of renewable energy in final energy consumption, and a 20% increase in energy efficiency.

²LOI n° 2009-967 du 3 août 2009 de programmation relative à la mise en œuvre du Grenelle de l’environnement (2009)

³In French: Schémas Régionaux Climat, Air, Énergie, i.e. literally: regional schemes for climate, air and energy.

⁴LOI n° 2010-788 du 12 juillet 2010 portant engagement national pour l’environnement (2010)

⁵In French: Schémas Régionaux de Raccordement au Réseau des Énergies Renouvelables, i.e. literally: regional network connection schemes for renewable energy sources.

⁶<https://capareseau.fr/>

and another scheme is to be designed and published, with new reserved capacities and associated network charges. However, nothing is planned in case the target is not met. This issue, among others, has led to some criticisms towards S3REnRs⁷. Thus, the goal of this paper is to assess its efficacy, i.e. whether it provides efficient locational price signals and enhances the development of renewable energy (through the reduction of the uncertainty about network connection charges). Our analysis reveals that this is indeed the case for wind energy, which we have chosen as it is the second RES technology in France (after hydroelectricity). It is also the leading technology being developed, along with solar photovoltaics (PV). The latter is however more difficult to analyse, because of multiple support schemes depending in particular on capacity thresholds and types of installation.

In order to do so, we develop a spatial panel model, whose dependent variable is the number of connection requests of wind farms of more than 100 kW. The model takes into account the spatial autocorrelation of both the dependent and independent variables such as the network connection charge. Since we are dealing with regionally differentiated schemes, we expect RES developers to choose a production site not only based on its production potential (i.e. wind speeds), but also on the value of the network charge. Hence, if a site with a strong potential is located on two or more neighbouring regions, installation is more likely to occur in the “cheapest” one. In other words, we can think of neighbouring regions as substitutes for one another. This is confirmed by our results, as they reveal the existence of negative and significant spatial autocorrelation. This contrasts with previous spatial analyses of RES, that have mainly focused on solar PV, but on a much smaller scale (municipalities or even streets in a city). In these studies, a positive spatial autocorrelation (i.e. a positive influence from the vicinity) was found, which was interpreted as peer effects (see for example Dharshing, 2017 for an application to German counties and a review of the literature on PV). Using a unique data set of connection requests provided by Enedis, which we aggregate into 1154 observations of 21 regions over 74 quarters, we show that on average, an increase of the network charge of 1 €/kW in a region reduces quarterly connection requests by 300 kW in the concerned region while increasing them by 138 kW in the neighbouring ones.

Furthermore, the development of wind energy, like other RES, is expected to exhibit an intrinsic diffusion process, as originally described by Bass (1969) for durable goods. Thus, we take into account this characteristic, adding an “epidemic” term to the equation. We show that past installations have had a positive and significant impact on the diffusion of wind energy, which is in line with most of the

⁷See for instance the early criticisms of the French Energy Regulator (in French): <http://www.cre.fr/documents/deliberations/avis/energies-renouvelables/consulter-la-deliberation>.

literature on renewable energy. However, we do not observe a “stock” effect yet, which shows that the growth is still on the increase.

Finally, we take into account residual autocorrelation, which is on the contrary found to be positive. This highlights the existence of spatially correlated unobservable variables. These could be wind speeds, as they are positively correlated and undoubtedly have an influence on the choice of location of a wind farm. The remainder of the paper is then organised as follows: section 2 provides a review of the literature, and section 3 presents the data used in our analysis. The spatial panel model is then detailed in section 4, followed by the presentation and discussion of the results in section 5. Section 6 concludes the paper.

2 Literature review

Our article is based on several strands of the literature on RES. The first one is quite general and deals with network regulation and its impact on RES development and spatial location; the second is based on the literature on diffusion, which has widely been applied to RES; the third one studies spatial interactions in RES development.

First of all, few authors have studied the impact of network regulatory rules on the development and spatial location of distributed RES. In a rather qualitative fashion, Anaya and Pollitt (2015) analyse regulation and trends in Germany, Denmark and Sweden, focusing on network access and connection charges as well as support mechanisms. They conclude that early support of RES, as in Germany, is a key driver of their adoption. They also compare connection mechanisms and conclude that the “deep cost” methodology is likely to have a negative impact on the development of RES compared to a “shallow cost” one (in which no reinforcement charges are paid), especially in the case of very high connection charges. Previously, Lopes et al. (2007) and Klessmann et al. (2008) had already briefly identified the role of “deep”, “shallow”, and “shallowish”⁸ network connection charges. On a slightly different subject, Brandstätt et al. (2011) compare the effectiveness of locational energy pricing, locational network pricing, and “smart contracts” in reducing network investments in smart distribution grids. We trust that our research will contribute to this literature by presenting the rather unique French S3REnR network connection schemes and providing quantitative impacts of these schemes.

Secondly, in order to isolate the effect of the S3REnR regulation on wind energy development, it is essential to control for the diffusion process followed by this somewhat new technology. Indeed, several

⁸Under such charges, only some reinforcement costs are borne by the producer. The French S3REnR schemes could come under this terminology.

studies have modelled the deployment of electric renewables as following an “S-curve”, in the line of the seminal work of Griliches (1957), such as Schilling and Esmundo (2009) for solar photovoltaics. Others have used diffusion models *à la* Bass (1969), mostly to assess the impact of subsidies and/or peer (social) effects on the development of solar photovoltaics (e.g. Bollinger and Gillingham, 2012; Richter, 2013). In the case of wind energy, Liu and Wei (2016) found that the development of wind power in China has been driven by financial incentives as well as by epidemic effects, using a linear regression equation from a logistic growth function. They follow Benthem et al. (2008), who had previously addressed the subject of subsidies for solar photovoltaics in California in the presence of learning-by-doing. More recently, Baudry and Bonnet (2018) used a micro-founded diffusion model to analyse the effectiveness of demand-pull policies on wind energy development in several European countries.

Ultimately, since we are dealing with geographical data, spatial dependence is also likely to occur and hence bias the estimators if not taken into account (Elhorst, 2014). Consequently, several authors have highlighted the existence of spatial dependence, either when modelling the diffusion processes of RES or when studying their determinants of adoption. For instance, Balta-Ozkan et al. (2015) analyse the deployment of solar PV in the UK using a cross-section spatial econometrics approach, and find that there are significant regional spillover effects. Spatial panel models have also been used, for example by Graziano and Gillingham (2015), who show that adoptions of residential PV in Connecticut (US) have also been driven by neighbouring installations (peer effects), while Müller and Rode (2013) previously presented similar evidence in the city of Wiesbaden (Germany) using a spatial panel logit model. More recently, Dharshing (2017) performed a spatial panel econometrics study on the dynamics of adoption of residential solar panels in Germany. In all these studies, spatial spillovers are positive and are then interpreted as peer effects at the local level. To the best of our knowledge however, no one has investigated the presence of spatial dependence in the case of wind power yet. Wind power being usually much more capital intensive than small-scale PV, there are fewer projects than PV ones. As a consequence, higher spatial aggregation is required, so that positive spillovers are likely to be “diluted” and hence be absent at this scale. On the contrary, we will show that spatial autocorrelation is negative as a result of substitution in the choice of a location, but that there exist positive residual autocorrelation. Our model thus constitutes a rare example among spatial econometric models, whilst keeping an intuitive interpretation⁹.

⁹As noted by Anselin and Bera (1998): “Of the two types of spatial autocorrelation, positive autocorrelation is by far the more intuitive. Negative spatial autocorrelation implies a checkerboard pattern of values and does not always have a meaningful substantive interpretation”.

3 Data

In order to perform our analysis, we use publicly available dates of enforcement and shares of connection charges for all 21 regional schemes, as well as connection requests data provided by Enedis for wind farms with a capacity higher than 36 kW, from January 1998 to June 2016.

3.1 Network connection charges

On the one hand, we used publicly available data on S3REnRs. The documents relative to these network connection schemes are published on the RTE's website¹⁰. The corresponding documents contain a lot of information: a description of the regional network and its evolution, how the scheme was prepared and realised, which reinforcements have been selected and how much they cost, how much reserved capacity¹¹ there is per substation, etc. They are published along with other documents, such as public consultation reports, technical and financial status, transfer¹² or saturation¹³ notifications. All this information can be very useful to RES project developers in particular. For the purpose of our study however, we are only interested in the date of enforcement of the scheme, and the related network charge, in €/kW, and their possible changes (only one region - Champagne-Ardenne, has been concerned with a change so far, as a saturation was anticipated¹⁴).

Figure II.1 below shows the variation of the network charge per region, and table II.1 presents some descriptive statistics. We have used the first value of the charge in Champagne-Ardenne, which rose from 49.26 to 53.17€/kW at the end of 2015. From these can be seen that network charges are rather heterogeneous, although six regions (out of twenty-one) have a charge almost equal to 10€/kW, and eleven have a charge "concentrated" between 9€/kW and 20€/kW only. The aforementioned features appear clearly on the whole data set (II.7) or the histogram (figure II.9) in appendix A. Nevertheless, eight values are relatively spread between 20 and 70€/kW.

In addition, these charges can be compared with the other driving costs of a wind farm project. As an indication, CRE (2014) and SER (2014) give a cost magnitude of about 1000€/kW for wind turbines,

¹⁰<https://www.rte-france.com/fr/article/les-schemas-regionaux-de-raccordement-au-reseau-des-energies-renouvelables-des-outils> (in French).

¹¹The schemes are based on a regional target for RES capacity, which is then subdivided in "reserved capacities" for each substation, that cannot be used for non-RES projects.

¹²Reserved capacity at a substation can be "transferred" to another substation within the same scheme, provided the global capacity and the network charge remain unchanged. This allows some flexibility in the scheme, if all substations are not used as originally planned.

¹³When all reserved capacity has been allocated to RES projects, the scheme is said to be saturated, and a new scheme is to be designed and published. Until then, the network charge remains unchanged. So far only two regions - Picardie and Nord-Pas-de-Calais, have their scheme saturated, but no revision has been published yet.

¹⁴See the new scheme (RTE, 2015).

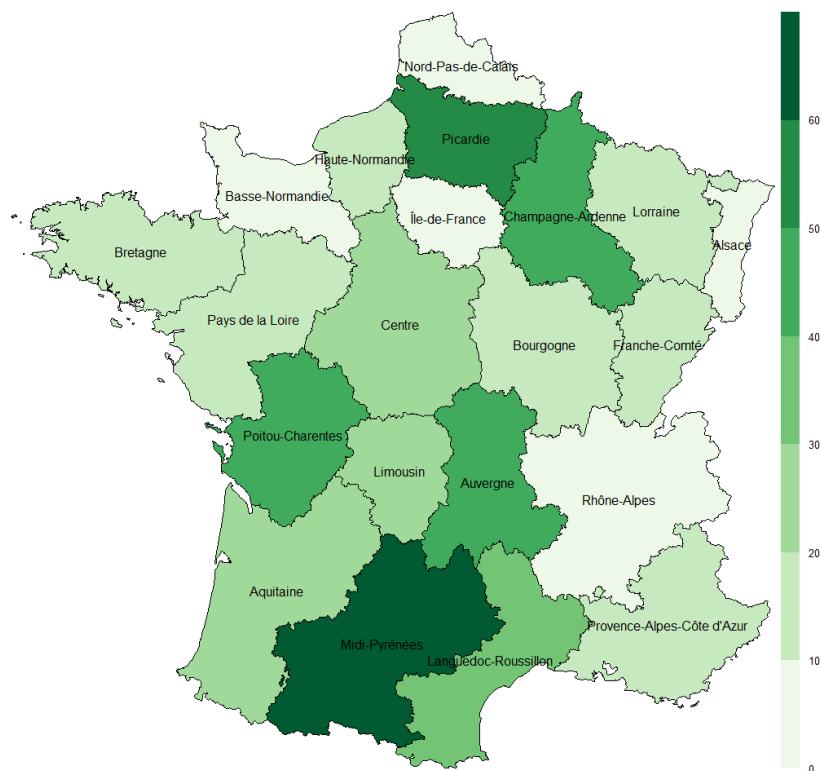


Figure II.1 – Network reinforcement charges per region (€/kW), before revision.

Min	Q1	Med.	Mean	Q3	Max	S.D.
0	10.11	18.21	23.72	35.63	69.90	19.40

Table II.1 – Descriptive statistics of regional network reinforcement charges (€/kW), before revision

which represent roughly 75% of total costs. Although the network reinforcement charges are very small compared to the cost of the turbine, we need to remember that wind farms have been subsidised thanks to feed-in tariffs, which have now been replaced by feed-in premiums. These subsidies aim at giving an “adequate” return on investment to project developers. As a result, they take into account the capital and operating costs, but not the regional charges, or at least not on a per-region basis. Consequently, we can still expect these to have an impact on the location choice of wind farms.

Dates of enforcement are also quite heterogeneous in time, and it took more than three years to have all schemes come into effect. In order to have enough data per period, we chose to aggregate it at the quarterly time step. This keeps the heterogeneity of dates of enforcement, as at most four schemes came into force during the same quarter (Q4 2012). As they have not particularly been enforced at the beginning or end of a quarter, we consider that the share of reinforcement costs was still equal to zero during the quarter of implementation, and we control this simplification by adding a dummy variable for the quarter in question. This dummy is also a measure of the effectiveness of the scheme. In particular,

we expect it to have a lower coefficient than the post-enforcement dummy, since it captures the effect of the reform for less than a quarter.

3.2 Network connection requests

On the other hand, we used data provided by Enedis, the distribution system operator (DSO) for 95% of French customers. More precisely, we have information on the date at which they entered the “waiting list”, which makes them eligible for the applicable feed-in tariff and liable for the network charge. We also have details on their location (city) and capacity.

After a request is addressed to the network operator, it has three months to send back a technical and financial proposition, which is then valid for three months. When the proposition is accepted, the project enters the waiting list, for which it stays on average for 782 days. However, about 35% of projects are abandoned and withdrawn from the waiting list without being connected, in which case the mean stay in the waiting list is still of 427 days. If on the contrary the connection is completed, it is of 1010 days, and the longest connection project took 4409 days (12 years).

Thus, due to the long delay between the connection request and the actual connection or the abandonment of the project, it is impossible to study the number of requests that effectively led to a connection without removing a large part of the sample. Even doing so, we would remove projects that may have led to a connection in the future. We have thereupon decided to focus on connection requests, which nonetheless give a good proxy of the future number of wind farms (one could still assume a constant rate of abandonment). They are also responsible for the lengthening of the waiting list and hence for the possible saturation of the schemes and the triggering of network reinforcements.

This data is quite relevant for the analysis of the regional schemes, since up to mid-2016 (which is when our data set finishes) 89% of wind capacity has been connected to Enedis’ network, and 71% of the wind-energy waiting list is on Enedis’ network as well. It increases mainly on its network too (RTE et al., 2016). This can be explained by the fact that the capacity limit between the distribution and the transmission networks is equal to 12 MW for production units, with a possible extension up to 17 MW, while the average size of a wind farm was 15.3 MW in 2016 (France Énergie Éolienne, 2017). Furthermore, bigger wind farms tend to ask for several connections to the distribution network rather than one connection to the transmission network. This can be seen by looking at the number of connection requests that occur the same day in the same city. Indeed, we have 20.3% of “multiple connections”, which are mostly “double connections” (16.6%). The comparison of statistics in table II.2

and II.3 below also highlights this fact. However, aggregated request can only be used as a proxy for the study of multiple connections, since some wind farms are connected to substations in different cities, and sometimes at different dates. This probably leads to an underestimation of this phenomenon. On the contrary, there could be several connection requests in the same city at the same date for distinct projects, but this seems very unlikely. A more rigorous analysis would require a long and thorough examination of the data set and would be beyond the scope of this study.

Unfortunately, we do not have connection requests data from RTE, nor from the other small DSOs (approximately 5% of DSOs' customers). However, the number of connections on RTE's network is rather limited, and the use of regional fixed effects should control for the presence of some relatively large DSOs in some regions. Moreover, we have 78 out of 2388 connection requests for which we do not have the location. This accounts for 3.4% of the data in terms of number of observations as well as connection capacity.

Single requests	12000	10000	8000	11500	6000	9200	4000	9000	6900	2000
N	410	285	143	124	77	72	59	49	47	38
Aggregated requests	12000	10000	8000	11500	6000	4000	16000	13800	24000	9200
N	255	171	101	77	61	40	37	34	32	30

Table II.2 – Ten most frequent capacities for single and aggregated (city-day) connection requests (kW)

	N	Min	Q1	Median	Q3	Max	Mean	Std. dev.
Single requests	2308	106	7500	10000	12000	17000	9225	3564
Aggregated requests	1837	106	8000	11000	13800	99750	11590	7561

Table II.3 – Descriptive statistics for single and aggregated (city-day) connection requests (kW)

Since we use connection requests for wind projects of more than 100 kW, i.e. those concerned by the network charge, there could be some “down-sizing” behaviour for wind projects just above 100 kW to avoid paying the network charge. However, projects under 100 kW represent only 0.002% of total capacities (and 0.75% of the number of connection requests), and are therefore negligible. This is confirmed by the non-truncated histogram of connection requests capacities in figure II.2, which also highlights the 12 MW and 17 MW limits¹⁵. The histogram also reveals the fact that most wind farms probably rely on 2 MW-turbines, which is also confirmed by table II.2, as most frequent connection requests are multiples of 2 MW.

Figure II.3 displays the temporal evolution of quarterly demand for wind projects of more than 100 kW on Enedis' network. It is clear from this graph that the dynamic is very different from one

¹⁵We have removed two “outliers” at 152.300 MW and 64.580 MW, which correspond to abandoned wind farm projects. It is not clear why such big projects were in the DSO's register instead of the TSO's one.

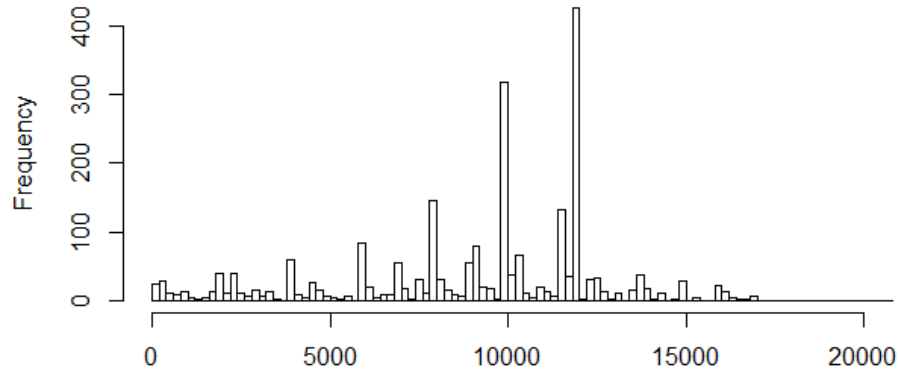


Figure II.2 – Histogram of connection requests capacities (kW)

region to another, as some regions have no wind farm at all (Aquitaine) or almost none (e.g. Alsace and Provence-Alpes-Côte d’Azur). On the contrary, Picardie and Champagne-Ardenne (and to a lesser extent Nord-Pas-de-Calais) are the most advanced regions in terms of installed wind capacity, as can be seen on figure II.6 and II.5 in the next subsection. This explains why the scheme in Picardie is already saturated and the ones in Champagne-Ardenne and Nord-Pas-de-Calais have been revised.

Figure II.4 helps visualise the actual heterogeneity between regions, as it displays the quarterly mean demand for wind farms with a 95% confidence interval. We see that the confidence interval can be up to twice as large as the mean, which is the sign of a very strong inter-regional dispersion.

3.3 Installed base

Following the work of Bass (1969), we will use the installed base, i.e. the cumulative connected capacity in a given quarter, as an indicator of diffusion. Indeed, the development of wind energy is expected to follow an intrinsic diffusion process, which needs to be controlled for. However, it would not be relevant to compute the installed base from cumulative demands as is usually the case, for the reasons we have just mentioned (delays and abandonment of projects). Furthermore, as pointed out by Narayanan and Nair (2013), the use of the cumulative stock of the dependent variable in a panel regression gives biased and inconsistent estimators because it introduces a covariate which is serially correlated with the dependent variable. They advocate the use of an instrumental variable, which can be very difficult to find, or a bias-correction approach, which requires no error autocorrelation.

Noting this issue, Bollinger and Gillingham (2012) show in the case of solar panels that if the lag between the adoption decision and the installation is sufficiently large (with respect to the order of autocorrelation of errors), then the estimators are consistent and unbiased. This is particularly suitable

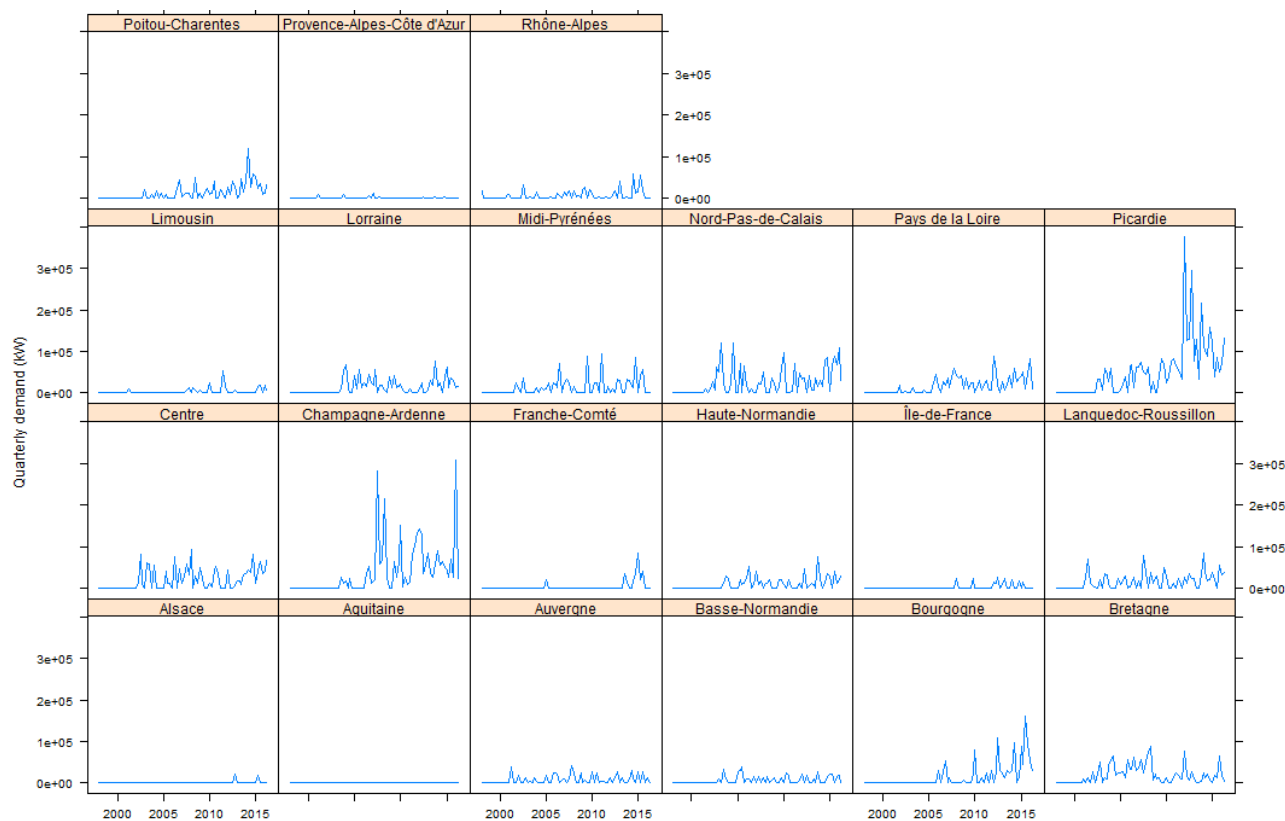


Figure II.3 – Quarterly demand for wind projects of more than 100 kW

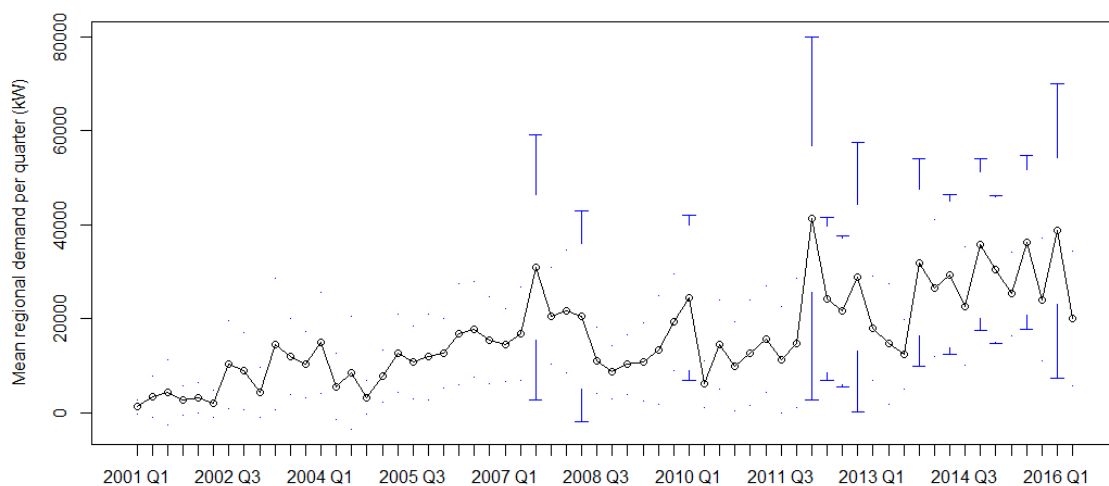


Figure II.4 – Heterogeneity of connection requests between regions

for our study, because of the very long delay between the request and the actual connection. Figure II.5 and II.6 below display the evolution of the installed base per region and their geographical distribution at the end of June 2016. It can be noted that it is highly heterogeneous, which is a direct consequence of the heterogeneity of connection requests. Also, figure II.5 shows that most diffusion curves do not have the shape of an S yet, so that we can consider the technology to still be at a fairly early stage. In particular, this excludes the use of the squared installed base as a diffusion variable, which usually aims at capturing the “stock” effect, i.e. the saturation of the market.



Figure II.5 – Installed based per region

4 Modelling strategy

Assessing the impact of the S3REnR charge on wind energy deployment requires to consider the data set as a panel, despite the strong observed heterogeneity between regions. Indeed, independent regressions could not give us an estimate of this effect. At best we could get an average value of the impact of the scheme per region, for example using a difference-in-differences approach. However, this would ignore the intensity of the reinforcement charge, which can vary widely across regions. Ergo, we develop a panel data model with region and time fixed effects in order to capture as much heterogeneity as possible. The data being geographical, we also take spatial interactions into account, as explained in the following subsection.

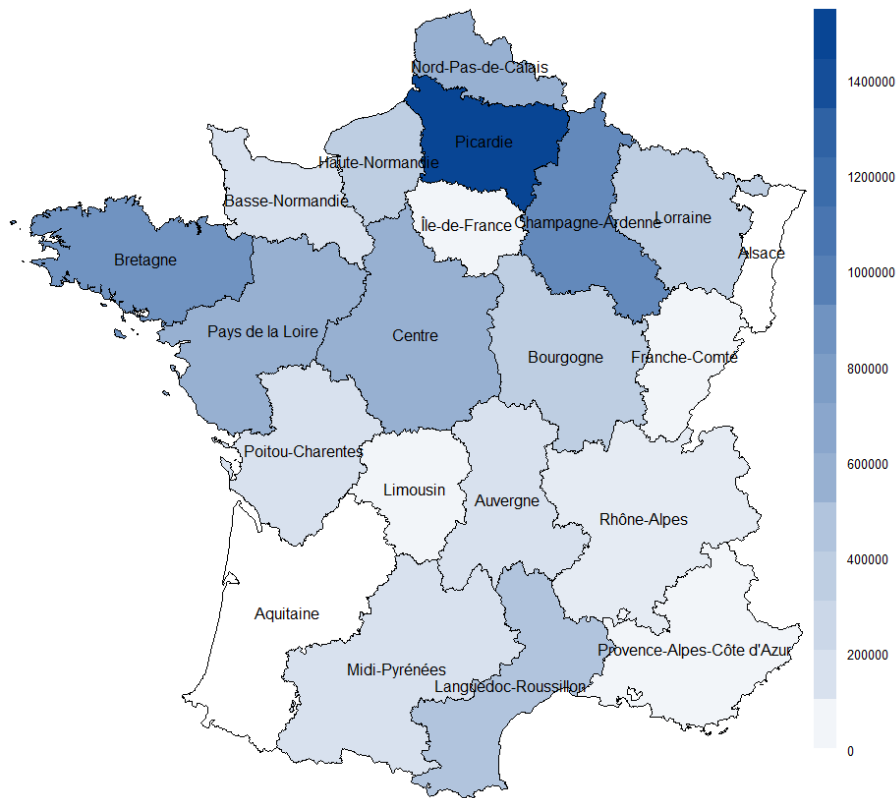
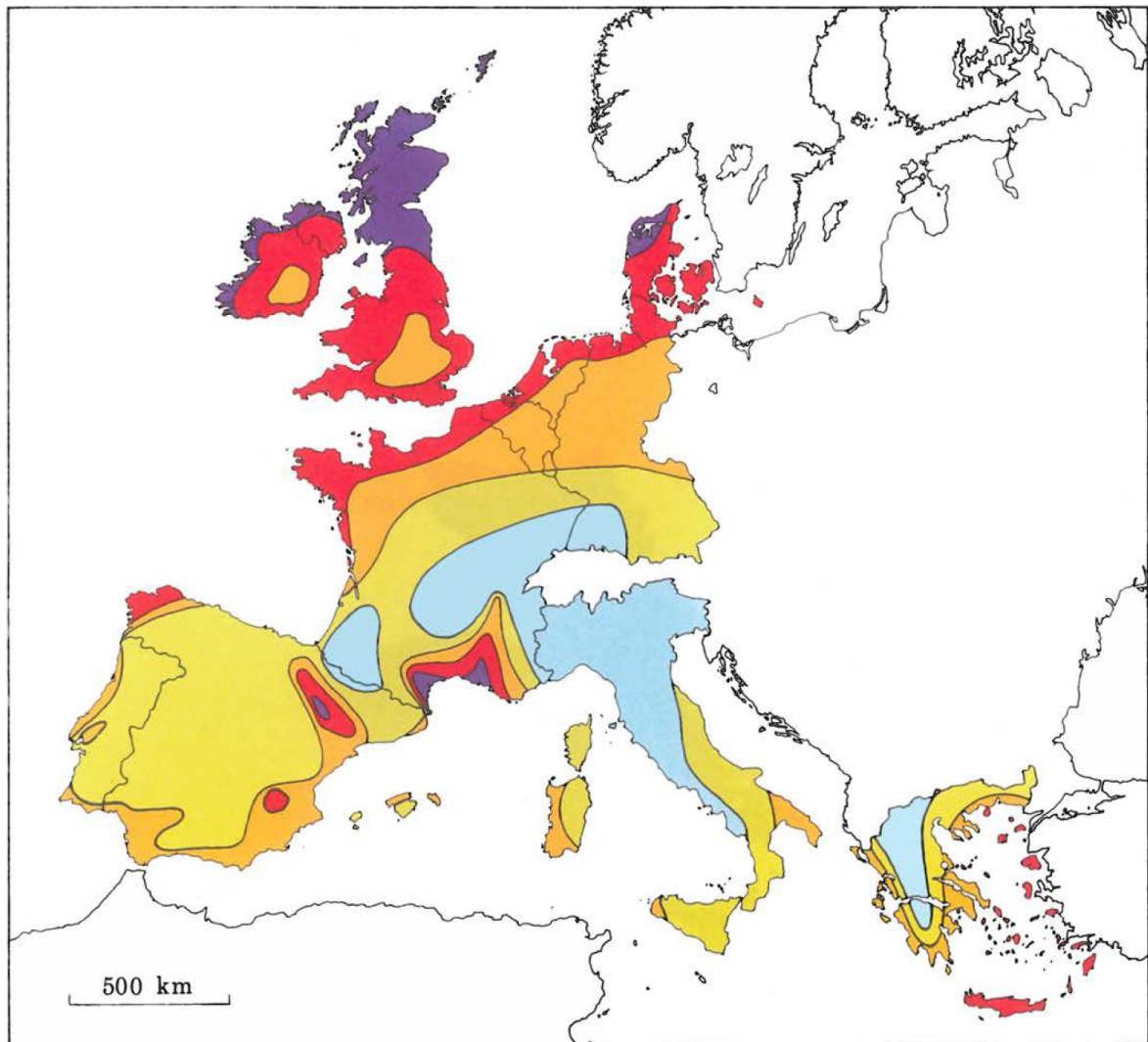


Figure II.6 – Regional cumulative wind capacities (kW) connected to Enedis' network, mid-2016

4.1 Spatial interactions

Since we are dealing with geographical data, it is necessary to investigate possible spatial autocorrelation of the variables in order to avoid having biased and inconsistent estimators. In particular, spatial interaction can be present in the three following forms. First of all, it can be endogenous, when the outcome in a region impacts the outcome in a neighbouring one, for example as a consequence of peer effects or substitution, as described in section 1. Spatial interaction may also be exogenous, when it comes from the covariates, i.e. if a variable change in a region has an effect in the neighbouring ones. This could be the case for network connection charges. Thirdly, there can be a residual spatial interaction, when spatially correlated unobservable variables affect the dependent variable. For instance, wind speeds are expected to be a rather influential factor in the location choice of a wind farm, and they are spatially autocorrelated (positively), as can be seen from figure II.7. In France, winds are strongest on the Channel and Atlantic coasts, as well as on the Mediterranean coast. Wind corridors such as the Rhône valley in the southeast also exist. Although wind is not unobservable strictly speaking, it is difficult to integrate it as an explanatory variable for several reasons. Firstly, there is no simple relationship between wind speeds and wind energy potential. It is in general nonlinear and dependent

on the technology used. Secondly, even if this relationship was known, wind speeds (and hence potential output) can vary within a single region. In this case, a unique indicator will not capture the diversity of wind regimes within a same region. For example, one could use the maximum, mean or median value, or other statistic, but there is no obvious choice. Finally, the use of a single-valued (i.e. non-panel) covariate per region would prevent us from using individual fixed effects, that provide the means to capture other unobservable variables as well.



Wind resources ¹ at 50 metres above ground level for five different topographic conditions										
	Sheltered terrain ²		Open plain ³		At a sea coast ⁴		Open sea ⁵		Hills and ridges ⁶	
	ms ⁻¹	Wm ⁻²	ms ⁻¹	Wm ⁻²	ms ⁻¹	Wm ⁻²	ms ⁻¹	Wm ⁻²	ms ⁻¹	Wm ⁻²
	> 6.0	> 250	> 7.5	> 500	> 8.5	> 700	> 9.0	> 800	> 11.5	> 1800
	5.0-6.0	150-250	6.5-7.5	300-500	7.0-8.5	400-700	8.0-9.0	600-800	10.0-11.5	1200-1800
	4.5-5.0	100-150	5.5-6.5	200-300	6.0-7.0	250-400	7.0-8.0	400-600	8.5-10.0	700-1200
	3.5-4.5	50-100	4.5-5.5	100-200	5.0-6.0	150-250	5.5-7.0	200-400	7.0-8.5	400-700
	< 3.5	< 50	< 4.5	< 100	< 5.0	< 150	< 5.5	< 200	< 7.0	< 400

Figure II.7 – Wind speeds in Europe. Source: Troen and Lundtang Petersen (1989).

4.2 Spatial panel model

In order to take spatial interactions into account, one needs to define a vicinity relationship between the $N = 21$ regions under study. In spatial econometrics, the relationship takes the form of a $N \times N$ symmetric matrix W , whose coefficients w_{ij} (weights) describe the vicinity relationship between regions i and j , and are usually distance or contiguity-based. Distance-based coefficients can be useful for instance in “gravity-like” models and have the advantage of being parameterised in relatively “simple” spatial models. In our case, we find it more relevant to use a contiguity-based matrix, as is often the case in spatial econometrics. In particular, we use a first-order contiguity-based matrix, whose weights w_{ij} are equal to 1 if regions i and j are considered as neighbours, and 0 otherwise¹⁶. More precisely, we use a rook-style weight matrix, where regions that share a common edge are considered as neighbours¹⁷, as represented by the graph in figure II.8. This choice is frequent in spatial econometrics, and quite natural for our study, since we are interested in possible substitution between neighbouring regions. Indeed, the potential location of a wind farm is not likely to extend over non-contiguous regions, as exploration of potential sites can be relatively costly for wind energy companies.



Figure II.8 – Graph of rook neighbours

As a consequence of all possible spatial interactions described in the previous subsection, we choose to model connection requests capacity using the following general nesting spatial (GNS) panel model

¹⁶ $w_{ii} = 0$, i.e. a region is not considered to be its own neighbour.

¹⁷A similar possibility, the queen-style weight matrix, considers that regions that share a common edge or corner are neighbours. In our case, this would lead to the exact same matrix as the rook-style one.

with space and time fixed effects:

$$\begin{cases} S = \rho(\mathbf{1}_T \otimes W_N)S + X\beta + (\mathbf{1}_T \otimes W_N)X\theta + (\iota_T \otimes \nu) + (\delta \otimes \iota_N) + u \\ u = \lambda(\mathbf{1}_T \otimes W_N)u + \varepsilon \end{cases} \quad (\text{II.1})$$

where W_N is the $N \times N$ row-standardised weight matrix¹⁸, \otimes denotes the Kronecker (or tensor) product and $\mathbf{1}_T$ is the identity matrix of dimension T , so that $\mathbf{1}_T \otimes W_N$ is an $NT \times NT$ block matrix whose diagonal elements are T W_N matrices. The dependent variable S is represented in stacked form as a $NT \times 1$ vector, as well as the error terms ε and u . Independent variables X are stacked in a $NT \times K$ matrix, where K is the number of covariates. The parameters to be estimated are hence: ρ and λ , the spatial autoregressive and spatial error coefficients; β and θ , the coefficients of covariates and spatially lagged ones, of length K ; ν , a vector of individual fixed effects of length N ; δ , a vector of time fixed effects of length T , and ι_N (resp. ι_T) is a vector of length N (resp. T) filled with ones. Moreover, it is assumed that the idiosyncratic error vector ε verifies: $\mathbb{E}[\varepsilon] = 0$ and $\mathbb{E}[\varepsilon\varepsilon'] = \sigma^2\mathbf{1}_{NT}$, and is identically and independently distributed. Additionally, regional and time fixed effects verify $\nu'\iota_n = 0$ and $\delta'\iota_T = 0$. For simplicity, the model can be rewritten in the following “instantaneous” form, omitting the N subscript for the weight matrix:

$$\begin{cases} S_t = \rho W S_t + X_t\beta + W X_t\theta + \nu + \delta_t\iota_N + u_t \\ u_t = \lambda W u_t + \varepsilon_t \\ \varepsilon_t \rightsquigarrow IID(0, \sigma^2) \end{cases} \quad (\text{II.2})$$

where S_t , u_t and ε_t are vectors of length N , and X_t is a $N \times K$ matrix.

So, the GNS model contains the three types of spatial interactions described above: endogenous (ρ), exogenous (θ) and residual (λ). However, it has been criticised for often giving non-significant estimates (Elhorst, 2014), and it is thus rarely used in spatial econometrics. Researchers usually use several restrictions of the GNS model, which are similar to time series models (in their denomination). If covariates are only considered locally (i.e. when $\theta = 0$), we have a spatial autoregressive combined (SAC), or spatial autoregressive errors (SARAR) model. If in addition $\lambda = 0$ it is called a spatial autoregressive (SAR) model, and if on the contrary $\rho = 0$ it is a spatial error (SEM), or spatial moving average (SMA) one. A less frequent kind of model is the spatial cross regressive, or spatial lag independent variables (SLX) one where only $\theta \neq 0$. Finally, a SAR (resp. SEM) with spatially lagged covariates is called a

¹⁸The matrix is standardised so that the sum of the terms in each row is equal to 1 (or zero if a region has no neighbour)

spatial Durbin (error) model (SD(E)M).

Elhorst (2014) recommends using the two latter, but warns that “both models tend to produce spillover effects that are comparable to each other in terms of magnitude and significance, and because interaction effects among the dependent variable on the one hand and interaction effects among the error terms on the other hand are only weakly identified. Precisely for this reason, the general nesting spatial (GNS) model is not of much help either. It generally leads to a model that is overparameterized, as a result of which the significance levels of the variables tend to go down.” (p.33). In our case, all spatial interactions are justified from an economic and physical (in the case of wind speeds) point of view. Consequently, we have decided to keep the GNS model, whose estimates are almost all statistically significant, as we will show in the next section.

Finally, the independent variables in X are: the installed base Y defined earlier, the regional S3REnR charge T (which is considered to be zero up to the quarter of enforcement t_i , included), a dummy variable for when the regional scheme is enforced, and a dummy variable equal to 1 afterwards. The use to these two dummy variables takes into account the fact that the enforcement does not usually happen at the beginning or end of a quarter. Furthermore, the enforcement quarter dummy aims at capturing a possible “deadline” effect, i.e. a possible “rush” before the enforcement, in order to avoid paying the network charge.

5 Results and interpretation

5.1 Estimation results and first interpretations

We estimate the model II.2 over the whole sample ($T = 74$ and $N = 21$) using the R package `splm` developed by Millo and Piras (2012). The main estimation results are displayed in table II.4 below, while time and region fixed effects can be found in appendix B. The R-squared is $R^2 = 0.308879$, which is an “acceptable” value (although not of much interest) for panel models, and the results are robust when considering time lags of the installed base as well as a SAC specification.

Because of the endogenous spatial correlation, we cannot readily interpret the numerical value of all these coefficients (see next subsections). Nonetheless, we can do so for the spatial autocorrelation parameters ρ and λ . First of all, they are both highly significant. Secondly, the former is negative, contrarily to what has been observed for residential solar panels. So, we do not observe peer effects, but rather some substitutability between regions: the more connection requests in a given region, the less connection requests in the neighbouring ones. In a way, a negative ρ can be interpreted as the “marginal

	Estimate	Std. Error	t-value	p-value
ρ	-0.4272	0.1090	-3.92	0.0001
λ	0.3277	0.0902	3.63	0.0003
Y	0.0415	0.0051	8.17	0.0000
$W \times Y$	-0.0068	0.0093	-0.73	0.4628
T	-285.8	92.85	-3.08	0.0021
$W \times T$	-363.2	177.6	-2.04	0.0409
$\mathbf{1}[t > t_i]$	7,579	4,297	1.76	0.0778
$W \times \mathbf{1}[t > t_i]$	10,801	9,283	1.16	0.2446
$\mathbf{1}[t = t_i]$	12,904	5,395	2.39	0.0168
$W \times \mathbf{1}[t = t_i]$	20,676	11,069	1.87	0.0618

Table II.4 – Estimation results of the GNS panel model

rate of substitution” between two neighbouring regions, all other things held constant. This could have several explanations, the most simple of which is the existence of arbitrage when the choice of a region is to be made. Indeed, as the number of “large” wind energy projects is rather limited¹⁹, the location choice of a wind farm in a region may come at the expense of a neighbouring but as promising one (all other things being equal). On the contrary, the residual autocorrelation coefficient λ is positive. This may reflect the autocorrelation of wind speeds, as described in the previous section, but other unobservable variables such as population or income may also be spatially correlated (although not necessarily at such a large scale).

Finally, we see that ρ and λ are well identified. This may be due to the fact that they have opposite signs, whereas negative spatial autocorrelation seems to be pretty rare elsewhere in spatial econometrics, which probably makes the two coefficients less identifiable. In particular, results are relatively robust under the other specifications described above, unless the estimates of ρ and λ when one of them is set to zero. Indeed, in that case it can be hard to determine whether spatial interaction is endogenous or residual. Ergo, the estimation of one of the two parameters when the other is zero gives an “average” value of the two, which in our case is roughly equal to -0.1. In the SAC (SARAR) specification however, both estimates are very close to the ones of the GNS model.

5.2 Interpreting coefficients: simplified example

Similarly to autoregressive models in time series, the coefficients of spatially autoregressive models cannot be interpreted directly²⁰. To see this, let us first consider a simplified SDM model with only two neighbouring regions and one covariate X . For the sake of simplicity, we do not write the error term, as

¹⁹In comparison, the number of small-scale PV projects is very large, so that the market could almost be considered as atomistic.

²⁰If there is no spatial autocorrelation, i.e. if $\rho = 0$, the interpretation of the coefficients is the same as in an OLS regression. This is the case in particular for SEM, SDEM and SLX models.

it plays no role in the computation of the marginal effects. Thus, we have the two following equations:

$$\begin{cases} S_{1t} = \alpha_1 + \beta X_{1t} + \theta X_{2t} + \rho S_{2t} \\ S_{2t} = \alpha_2 + \beta X_{2t} + \theta X_{1t} + \rho S_{1t} \end{cases} \quad (\text{II.3})$$

which can be solved for example either by substituting variables in the two equations, or computing the inverse of the matrix $\mathbf{1} - \rho W$. Solving the system leads to:

$$\begin{cases} S_{1t} = \frac{\alpha_1 + \rho\alpha_2}{1 - \rho^2} + \frac{\beta + \rho\theta}{1 - \rho^2} X_{1t} + \frac{\theta + \rho\beta}{1 - \rho^2} X_{2t} \\ S_{2t} = \frac{\alpha_2 + \rho\alpha_1}{1 - \rho^2} + \frac{\beta + \rho\theta}{1 - \rho^2} X_{2t} + \frac{\theta + \rho\beta}{1 - \rho^2} X_{1t} \end{cases} \quad (\text{II.4})$$

From this simple resolution it is clear that demands in both regions are interrelated, and that a change in X_i will have both a (direct) impact on S_i , with a sign equal to $\beta + \rho\theta$'s sign, and an (indirect) impact on S_j ($i \neq j$), with a sign equal to $\theta + \rho\beta$'s sign. When $\theta = 0$, the direct impact is ‘‘amplified’’ by $\frac{1}{1 - \rho^2} > 1$. This is a result of ‘‘feedback’’, i.e. the fact that a region is a neighbour of its neighbours, and is impacted by even powers of ρW accordingly.

From equation II.3, we see that if $\rho > 0$, an increase of the dependent variable in a region increases it also in the neighbouring one, i.e. there is a complementarity effect. If on the contrary $\rho < 0$, there is a substitution effects. Furthermore, if $\rho > 0$ and $|\theta|$ is ‘‘small enough’’ compared to $|\beta|$ (or if θ and β have the same sign), then the direct and indirect marginal effects of X have the same sign, so that the regions are indeed complements with respect to the variable X . Conversely, if $\rho < 0$ and $|\theta|$ is ‘‘small enough’’ (or if θ has the sign of $-\beta$), they have opposite signs, and the regions are indeed substitutes. In our case for example, a higher S3REnR charge in a given region is expected to decrease the number of connection requests within this region, but a higher charge in neighbouring regions is expected to increase it if substitution between region is possible.

Finally, it is also interesting to write the gradient of $S = (S_1, S_2)$ with respect to $X = (X_1, X_2)$, as this representation will be use in the next subsection for the general case:

$$\frac{dS}{dX} = \begin{pmatrix} \frac{\partial S_1}{\partial X_1} & \frac{\partial S_1}{\partial X_2} \\ \frac{\partial S_2}{\partial X_1} & \frac{\partial S_2}{\partial X_2} \end{pmatrix} = \begin{pmatrix} \frac{\beta + \rho\theta}{1 - \rho^2} & \frac{\theta + \rho\beta}{1 - \rho^2} \\ \frac{\theta + \rho\beta}{1 - \rho^2} & \frac{\beta + \rho\theta}{1 - \rho^2} \end{pmatrix} \quad (\text{II.5})$$

The diagonal terms are therefore the marginal effects of covariates X_1 and X_2 on S_1 and S_2 , respectively. The off-diagonal terms are the marginal impacts of X_2 (resp. X_1) on S_1 (resp. S_2).

5.3 Interpreting coefficients: general case

More generally, equation II.2 can be rewritten:

$$S_t = (\mathbf{1} - \rho W)^{-1}(X_t\beta + WX_t\theta + \nu + \delta_t\iota_N + u_t) \quad (\text{II.6})$$

Using the Taylor expansion of the inverse matrix: $(\mathbf{1} - \rho W)^{-1} = \mathbf{1} + \rho W + \rho^2 W^2 + \dots$, we see that in fact an infinite number of spatially lagged values of the covariates and of the error term appear in the equation for S , corresponding to neighbours of neighbours, etc. Also, as $|\rho| < 1$, the closest neighbours have the most influence. LeSage and Pace (2009) suggest that the marginal effect be decomposed into a direct effect and an indirect (or spillover) effect, the sum of which is the total effect (which can only be considered when the change in a covariate occurs globally and identically). Indeed, we can write the marginal effects of the r^{th} covariate on the dependent variable as the following $N \times N$ matrix, which is the generalisation of equation II.5:

$$\frac{\partial S}{\partial x_r'} = (\mathbf{1} - \rho W)^{-1}(\mathbf{1}_N\beta_r + W\theta_r) \quad (\text{II.7})$$

As in the simplified case, the partial derivative at line i and column j quantifies how an infinitesimal change of covariate r in region j impacts S in region i . In particular, the diagonal terms represent the direct marginal effects and off-diagonal elements the indirect ones. From there, we can compute average direct, indirect and total marginal effects, the latter being the sum of the two former ones²¹.

Finally, measures of dispersion of the estimated direct, indirect and total marginal effects are also needed for inference. Indeed, due to their computation, nothing can be said for these from the standard deviations and levels of significance of the “raw” estimates. Again, we follow LeSage and Pace (2009), who suggest to produce empirical distributions of the parameters “using a large number of simulated parameters drawn from the multivariate normal distribution of the parameters implied by the maximum likelihood estimates” (p.39). LeSage and Pace (2014) then suggest to use medians as point estimates and scaled median absolute deviations (MAD) as measures of dispersion, which are more robust to outliers and distribution asymmetry than the sample mean and standard deviation.

²¹In SDEM and SLX models, (in)direct effects are simply the coefficients of the (spatially lagged) covariates, since there is no endogenous spatial autocorrelation.

5.4 Direct, indirect and total marginal effects

Table II.5 below shows the simulated direct, indirect and total marginal effects, along with p-values, levels of significance, and 95% confidence intervals, as recommended e.g. by Armstrong (2012). These are based on 10,000 simulations realised using a personal program written in R.

	Direct	Indirect	Total
Y (kW/kW)	0.0435*** (2×10^{-16}) [0.0344;0.0524]	-0.0132*** (3×10^{-4}) [-0.0195;-0.0077]	0.0302*** (6×10^{-12}) [0.0230;0.0375]
T (€/kW/kW)	-300*** (0.002) [-460;-137]	138*** (0.010) [61;239]	-155** (0.033) [-279;-39]
$\mathbb{1}[t > t_i]$ (kW)	7,855* (0.082) [484;15,457]	-3,717 (0.105) [-8,063;-420]	3,915 (0.209) [-1,093;9,178]
$\mathbb{1}[t = t_i]$ (kW)	13,497** (0.018) [4,381;22,866]	-6,726** (0.036) [-12,786;-2,268]	6,394* (0.091) [480;13,064]

Note: p-values are in parentheses.

Asterisks denote significance levels of 99% (***), 95% (**), and 90% (*).

95% confidence intervals are in brackets.

Table II.5 – Direct, indirect and total marginal effects of the GNS model

As expected, the direct and total marginal effects have the sign of the coefficients of the non-lagged variables in table II.4, and the indirect ones have the opposite sign. The direct marginal effects are higher, which is a consequence of the “feedback”, but the increase is more than compensated by the indirect effects, so that the total effects are smaller than the non-lagged estimates. This illustrates the difficulty to interpret the “raw” estimates. Only the post-enforcement quarter dummy has little significance, especially in its total marginal effect.

Concerning the installed base, we see that on average, an additional MW in a region increases the quarterly requests by 43.5 kW, and an additional MW in each region leads to an increase of 30.2 kW. These values may seem small but can nevertheless lead to an important increase in the long run, as long as there is no “stock” effect.

An increase of the network charge in a region T of 1€/kW reduces the connection requests by 300 kW and increases it by 138 kW in neighbouring regions, as a consequence of substitution. These values are quite significant and relatively high, which shows that the schemes have sent appropriate locational signals. For instance, the inter-quartile difference of network charges is equal to 25.52€/kW, which means a (direct effect) difference of 7,656 kW in quarterly connection requests, while the mean capacity

request is equal to 9,225 kW (see table II.3). In the short run, the implementation of the schemes have had a positive impact on the connection requests, which may be due to a “deadline” effect. On average, 6,394 additional kW have been installed in each region due to the enforcement of the schemes. In the long run, the impact would be of 3,915 kW/quarter, although this estimate is not very significant (contrarily to the direct impact).

Finally, table II.6 below displays the overall direct, indirect and total effects of the network charge plus scheme enforcement per region (i.e. $\beta_T \times T + \beta_{\mathbf{1}_{[t > t_i]}}$). We see that the direct and total impacts are positive in 15 out of 21 regions, and negative in 6. Thus, the positive effect of the schemes compensates the negative one of the network charge in most regions. On average, the schemes have only slightly increased the quarterly demand for wind projects, and are consequently almost neutral regarding the capacity requests at the national level. Nevertheless, they have led to a more efficient (in the sense of network constraints) spatial distribution of these requests, which was one of the goals of this regulation. Although these values do not reflect the exact reality, since they have been computed using statistical estimates, it is interesting to analyse them by looking at neighbouring regions. For instance in the South, the Rhône-Alpes region may have benefited from a rather low network charge while its neighbours Auvergne and Languedoc-Roussillon were negatively affected. Similarly, in the North, Nord-Pas-de-Calais and Haute-Normandie may have benefited from a low charge as well as from a high charge in the neighbouring Picardie. Looking at the map of connected wind farms in appendix C, we can see that there exist several wind farms close to the borders of these regions. This makes the above explanations quite plausible. In addition, substitution may also occur on a larger scale than just across the borders, depending on how large potential sites are.

6 Conclusions and policy implications

We have shown that regional network connection schemes for renewable energy have had a significant impact on the diffusion of wind energy. This relatively unique regulation consists in a per-kW fee that aims at sharing network reinforcement costs among RES producers of more than 100 kW. This charge is differentiated between regions, which enhances locational arbitrage opportunities when adjacent regions have distinct charges or when only some of them have implemented their scheme. This substitution can be seen through the study of spatial autocorrelation, which is found to be negative, as is the impact of the network charge. The regulatory framework also aims at removing the uncertainty on connection charges due to the deep-cost methodology that prevails in France, and we show that this is indeed the

Region	Charge (€/kW)	Direct	Indirect	Total
Alsace	0	7,855	-3,717	3,915
Aquitaine	23.37	843	-441	300
Auvergne	48.4	-6,657	2,948	-3,587
Basse-Normandie	9.81	4,911	-2,334	2,384
Bourgogne	16.92	2,829	-1,353	1,245
Bretagne	10.11	4,840	-2,270	2,303
Centre	20	1,822	-876	784
Champagne-Ardenne	49.26	-6,876	3,077	-3,794
Franche-Comté	10.64	4,671	-2,217	2,235
Haute-Normandie	10.19	4,837	-2,271	2,297
Île-de-France	1.5	7,418	-3,503	3,685
Languedoc-Roussillon	35.63	-2,807	1,232	-1,628
Limousin	22.56	1,073	-534	383
Lorraine	18.21	2,373	-1,184	1,002
Midi-Pyrénées	69.9	-13,022	5,944	-6,936
Nord-Pas-de-Calais	9.19	5,156	-2,417	2,501
Pays de la Loire	13.38	3,889	-1,805	1,812
Picardie	58.6	-9,722	4,343	-5,163
Poitou-Charentes	42.36	-4,734	2,158	-2,667
Provence-Alpes-Côte d'Azur	18.48	2,358	-1,111	998
Rhône-Alpes	9.51	5,002	-2,364	2,460
Average	23.7	765	-414	216

Table II.6 – Expected regional effects of the regional connection schemes (kW/quarter)

case, as the overall effect is almost neutral on average and positive for most regions.

Moreover, we have shown that the cumulative installed capacity has had a positive and significant impact on connection requests. This highlights the “epidemic” behaviour of the diffusion process, which is sometimes neglected in the assessment of renewable energy policies. Similarly, spatial interactions are often forgotten in econometric studies. This is unfortunate, as their omission usually gives biased and inconsistent estimators. Hence, we hope that our positive results will encourage more econometricians to use spatial models in the future.

In the end, the conclusive results of the French regulation could lead other countries to use similar schemes to help promote renewable energy and planning its development by taking the existing network constraints into account. This may avoid or delay unnecessary and costly network reinforcements, if these are charged in a “reasonable” way to the producers. However, the French schemes also have some drawbacks. For example, once the regional target is attained, another target and a new scheme have to be defined. On the contrary, if the target is never met, or not in time, some producers may have payed for unnecessary reinforcements. Also, although the choice of proportional charges is easy to understand and may seem rather natural, one could think of other cost-sharing methodologies, as discussed in the

cooperative game theory literature. Finally, one could also challenge the choice of the regional scale for such schemes. Indeed, transmission and distribution networks may differ in topology within the same region, hence leading to potential inefficiencies. Despite their imperfections, these schemes remain quite innovative in a highly regulated energy sector, and have proven to have achieved their goals.

Appendices

A Regional connection schemes data

Region	Enforcement date (d/m/y)	Enforcement quarter	Network reinforcement charge (€/kW)
Alsace	21/12/2012	2012 Q4	0
Aquitaine	15/04/2015	2015 Q2	23.37
Auvergne	28/02/2013	2013 Q2	48.40
Basse-Normandie	16/09/2014	2014 Q3	9.81
Bourgogne	21/12/2012	2012 Q4	16.92
Bretagne	07/08/2015	2015 Q3	10.11
Centre	20/06/2013	2013 Q2	20.00
Champagne-Ardenne	27/12/2012	2012 Q4	49.26
Champagne-Ardenne (modified)	29/12/2015	2015 Q4	53.17
Franche-Comté	12/09/2014	2014 Q3	10.64
Haute-Normandie	24/10/2014	2014 Q4	10.19
Île-de-France	04/03/2015	2015 Q1	1.50
Languedoc-Roussillon	08/01/2015	2015 Q1	35.63
Limousin	16/12/2014	2014 Q4	22.56
Lorraine	18/11/2013	2013 Q4	18.21
Midi-Pyrénées	08/02/2013	2013 Q1	69.90
Nord-Pas-de-Calais	21/01/2014	2014 Q1	9.19
Pays de la Loire	13/11/2015	2015 Q4	13.38
Picardie	26/12/2012	2012 Q4	58.60
Poitou-Charentes	07/08/2015	2015 Q3	42.36
Provence-Alpes-Côte d'Azur	26/11/2014	2014 Q4	18.48
Rhône-Alpes	15/01/2016	2016 Q1	9.51

Table II.7 – Regional connection schemes data set

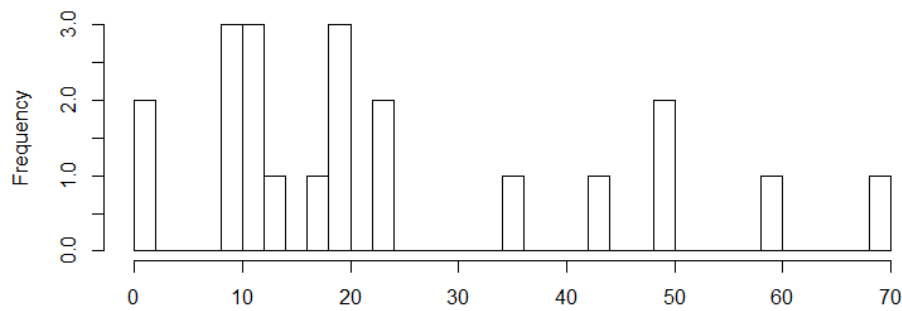


Figure II.9 – Histogram of network connection charges (€/kW)

B Fixed effects of the GNS panel model

	Estimate	Std. Error	t-value	p-value
Intercept	13658.83	1260.89	10.83	0.00

Quarter	Estimate	Std. Error	t-value	p-value
1998 Q1	-12331.80	4553.97	-2.71	0.01
1998 Q2	-13658.83	4553.97	-3.00	0.00
1998 Q3	-13658.83	4553.97	-3.00	0.00
1998 Q4	-13658.83	4553.97	-3.00	0.00
1999 Q1	-13658.83	4553.97	-3.00	0.00
1999 Q2	-13658.83	4553.97	-3.00	0.00
1999 Q3	-13658.83	4553.97	-3.00	0.00
1999 Q4	-13658.83	4553.97	-3.00	0.00
2000 Q1	-13658.83	4553.97	-3.00	0.00
2000 Q2	-13658.83	4553.97	-3.00	0.00
2000 Q3	-13658.83	4553.97	-3.00	0.00
2000 Q4	-13128.02	4553.97	-2.88	0.00
2001 Q1	-11918.91	4553.97	-2.62	0.01
2001 Q2	-8555.58	4553.97	-1.88	0.06
2001 Q3	-7574.03	4553.97	-1.66	0.10
2001 Q4	-9838.71	4553.97	-2.16	0.03
2002 Q1	-9300.38	4553.97	-2.04	0.04
2002 Q2	-11126.08	4553.97	-2.44	0.01
2002 Q3	2467.16	4553.97	0.54	0.59
2002 Q4	-1776.35	4553.98	-0.39	0.70
2003 Q1	-8289.61	4553.98	-1.82	0.07
2003 Q2	6835.43	4553.99	1.50	0.13
2003 Q3	4561.22	4554.01	1.00	0.32
2003 Q4	717.88	4554.01	0.16	0.87
2004 Q1	8378.78	4554.01	1.84	0.07
2004 Q2	-6821.93	4554.01	-1.50	0.13
2004 Q3	-3484.94	4554.05	-0.77	0.44
2004 Q4	-9374.52	4554.12	-2.06	0.04
2005 Q1	-2611.69	4554.12	-0.57	0.57
2005 Q2	3659.75	4554.38	0.80	0.42
2005 Q3	1909.55	4555.15	0.42	0.68
2005 Q4	1297.88	4556.71	0.28	0.78
2006 Q1	3634.68	4558.26	0.80	0.43
2006 Q2	10894.41	4561.85	2.39	0.02
2006 Q3	9654.99	4568.95	2.11	0.03
2006 Q4	7826.10	4577.97	1.71	0.09
2007 Q1	5428.56	4583.60	1.18	0.24
2007 Q2	8456.60	4589.26	1.84	0.07
2007 Q3	29937.95	4598.13	6.51	0.00
2007 Q4	13056.49	4609.32	2.83	0.00
2008 Q1	15856.06	4611.44	3.44	0.00
2008 Q2	12157.34	4622.11	2.63	0.01
2008 Q3	-834.86	4642.85	-0.18	0.86
2008 Q4	-6099.02	4663.67	-1.31	0.19

Quarter	Estimate	Std. Error	t-value	p-value
2009 Q1	-3122.99	4682.30	-0.67	0.50
2009 Q2	-2061.68	4702.77	-0.44	0.66
2009 Q3	1039.38	4711.72	0.22	0.83
2009 Q4	8727.06	4736.49	1.84	0.07
2010 Q1	4279.41	4747.98	0.90	0.37
2010 Q2	-10401.89	4765.46	-2.18	0.03
2010 Q3	2439.00	4785.30	0.51	0.61
2010 Q4	-4456.64	4811.45	-0.93	0.35
2011 Q1	-1557.99	4834.10	-0.32	0.75
2011 Q2	1335.07	4845.17	0.28	0.78
2011 Q3	-4266.10	4874.41	-0.88	0.38
2011 Q4	-158.52	4888.69	-0.03	0.97
2012 Q1	42373.60	4898.91	8.65	0.00
2012 Q2	14026.62	4915.77	2.85	0.00
2012 Q3	10855.68	4943.71	2.20	0.03
2012 Q4	14988.78	5498.87	2.73	0.01
2013 Q1	-3516.84	5296.05	-0.66	0.51
2013 Q2	-5803.78	5442.14	-1.07	0.29
2013 Q3	-2984.61	5494.88	-0.54	0.59
2013 Q4	19814.30	5606.59	3.53	0.00
2014 Q1	8328.60	5708.62	1.46	0.14
2014 Q2	17568.97	5751.89	3.05	0.00
2014 Q3	-2703.37	6113.82	-0.44	0.66
2014 Q4	8235.28	6664.42	1.24	0.22
2015 Q1	4414.29	7156.27	0.62	0.54
2015 Q2	-1122.16	7447.25	-0.15	0.88
2015 Q3	9859.11	7782.28	1.27	0.21
2015 Q4	-4378.45	8100.20	-0.54	0.59
2016 Q1	-3238.09	8431.23	-0.38	0.70
2016 Q2	-5588.10	8636.01	-0.65	0.52

Table II.8 – Time fixed effects

Quarter	Estimate	Std. Error	t-value	p-value
Alsace	-11740.60	2705.85	-4.34	0.00
Aquitaine	-9183.25	2545.21	-3.61	0.00
Auvergne	-2771.48	2715.80	-1.02	0.31
Basse-Normandie	-3274.91	2936.67	-1.12	0.26
Bourgogne	3871.00	2685.84	1.44	0.15
Bretagne	-2751.45	2938.84	-0.94	0.35
Centre	-8.61	2819.01	-0.00	1.00
Champagne-Ardenne	11433.49	2843.67	4.02	0.00
Franche-Comté	-8299.50	2709.97	-3.06	0.00
Haute-Normandie	-622.24	2794.20	-0.22	0.82
Île-de-France	-377.90	2930.52	-0.13	0.90
Languedoc-Roussillon	-2847.65	2655.58	-1.07	0.28
Limousin	-6071.56	2622.98	-2.31	0.02
Lorraine	-1345.37	2759.56	-0.49	0.63
Midi-Pyrénées	-3204.37	2675.93	-1.20	0.23
Nord-Pas-de-Calais	20745.83	3439.32	6.03	0.00
Pays de la Loire	2202.55	2841.97	0.78	0.44

Quarter	Estimate	Std. Error	t-value	p-value
Picardie	29915.83	3043.46	9.83	0.00
Poitou-Charentes	436.21	2624.18	0.17	0.87
Provence-Alpes-Côte d'Azur	-9101.09	2590.67	-3.51	0.00
Rhône-Alpes	-7004.94	2592.32	-2.70	0.01

Table II.9 – Region fixed effects

C Map of connected wind farms

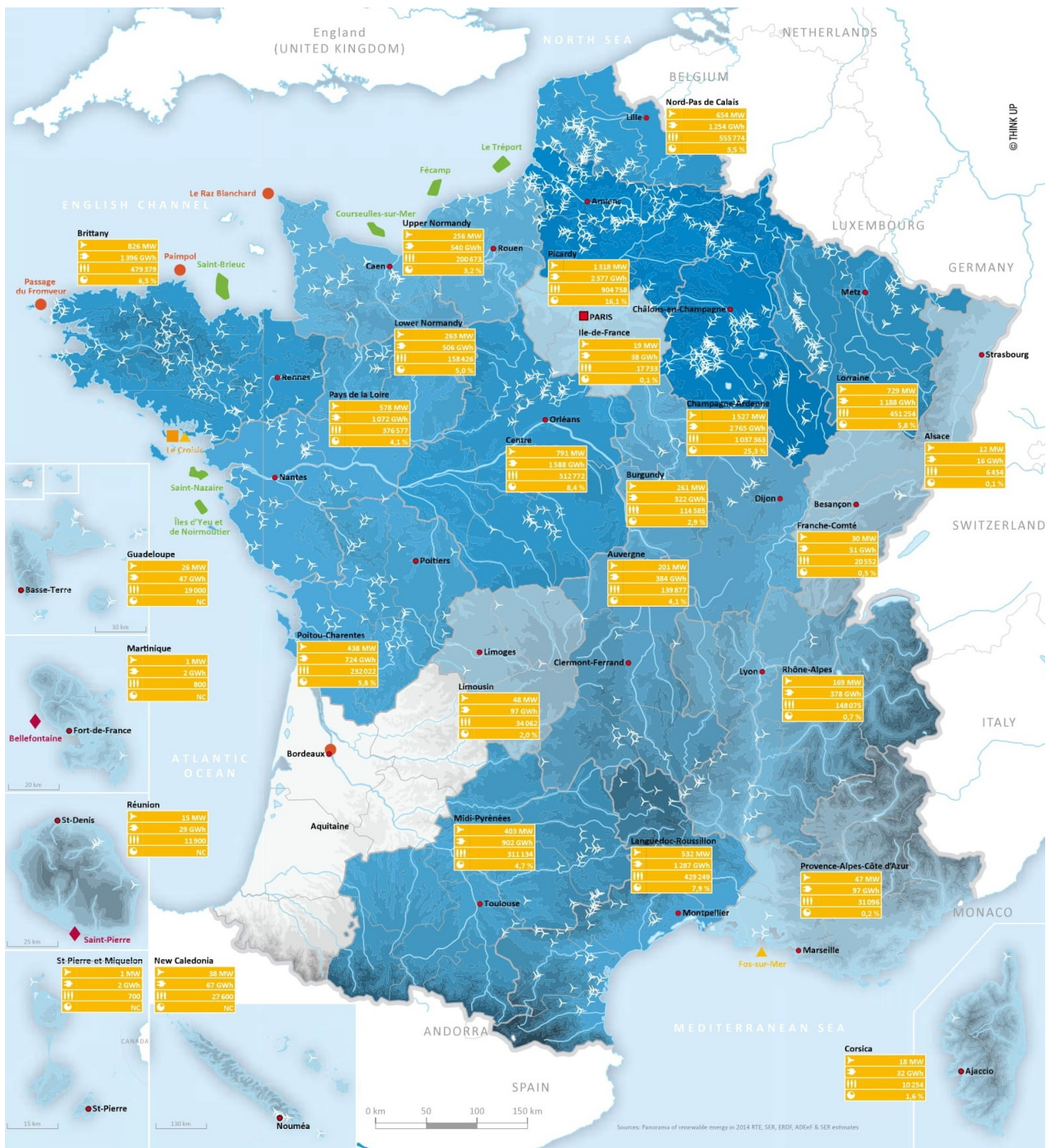


Figure II.10 – Map of wind connected wind farms on January 1st, 2015. Source: Windustry France (2015). Note: Values of connected capacity do not match our data exactly as we only have connections on Enedis’ network.

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Chapter III

Self-rationing revisited: extensions and application to prosumers

About this chapter

Having started this article during the last semester of my PhD, I have not had the time to present it in seminars, except rather informally at the FAEE summer workshop in July 2018 in Paris. Nevertheless, I had fruitful conversations with Anna Creti and René Aïd at Dauphine, as well as with Laurent Gilotte and Mathieu Bordigoni at Enedis. I also received valuable comments from Nicolas Astier at the FAEE workshop. I thank all five of them for their help and interest in this work.

Abstract

In some countries, electricity network (or utility) tariffs include a capacity charge for residential customers, in addition to the more traditional energy rate. This charge is determined by the consumer's subscribed capacity, which limits his instantaneous consumption. This paper investigates how this self-rationing framework can be adapted to modern electricity retail markets, where real-time pricing is technically feasible and where consumers can install a decentralised production unit (DPU) and become "prosumers". Thus, after a thorough review of the literature, we extend the traditional setup of Panzar and Sibley (1978) to take these specificities into account. The distribution network being subject to economies of scale, we compute second-best energy and capacity prices. We prove that although the second-best price of energy is always higher than marginal cost, it is not always the case for the price of capacity, which highly depends on peak and off-peak elasticities. Then, we analyse how these prices should vary in the presence of prosumers, in the short and in the long run. In particular, we show that they can increase or decrease, depending on the attained level of prosumers.

1 Introduction

Although there is almost a consensus on the fact that electricity networks are natural monopolies¹ and as a consequence should be regulated, there is no consensus on the form this regulation should take, especially when it comes to distribution network (or, in the US, public utility) tariffs. For example in Europe, we observe a variety of such tariffs, as illustrated by table III.1 in appendix A.1. Almost all countries rely on an energy charge, often with a fixed fee (17 out of 28 countries), and nine have in addition a capacity charge. The Dutch case is particular, as there are only fixed and capacity charges in the Netherlands, in a “telecommunications fashion”. Also, with the exception of Spain and Sweden (and of course the Netherlands), all tariffs put more weight on the energy part. Even though for commercial and industrial customers the capacity charge can refer to the maximum demand reached during a billing period, AF-Mercados EMI et al. (2015) note that for households maximum power is controlled by the means of a circuit breaker. In this case, we can talk of subscribed, access, or contracted capacity instead of maximum demand to avoid ambiguity, and of self-rationing, in opposition to price rationing or priority service (“interruptible contracts”). Although commercial and industrial customers are billed based on the real maximum power, AF-Mercados EMI et al. (2015) mention that they often have a capacity subscription but are not constrained by it and they instead pay a high fee if they consume more than their contractual capacity. In the US, demand charges rarely concern residential customers and hence usually refer to maximum demand charges (MDCs).

Within a country, the distribution tariff can be further complicated, in particular with time differentiation and consumer segmentation. In France, the energy rate depends on the capacity subscription, as shown in table III.2 in appendix A.2. In its fifth version of the tariff, called TURPE² 5, there are five categories: short use CU, with one or four time ranges; mid use MU, with one or two (peak/off-peak) time ranges; and long use LU, with no time differentiation. We notice that the lower the time differentiation, the higher the capacity charge and the lower the energy charge. Although the energy rate can take up to four different values, depending on the time of day (for instance, “peak” time runs from 7 a.m. to 11 p.m.) and season (the “high” season runs from December to February, and includes 61 additional days to be determined - in practice, it covers the winter, from November to March), “old” meters are at best only able to differentiate between peak and off-peak. In addition, while new, “smart” meters are being deployed and can distinguish between up to ten time periods, in fact residential customers are usually

¹See for example Filippini (1998), Growitsch et al. (2009) or Farsi et al. (2010) for empirical evidence on economies of scale in electricity distribution.

²Tarif d’utilisation du réseau public d’électricité, i.e. literally: public electricity network use tariff.

not faced directly with the distribution tariff, which is paid by directly their electricity supplier. The latter may, in return, charge the customer in a different manner. These peculiarities can for example be observed in the regulated retail prices still proposed by the incumbent EDF, which consist in only two tariffs for residential customers: one without time differentiation, and one with peak/off-peak prices.

These differences in network tariffs raise a number of questions. The first of which is a rather naive one: what tariff should be adopted? More precisely, is a capacity charge justified, how should it be designed, and how much should it weigh in the total bill? Also, how can a capacity charge be used in conjunction with time-of-use (TOU) energy rates, as in the French case? This last question is likely to become more and more important, as “smart” meters are being deployed, enabling the use of TOU rates and even real-time pricing. In addition, network tariffs are intimately linked to an objective of cost recovery, since the existence of a natural monopoly rules out first-best marginal cost pricing as a viable option. Thus, can energy and capacity prices be used to achieve this goal, and how?

Besides, recent years have seen the emergence and development of electricity “prosumption” (or self-consumption), with “prosumers” producing (partially or totally) their own electricity using a decentralised production unit (DPU) such as a rooftop solar panel. In the absence of dedicated subsidies, network tariffs directly affect the profitability of electricity prosumption, and hence its proportion in the system. In return, despite some possible environmental benefits (e.g. reduction of greenhouse gas emissions), self-consumption, and decentralised generation (DG) in general, raise additional issues regarding network tariffs.

On the one hand, DG has an influence on network management and investment needs: it may cause short-run management costs, for instance due to reverse flows, but also reduce power losses if electricity is consumed locally. In the long run, it may reduce the overall network capacity, if consumption can be synchronised with production (possibly using a storage device). Tariffs should therefore send efficient price signals to help minimise short-term congestion and management costs, and long-term investment costs.

On the other hand, self-consumption is often accused of worsening the cost recovery issue DSOs and public utilities. Indeed, as we have seen, most tariffs rely on an energy (or volumetric) charge, and some on a capacity charge as well. In the presence of prosumers, the volume consumed from the network decreases, which creates less revenue for the DSO. This is particularly true when net-metering is applied, i.e. when only net imports are used instead of differentiating imports and exports as is the case in net billing³. This requires either a “smart” meter or two “traditional” ones in order to measure

³Net purchasing, and dual or double metering are other denominations.

flows in both directions. Even if net purchasing can theoretically solve the issues raised by net metering (Gautier et al., 2018), it requires of course that optimal prices be implemented. In addition, capacity charges are also likely to decrease the revenue available to the DSO, as prosumers may choose a lower capacity subscription. They will do this if they manage to synchronise most of their consumption with their production, possibly using a storage device such as a battery.

As a consequence, tariffs should be designed so as to raise enough revenue for the DSO while sending least-distorting incentives towards an efficient use of the grid in the short as in the long run, and towards a sensible promotion of self-consumption. Building on the existing literature on self-rationing and on more recent contributions on DG and prosumption, this article addresses these issues in a theoretical framework. In particular, we show that the “traditional” model of self-rationing can be extended to include time-varying prices and prosumers, which we treat separately for the sake of simplicity. We also briefly examine the cases of non-coincident as well as interdependent demands.

Under relatively standard assumptions, we derive second-best prices for energy and capacity with and without prosumers and discuss the role of several parameters such as peak and off-peak elasticities. We study four scenarios based on two criteria.

Firstly, we distinguish the short and long-term perspectives: in the short run, capacity costs are sunk and prosumers worsen the issue of cost recovery, whereas in the long run costs are variable and the network can adapt to the new environment.

Secondly, we compare the situation in which consumers can choose their contracted capacity (such as in France) to the hypothetical situation in which they pay according to their connected load. Such a pricing scheme would work like a (possibly discriminating) fixed fee, as it forces the consumer to pay for the built capacity, whether he fully uses it or not. This seems more adapted to a short run situation, as it creates inefficiencies in the long run. Admitting it could make sense for consumers who build a new house and ask for a new connection, it may seem unfair to other users, who did not decide the capacity level of their installation. It exists for example in Malaysia, where it is applied to new medium and high voltage consumers, but only when maximum load remains lower than 75% of the connected load⁴. In this case, it aims at discouraging new customers to ask for unnecessary capacity.

Finally, the remainder of the article is organised as follows. In section 2, we put together a comprehensive literature review on self-rationing, which is possible since it is rather limited. We also discuss the literature on cost recovery and the more recent one on prosumers. Then, we expose a general formulation of the self-rationing problem in section 3, before presenting a solution to the consumer program

⁴<https://www.tnb.com.my/commercial-industrial/charges-penalties>

in the case of time-independent demand and stochastic prices, along with some examples. In section 5, we focus instead on time-dependent consumers facing uniform prices, as in the original self-rationing literature. Restricting ourselves to a two-period situation, we derive second-best prices, and we explore extensions to non-coincident and interdependent demands in appendix B. Prosumers are then introduced in section 6 using the same two-period model, and second-best prices are computed in the four scenarios described above. Section 7 concludes.

2 Literature review

2.1 Self-rationing

On the one hand, this paper is directly inspired by the literature on self-rationing, which is, surprisingly, rather limited. Indeed, scholars have much more often treated the issue of rationing using prices, and in particular peak-load pricing, following the seminal work of Boiteux (1949, 1960), Houthakker (1951) and Steiner (1957), just to name the main early contributions. Nevertheless, there are some similarities between peak-load pricing and self-rationing, which we will highlight in this paper. Although self-rationing can be applied to several network industries, most authors have stated electricity as the main (and almost unique) application, as is also the case for peak-load pricing.

Self-rationing was initially studied by Panzar and Sibley (1978), to which we will refer to as P-S. In their model, consumers buy a “fuse”⁵ limiting their electricity consumption to a predetermined capacity. Energy and capacity are priced linearly, and their respective marginal costs are constant. Assuming that the installed capacity is equal to the sum of all subscribed capacities, P-S show that welfare-maximising energy and capacity prices under self-rationing are the marginal costs. Furthermore, if all consumers react similarly to the state of nature (e.g. temperature)⁶, then it also yields the first-best optimum. If this is not the case, welfare will generally be lower than “if ex post rationing via greatest willingness to pay could in fact be accomplished *costlessly*” (p. 892). The main reason for that is the risk of “excess load relief”, or “idle capacity”. Indeed, some consumers may be constrained by their fuse without the system being at maximum capacity. The second reason is that even if all consumers are constrained, there is no reason for their marginal willingness to pay to be equal. In both cases, welfare would be improved if capacity could be reallocated or traded costlessly between customers. Also, installed capacity would

⁵In fact, it would rather be a circuit breaker, as a fuse can only be used once. Also, consumers would not directly “buy” it, but rather its capacity, which may vary without changing the whole device. With “old” meters this may require an intervention on the meter, but it can be done remotely with relatively new meters such as “smart” ones.

⁶Formally, when the utility function of consumers is weakly separable in consumed quantity and consumer type.

not have to be equal to the sum of all subscriptions.

In a more general framework, Oren et al. (1985) extend the P-S model by deriving the optimal monopolistic pricing of a service with two attributes (such as consumption rate - i.e. power - and duration, or quantity and quality) subject to capacity constraints in each attribute. They consider a general cost function that includes fixed, capacity, and non-constant marginal costs, and derive corresponding nonlinear prices. They show that usage, capacity and subscription prices follow the inverse-elasticity rule and are defined recursively, which enables to compute them numerically. However, they do not address the two problems identified by P-S.

Schwarz and Taylor (1987), to which we will refer as S-T, generalise the P-S model by letting the fuse capacity be attained several times during a billing period, thus leading to a higher capacity than in P-S. Furthermore, they consider imperfectly correlated customers, so that installed capacity may be lower than the total subscribed capacity. In particular, if total expected demand varies proportionally with the sum of capacity subscriptions, so does the optimal capacity price with respect to the marginal cost of capacity. However, this does not fully solve the issue of idle capacity. If there is no strict proportionality between installed and subscribed capacity, they argue that the capacity charge should be different among customers.

Woo (1990) combines self-rationing (P-S and S-T) with priority service (e.g. Chao and Wilson, 1987; Marchand, 1974; Wilson, 1989). He suggests that consumers be able consume above their fuse capacity, but that the system operator may limit their consumption if necessary (it is not clear how that would be possible in practice) when total consumption reaches system capacity. Although this scheme would indeed improve welfare in the case of uncorrelated consumers, it does not completely solve the issue of “excess load relief”, as pointed out by Doucet and Roland (1993) and acknowledged by Woo (1993), as it brings back to fuse capacity the consumption of those consuming above it.

Meanwhile, Woo (1991) studies how already built capacity should be priced and allocated so that fixed and capacity costs are recovered. As in P-S, he demonstrates that if consumers react similarly to the state of nature, then his pricing scheme is optimal. Later, Doorman (2000) studies “random allocation” and “optimal allocation according to willingness to pay” of the remaining (“idle”) capacity when fuses (or, in his terms, load-limiting devices - LLD) are activated. Although the latter option would entail marginal cost pricing and maximum welfare, it would be harder to implement than the former. He summarises his findings in Doorman (2003).

Lee (1993) extends the model of S-T by adding the possibility for the utility to purchase “electricity

from third-party suppliers (e.g., independent power producers, IPPs) at some cost greater than its own operating cost.” This may also model a peak technology with zero capacity cost. Since the utility is constrained to sell electricity at a uniform price, both energy and capacity prices are affected by this additional technology, and first-best prices are derived.

Bernard and Roland (2000) analyse self-rationing jointly with “regular service”. They show that if peak demand is less elastic than average demand, then the profit constraint on the regulated monopoly is binding (although costs are linear), and “there exists a cross-subsidy from the self-rationing program to regular service”. If there is in addition a no-cross-subsidy constraint, then the set of regular service users is not empty only if there is a transaction cost (in their model, a fixed fee) incurred by self-rationed consumers.

Finally, it is interesting to note that self-rationing is in a way similar to access capacity pricing in the telecommunications industry, which is also close to the peak-load pricing literature. However in the latter case, the question concerns access capacity pricing by an incumbent to potential entrants⁷.

2.2 Prosumers and network cost recovery

On the other hand, we are interested in utility or network tariffs in the presence of prosumers. On the contrary to self-rationing, the literature on “prosumption” is relatively recent, and has followed the emergence and growth of decentralised generation during the last two decades. In particular, most of this literature has focused on optimal promotion policies (e.g., Brown and Sappington, 2017b), tariff design and (sunk) cost recovery. The latter subject is older and more general, and is not only related to the development of distributed generation. Indeed, the issue of cost recovery for a natural monopoly⁸ is a very old one in the economics literature, and began with the so-called “marginal cost controversy”⁹. Hotelling (1938) was a pioneer in discussing this issue, followed by Coase (1946, 1947), among others. A decade later, Boiteux (1956) derived second best prices for a monopoly subject to a budget constraint and showed that these prices must follow the inverse elasticity rule. This result had been already found by Ramsey (1927) for optimal taxation, and was later summarised by Baumol and Bradford (1970).

However, these early contributions have rarely been applied to the electricity sector. Rather, network (or utility) tariffs have more relied on averaged cost, tiered (declining- or increasing-block), and time-of-use (TOU) pricing, sometimes with additional fixed or capacity charges. Borenstein (2016) discusses

⁷See for example Calzada (2007) for a review of this literature.

⁸See Baumol (1977) for a discussion on the definition of a natural monopoly and on relationships among several cost concepts.

⁹See for example the review of Frischmann and Hogendorn (2015).

the pros and cons of several tariff designs aimed at recovering fixed costs. In particular, he considers (maximum) demand charges (MDCs) to be unjustified economically, in contrast with Seeto et al. (1997), who argue that “a Hopkinson tariff^[10] with demand subscription [i.e. self-rationing] is superior to TOU rates”.

It is important to note that in the United States, capacity (or demand) charges usually refer to maximum demand¹¹ reached during a billing period (e.g., a month) rather than to subscribed capacity by the consumer (which is usually the same over several billing periods). In the latter case, access capacity is charged whether it will be reached or not. Thus, it is a much more precise load-management tool for the utility. However, both methodologies are inefficient in that the maximum demand of a consumer may not coincide with system or network peak. Although MDCs are much more widespread than access capacity pricing, at least for commercial and industrial customers¹², there seems to be even less theoretical literature on this subject than on self-rationing. Berg and Savvides (1983) seem to have been the first to model consumers’ behaviour subject to a MDC. They show in particular that the resulting budget line is kinked, so that the demand curve is not continuously differentiable and may even be discontinuous. Similarly, we will show that the capacity demand function as well as average demand are not continuously differentiable either. As opposed to self-rationing however, there exist some empirical studies on demand charges: Veall (1983), Caves et al. (1984) Taylor and Schwarz (1986, 1990), which showed that a demand charge could indeed help reduce peak consumption.

Distributed generation (DG) further complicates the issues related to network tariffs such as cost recovery or equity, and calls for new tariff designs (Picciariello et al., 2015a). For example, under net (or single) metering, prosumers are charged according to their electricity consumption, net of DPU production. In other words, DPU production is valued at the retail price, which includes in particular volumetric taxes (some of which are the cost of subsidies to renewable energy sources) and network charges, which should increase in order for the TSO and DSO to break even. Thus, in addition to being inefficient (Brown and Sappington, 2017a), net metering has distributional effects, with “regular” consumers subsidising prosumers (Eid et al., 2014; Picciariello et al., 2015b; Johnson et al., 2017). In return, there might be an overinvestment in DG, and possibly a so-called “death-spiral”. For example in Wallonia, Gautier and Jacqmin (2018) show that an increase in 1c€/kWh of the network tariffs led to an increased new DPU installations by roughly 5%.

¹⁰Hopkinson rates or tariff (also known as Wright rates), are another name for a maximum demand charge (although Hopkinson suggested the use of the “connected load” (Hopkinson, 1892).

¹¹Typically, it is the average demand over 15, 30 or 60 minutes rather than the maximum instantaneous power that is recorded.

¹²See for example Neufeld, 1987 or Yakubovich et al., 2005 for a historical perspective.

However, net metering is not the only cause for that, but it is rather the combination of net metering with (mostly) volumetric charges that is problematic. In particular, net metering is not used everywhere. Nevertheless, Gautier et al. (2018) show that under net purchasing, the inefficiencies arising from net metering disappear. Other authors argue that the use of higher demand charges would be an appropriate solution (Hledik and Greenstein, 2016; Simshauser, 2016). However, Schittekatte et al. (2018) challenges these claims. Indeed, using a game-theoretical optimisation model, they study the efficiency and equity of several network tariffs when network costs are sunk: volumetric with net metering and net billing, and capacity-based charges. In particular, they show that net billing outperforms a capacity-based tariff.

Finally, in a recent paper Brown and Sappington (2018) analyse the role of MDCs in the presence of DG under net metering. Using both theoretical modelling and numerical simulations, they show that MDCs can help increase welfare and secure gains for regular consumers, and sometimes for prosumers as well.

3 General case

3.1 Preferences

Following the literature on self-rationing, let us consider a continuum of consumers indexed by $\theta \in [\theta_L, \theta_H]$. Their aim is to maximise their expected utility $\mathbb{E}[U(\mathbf{q}, Y, t, n, \theta)]$ subject to the budget constraint $M = Y + \mathbf{p} \cdot \mathbf{q}$, where \mathbf{p} and \mathbf{q} are the (possibly continuous) vectors¹³ of electricity prices and consumptions over the studied period of length N , M is the available income, Y the numeraire commodity, t the (possibly multidimensional) state of nature such as temperature, and n is time. For simplicity and comparability with the literature, we assume the utility of all consumers to be quasilinear in income, i.e.:

$$U(\mathbf{q}, Y, t, n, \theta) = Y + u(\mathbf{q}, t, n, \theta) \quad (\text{III.1})$$

Thus, expected utility maximisation is equivalent to expected consumer surplus maximisation, or equivalently, demand is independent of income and consumers are risk-neutral (Stennek, 1999). This assumption is standard in the literature and has been discussed abundantly¹⁴. Furthermore, unless specified otherwise, we do not consider inter-temporal substitution¹⁵, so that we can write the instantaneous gross consumer surplus as $u_i(q_i, \theta) = \int_0^{q_i} P_i(q, \theta) dq$, where $i = (t, n)$, $P_i(q_i, \theta) = \frac{\partial u_i}{\partial q}(q_i, \theta)$ is the (conditional,

¹³Vectors are written in bold and \cdot denotes the inner product.

¹⁴See Willig (1976) for a discussion on the use of consumer surplus as a welfare measure for non-random prices, and Schlee (2008) for random prices.

¹⁵Interdependent demands are treated in appendix B.3.

or instantaneous) inverse demand function, or marginal willingness-to-pay, and does not depend on the consumption at other instants and states of nature. We can also define a demand function $D_i = P_i^{-1}$, which only depends on the current price p_i .

3.2 First-best: peak-load pricing

As a benchmark, let us quickly derive the first-best solution, which is only possible if the consumer can be charged in real time. Let us suppose that network capacity Q is built at cost $C_N(Q)$ and that at instant n , producing and supplying a quantity $q_n \leq Q$ of electricity costs $C_n(q_n)$. Since we are interested in network tariffs only, we assume that the only constraint is the limited network capacity. In practice we could consider a system capacity cost that would include plant and network capacity. Consequently, the social planner's program is the following:

$$\begin{cases} \text{Max}_{q_i, Q} \{ \mathbb{E}[u_i(q_i) - C_i(q_i)] - C_N(Q) \} \\ \text{s.t. } \forall i \ q_i \leq Q \end{cases} \quad (\text{III.2})$$

When $q_i < Q$ the constraint is not binding and we have $P_i(q_n) = C'_i(q_i)$, i.e. the price p_i paid by consumers should be equal to the marginal cost of supplying electricity. When $q_i = Q$, the price is given by the intersection of the demand and supply functions, so that $p_i = P_i(Q) \geq C'_i(Q)$, and the optimal level of capacity is given by:

$$\mathbb{E}[(P_i(Q) - C'_i(Q))^+] = C'_N(Q) \quad (\text{III.3})$$

where $(x)^+ = \underset{\text{not.}}{\text{Max}}(0, x)$. Equation 3.2 simply states that at the optimum the marginal cost of network capacity is equal to the congestion rent when capacity is fully used. This is a special case of peak-load pricing, as introduced by Boiteux (1949). In particular, it shows that at the optimum the capacity constraint must be saturated during at least one state of the world with strictly positive measure. It follows that a network whose capacity is never saturated is sub-optimal.

Unfortunately, it is well known that if the capacity cost function C_N is subadditive (which is the case in presence of increasing returns to scale for a mono-product firm), then costs are not fully recovered under this pricing scheme. The second-best optimum (in which the network operator has a zero profit) is then given by the famous Ramsey-Boiteux prices (Ramsey, 1927; Boiteux, 1956), that create the least distortion with respect to marginal cost pricing.

3.3 Consumer program

Each consumer is to choose *ex ante* a subscribed capacity (also called fuse or access capacity) A , which limits his consumption by the means of a circuit breaker, and for which he pays a fixed amount $T(A)$ ¹⁶.

Although most recent metering devices can measure both the active and reactive powers, so that the access capacity is often given in kVA¹⁷, we will assume for simplicity that all the power is active, so that virtually “kVA=W”. This is also called the direct current (DC) approximation, since there is no reactive power in a DC circuit. In practice however, many domestic appliances use both active and reactive power, e.g. computers, televisions, refrigerators, LED bulbs, washing machines, phone chargers, etc. This may force some consumers to change their access capacity when their metering device is replaced by their distribution system operator (DSO). In France, only customers with access capacity higher than 36 kVA are charged on both their active and reactive powers.

In France, residential consumers usually choose between 3, 6, 9, or 12 kVA¹⁸, even though the capacity of the lines they are connected to may be higher than that¹⁹. According to AF-Mercados EMI et al. (2015), the average contracted capacity in Europe is 6 kW (or kVA). In Belgium, where there is no capacity charge, most meters are limited to 40 A, i.e. 8.8 kVA (tension is 220 V)²⁰. The chosen capacity usually depends on the number of electric appliances, and in particular on the type of heating system. In the low-voltage domain, subscribed capacities can go up to 36 kVA, still in a discrete fashion. For simplicity however, we will suppose that access capacity can vary continuously.

We wish to determine the value of A chosen by the consumer when his demand D_i and the retail price p_i are stochastic with known joint distribution. When choosing his capacity level, the consumer faces a trade-off between the additional surplus he can get from low prices thanks to a higher capacity, and the price of the capacity. The consumer thus maximises the following expected surplus with respect

¹⁶In practice he pays it for a billing period, typically a month or a year. As discussed in the previous section, in the seminal papers on self-rationing consumers were said to “buy a fuse” of limiting capacity A .

¹⁷The volt-ampere, or VA, is the unit used to measure the apparent power, which is the square root of the sum of the squares of real (active) power (in watts - W) and reactive power (in volt-ampere reactive - var).

¹⁸Capacity subscriptions within these bounds are also possible, not are usually not proposed by electricity retailers. Tariffs for residential customers also include 15, 18, 24, 30 and 36 kVA and values in between.

¹⁹In reality, it is rather difficult to give a definition of the “connection capacity” of a customer, because it does not only depend on the capacity of the last cable which connects him, but also upstream cables, transformers, etc. However, a single residential customer is not likely to affect the whole system upstream by changing his access capacity.

²⁰CallMePower (2018).

to A :

$$\begin{aligned}
 ES &= \mathbb{E}[S_i(D_i(p_i)) - p_i D_i(p_i) | A \geq D_i(p_i)] \times \mathbb{P}[A \geq D_i(p_i)] \\
 &+ \mathbb{E}[S_i(A) - p_i A | A \leq D_i(p_i)] \times \mathbb{P}[A \leq D_i(p_i)] \\
 &- T(A)
 \end{aligned} \tag{III.4}$$

which leads to the following optimality conditions:

$$\begin{cases} \frac{\partial ES}{\partial A} = \mathbb{E}[P_i(A^*) - p_i | A^* \leq D_i(p_i)] \times \mathbb{P}[A^* \leq D_i(p_i)] - T'(A^*) \leq 0 \\ A^* \geq 0, A^* \cdot \frac{\partial ES}{\partial A} \Big|_{A=A^*} = 0 \end{cases} \tag{III.5}$$

This is equivalent to equation (5) in S-T (which was itself an extension of equation (5) in P-S), but with time-varying prices and a possibly non-linear capacity price. The consumer equalises the expected marginal net surplus he can get from consuming a quantity A^{21} when he is constrained to do so with the marginal cost he faces.

Finally, it is possible to have $\mathbb{P}[A \leq D_i(p_i)] = 1$, i.e. the consumer always consumes his maximum available capacity. This situation is similar to the “shifting peak” initially described by Steiner (1957). This can arise for instance if the marginal cost of capacity is very high and/or the price of electricity is very low, or if the demand is constant (e.g. for an industrial customer producing 24/7). In this case, the problems simplifies to:

$$\mathbb{E}[P_i(A) - p_i] = T'(A) \tag{III.6}$$

In the following, we will mainly focus on “firm peak” cases, as it is more consistent with reality (for residential customers at least).

3.4 Social planner’s program

When we consider a population of consumers indexed by θ , P-S and S-T have shown that in the case of weakly separable preferences in consumption (q) and θ , i.e. when $u(q, i, \theta) = u(h(q, \theta), i)$, pricing at marginal cost yields the first best. This assumptions means that the consumers’ reaction to the state of the world t (e.g., temperature) is “similar”. Extending their result to the case of time-varying supply costs (i.e. $p_i = C'_i(q)$ and $T' = C'_N$) is straightforward and was done by Oren et al. (1985).

When this assumption is not true, S-T show that marginal cost pricing still stands for energy, but

²¹In the remainder of the article, we will use A instead of A^* in order to alleviate notations.

not for capacity, which should not be priced identically for all consumers.

4 Time-independent consumer facing stochastic prices

4.1 Analytical solution

In this section, we consider a time-independent consumer facing stochastic prices. This enables us to derive simplified expressions for the capacity demand function. It is a natural and complementary extension of the traditional setup, which considers uniform prices but varying demand. In particular, it highlights how a self-rationing consumer would choose his access capacity when faced with real-time prices (RTP), as may become the case in a somewhat near future thanks to so-called “smart meters”.

More precisely, we assume that the price is exogenous and stochastic with known probability and cumulative density functions g and G on $[p_L; p_H]$, and mean $\mathbb{E}[p_t] \stackrel{\text{not.}}{=} \bar{p}$. This situation could arise for example if the consumer is on a real-time meter, that perfect competition on the wholesale market leads to electricity prices equal to the marginal cost of production, and that his consumption has no effect on the price.

Under the assumption that T is an increasing function of A , we necessarily have $A \leq D(p_L)$, as it would not make sense for the consumer to buy more capacity than his maximum consumption. On the contrary, there are two possibilities regarding high prices: either $A \leq D(p_H)$ (shifting peak) or $A \geq D(p_H)$ (firm peak). In the former case, the problem is easy to solve, as we then have $D(p_t) = A$ for all i , and equation III.6 rewrites:

$$A = D[\bar{p} + T'(A)] \leq D(\bar{p}) \quad (\text{III.7})$$

In this special case, the marginal cost of capacity faced by the consumer (or, in the case of a linear tariff, the price of capacity) plays the same role as the electricity price, which in the case of real-time pricing and perfect competition is the marginal cost of electricity. The second-order condition yields $\mathbb{E}[P'(A)] - T''(A) \leq 0$, and we must also make sure that $A \leq D(p_H)$, i.e. $T'(A) \geq p_H - \bar{p}$. The consumer will thereupon consume less than what he would wish to do in every state of the world if the marginal cost of capacity he faces is bigger than the difference between the highest price and the mean price. Finally, this formula only makes sense if $A \geq 0$, or $T'(A) \leq P(0) - \bar{p}$, and if $ES \geq 0$ (which depends on the level of the fixed charge A). If T is an affine function of A , e.g. if $T(A) = m + kA$, then the formula

becomes explicit:

$$A = D(\bar{p} + k) \quad (\text{III.8})$$

Let us now consider the situation in which the consumer is not constrained in high-price states of the world, i.e. $A \geq D(p_H)$, or $P(A) \leq p_H$. Then, equation III.5 can be rewritten, dropping the index i :

$$\int_{p_L}^{P(A)} [P(A) - p]g(p)dp = T'(A) \quad (\text{III.9})$$

and the second-order condition is: $P'(A)G[P(A)] - T''(A) \leq 0$. When the upper bound of the integral reaches p_H , we get the result of the shifting-peak case. Integrating by parts, we obtain the following implicit formula for A:

$$\int_{p_L}^{P(A)} G(p)dp = T'(A) \quad (\text{III.10})$$

It may also be easier to use instead $p^* = P(A) \Leftrightarrow A = D(p^*)$, so that the equation becomes:

$$\int_{p_L}^{p^*} G(p)dp = T'[D(p^*)] \quad (\text{III.11})$$

This equation has a solution if and only if $\int_{p_L}^{p_H} G(p)dp \geq T'[D(p_H)]$, and in this case the solution is unique if for example $T'' \geq 0$, as we then have an increasing left-hand side and a decreasing right-hand side in the equation. If $\int_{p_L}^{p_H} G(p)dp \leq T'[D(p_H)]$, we are in the shifting-peak case $A \leq D(p_H)$ described above.

When capacity is priced linearly, i.e. $T' = k$, we have in addition the following partial derivative:

$$\frac{\partial A}{\partial k} = \frac{1}{P'(A)G[P(A)]} < 0 \quad (\text{III.12})$$

Thus, when $k = 0$, $P(A) = p_L$ and the above derivative becomes infinite. This is also the case when p is constant and P is stochastic (as in P-S and S-T). When $p^* = p_H$, it is equal to $\frac{1}{P'(A)} = D'(\bar{p} + k)$ and is hence continuous.

4.2 Examples

Peak and off-peak prices

As a first illustration, let us consider the simple case in which prices can only be equal to p_L or p_H , with $p_L < p_H$ and $\mathbb{P}[p = p_H] = \lambda$. Then it is easy to show that A is given (implicitly) by:

$$A = \begin{cases} D\left[p_L + \frac{T'(A)}{1 - \lambda}\right] & \text{if } A \geq D(p_H) \Leftrightarrow T'(A) \leq (1 - \lambda)(p_H - p_L) \\ D[\bar{p} + T'(A)] & \text{if } A \leq D(p_H) \Leftrightarrow T'(A) \geq (1 - \lambda)(p_H - p_L) \end{cases} \quad (\text{III.13})$$

From this example we can easily see that if $T' > 0$ then A is a decreasing function of the probability of high price λ : the less prices are low, the less it becomes interesting to invest in additional capacity to benefit from these prices (case 1). Above a certain threshold, which is also decreasing with λ , the consumption becomes always equal to the capacity, which is a decreasing function of the average price $\bar{p} = \lambda p_H + (1 - \lambda)p_L$, and hence of λ .

Continuous prices

Let us now examine some examples with prices that are uniformly distributed among $[0, 1]$, $T(A) = m + kA$, and demand is linear with $D(p) = \text{Max}(1 - p, 0)$. The shifting-peak case requires that $k \geq p_H - \bar{p} = 1/2$. Then, $A = 0$, as $k + \bar{p} \geq 1$. For $k \leq 1/2$, we can deduce from equation III.11 that $p^* = \sqrt{2k}$, which holds as long as $p^* \leq 1 \Leftrightarrow k \leq 1/2$. In the end, we come to the following capacity demand function:

$$A(k) = \begin{cases} 1 - \sqrt{2k} & \text{if } k \leq \frac{1}{2} \\ 0 & \text{if } k \geq \frac{1}{2} \end{cases} \quad (\text{III.14})$$

If we consider the less elastic demand function $D(p) = 1 - p/2$, we obtain the same result, as neither the valuation of a free good nor the mean price have changed. If the demand changes proportionally: $D(p) = \alpha(1 - p)$, the result is not changed either. However if the demand becomes $D(p) = 2 - p$ while

keeping the same price distribution then the capacity demand function becomes:

$$A(k) = \begin{cases} 2 - \sqrt{2k} & \text{if } k \leq \frac{1}{2} \\ \frac{3}{2} - k & \text{if } \frac{1}{2} \leq k \leq \frac{3}{2} \\ 0 & \text{if } k \geq \frac{3}{2} \end{cases} \quad (\text{III.15})$$

In all the above mentioned examples, a too high value of k prevents the consumer from buying, even though he would like to do so. The average consumption of the consumer is also a function of k and can be computed easily as well, for instance for this last choice of the demand function:

$$\mathbb{E}[q](k) = \begin{cases} G(p^*(k))A(k) + [1 - G(p^*(k))]\mathbb{E}[D(p)|p \geq p^*(k)] & \text{if } k \leq \frac{1}{2} \\ A(k) & \text{if } \frac{1}{2} \leq k \leq \frac{3}{2} \\ 0 & \text{if } k \geq \frac{3}{2} \end{cases} \quad (\text{III.16})$$

$$= \begin{cases} \frac{3}{2} - \left(\frac{3}{\sqrt{2}}\sqrt{k}\right) + 3k - \sqrt{2}k^{3/2} & \text{if } k \leq \frac{1}{2} \\ \frac{3}{2} - k & \text{if } \frac{1}{2} \leq k \leq \frac{3}{2} \\ 0 & \text{if } k \geq \frac{3}{2} \end{cases} \quad (\text{III.17})$$

Thence, both capacity demand and mean consumption are decreasing with k , which was expected. Furthermore, we can identify three domains: a firm peak region for $0 \leq k < \frac{1}{2}$, a shifting peak one for $\frac{1}{2} \leq k < \frac{3}{2}$, and a no-consumption one for $k \geq \frac{3}{2}$. In this last region, there is no consumption even though it would be desirable, given that the price of electricity can still be as low as 0. Too high capacity prices may therefore harm some consumers. On the contrary, a “full” real-time pricing approach (i.e. without capacity charge) would not prevent consumers willing to consume during low prices from doing so (but may lead to higher transaction costs, as discussed in the next section).

In addition, as can be seen in figure III.1, contrarily to the capacity demand function, mean consumption is not differentiable at the limit between the firm-peak and the shifting-peak regions. This is similar to what was observed by Berg and Savvides (1983) for maximum demand charges.

5 Time-varying consumer facing uniform prices

In this section we consider the case of a time-dependent consumer facing a uniform price p . This is the case for example when consumers are equipped with traditional meters which do not allow real-time

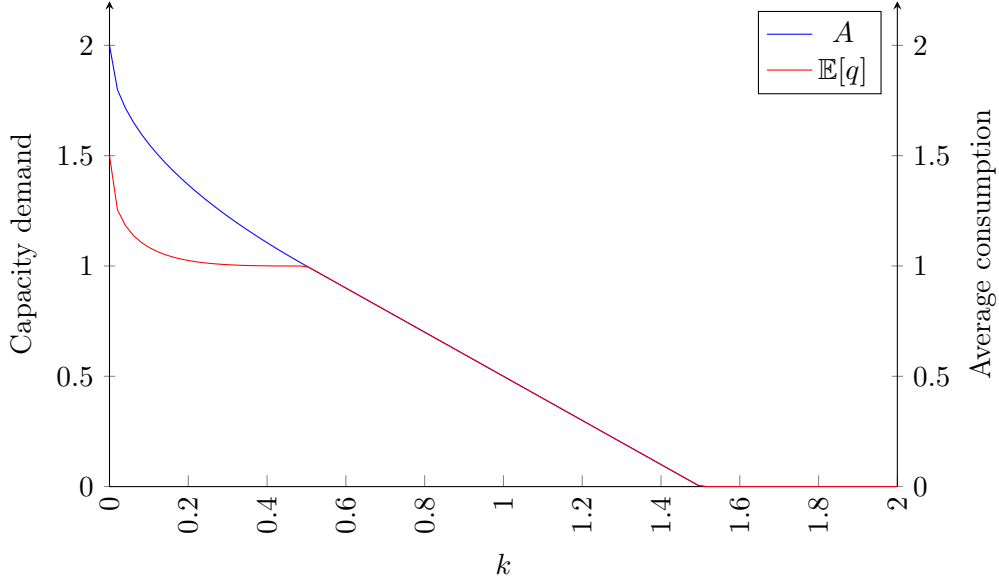


Figure III.1 – Capacity demand function and average consumption

pricing. This is the usual setup of the self-rationing literature and the previously mentioned results apply. However, we will present a simplified version of this setup, that will help us introduce several extensions.

5.1 Simplified consumer program and examples

The demand is supposed to be stochastic and indexed by t , with known pdf f and cdf F on $[t_L; t_H]$, and mean \bar{t} . For simplicity, we consider a representative consumer (which is equivalent to having weakly separable preferences), and that P_t increases with t , as in the literature. However, we will relax these assumptions to analyse non-coincident demands in appendix B.2. As in the previous section, there are two possible cases: either $P_{t_L}(A) \geq p \Leftrightarrow A \leq D_{t_L}(p)$ (shifting peak) or $P_{t_L}(A) \leq p \Leftrightarrow A \geq D_{t_L}(p)$ (firm peak). In the shifting-peak case, the consumption is always equal to A and equation III.6 gives the following first and second-order conditions:

$$\begin{cases} \mathbb{E}[P_t(A)] = p + T'(A) \\ \mathbb{E}[P'_t(A)] - T''(A) \leq 0 \end{cases} \quad (\text{III.18})$$

It is also required that A be indeed lower than $D_L(p)$. In order to make the model tractable, we can for example suppose the following dependence of the demand function: $P_t = tP$, so that in the shifting-peak case:

$$\bar{t}P(A) = p + T'(A) \quad (\text{III.19})$$

and $A \leq D_L(p) = D\left(\frac{p}{t_L}\right)$ rewrites $T'(A) \geq \frac{\bar{t} - t_L}{t_L}p$. Those equations are similar to the ones encountered in the stochastic price case. If in addition we have $T(A) = m + kA$ then:

$$A = D\left(\frac{p+k}{\bar{t}}\right) \quad (\text{III.20})$$

which is similar to equation III.8 for stochastic prices. If $P_{t_L}(A) \leq p \Leftrightarrow A \geq D_{t_L}(p)$, then let us define as in the literature t^* such that $t^*P(A) = p \Leftrightarrow A = D\left(\frac{p}{t^*}\right)$. Formula thus III.5 gives:

$$P(A) \int_{\frac{p}{P(A)}}^{t_H} tf(t)dt = p \left[1 - F\left(\frac{p}{P(A)}\right) \right] + T'(A) \quad (\text{III.21})$$

which rewritten in terms of t^* gives:

$$\frac{p}{t^*} \int_{t^*}^{t_H} tf(t)dt = p[1 - F(t^*)] + T' \left[D\left(\frac{p}{t^*}\right) \right] \quad (\text{III.22})$$

which is similar to equation III.11.

Let us now consider a two-period case, in which the demand is low with probability λ and high with probability $1 - \lambda$. This brings the following implicit expression for A , which is similar to equation III.13 for the two-price case:

$$A = \begin{cases} D_H \left[p + \frac{T'(A)}{1 - \lambda} \right] & \text{if } A \geq D_L(p) \\ \lambda P_L(A) + (1 - \lambda)P_H(A) = p + T'(A) & \text{if } A \leq D_L(p) \end{cases} \quad (\text{III.23})$$

If in addition $P_t = tP$ then we obtain: $A \leq D_L(p) \Leftrightarrow T'(A) \geq (1 - \lambda) \left(\frac{1}{t_L} - \frac{1}{t_H} \right) p$. If we denote by \tilde{t} the harmonic mean of t , i.e. such that: $\frac{1}{\tilde{t}} = \frac{\lambda}{t_L} + \frac{1 - \lambda}{t_H}$, the condition rewrites: $T'(A) \geq \frac{p}{t_L} + \frac{p}{\tilde{t}}$, which is very similar to the condition $T'(A) \geq p_H - \bar{p}$ obtained in the two-price case.

From now on, we will use this simplified model in the firm-peak case to describe some properties and extensions of the access capacity demand function. To lighten the presentation, we present some properties regarding the elasticities of the capacity demand function in appendix B.1, and extensions to non-coincident demands and interdependent demands in appendices B.2 and B.3.

5.2 First-best prices

Peak-load pricing

Denoting C_S the cost function of the electricity supplier, the first-best solution would be to charge the marginal cost $p_L = C'_S[D_L(P_L)]$ when the demand is low, and $p_H = P_H(A) = C'_S(A) + \frac{C'_N(A)}{1-\lambda}$ when the demand is high, which also give the optimal amount of capacity A^{FB} . In the case of constant production marginal cost b and constant capacity marginal cost β , we reach the following prices and installed capacity:

$$\begin{cases} p_L = b \\ p_H = b + \frac{\beta}{1-\lambda} \\ A^{FB} = D_H\left(b + \frac{\beta}{1-\lambda}\right) \end{cases} \quad (\text{III.24})$$

Note that the expression for these prices is nothing more than the one given by Williamson (1966). Hence, with constant marginal costs and no fixed cost, the network operator recover its costs during peak load periods if it receives the premium paid on the electricity price when demand is high. Similarly, in the absence of fixed production cost, the electricity supplier recovers its costs fully in both periods.

Optimal energy and capacity prices

Suppose now that the social planner can only set a uniform energy price p and capacity price k (i.e. $T(A) = kA$), and perfectly knows the consumer's behaviour. The social planner's program is then modified as follow:

$$\text{Max}_{p,k} \begin{cases} \lambda \left[\int_0^{D_L(p)} P_L(q) dq - C_S[D_L(p)] \right] \\ + (1-\lambda) \left[\int_0^{D_H\left(p + \frac{k}{1-\lambda}\right)} P_H(q) dq - C_S \left[D_H \left(p + \frac{k}{1-\lambda} \right) \right] \right] \\ - C_N \left[D_H \left(p + \frac{k}{1-\lambda} \right) \right] \end{cases} \quad (\text{III.25})$$

Still assuming constant production marginal cost b , constant capacity marginal cost β , we get the following first-order conditions with respect to p and k , respectively:

$$\begin{cases} (k - \beta + (1-\lambda)(p-b)) D'_H \left(p + \frac{k}{1-\lambda} \right) + \lambda(p-b) D'_L(p) = 0 \\ k = \beta - (1-\lambda)(p-b) \end{cases} \quad (\text{III.26})$$

which leads to:

$$\begin{cases} p = b \\ k = \beta \\ A = A^{FB} = D_H\left(b + \frac{\beta}{1 - \lambda}\right) \end{cases} \quad (\text{III.27})$$

Ergo, pricing electricity and capacity at their marginal costs leads to the first-best equilibrium as long as there is a single technology of production with constant marginal cost and that preferences are weakly separable, as originally shown by P-S. An analogy with wholesale electricity markets can be made at this stage. Indeed, if there is only one technology of production with constant marginal cost b and long-run capacity cost β , it is optimal to have an uncapped energy-only market as well as a regulated energy market with capacity payments (or competitive capacity market). If there are two periods such as in our model, an energy-only market design would achieve spot prices p_L and p_H as defined above. On the contrary, a regulated energy market where energy is always priced at its marginal cost would give $p = b$, and a capacity payment equal to $k = \beta$ would allow the recovery of capacity costs. In both cases, if there are no economies of scale, all costs are recovered.

Self-rationing with peak-load pricing

Whenever there are more than two periods with unconstrained technologies of production, the first-best will not be achieved by the use of only two price instruments. Contrarily, it is obvious that using the three instruments p_L , p_H and k , the two-period problem is overdetermined, even if there are two different marginal costs $c_L \leq c_H$ that correspond to the low and high demand periods. Although we still have $p_L = c_L$, p_H and k are linked by the following equation:

$$\frac{k - \beta}{1 - \lambda} + p_H - c_H = 0 \quad (\text{III.28})$$

so that a continuum of possible prices can lead to the optimum. An additional independent equation would then be required to determine a unique solution. Nevertheless, two “natural” solutions would be to set either $p_H = c_H$ and $k = \beta$ or $p_H = c_H + \frac{\beta}{1 - \lambda}$ and $k = 0$.

However, when the number of states becomes “important”, setting $k = 0$ and relying only on energy prices may become costly (in terms of transaction costs) for the consumer, who would have to adapt his consumption to what could come close to “real-time” prices. Therefore, using self-rationing with capacity pricing may help achieve a more efficient outcome. Indeed, subscribed capacity is a rather simple notion

to understand, and contrarily to energy prices, the price of capacity does not change with time. If electricity prices can be relatively anticipated, the consumer will choose his capacity subscription in a similar way to what we presented in the previous section. On that account, the consumer may wish to limit the number of possible price signals he may receive, in exchange for being priced according to his access capacity.

5.3 Second-best pricing

The absence of fixed costs may be true in a long-term perspective, but in the short or medium term, the network capacity cannot be adjusted as desired. This can be modelled as fixed costs, that need to be recovered by the network tariff. Even though marginal cost pricing still leads to the first-best outcome, fixed costs are undoubtedly not recovered. Furthermore, the issue of cost recovery is not just limited to fixed costs, and emerges as soon as we are dealing with a natural monopoly, i.e. whose cost function is sub-additive. In this case, the social planner maximises social welfare subject to a zero-profit (or minimum profit) constraint. In the case of constant marginal costs, this yields:

Proposition 1. *In a firm-peak situation with two states of the world, uniform energy and capacity second-best prices are given by:*

$$\begin{cases} p^{SB} = b - \frac{\mu}{1+\mu} \frac{D_L(p^{SB})}{D'_L(p^{SB})} \\ k^{SB} = \beta + (1-\lambda) \frac{\mu}{1+\mu} \left[\frac{D_L(p^{SB})}{D'_L(p^{SB})} - \frac{D_H\left(p^{SB} + \frac{k^{SB}}{1-\lambda}\right)}{D'_H\left(p^{SB} + \frac{k^{SB}}{1-\lambda}\right)} \right] \end{cases} \quad (\text{III.29})$$

where $\mu > 0$ is the Lagrange multiplier associated with the DSO/utility budget constraint. Hence, p follows the famous Ramsey inverse-elasticity rule:

$$\frac{p^{SB} - b}{p^{SB}} = \frac{\mu}{1+\mu} \frac{1}{\varepsilon_L(p^{SB})} > 0 \quad (\text{III.30})$$

where $\varepsilon_L = -pD'_L/D_L$ is the low-demand price elasticity. Conversely, the expression for k is more complicated, and the additional term with respect to the marginal cost does not even have a clear sign. For example, with constant elasticities ε_L and ε_H , we have:

$$\frac{k^{SB} - \beta}{k^{SB}} = \frac{\mu}{1+\mu} \left[\frac{1}{\varepsilon_H} + (1-\lambda) \frac{p^{SB}}{k^{SB}} \left(\frac{1}{\varepsilon_H} - \frac{1}{\varepsilon_L} \right) \right] \quad (\text{III.31})$$

Assuming $p^{SB} + \frac{k^{SB}}{1-\lambda} > 0$, we then obtain the following corollary:

Corollary 1.1. *When peak and off-peak demands have constant but different elasticities, second-best prices put more relative weight on capacity than on energy if and only if peak demand is less elastic than off-peak demand, in which case capacity is also priced at a premium:*

$$\frac{k^{SB} - \beta}{k^{SB}} \geq \frac{p^{SB} - b}{p^{SB}} \Leftrightarrow \varepsilon_H \leq \varepsilon_L \Rightarrow k^{SB} > \beta \quad (\text{III.32})$$

This result is consistent with the inverse-elasticity rule, even though it writes a little differently. Nevertheless, if we note $p_L^{SB} = p^{SB}$ and $p_H^{SB} = p^{SB} + \frac{k^{SB}}{1-\lambda}$, which would correspond to low and high prices in the case of peak-load pricing, it is easy to show that they both follow the inverse-elasticity rule. Thus, the fact that k may be lower than β is similar to the potential reversal in peak and off-peak prices described by Bailey and White (1974).

In particular, if peak demand is highly elastic, it may even be optimal to subsidise access capacity. This is due to the fact that energy and capacity are complements. Indeed, the general formula for second-best prices, given for example in Crew and Kleindorfer (1986), p.20, writes:

$$\sum_{j \in N} \frac{(p_j - C_j)}{X_i} \frac{\partial X_i}{\partial p_i} = \sum_{j \in N} \frac{R_j}{R_i} \frac{(p_j - C_j)}{p_j} \eta_{ji} = -\frac{\mu}{1 + \mu}, \quad i \in N \quad (\text{III.33})$$

where $\eta_{ji} = \frac{p_i}{X_j} \frac{\partial X_j}{\partial p_i}$ is the (cross-)elasticity and $R_i = p_i X_i$ is the revenue from product i . Then, since they consider a quasi-linear utility function, Hicksian and Marshallian demands coincide, so that the notions of gross and net substitutes/complements coincide. In particular, cross-derivatives are equal²², so that the formula becomes:

$$\sum_{j \in N} \frac{(p_j - C_j)}{p_j} \eta_{ij} = -\frac{\mu}{1 + \mu}, \quad i \in N \quad (\text{III.34})$$

or, in the two-product case:

$$\frac{(p_i - C_i)}{p_i} = -\frac{1}{\Delta} \frac{\mu}{1 + \mu} \left(\eta_{jj} - \frac{R_j}{R_i} \eta_{ji} \right), \quad i \neq j \in \{1, 2\} \quad (\text{III.35})$$

where $\Delta = \eta_{11}\eta_{22} - \eta_{12}\eta_{21}$ is positive if own-price elasticities dominate cross-elasticities. As pointed out by Bernard and Roland (2000) formula III.35 can be applied to subscribed capacity and mean consumption \bar{A} ($= \lambda D_L + (1-\lambda)A$ in our case). They also show (p.180) that in order to have a markdown

²²This is also known as the ‘‘integrability condition’’, which also makes consumer surplus path-independent in the case of interdependent demands (Hotelling, 1932).

on either energy or capacity prices “we must either have the own-price elasticity of subscribed power (evaluated at optimal prices) dominated by the average consumption cross-elasticity with respect to subscribed power price k or the own-price elasticity of average consumption dominated by the subscribed power cross-elasticity with respect to the price of energy.” Our result shows that in a two-state case, there can only be a mark-down on k , while there is necessarily a mark-up on p . Moreover, we give an interpretation in terms of peak and off-peak elasticities, which we believe are more easy to compare than subscribed power and mean consumption elasticities (the former can be defined from peak demand elasticity, as shown in appendix B.1).

Unfortunately, it is not clear whether peak or off-peak demand is more elastic, as there are arguments in favour of both situations. On the one hand, one might argue that off-peak consumption consists in “basic” and rather constant (in a given time period) needs such as lighting, heating and cooling, whereas peak consumption may include additional appliances such as televisions, computers, washing machines, electric vehicles, etc. Ergo, it appears that peak consumption can more easily be shifted and is therefore more elastic. On the other hand, the “basic” needs mentioned above usually coincide with peak demand. For example in France, there is a peak in electricity consumption on winter evenings. This is due to individual electric heating and lighting²³, which are less used during the day. In this case, peak demand may appear less elastic. So, peak and off-peak elasticities appear to be time-contingent, which further complicates the analysis. In addition, when elasticities are not constant with respect to energy rates, this result does not hold. For example, we have:

Corollary 1.2. *When peak and off-peak demand functions are linear and proportional (in which case the elasticity increases from 0 to infinity as the price increases from 0 to the “no-buy” threshold), capacity is always subsidised:*

$$\frac{k^{SB} - \beta}{k^{SB}} = \frac{-\mu}{1 + \mu} < 0 \quad (\text{III.36})$$

$$\Leftrightarrow k^{SB} = \frac{1 + \mu}{1 + 2\mu} \beta < \beta \quad (\text{III.37})$$

Finally, we can show that under constant marginal costs b and β , and fixed costs F , the zero-profit condition yields:

$$\frac{\mu}{1 + \mu} = - \frac{F D'_L D'_H}{\lambda D_L^2 D'_H + (1 - \lambda) D_H^2 D'_L} \quad (\text{III.38})$$

where D_L and D'_L (resp. D_H and D'_H) are evaluated at p^{SB} (resp. $p^{SB} + \frac{k^{SB}}{1-\lambda}$). This reminds us that

²³The importance of lighting decreases as light bulbs become more efficient, especially thanks to LEDs.

although p^{SB} and k^{SB} seem to be determined independently, they are in fact determined jointly, along with the Lagrange multiplier. This will become important when we consider prosumers in section 6. Plugging this into equation III.29 gives:

$$\begin{cases} p^{SB} = b + \frac{FD_L D'_H}{\lambda D_L^2 D'_H + (1-\lambda) D_H^2 D'_L} \\ k^{SB} = \beta - (1-\lambda) F \frac{D_L D'_H - D_H D'_L}{\lambda D_L^2 D'_H + (1-\lambda) D_H^2 D'_L} \end{cases} \quad (\text{III.39})$$

Finally, note that we obtain the prices for a profit-maximising integrated monopolist (IM) for $\mu \rightarrow +\infty$, as is standard:

$$\begin{cases} \frac{p^{IM} - b}{p^{IM}} = \frac{1}{\varepsilon_L(p^{IM})} \\ k^{IM} - \beta = (1-\lambda) \left[\frac{D_L(p^{IM})}{D'_L(p^{IM})} - \frac{D_H\left(p^{IM} + \frac{k^{IM}}{1-\lambda}\right)}{D'_H\left(p^{IM} + \frac{k^{IM}}{1-\lambda}\right)} \right] \end{cases} \quad (\text{III.40})$$

For linear and proportional demands $D_i(p) \propto D(p) = \alpha - \gamma p$, these expressions become:

$$\begin{cases} p^{IM} = \frac{\alpha + \gamma b}{2\gamma} \\ k^{IM} = \frac{\gamma}{2} \end{cases} \quad (\text{III.41})$$

Interestingly, in this special case the electricity price is hence identical to what a monopolist would charge on a single market where the demand function is D . It is also easy to show that:

$$A^{IM} \leq A^{FB} \Leftrightarrow D\left(b + \frac{\beta}{1-\lambda}\right) \geq 0 \quad (\text{III.42})$$

which is the case by construction. Thus, although capacity is subsidised, it is still lower than its optimal value.

6 Self-rationing with prosumers

In this section, we introduce prosumers and derive their consumption program, before deriving first- and second-best prices under several scenarios.

6.1 Prosumer program

We extend the simplified two-period model of the previous section by adding the possibility for consumers to install a decentralised production unit (DPU) such as a rooftop solar panel. For simplicity, we assume synchronous and independent demands, constant marginal cost of supply b and of capacity β , and uniform energy and capacity prices p and k . Furthermore, we assume that the DPU produces at full capacity during low-demand periods, but only a fraction δ during high-demand ones. We make the additional assumption of net metering and that all DPU production is consumed by consumers and prosumers in both periods. As already discussed, net-metering assumption leads to a sub-optimal pricing policy, but in our simplified model with no costs associated with DG, it does not matter. Alternatively, it is tantamount to consider that all DPU production is consumed by the prosumer in each period, so that he does not export. This could become the case in the long-run with batteries or load-management programs. Anyway, we are more interested in how a capacity charge influences the choice of installing a DPU and on cost-recovery.

Although we could have introduced a “cost” incurred by the choice of δ by the consumer²⁴, we keep it exogenous for simplicity reasons. We also keep λ exogenous, as before. The consumer now chooses consumed quantity q_L (resp. q_H) when his demand is low (resp high), and DPU capacity d , that solve the following maximisation problem, where $T'(A) = k$ is the price of access capacity and $C(d)$ is the cost of DPU capacity:

$$\text{Max}_{q_L, q_H, d} \begin{cases} \lambda \left[\int_0^{q_L} P_L(q) dq - p(q - d) \right] \\ +(1 - \lambda) \left[\int_0^{q_H} P_H(q) dq - p(q_H - \delta d) \right] \\ -T(q_H - \delta d) - C(d) \end{cases} \quad (\text{III.43})$$

We follow Gautier et al. (2018) by assuming the size of a DPU is fixed and equal to d^{25} , and that the marginal cost z of DPU is constant for a given consumer, with its value being distributed on the (possibly infinite) interval $[z_L, z_H]$ with cumulative and probability distribution functions H and $H' = h^{26}$. The distribution of the marginal cost of DPU may reflect the heterogeneity of location (weather, type of building) or income. Indeed, solar panels produce more in sunny regions than in less sunny ones, and are consequently more profitable in the former. Also, richer consumers are more likely to afford a DPU, and those with a house more likely to be able to install one.

²⁴For example, a battery would enable to increase δ . Alternatively, it could allow to shift production.

²⁵In their article, they denote DPU capacity by k .

²⁶Denoted F and f in Gautier et al. (2018).

The first-order condition on d of the maximisation problem gives a corner solution: all consumers such that $z \leq \hat{z}(p, k) = \tilde{\lambda}p + \delta k$ (where $\tilde{\lambda} = \lambda + \delta(1 - \lambda)$) install a DPU; others do not. As a deduction, the proportion of prosumers is endogenously given by $H[\hat{z}(p, k)]$, and the global cost of DPU is $\int_{z_L}^{\hat{z}(p, k)} z'h(z')dz'$. If consumers cannot choose their access capacity A , $T(A)$ acts as a fixed fee, and has no influence on the consumption choices. Then, the proportion of prosumers is given by $H[\tilde{\lambda}p] \underset{not.}{=} H[\tilde{z}(p)]$.

6.2 Long-run optima

Without economies of scale

In the long run, in the absence of increasing returns to scale, it is still optimal to charge prices $p = b$ and $k = \beta$, if consumers can choose their access capacity. This will lead to the long-run first-best level of prosumers $H[z(b, \beta)]$ and total access capacity $A^{FB} = D_H\left(b + \frac{\beta}{1 - \lambda}\right)$ for regular consumers, and $A^{FB} - \delta d$ for prosumers²⁷. The optimal network size is hence $Q^{FB} = A^{FB} - H[z(b, \beta)]\delta d$.

However, if consumers cannot choose their capacity subscription A (but the social planner imposes it), k is no longer a relevant variable for consumption choices (unless it becomes so high that consumers prefer not to consume, but we have ignored this possibility). Nevertheless, in the long run, the social planner anticipates that prosumers will be in proportion $H[\tilde{z}(p)]$. Assuming the social planner knows who the consumers and prosumers are, it installs a total capacity $(1 - H[\tilde{z}(p)])A$ for consumers and $H[\tilde{z}(p)](A - \delta d)$ for prosumers, so that the global network capacity is $\tilde{Q}(p) = A - \delta H[\tilde{z}(p)]d$. Thus, it solves the following program:

$$\text{Max}_{A, p} \begin{cases} \lambda \left[\int_0^{D_L(p)} P_L(q) dq - b(D_L(p) - H[\tilde{z}(p)]d) \right] \\ + (1 - \lambda) \left[\int_0^A P_H(q) dq - b(A - H[\tilde{z}(p)]\delta d) \right] \\ - \beta(A - H[\tilde{z}(p)]\delta d) - \int_{z_L}^{\tilde{z}(p)} z'h(z') dz' \end{cases} \quad (\text{III.44})$$

Then, maximising with respect to A and p gives $A = A^{FB}$, and:

$$\tilde{p} = b + \frac{\delta d \beta \tilde{\lambda} h[\tilde{z}(\tilde{p})]}{d \tilde{\lambda}^2 h[\tilde{z}(\tilde{p})] - \lambda D'_L(\tilde{p})} > b \quad (\text{III.45})$$

Henceforth, the price of energy has to be above its marginal cost as soon as $\delta > 0$. Indeed, since

²⁷For simplicity, we will use the same notations for individual and group demands and access capacities. It is equivalent to consider a unique prosumer of "size" $H(z)$ and a unique regular consumer of "size" $1 - H(z)$.

the price of energy has become the only incentive to invest in DPU, the social planner raises it in order to increase the number of prosumers. However, it is easy to show that $\tilde{z}(\tilde{p}) \leq \hat{z}(b, \beta)$ i.e. the level of prosumers is lower than in the first-best case. So, we necessarily have $\tilde{Q}(\tilde{p}) > Q^{FB}$. Then, k can be chosen so that the profit is equal to zero, which yields:

$$\frac{\tilde{k} - \beta}{\beta} = - \frac{\delta \tilde{\lambda} d[(1 - \lambda)(A^{FB} - \delta dH[\tilde{z}(\tilde{p})]) + \lambda(D_L(\tilde{p}) - dH[\tilde{z}(\tilde{p})])h[\tilde{z}(\tilde{p})]}{(A^{FB} - \delta dH[\tilde{z}(\tilde{p})])(\tilde{\lambda}^2 dh[\tilde{z}(\tilde{p})] - \lambda D'_L(\tilde{p}))} < 0 \quad (\text{III.46})$$

As a consequence, the price of access capacity has to be lower than its marginal cost, whilst energy is priced at a premium. Moreover, since for $\delta = 0$ we have $\tilde{p} = b$ and $\tilde{k} = \beta$, by continuity, when $\delta \ll 1$, its marginal effect on \tilde{p} (resp. \tilde{k}) is positive (resp. negative), i.e. the more DPU produces during peak periods, the higher (resp. lower) the energy (resp. capacity) charge, and hence the higher the inefficiency of such a tariff design.

All in all, disallowing consumers to choose their access capacity prevents the achievement of the first-best optimum in the long run. This is due to the fact that prosumers only take into account the possible reduction of the energy part of their electricity bill, which leads to an underinvestment in DPU. In such a situation, TOU prices $p_L = b$ and $p_H = b + \frac{\beta}{1 - \lambda}$ would be more appropriate. They would restore the optimum, as prosumers would be able to save money during peak-load prices. On that account, they would have the right incentive to invest in a DPU and the first-best level of prosumers would be attained. The network operator would then build the first-best capacity accordingly.

Economies of scale

In practice, even in the long run, there may be economies of scales, otherwise electricity networks would not be viewed as natural monopolies. As we have seen that it is more efficient to let consumers choose their capacity subscriptions, we will focus on this specification. The question is then to determine how second-best prices p^{SB} and k^{SB} computed in the previous section are modified in the presence of prosumers. In that case, the social planner's program is modified and becomes:

$$\text{Max}_{p,k} \begin{cases} \lambda \left\{ \int_0^{D_L(p)} P_L(q) dq - b[D_L(p) - H[\hat{z}(p, k)]d] \right\} \\ + (1 - \lambda) \left\{ \int_0^{D_H(p + \frac{k}{1-\lambda})} P_H(q) dq - b \left[D_H \left(p + \frac{k}{1-\lambda} \right) - H[\hat{z}(p, k)]\delta d \right] \right\} \\ - C_N \left[D_H \left(p + \frac{k}{1-\lambda} \right) - H[\hat{z}(p, k)]\delta d \right] - \int_{z_L}^{\hat{z}(p,k)} z' h(z') dz' \\ \text{s.t. } \pi(p, k) = 0 \end{cases} \quad (\text{III.47})$$

When marginal cost of capacity is constant and equal to k , we can derive the following second-best prices:

$$\begin{cases} \hat{p}^{SB} = b - \frac{\mu}{(1 + \mu)} \frac{(D_L - dH)D'_H + (1 - \lambda)(D_H - \delta D_L)\delta hd}{(D'_L - \lambda hd)D'_H - (1 - \lambda)\delta^2 D'_L hd} \\ \hat{k}^{SB} = \beta + (1 - \lambda) \frac{\mu}{(1 + \mu)} \frac{(D_L - Hd)D'_H - (D_H - \delta Hd)D'_L + \tilde{\lambda}(D_H - \delta D_L)hd}{(D'_L - \lambda hd)D'_H - (1 - \lambda)\delta^2 D'_L hd} \end{cases} \quad (\text{III.48})$$

where $\mu > 0$ is the Lagrange multiplier associated with the profit constraint, D_L and D'_L (resp. D_H and D'_H) are evaluated at \hat{p}^{SB} (resp. $\hat{p}^{SB} + \frac{\hat{k}^{SB}}{1-\lambda}$), and H and $h = H'$ at $\hat{z}(p, k)$. When $d = 0$ or if $H = h = 0$ (i.e. if there are no prosumers), we find the expressions previously obtained for p^{SB} and k^{SB} (equation III.39). Then, in order to describe the effect of DPU on second-best prices, we have to take into account the dependence of DPU parameters on μ . Assuming the existence of a fixed cost $F > 0$, solving for μ using the zero-profit condition yields:

$$\begin{cases} \hat{p}^{SB} = b + F \frac{(D_L - Hd)D'_H + (1 - \lambda)(D_H - \delta D_L)\delta hd}{\lambda(D_L - Hd)^2 D'_H + (1 - \lambda)[(D_H - \delta Hd)^2 D'_L - \lambda(D_H - \delta D_L)^2 hd]} \\ \hat{k}^{SB} = \beta - (1 - \lambda)F \frac{(D_L - Hd)D'_H - (D_H - \delta Hd)D'_L + \tilde{\lambda}(D_H - \delta D_L)hd}{\lambda(D_L - Hd)^2 D'_H + (1 - \lambda)[(D_H - \delta Hd)^2 D'_L - \lambda(D_H - \delta D_L)^2 hd]} \end{cases} \quad (\text{III.49})$$

To help us test the validity of these expressions, we can for instance look at limit cases, such as when $\lambda = 1$ (low demand only). It is then easy to see that $\hat{k}^{SB} = \beta$ and

$$\hat{p}^{SB} = b + \frac{F}{D_L(\hat{p}^{SB}) - H(\hat{p}^{SB} + \delta\beta)d}$$

i.e. capacity is priced at marginal cost and electricity at average cost. Similarly, when $\lambda = 0$ (high

demand only) we get:

$$\hat{p}^{SB} + \hat{k}^{SB} = b + \beta + \frac{F}{D_H(\hat{p}^{SB} + \hat{k}^{SB}) - H[\delta(\hat{p}^{SB} + \hat{k}^{SB})]\delta d}$$

Although equation III.49 can be difficult to interpret, we can notwithstanding deduce the following propositions.

Proposition 2. 1. *At the first order in δ , the long-run second-best price of energy is above marginal cost, i.e. $\hat{p}^{SB} \geq b$, and the attained level of prosumers is higher than the first best.*

2. *Furthermore, in the case of constant elasticities, if $\varepsilon_H \leq \varepsilon_L$, then $\hat{k}^{SB} \geq \beta$.*

Proof. The inequality $\hat{p}^{SB} \geq b$ is true for $\delta = 0$, since the denominator in equation III.49 is negative and $D_L \geq dH$ by assumption. By continuity, it remains true for $0 \leq \delta \ll 1$. For the same continuity reasons, the second-best level of prosumers is higher than the first-best level $H[\hat{z}(b, \beta)]$.

Knowing whether \hat{k}^{SB} is positive or negative is more complicated. When $\delta = 0$, the numerator is reduced to:

$$(D_L - Hd)D'_H - D_H D'_L + \lambda D_H d H' = D_L D'_H - D_H D'_L - D'_H H d + \lambda D_H h d \geq D_L D'_H - D_H D'_L$$

When comparing this expression with the one obtained for k^{SB} in equation III.39, we see that both denominators being negative, the inequality $\hat{k}^{SB} \geq \beta$ is easier to satisfy than $k^{SB} \geq \beta$. In particular, $\varepsilon_H \leq \varepsilon_L$ is a sufficient condition for having $\hat{k}^{SB} \geq \beta$, as it was already sufficient for $k^{SB} \geq \beta$. By continuity, this remains true for $\delta \ll 1$. \square

Proposition 3. *At the first order in δ , if the fixed cost F is unchanged in the presence of prosumers, long-run second-best prices satisfy:*

1. *If locally $-(2D_L - Hd)HD'_H \leq hD_H^2$, then $b \leq \hat{p}^{SB} \leq p^{SB}$.*

If in addition $\hat{k}^{SB} \leq \beta$, then $k^{SB} \leq \hat{k}^{SB} \leq \beta$.

2. *If locally $-(2D_L - Hd)HD'_H \geq hD_H^2$ and $k^{SB} \geq \beta$, then $\hat{k}^{SB} \geq k^{SB} \geq \beta$.*

Proof. Concerning energy prices, both numerators are negative (at least when $\delta \rightarrow 0$ in the presence of prosumers), and it is higher (or lower in absolute value) in equation III.49 than in III.39. For capacity prices, the numerator in the expression for \hat{k}^{SB} is higher than in the one for k^{SB} , and both fractions are preceded by a negative sign. Consequently, we have $k^{SB} \geq \beta \Rightarrow \hat{k}^{SB} \geq \beta$ and $\hat{k}^{SB} \leq \beta \Rightarrow k^{SB} \leq \beta$.

Besides, in equation III.39 as well as in III.49, denominators are the same for energy and capacity prices and are both negative. In addition, it is easy to show that when $\delta \rightarrow 0$, the denominator in III.49 is higher (lower in absolute value) than the one in III.39 if and only if $-(2D_L - Hd)HD'_H \geq hD_H^2$. \square

Whereas proposition 2 gives indications on whether prices should be above or under marginal costs, proposition 3 compares second-best prices with and without prosumers. As we have shown, these are highly dependent on the attained level of prosumers $H(z)$, and in the case of capacity prices, on peak and off-peak elasticities, as was already the case without prosumers. For example, we have the following:

Corollary 3.1. *When the number of prosumers is low, i.e. when $H \rightarrow 0$, then $b \leq \hat{p}^{SB} \leq p^{SB}$. If in addition $\hat{k}^{SB} \leq \beta$, then $k^{SB} \leq \hat{k}^{SB} \leq \beta$.*

Proof. Follows from the first part of proposition 3 and the fact that $\frac{H(z)}{h(z)} \xrightarrow{z \rightarrow 0} 0$ for all probability distributions (this is straightforward using a Taylor development of H around zero). \square

It follows that for an early development of prosumption, the second-best price of energy should decrease if fixed costs are unchanged. If in addition the price of capacity happens to be lower than its marginal cost (this necessitates in particular that ε_H be higher than ε_L , although it is not a sufficient condition), then it should increase with respect to the no-prosumer case.

Conversely, if the peak elasticity is lower than the off-peak one ($\varepsilon_H \leq \varepsilon_L$), not only will capacity be priced above marginal cost (proposition 2), but the second part of proposition 3 shows that a high proportion of prosumers might further increase it with respect to the no-prosumer case. Indeed, the inequality $-(2D_L - Hd)HD'_H \geq hD_H^2$ is verified in particular when the ratio H/h is “high”. Typically, this may be the case when $H \rightarrow 1$, i.e. when $z \rightarrow z_H$, provided $h \rightarrow 0$ at the same time. This property is true for all distributions with infinite support to the right, but it may not be satisfied for distributions with finite support such as the uniform one. However, what interests us is whether this can be verified for actual distributions of DPU marginal costs. If for instance z refers to a “levelised cost of capacity”, then it is inversely proportional to solar irradiance. Figure III.2 displays the histogram of the inverse of solar irradiation in France based on PVGIS data²⁸. From this, we see that for high values of inverse irradiation, i.e. for high DPU cost, the density decreases strongly, so that the inequality $-(2D_L - Hd)HD'_H \geq hD_H^2$ is likely to hold in this region. It may be valid elsewhere as well, if there is a sufficient decrease in h locally.

²⁸Available at http://re.jrc.ec.europa.eu/pvgis/download/solar_radiation_classic_laea_download.html.

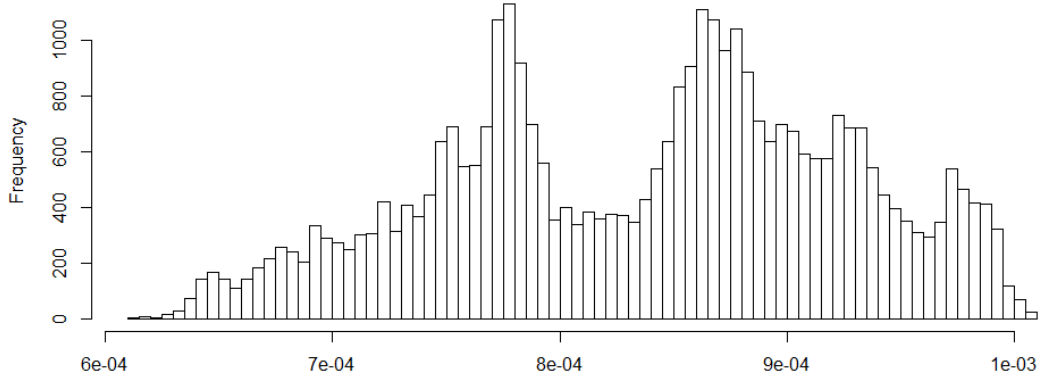


Figure III.2 – Histogram of the inverse of horizontal solar irradiation in France

6.3 Short-run optima

In the short run, the built network capacity is fixed, equal to Q_0 , and cannot be adjusted. Therefore, short-term first-best prices and level of prosumers are $p = b$, $k = 0$, and $H[\tilde{z}(b)] < H[\hat{z}(b, \beta)]$, and are the same whether consumers can choose their capacity subscription or not. If consumers have no choice over it, it can simply be imposed at its historical value: $A = Q_0$, and setting $k = \beta$ enables the DSO to break even. In this case, kA acts as a fixed fee, which is the same for consumers and prosumers alike and hence does not create distortions. This contrasts with the long-run perspective, in which such a pricing scheme was not optimal as it led to too few prosumers and an unduly high network capacity.

If consumers can change their contracted capacity, first-best prices are still $p = b$ and $k = 0$. However, these prices prevent the DSO from breaking even. Even if $Q_0 = Q^{FB}$, setting $k = \beta$ does not solve this issue. Indeed, $kA(k)$ does not act as a fixed fee anymore, as prosumers can now reduce their access capacity. Then, increasing prices helps recover more costs, but also leads to more prosumers than the short-run optimum, which in return reduces sources of revenue for the DSO.

Woo (1991) analyses the issue of capacity allocation and cost recovery in the presence of heterogeneous consumers (but without prosumers). Assuming energy is priced at “(constant) marginal fuel cost”, the author shows that capacity is priced so as costs to be recovered, i.e. so that (with our notations²⁹): $kS(k) = \beta Q_0 + \beta_0$, where S is the sum of all capacity subscriptions. Capacity is then allocated using an allocation factor $\alpha(k) = \frac{Q_0}{S(k)}$, i.e. each consumer has an effective subscription αA . The allocation factor can be lower or higher than 1, depending on the system or network being in a situation of under- or overcapacity.

In our case, the presence of prosumers further complicates the problem as it endogenously changes

²⁹In the original paper, the capacity charge and the energy rate are denoted by p and z , respectively.

prosumers' capacity subscriptions. Furthermore, we allow the energy rate as well as the capacity charge to contribute to cost recovery. We can nonetheless simplify the issue in assuming prosumers and consumers are heterogeneous only with respect to the marginal cost of DPU z . Also, we assume that $S = Q_0$, which is equivalent of assuming the existence of an allocation factor such as in Woo (1991). Under these assumptions, second-best prices are the same as in the long-run case (equation III.49) with $\beta = 0$ (remember that in the short term capacity is supposed to be fixed), so that the propositions of the previous subsection apply.

In the end, in the short run the DSO can break even: either by preventing customers to choose their access capacity and by making pay $p = b$ and $k = \beta$ to everyone; or by allowing customers to choose their subscription and accordingly charging energy above marginal cost, at least for $\delta \ll 1$. Then, the capacity charge can be either positive or negative, with its sign depending in particular on price elasticities and on the number of prosumers.

7 Conclusion

Although self-rationing with capacity subscriptions has been adopted by a certain number of countries, in particular in Europe, little research has been done on its impacts on modern electricity markets, where for example consumers can face time-varying rates and invest in decentralised production units (DPU). After a thorough review of the literature, we have developed some extensions of the traditional self-rationing model initially proposed by Panzar and Sibley (1978), and made several comparisons with peak-load pricing, which can be considered as the benchmark. First of all, we have shown that stochastic prices can be used instead of uniform prices, and that for time-independent demand functions this yields a relatively tractable expression. We have illustrated this with some examples, which reveal that a too high capacity price may harm consumers in reducing their consumption even though consumption would be socially desirable. Then, we have proposed a simplified version of the P-S model in order to introduce some extensions such as non-coincident demands and interdependent demands. While the later did not bring much insight to the traditional framework, the former was shown to complicate it and introduce adverse-selection issues, which would not arise under peak-load pricing.

In addition, second-best prices were investigated, and we found that while the second-best price of energy follows the inverse-elasticity rule, it is not the case for capacity, which may even be subsidised. Moreover, peak and off-peak demand elasticities are fundamental to the discussion, as could be expected. Finally, the model was applied to a population with prosumers. Under standard simplifying assumptions,

we showed that disabling the possibility to choose one's capacity subscription could be useful in the short term, but led to inefficiencies in the long run. Thus, we computed short and long-run second best prices when capacity can be chosen freely. Whereas second-best energy rates were proven to be above marginal cost, the discussion on capacity prices was more involved. Nevertheless, we managed to derive several sufficient conditions that enable to compare second-best prices to marginal costs, and with or without prosumers. Future research could include adverse selection, i.e. when a menu of energy and capacity rates is proposed, as is the case for example in France and as should be the case when demands are not perfectly synchronised. The study of prosumers could furthermore be extended to take into account energy losses, network management costs, and net billing instead of net metering. Finally, the question of the implementation of such second-best prices could be addressed as well, as analytical expressions do not always yield unequivocal interpretations.

Appendices

A Distribution tariffs in Europe and France

A.1 Overview of European distribution tariffs

Country	Fixed	Capacity	Share(Fixed+capacity)	Energy	Share(Energy)
Austria	Yes	No	9%	Yes	91%
Belgium	Yes	No	N.A	Yes	NA
Bulgaria	N.A	N.A	N.A	N.A	NA
Croatia	No	No	0%	Yes	100%
Cyprus	Yes	No	25%	Yes	75%
Czech Republic	Yes	No	11%	Yes	89%
Denmark	Yes	No	N.A	Yes	NA
Estonia	No	Yes	N.A	Yes	NA
Finland	No	Yes	N.A	Yes	NA
France	Yes	Yes	20%	Yes	80%
Germany	Yes	No	18%	Yes	82%
Greece	No	Yes	7%	Yes	93%
Hungary	Yes	No	4%	Yes	96%
Ireland	Yes	No	N.A	Yes	NA
Italy	Yes	Yes	34%	Yes	66%
Latvia	N.A	N.A	N.A	N.A	NA
Lithuania	Yes	No	N.A	Yes	NA
Luxembourg	Yes	No	10%	Yes	90%
Malta	Yes	No	0%	Yes	100%
Poland	Yes	No	27%	Yes	73%
Portugal	No	Yes	38%	Yes	62%
Romania	No	No	0%	Yes	100%
Slovakia	No	Yes	35%	Yes	65%
Slovenia	No	Yes	29%	Yes	71%
Spain	No	Yes	84%	Yes	16%
Sweden	Yes	No	79%	Yes	21%
The Netherlands	Yes	Yes	100%	No	0%
United Kingdom	Yes	No	14%	Yes	86%

Table III.1 – Distribution tariff structure for residential customers in 2015 in Europe (computations based on data found in AF-Mercados EMI et al., 2015)

A.2 The French residential distribution tariff

Tariff	Capacity charge (€/kVA)	Energy charge (c€/kWh)			
	Yearly	Peak high	Off-peak high	Peak low	Off-peak low
CU 4	3.72	7.36	3.67	1.88	1.35
CU	4.32	3.67			
MU 4	5.88	5.63	3.25	1.31	0.98
MUdT	6.84	3.89	2.38	3.89	2.38
LU	58.56	1.38			

CU: short use; MU: medium use; MUdT: medium use with temporal differentiation; LU: long use.

Table III.2 – Access capacity and energy charge for low-tension (≤ 36 kVA) customers in 2018 in France. Source: Enedis (2018).

B Properties and extensions of the two-period model

B.1 Elasticities

It may be interesting to know the elasticity of the subscribed capacity with respect to prices p and k for various reasons. For instance, elasticities play a central role in second-best pricing. In order to do this, we restrict ourselves to the two-state case, with $A(p, k) = D_H\left(p + \frac{k}{1-\lambda}\right)$, and we assume that the (energy) demand function has a constant elasticity ε_H : $D_H(p) = D_{H0}p^{-\varepsilon_H}$. Then, it is easy to show that the elasticities of access capacity with respect to p and k are:

$$\begin{cases} \varepsilon_{A/p} = \frac{\varepsilon_H}{1 + \frac{k}{1-\lambda}} \\ \varepsilon_{A/k} = \frac{\varepsilon_H}{1 + (1-\lambda)\frac{p}{k}} \end{cases} \quad (\text{III.50})$$

Thus, if $p > 0$, both elasticities are small than ε if and only if $k > 0$. Also, the elasticity of capacity demand with respect to the energy rate does not depend on the latter. This is due to the fact that the price elasticity of energy demand is constant (and also independent of k). Furthermore, the demand for access capacity is less elastic (with respect to both prices) than the demand for energy, and we can show that $\varepsilon_{A/p} \leq \varepsilon_{A/k} \Leftrightarrow k \geq (1-\lambda)\sqrt{p}$, i.e. for relatively high values of k , the consumer will be more elastic with respect to k . This result is interesting, as a if a regulator wishes to reduce the overall subscribed capacity, it is more effective to do it by increasing the part of the tariff (energy or capacity) which is already dominant in the sense of this inequality. Finally, for $k = 0$ (resp. $p = 0$), we have $\varepsilon_{A/p} = \varepsilon$ and

$\varepsilon_{A/k} = 0$ (resp. $\varepsilon_{A/k} = \varepsilon$), which is rather intuitive.

B.2 Non-coincident demands

In this section, we briefly explore the case of non-coincident demands. As pointed out by Schwarz and Taylor (1987), if peak consumption is not coincident among consumers, then the maximum Q_{max} of expected demands Q_n should be different from the sum S of all subscriptions, and probably lower. This is verified for example in France, where self-rationing is used and where a coefficient (a “use factor”) is applied between S and Q ³⁰. Furthermore, they argue that it would probably not be optimal to charge capacity identically among consumers, unless $\frac{\partial Q_n}{\partial S} = C$, in which case $k = C\beta$ is optimal.

Let us now consider a simplified setting, which relies on the two-period model established before. We assume that consumers are divided in two groups, labelled $i \in \{1, 2\}$, whose demands are perfectly negatively correlated. That is, with probability λ , group 1 consumes $D_{L1}(p_1)$, while group 2 consumes $D_{H2}\left(p_2 + \frac{k_2}{\lambda}\right)$, and reciprocally (we assume that each group is in a “firm peak” situation, i.e. $D_{Li}(p_i) < D_{Hi}\left(p_i + \frac{1}{1-\lambda_i}\right)$, with $\lambda_1 = \lambda = 1 - \lambda_2$). We denote by ν the proportion of group 1, and we assume that it is the “peaking” group, i.e. that:

$$Q = \text{Max}\left\{\nu D_{H1}\left(p_1 + \frac{B_1}{1-\lambda}\right) + (1-\nu)D_{L2}(p_2), \nu D_{L1}(p_1) + (1-\nu)D_{H2}\left(p_2 + \frac{B_2}{\lambda}\right)\right\} \quad (\text{III.51})$$

$$= \nu D_{H1}\left(p_1 + \frac{B_1}{1-\lambda}\right) + (1-\nu)D_{L2}(p_2) \quad (\text{III.52})$$

Note that with this formulation, Q is in general not proportional to $S = \nu D_{H1}\left(p_1 + \frac{B_1}{1-\lambda}\right) + (1-\nu)D_{H2}\left(p_2 + \frac{B_2}{\lambda}\right)$. Then, optimal consumption quantities are given by:

$$q_1 = D_{L1}(b), \quad A_1 = D_{H1}\left(b + \frac{\beta}{1-\lambda}\right), \quad q_2 = D_{L2}\left(b + \frac{\beta}{1-\lambda}\right), \quad A_2 = D_{H2}(b) \quad (\text{III.53})$$

which are obviously satisfied by the following discriminating prices:

$$\begin{cases} p_1 = b, & k_1 = \beta \\ p_2 = b + \frac{\beta}{1-\lambda}, & k_2 = -\frac{\lambda\beta}{1-\lambda} \end{cases} \quad (\text{III.54})$$

³⁰In the same manner, we could consider that a consumer applies a similar coefficient to the sum of the capacities of all his electrical appliances in order to determine his subscribed capacity. Although this approach can be used in a bottom-up modelling of electricity demand, in our case it would ignore the price of capacity in which we are interested.

or alternatively by non-discriminating off-peak and peak prices $p_L = b$ and $p_H = b + \frac{\beta}{1-\lambda}$. Consequently, at the optimum consumers of group 2 pay a peak-load price for the consumed electricity but are perfectly compensated by a capacity subsidy, while consumers of the “peaking” group (1) are charged as in the coincident-peak case. Moreover, in the absence of increasing returns to scale, the DSO or utility breaks-even. There are however two issues related to these optimal prices. First, it may be difficult for a regulator to accept the idea of subsidising capacity. Second and more importantly, the issue of adverse selection may arise. Indeed, focusing only on the electricity bill, if consumers were to choose between prices (p_i, k_i) , $i = 1, 2$, they would both choose (p_2, k_2) . Assuming that the quantities consumed and the gross surplus vary little with prices, the differences in bills between price schemes 1 and 2 are equal to $\frac{\lambda}{1-\lambda}\beta(D_{H1} - D_{L1})$ and $\beta(D_{H2} - D_{L2})$, and are hence both positive in the individual firm-peak case. Although the study of adverse selection is beyond the scope of this article, we find it necessary to underline it here, as it has many practical consequences.

Interestingly, these results contrasts with the one of Schwarz and Taylor (1987), who state that energy must be priced at marginal cost. If we constrain the use of a single price p for all consumers, the optimal values are given by:

$$\begin{cases} p = b + \frac{r(1-\nu)D'_{L2}}{\lambda\nu(1-\nu)D'_{L1} + (1-\lambda)(1-\nu)D'_{L2}} > b \\ B_1 = \frac{r\lambda\nu D'_{L1}}{\lambda\nu(1-\nu)D'_{L1} + (1-\lambda)(1-\nu)D'_{L2}} > 0 \\ B_2 = -\frac{r\lambda(1-\nu)D'_{L2}}{\lambda\nu(1-\nu)D'_{L1} + (1-\lambda)(1-\nu)D'_{L2}} < 0 \end{cases} \quad (\text{III.55})$$

In this case adverse selection is definitely a problem, as all consumers would choose B_2 . Moreover, the DSO or utility may make a positive or negative profit. The difference with S-T’s result (marginal cost pricing of energy) probably comes from the fact that they consider that all consumers react similarly to the state of nature (e.g., temperature) t , since they assume (as did P-S) that $\frac{\partial P}{\partial t} > 0$ for all consumers, whereas in our example consumers react in opposite ways to the state of nature.

This result also seems in contradiction with Brown and Sappington (2018), who show that MDCs (which are different from the capacity charge we consider here) can increase welfare with respect to TOU pricing when peak demands are divergent. They argue that in this case the MDC introduces a discrimination in the TOU price received by consumers and prosumers, and thus helps improve welfare. In our simplified model, we saw that TOU prices p_L and p_H lead to the first best optimum, so that the capacity charge would be useless. The difference may however arise from the fact that Brown and

Sappington (2018) consider: three time periods instead of two, quadratic production costs, and positive costs incurred by DG production on transmission, distribution and network management (TDM) costs. In addition, their result was partly anticipated by Crew and Kleindorfer (1979), p.191-192, and will lead us to our next subsection:

“The above examples indicate that maximum-demand charges may not be ruled out as inefficient, especially when diversity and substitution possibilities are large. In effect maximum-demand charges allow each consumer group to self-select their peak period while none the less providing the right signal to each group as to the social costs of peak demand. In the absence of such maximum-demand charges, however, one or other of these groups could avoid the peak charge by shifting demand to their next most preferred period, with possibly deleterious aggregate effects. Of course, if there were no diversity (identical preferences), or if demands were time inelastic (no period substitution effects), then one could accomplish the same efficient demand manipulation via simple peak-load pricing. Such empirical evidence³¹ as there is available on European experience with peak-load pricing suggests, however, that while significant changes in system utilisation can take place with peak-load pricing, controlling the time shifts in demand in response to peak-load pricing is also a problem. From the point of view of recovering costs as well as in providing appropriate price incentives to consumers, therefore, it may well be that maximum-demand charges are desirable ingredients of practical peak-load tariffs.”

B.3 Interdependent demands

In this section, let us briefly expose the case of interdependent demands when there are two time periods and one representative consumer. The rationale between interdependent demands is the following: if a consumer faces varying prices, he may shift loads from one period to another. In particular, we generally expect the consumptions in high and low price periods to be substitutes³². In the peak-load pricing literature, it has been relatively little investigated. It was first formalised by Pressman (1970), using the line integral formulation and the integrability conditions formulated by Hotelling (1932, 1935) with exogenously given pricing periods of equal length. As we just saw in the previous subsection, Crew and Kleindorfer (1979) analyse interdependent demands with a MDC in a simple three-period

³¹Mitchell et al. (1978) give a detailed account of the effects of time-of-day pricing in Europe.

³²With more than two time steps, consumptions in two adjacent periods could be complements. For example for a “long” process such a washing machine cycle, a lower price in a given period could trigger consumption in the given period and in the following, if the price is not expected to increase too much.

framework. Burness and Patrick (1991) generalises the peak-load pricing problem with continuous³³ and interdependent demand and endogenously chosen periods. More recently, their model was adapted by Calzada (2007) in a telecommunications context.

Following Pressman (1970), when there are two periods of equal lengths, consumer surplus between $(q_1, q_2) = (0, 0)$ and $(q_1, q_2) = (q_1^*, q_2^*)$ writes:

$$CS = \oint_C \mathbf{P}(\mathbf{q}) \cdot d\mathbf{q} - \mathbf{P}^* \cdot \mathbf{q}^* = \oint_{(0,0)}^{(q_1^*, q_2^*)} [P_1(q_1, q_2) dq_1 + P_2(q_1, q_2) dq_2] - (P_1^* q_1^* + P_2^* q_2^*) \quad (\text{III.56})$$

where C is a piece-wise smooth curve connecting $(0, 0)$ to $\mathbf{q}^* = (q_1^*, q_2^*)$, $\mathbf{P}^* = (P_1^*, P_2^*)$ and \mathbf{q}^* are the equilibrium price and quantity vectors. Then, quasilinear preferences imply that the integrability condition $\frac{\partial P_i}{\partial q_j} = \frac{\partial P_j}{\partial q_i}$ ($i \neq j$) is met, so that the line integral defined above is independent of the chosen path and can for example be rewritten:

$$\oint_C \mathbf{P} \cdot d\mathbf{q} = \int_0^{q_1^*} P_1(q_1, 0) dq_1 + \int_0^{q_2^*} P_2(q_1^*, q_2) dq_2 = \int_0^{q_2^*} P_2(0, q_2) dq_2 + \int_0^{q_1^*} P_1(q_1, q_2^*) dq_1 \quad (\text{III.57})$$

Unequal period lengths have been introduced by Burness and Patrick (1991), who write the surplus using the (instantaneous) demand function D as integrand³⁴, rather than the inverse demand function³⁵:

$$CS = \oint_C \sum_I \int_{t \in I} \mathbf{D}(\mathbf{p}, \mathbf{P}_J, t) dt d\mathbf{p}, \quad I, J \in \{U, L\}, \quad I \neq J \quad (\text{III.58})$$

where U and L are the peak and off-peak periods, respectively, and this time C connects (P_U, P_L) to (∞, ∞) ³⁶. Using again the integrability condition, we have (Lemma 1 in the original article):

$$CS = \int_{t \in U} \int_{P_U}^{\infty} D(p, P_L, t) dp dt + \int_{t \in L} \int_{P_L}^{\infty} D(p, \infty, t) dp dt \quad (\text{III.59})$$

$$= \int_{t \in L} \int_{P_L}^{\infty} D(p, P_U, t) dp dt + \int_{t \in U} \int_{P_U}^{\infty} D(p, \infty, t) dp dt \quad (\text{III.60})$$

In particular, the authors show that the integrability condition is true for time-averaged cross-derivatives,

³³See for example Craven (1971, 1985) and Dansby (1978).

³⁴The authors use the symbol Q , and other slightly different notations.

³⁵The authors argue that there exists an implicit function theorem for interdependent demands, so that if utility is determined by the consumption vector $\mathbf{q} = \{q(t), t \in [0, T]\}$, then demand is determined over the price vector $\mathbf{P} = \{P(t), t \in [0, T]\}$.

³⁶It is assumed that demand remains non-negative when prices tend towards infinity and that the integrals are well defined.

i.e.:

$$\int_{t \in I} \nabla_{P_J} D(P_I, P_J, t) dt = \int_{t \in J} \nabla_{P_I} D(P_J, P_I, t) dt, \quad I \neq J \quad (\text{III.61})$$

For that reason, one needs to be cautious not to use an instantaneous demand function that satisfy the integrability condition, when dealing with unequal period lengths. From here, it is straightforward to extend this expression to our case: low (resp. high) demand/prices with probability λ (resp. $1 - \lambda$). Then, expected consumer surplus writes³⁷:

$$ES(q, A) = \oint_C [\lambda P_L(q_L, q_H) dq_L + (1 - \lambda) P_H(q_L, q_H) dq_H] - \lambda p_L q - (1 - \lambda) p_H A - kA \quad (\text{III.62})$$

where C connects $(0, 0)$ to (q, A) and we still assume $q < A$ (firm peak). When the integrability condition is satisfied, i.e. $\lambda \frac{\partial P_L}{\partial q_H} = (1 - \lambda) \frac{\partial P_H}{\partial q_L}$, the integrand of the line integral is the gradient of a potential³⁸. From here, the derivatives of the line integral are nothing more than the corresponding coordinates of the gradient, so that we have the following first-order conditions:

$$\begin{cases} \frac{\partial ES}{\partial q}(q, A) = \lambda P_L(q, A) - \lambda p_L = 0 \\ \frac{\partial ES}{\partial A}(q, A) = (1 - \lambda) P_H(q, A) - (1 - \lambda) p_H - k = 0 \end{cases} \quad (\text{III.63})$$

which can be (at least locally) inverted in:

$$\begin{cases} q = D_L\left(p_L, p_H + \frac{k}{1 - \lambda}\right) \\ A = D_H\left(p_L, p_H + \frac{k}{1 - \lambda}\right) \end{cases} \quad (\text{III.64})$$

so that if peak and off-peak demands are substitutable, off-peak consumption increases as a consequence of peak-load and/or capacity pricing. If off-peak prices decrease, this leads to a decrease in peak consumption. Hence, interdependence of demands tends to flatten the load curve, as expected.

Nevertheless, we can show that with dependent or independent demands, the first best is still reached using peak and off-peak prices $p_L = b$ and $p_H = b + \frac{\beta}{1 - \lambda}$, or energy and capacity prices $p = b$ and $k = \beta$. The results obtained for non-coincident demands also hold in this framework. These results are not in contradiction with Crew and Kleindorfer (1979), who in fact considered two energy prices and a capacity charge in a three-period framework. In fact, subscribed capacity or maximum demand charges (which are equivalent in a deterministic setting) can be useful if there are less TOU prices than

³⁷At the difference of Burness and Patrick (1991), we prefer to keep the same order of arguments.

³⁸In the case of consumer surplus the potential is the indirect utility function.

the number of periods. The difference with the conclusions of Brown and Sappington (2018) may be due to their assumption of quadratic supply costs (as it increases the incentive for the social planner to reduce peak consumption), or to the fact that they consider prosumers and increasing TDM costs with DG capacity, or to the number of periods (three in their case).

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Chapter IV

How renewable production depresses electricity prices: evidence from the German market

About this chapter

This last chapter was actually my first work as a PhD student, and its subject was suggested to me by Frédéric Lantz, who coauthored the final paper published in *Energy Policy* (Martin de Lagarde and Lantz, 2018). I thus wish to thank two anonymous referees for their constructive comments. Also, I had the chance to present it multiple times: in June 2016 at the 39th International conference of the International Association for Energy Economics (IAEE) in Bergen (Norway); in November 2016 at the 21st Young Energy Economists and Engineers Seminar (YEES) in Edinburgh (Scotland); in November 2016 at the FAEE winter workshop in Paris; in May 2017 at the 5th International Symposium on Energy and Finance Issues (ISEFI) in Paris; and in June 2017 at an internal IFPEN seminar in Rueil-Malmaison. I am indebted to all participants of these seminars and in particular to Cédric Clastres for his review at the FAEE winter workshop.

Abstract

The urgency of climate change has led several countries to develop renewable energy in order to reduce CO₂ emissions, through the means of various subsidies. In the electricity sector, one drawback of such policies is the negative impact on electricity prices, known as the merit order-effect. This paper aims at assessing the impact of intermittent renewable production on electricity prices in Germany, which has experienced a significant increase of its renewable capacity over the last two decades. To do so, we use a two-regime Markov switching model, that enables to disentangle the impact of wind and solar generation, depending on the price being high or low. We find as expected that renewable production induces a negative marginal effect, which is stronger in regimes of relatively high prices. In addition, we show that both wind and solar productions have a significant impact on the frequency and expected duration of each regime. This has implications in terms of market design, security of supply, and support mechanisms for renewables.

1 Introduction

The development of renewable energy sources (RES) is often justified by the need to address global warming, through the reduction of green-house gases emissions, and is also led by the will to reach energy independence in fossil and fissile fuel-dependent countries. In the electricity sector, main RES are wind power and solar photovoltaic (PV). These technologies are spreading throughout the world and Europe, which has announced RES targets for the next decades: 20% in the final energy consumption by 2020 and 27% by 2030. To reach these goals, renewables often need to be subsidised, as they would generally not be competitive otherwise on the wholesale market¹. In addition to the aforementioned goals, the subsidisation of these energies aims at internalising the “learning effect”, i.e. the decrease of their cost along with their development. This is a positive externality that is by definition not taken into account by the market, and which would lead to too few investments in these technologies if not accounted for.

However, the development of electric RES challenges the current design of electricity markets. Indeed, they were originally designed to reflect the short-term production cost of electricity via the system marginal price, i.e. the marginal cost of the last unit needed to meet the demand. While marginal costs were traditionally driven by fuel costs such as coal, gas, oil, or uranium; wind and photovoltaic have on the contrary (almost) no marginal cost. Therefore, they tend to lower prices when they are producing, which is commonly known as the “merit-order effect” (Sensfuß et al., 2008). In addition, wind and solar energies are intermittent (or variable), albeit with seasonal patterns, while electricity prices are highly seasonal, with seasonality being driven mainly by demand at the daily, weekly and yearly time scales. Hence, RES generation is likely to have a different impact on electricity prices, depending on the state of the supply-demand equilibrium. Additionally, renewable production is expected to affect electricity also globally, and in particular its distribution, which is only partly captured by the analysis of the merit-order effect.

This article addresses these issues for the German day-ahead market by developing a two-regime Markov switching (MS) model. In particular, we are able to disentangle the merit-order effect in function of the price level, while keeping temporal coherence of the time series. Furthermore, we allow for time-varying probabilities (inhomogeneous model), in order to capture the impact of RES on the switching mechanism from “high” to “low” prices, and hence on the proportion and duration of each regime.

¹However, distributed renewable generation such as rooftop solar PV is becoming more and more profitable for end-users, as their levelized cost of electricity (LCOE) can in some places be lower than the retail tariff they are faced with (grid parity). Such consumers, often called “prosumers”, do not need to be subsidised by public funds (even though it is sometimes the case), but they can benefit from cross-subsidies via the distribution network tariff.

Studying the merit-order effect in Germany is quite relevant, as the country has had a huge development of wind and solar PV over the past two decades (RAP, 2015). Furthermore, since more than 40% of the electricity production in Germany (and Austria) is traded on the EEX day-ahead spot market, the related price is a relatively good indicator of the electricity supply-demand equilibrium. Hence, for these several reasons, the choice of Germany seems quite appropriate.

The remainder of the article is structured as follows. In section 2, we briefly explain the mechanism behind the merit-order effect as well as other consequences of renewable production on electricity prices. In section 3, we provide a review of the literature on the impact of RES production on electricity prices as well as on MS models applied to electricity prices and we explain which gap we aim at filling with this paper. Then, section 4 briefly describes the data we used. Section 5 then presents the modelling strategy, and empirical results are presented and discussed in section 6. Finally, section 7 concludes the article by providing the main findings and policy implications.

2 Theoretical analysis

In this section, we use basic microeconomic tools to illustrate how the merit-order effect arises and why it is differentiated depending on the price level. We explain also how renewable production is likely to impact the distribution of prices more globally.

Graphically, we can see that if at the equilibrium the inverse supply curve² is locally steep, the impact is expected to be higher than when it is locally flat. In Germany, on average the steepness of the inverse supply curve increases with load, i.e. it is convex (except in the negative-price zone). It may not be the case elsewhere, but for example Karakatsani and Bunn (2008) show that in the British market the aggregate supply function is also convex. Figure IV.1 illustrates this case by showing the variation of the merit-order effect with the load level.

Formally, this can be seen in the following way: if $D : p \mapsto D(p)$ (with $(D' < 0)$ and $S : p \mapsto S(p)$ (with $S' > 0$) are the expressions of the instantaneous demand and supply functions, the impact on the price of an infinitesimal shock of supply (e.g. RES production) or demand would be at the first order (proof in appendix A):

$$\frac{\partial p}{\partial Load} = \frac{-1}{\frac{\partial D}{\partial p} - \frac{\partial S}{\partial p}} = -\frac{\partial p}{\partial RES} > 0 \quad (\text{IV.1})$$

In reality, supply and demand are piecewise constant functions, as they are the result of a bidding process.

²The inverse supply function S^{-1} gives the price p in function of the supply quantity q . The inverse supply curve is thus defined by $p = S^{-1}(q)$.

Hence they have zero derivatives except in points of discontinuity where they are non-differentiable. Nevertheless, it is convenient to assume differentiability as it gives the right insight, and in the case of rather small increments it is a good approximation. From equation IV.1, it is clear that the higher the slope of the inverse supply function S^{-1} , the lower the slope of S (equal to its inverse), and thus the higher the marginal (merit-order) effect. Note also that on average the impact of wind, solar and load has no reason to be the same, as all variables and the supply and demand functions vary over time. In addition to this marginal effect, RES production is expected to have a more global impact on electricity prices, in particular on its conditional or unconditional distributions. For example, we could expect prices to be “low” more often, especially if complementary sites can be used for RES installations. Also, conditional volatility is expected to be higher in periods of “high” prices (because of the same slope argument), while unconditional volatility can be lower or higher, depending on how much more “low” prices (with lower conditional volatility) there are.

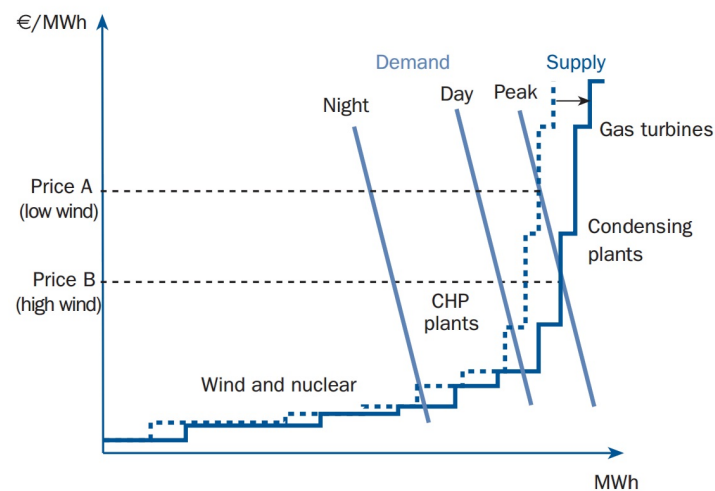


Figure IV.1 – Differences in the merit-order effect (source: Risø DTU)

3 Literature review

3.1 Impact of renewable production on electricity prices

The impact of subsidised renewable generation on electricity prices and its distributional implications have been widely discussed empirically and theoretically, e.g. by Meyer and Luther (2004), Munksgaard and Morthorst (2008), Sáenz de Miera et al. (2008), Sensfuß et al. (2008), Cutler et al. (2011), Tveten et al. (2013), Cludius et al. (2014), Kallabis et al. (2016) and Bublitz et al. (2017). In this topic, the use of time series econometrics to study the market impact of RES production is more recent and very

abundant as well. Many of them used ARMA-GARCH models, such as Woo et al. (2011) in Texas, Liu and Shi (2013) for the ISO-New England market, Ketterer (2014) in Germany or Karanfil and Li (2017) for the Danish intraday market, just to cite a few ones. All these analyses found a significant negative impact of RES generation on electricity prices and a positive one on conditional volatility (when modelled). However, the measured effect is necessarily averaged over the whole time series due to the used methods. Additionally, these studies mainly describe the merit-order effect, but do not tell how renewable production affects the proportion and duration of the price levels, which can be an issue for the profitability of plants relying on episodes of high prices.

Nevertheless, some authors have used other models in order to capture variability in the merit-order effect and additional properties. For example, Jónsson et al. (2010) quantify the impact of wind forecast on electricity prices for each hour of the day using a non-parametric approach. They also analyse the distributional impacts on the price under several scenarios, and show in particular that the unconditional volatility decreases with wind penetration. Unfortunately, they do not model the underlying mechanisms. In a different fashion, Paraschiv et al. (2014) estimate the impact of RES generation (and other variables) on electricity prices in Germany for each hour of the day, using time-varying coefficients. In particular, they show that the impact of wind (resp. solar) energy is more important during afternoon, evening and night hours (resp. noon peak hours).

However, electricity prices are expected to become less and less deterministic as the share of renewable generation increases and demand-response and storage become more available. This fact calls for a more flexible approach, which should be based on the level of prices rather than on predefined periods (hours, days, etc.). In this spirit, Keles et al. (2013) show that the wind power feed-in has a distinct impact on prices depending on the load and residual load levels (and hence implicitly on the price level) for each hour and day type. Their analysis is performed using linear regressions on ascending 2-MW load clusters, which are then used in a simulation of electricity prices. Unfortunately, their modelling does not take into account the temporal connection between the load clusters, nor discusses the impact on the price distribution.

3.2 Markov switching models and applications to electricity prices

The general literature on Markov switching models is also wide: Goldfeld and Quandt (1973) and Hamilton (1989, 1990) for a first introduction to MS models, Cai (1994), Hamilton and Susmel (1994) and Gray (1996) for MS-(G)ARCH models, and Hamilton (1996) for testing MS models). Finally, one

can also see Krolzig (1997) for MS-VAR, and Kim et al. (2008) concerning endogenous switching.

Since electricity cannot be stored at a wholesale scale, electricity prices are highly volatile, with the existence of both positive and negative price peaks, heavy tails, jumps, etc. Hence, first MS models applied to electricity were for prices “alone”, as they were able to capture these peculiarities (Deng, 1998; Ethier and Mount, 1998; Huisman and Mahieu, 2003; Janczura and Weron, 2010). On different topics, Haldrup and Nielsen (2006) and Haldrup et al. (2010) show that Nordic electricity prices present long-memory and regime-switching behaviours, and Cifter (2013) exhibits two distinct volatility regimes using a MS-GARCH model. Other authors have studied the impact of exogenous variables on the conditional mean (Zachmann, 2013), on transition probabilities of inhomogeneous MS models (Mount et al., 2006; Huisman, 2008), or both (Kanamura and Ōhashi, 2008). Finally, Veraart (2016) models the impact of wind production on electricity prices using a regime-switching Lévy semi-stationary process, with regimes depending on the wind penetration index.

3.3 Contribution of the paper to the literature

In the end, we believe that a MS model is an appropriate tool to answer our research question. Indeed, as mentioned above, it has already been shown that electricity prices present Markovian regime changes. In addition, MS models estimate time-varying coefficients, while keeping the temporal integrity of the time series, instead of dividing them in distinct series, that would for instance depend on the price level or on the hour of the day. Indeed, we will show in section 5 that after applying an appropriate transformation to the price time series, we can identify two distinct regimes, of respectively “high” and “low” prices. This feature is very suitable for regime-switching models as they can give mixture distributions. The estimation then shows that the regimes are serially correlated, hence justifying the Markovian switching mechanism. Furthermore, the autocorrelation and conditional autoregressive heteroskedasticity observed in electricity prices can also be captured (Krolzig, 1997). Finally, the chosen MS model allows us also to quantify some distributional impacts of RES production through the modelling of transition probabilities, which we link to the proportion and duration of the price regimes and hence on the distribution of prices.

4 Data

4.1 Overview of the data and first correlations

Our data is originally composed of four time series for the period 2014-2015, that come from various sources:

- hourly day-ahead electricity spot prices, obtained from EEX-Powernext;
- solar and wind electricity generation³, obtained from the four TSOs (TenneT, Amprion, 50Hertz, Transnet BW) websites, at the 15 minutes time step;
- hourly electricity load (from ENTSO-E website).

We summed the RES generation data of the TSOs and aggregated it to the hourly time step, in order to obtain 17,520 values for each variable. Figure IV.2 represents the corresponding final time series, and table IV.1 shows the correlation coefficients between the variables.

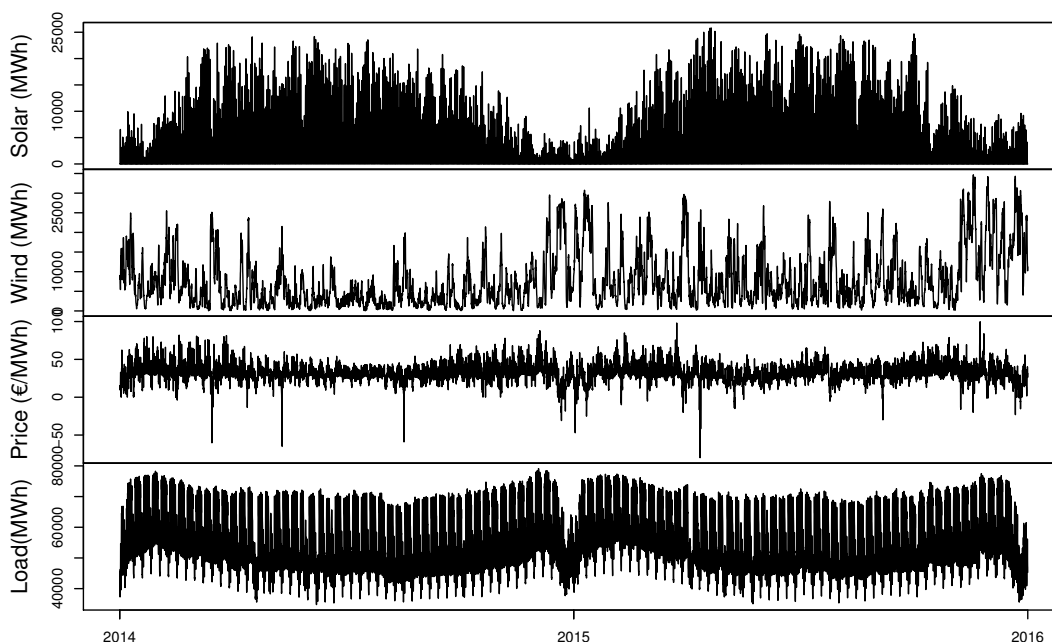


Figure IV.2 – Final data

As one would expect, solar energy has a strong yearly seasonality, with much more production during summer, while wind energy has a relatively opposite seasonality, and they are indeed negatively

³As suggested by Jónsson et al. (2010), the day-ahead forecast would be a better candidate than the actual energy output, since production decisions are taken on the basis of forecasts. However the forecast data provided by the TSOs was incomplete, and many actors have their own forecast, which may differ from the one made by the TSOs. Finally, using real production instead of forecast values should not dramatically change the value of the coefficients, but rather the goodness of fit.

	Wind	Price	Load
Solar	-0.157	-0.039	0.331
Wind		-0.424	0.037
Price			0.674

Table IV.1 – Pearson correlation coefficients between the variables

correlated. Obviously, solar generation follows also a daily pattern (day/night), which is not observed for wind. The electricity demand is very cyclical as well, with annual and daily patterns, the latter being probably the reason for the positive correlation with solar production. We also find these patterns in the price series, which is highly and positively correlated with load, negatively with wind, and almost not correlated with solar generation. The seasonality of these price and load time series will be more thoroughly discussed in section 4.4. Finally, although the electricity consumption is higher in winter, essentially because of heating and lighting, there is a huge decrease in demand (and hence in price) during the Christmas holidays, because of a drop in the industrial activity (Do et al., 2016).

4.2 Price statistics

Since we are interested in modelling the electricity prices, we need to take a deep look at the price time series, which is the goal of this subsection. Table IV.2 below present the main descriptive statistics of the price time series. First of all, we notice that the price is quite volatile, has heavy tails and is slightly skewed, which are common features of electricity prices, and can be the result of a regime-switching mechanism (Krolzig, 1997). As already seen in figure IV.2, there are negative prices (190 occurrences, i.e. a little more than 1% of the total), and high positive spikes as well. These well-known specificities of electricity prices are mostly due to the fact that electricity is (almost) non storable. Hence, demand must be met by production at all time, while conventional plants have flexibility constraints (limited ramp up/down in particular). Any change in demand and/or generation will then have an immediate impact on the price, that reflects the supply-demand equilibrium. The histogram (figure IV.3 below), the normal QQ-plot (figure IV.17, appendix B) and the boxplot (figure IV.18, appendix B) illustrate the previous analysis and show strong evidence of non-normality, which is confirmed by a Jarque-Bera test ((p-value < $2.2 \cdot 10^{-16}$)).

It is also interesting to look at the “complete” histogram in figure IV.19 (appendix B). Indeed, we can see that there are some isolated spikes, for example near zero, that probably correspond to marginal prices of some specific units and in particular RES. A closer look around zero shows that there is in fact

	Min	Q1	Median	Mean	Q3
Price (€/MWh)	-79.9	25.4	31.1	32.2	40.0
	Max	S.D.	C.V. ⁴	Skewness	Kurtosis
Price (€/MWh)	99.8	12.7	0.39	-0.3	6.2

Table IV.2 – Descriptive statistics of the electricity price

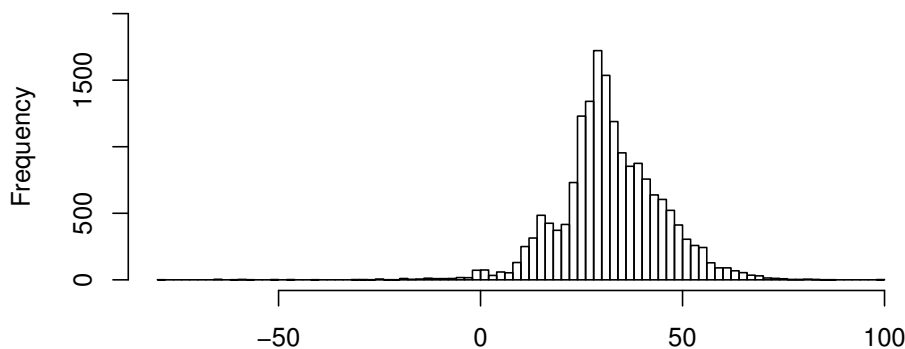


Figure IV.3 – Histogram of price (€/MWh)

a range of prices from approximately -0.10 to 0.10 €/MWh (figure IV.20 in appendix B).

Finally, we make sure that the price time series is stationary by performing two unit root tests: augmented Dickey-Fuller, Phillips-Perron; and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test (appendix B, table IV.8). All these tests show that the price time series is stationary.

4.3 Load-related statistics

If we now look at the histogram of load (figure IV.4, left), we see that there appears to be two modes, with respectively “high” and “low” demand. When studying relations between price, RES production and demand, it is frequent to consider the residual demand, i.e. demand minus RES generation. The histogram of the residual load is visible on figure IV.4 right. We clearly see that the “high-demand mode” has disappeared, which could be explained by the high correlation between demand and solar production due to their daily seasonality. The descriptive statistics of the load and residual load are shown in table IV.3. We see that although the residual demand is still not Gaussian, it is more volatile (due to the volatility of the wind and solar outputs), and has slightly heavier tails. It is also interesting to note that although RES production strongly contribute to off-peak load reduction (-28.9 GW), it only generates a 1.2 GW decrease of peak demand.

Furthermore, residual load (net demand) has a correlation coefficient with price of 0.88 , which makes

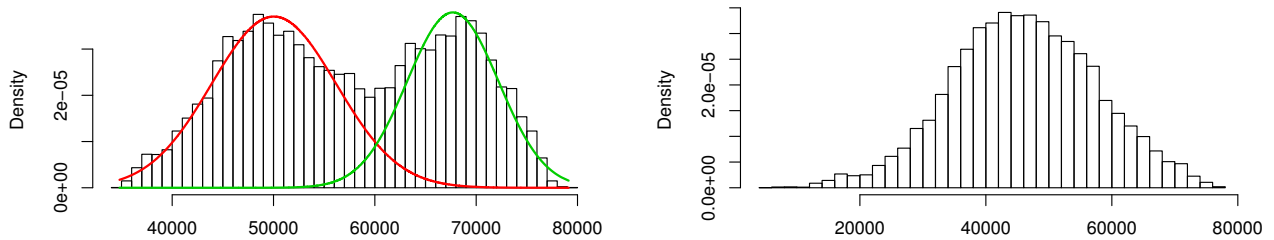


Figure IV.4 – Histogram and estimated mixture model densities of load (left), and histogram of residual load (right), in MWh

	Min	Q1	Median	Mean	Q3
Load (MW)	34,801	48,825	57,237	57,616	66,891
Residual load (MW)	5,903	38,214	45,845	45,939.9	53,905
	Max	S.D.	C.V.	Skewness	Kurtosis
Load (MW)	79,120	10,332	0.18	-0.02	1.8
Residual load (MW)	77,898	11,425	0.25	-0.1	2.9

Table IV.3 – Descriptive statistics of load and residual load

it a “better” candidate for the model than gross demand ($\rho = 0.67$). Similarly, it is often convenient to study the relative share of RES production, as suggested by Jónsson et al. (2010). In our case, they have higher correlation coefficients with price (-0.56 for wind and -0.095 for solar) than RES generation itself, but also with residual load (-0.62 and -0.18). This could possibly lead to high variance inflation factors, but as we will see in section 6, the obtained coefficients are significant and stable.

4.4 Price and load seasonality

Electricity prices are highly seasonal, mainly because of the demand seasonality. To illustrate this, the left graph on figure IV.5 below shows the power spectra (or periodograms) of the price and residual load time series. These enable to detect the dominant frequencies (or equivalently, periods) in the series. We find that the price and residual load have identical periods, i.e. 12h, 24h, 168h (a week) in particular, which was expected. Furthermore, the right graph on figure IV.5 represents the squared coherency spectrum, which is the amplitude of the cross-correlation function. It shows which percentage of the variance is shared by the two variables at each frequency⁵. This analysis confirms that the seasonality of electricity prices is mainly driven by the (residual) demand.

This seasonality affects the distributions of price and (residual) load, but our analysis strongly

⁵On this graph the frequency is obtained by dividing the abscissa by the number of observations, i.e. 17,520. The period is then the inverse of the frequency, as on the left figure. The smallest period is 2h as we are dealing with hourly data. Hence the maximum frequency is 0.5h^{-1} .

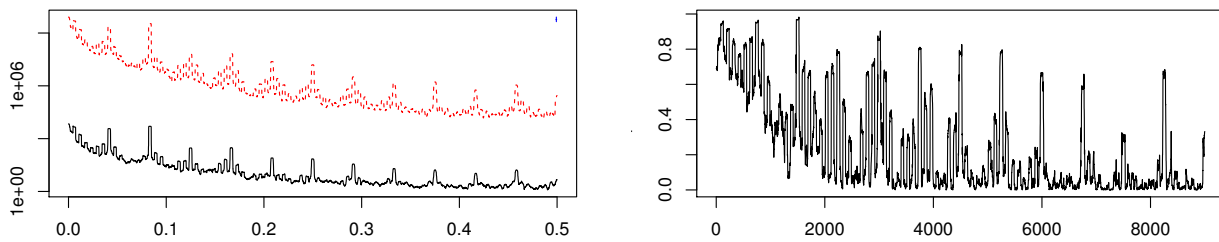


Figure IV.5 – Smoothed log-periodograms of price (black, left) and residual load (red, left) and squared coherency spectrum (right)

suggests that these variations will be correlated, given the very high correlation between the price and the residual load, both in the temporal and frequency domains. Thus, it seems sufficient to control for this seasonality using the residual load as a covariate in the model. In particular, we seek to keep the model as parsimonious as possible, as MS models can prove very difficult to estimate. Indeed, having too many regressors can lead to non-convergence or local convergence (i.e. wrong estimates). Furthermore, differentiating the model for each season and type day would require dividing the series accordingly and hence break the temporal integrity, which we wish to avoid as the series present some autocorrelation, that the MS model takes (at least partly) into account.

5 Methodology

In this section, we first present the transformation that we apply on the price time series, before exposing the model itself.

5.1 Variable transformation

It is quite common in time series analysis to perform a logarithmic (or sometimes a Box-Cox) transformation. Indeed, the logarithmic transformation has several interesting properties, from reducing the weight of extreme values (and more generally reducing non-normality). It also enables to interpret coefficients of regressions as elasticities, or to interpret first differences of the transformed data as rate of returns.

However, we cannot take the logarithm of the price, because of negative prices (1% of the total). This could be artificially prevented by adding an offset value to the series so that it would be strictly positive, enabling then to use the log transformation, as suggested by Sewalt and De Jong (2003). If the offset was low enough compared to the mean, it would produce little distortion, but in our case, the price goes as low as $-79.9\text{€}/\text{MWh}$, for a mean of $32.2\text{€}/\text{MWh}$ and a maximum of $99.8\text{€}/\text{MWh}$. Hence,

adding 80€/MWh to prices and taking the logarithm would then highly “compress” high prices together while maybe giving “too much” importance to negative prices.

Furthermore, we want to be able to distinguish the merit-order effect depending on the level of prices, while keeping a unique and coherent time series. It is rather obvious that the previously exposed methodology will not help us identify price regimes, as prices will be “stacked” together. Thus, in order to enhance regime identification while taking into account negative prices and reducing the importance of extreme values, we use an inverse hyperbolic sine transformation. This transformation was originally described by Johnson (1949) and more recently used by Schneider (2012) for electricity prices. This transformation is achieved by applying the inverse of the hyperbolic sine function, which is defined by the following expression, with offset and scale parameters $\xi, \lambda \in \mathbb{R}$:

$$\forall x \in \mathbb{R} \quad f(x, \xi, \lambda) = \sinh^{-1} \left(\frac{x - \xi}{\lambda} \right) = \ln \left[\frac{x - \xi}{\lambda} + \sqrt{\left(\frac{x - \xi}{\lambda} \right)^2 + 1} \right] \quad (\text{IV.2})$$

The behaviour of this function is logarithmic when $|x| \rightarrow \infty$ and linear when $x \rightarrow \xi$:

$$f(x, \xi, \lambda) \underset{x \rightarrow \xi}{\sim} \frac{x - \xi}{\lambda} \quad (\text{IV.3})$$

$$f(x, \xi, \lambda) \underset{|x| \rightarrow +\infty}{\sim} \text{sign}(x) \times \ln \left(\frac{2|x|}{\lambda} \right) = \text{sign}(x) \times \left[\ln \left(\frac{|x|}{\lambda} \right) + \ln 2 \right] \quad (\text{IV.4})$$

Hence, the logarithmic behaviour of the function will “compress” the extreme values, while its linear behaviour will on the contrary “expand” intermediate values, hopefully leading to the desired distribution. Figure IV.6 below represents the inverse hyperbolic sine function with $\xi = 0$ and $\lambda = 1$ in red, and in green the symmetric logarithmic function (with position factor $\ln 2$) and its symmetric with respect to the origin.

There are many ways to choose the values for λ and ξ . For example, one could use the values that give the most normal mixture distribution, or that is best fit by the model. In particular, the choice of ξ will strongly condition the range of each regime. However, for the sake of simplicity, we simply decided to take the mean value of the price for ξ . This choice enables us to separate the two regimes quite clearly, and gives them a relatively similar importance as the mean is quite close to the median. Additionally, we chose $\lambda = 1$ €/MWh for simplicity reasons also. As expected, the histogram of the transformed price (figure IV.7) lets appear two distinct modes, that could not be seen in the original histogram. We can highlight the bimodality of the distribution by trying to fit it as a mixture of two

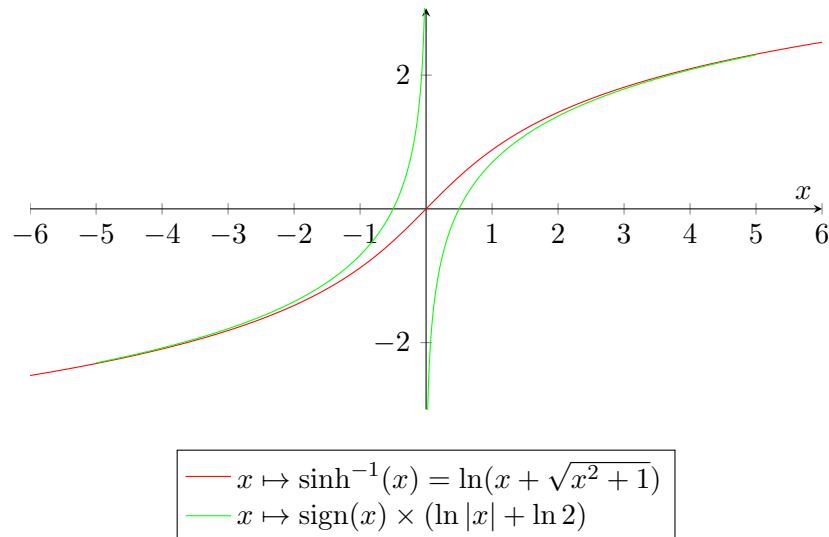


Figure IV.6 – Inverse hyperbolic sine (red) and symmetric logarithm (green) functions

normal distributions. This gives the red and green densities in figure IV.7: the two modes are well identified, but are not Gaussian (they have no reason to be, nor is it required by the model). However, extreme values are indeed reduced for each regime.

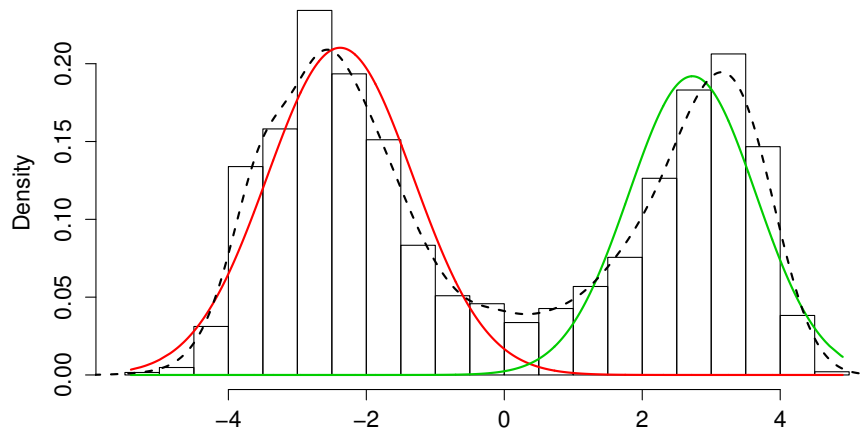


Figure IV.7 – Histogram, estimated mixture model densities and kernel density (dashed) of the transformed price

5.2 Model

Now that we have described and transformed the data, we develop an econometric model to quantitatively evaluate the impact of RES generation on electricity prices. We consider a discrete-time ($t \in \mathbb{N}$), two-regime MS model, in which the coefficients of the covariates and the variance of the residuals depend on the value of a latent unobserved state (or regime) variable $S \in \{1; 2\}$. The state variable is a Markov chain, i.e. the probability of switching from a regime is Markovian (it only depends on its current state,

and not its past):

$$\forall t \in \mathbb{N} \quad \mathbb{P}(S_t = j | S_{t-1} = i, S_{t-2}, \dots, S_0) = \mathbb{P}(S_t = j | S_{t-1} = i) = p_{ij}(t) \quad (\text{IV.5})$$

as visually described in figure IV.8. We denote by P the stochastic matrix associated with the process:

$$\forall t \in \mathbb{N} \quad P(t) = \begin{pmatrix} p_{11}(t) & p_{12}(t) \\ p_{21}(t) & p_{22}(t) \end{pmatrix} \quad \text{with: } \forall i \in \{1, 2\} \quad p_{i1} + p_{i2} = 1 \quad (\text{IV.6})$$

Then, we have by recurrence that: $\mathbb{P}(S_{t+k} = j | S_{t-1} = i) = P(t) \times \dots \times P(t+k)_{(i,j)}$. Furthermore, the

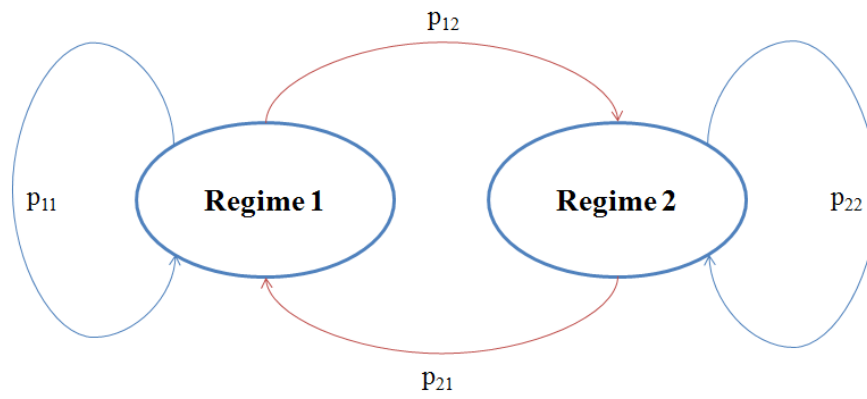


Figure IV.8 – Graph representing the Markov chain process

underlying Markov chain is supposed to be ergodic, i.e. irreducible (it is possible to switch from a state to another with positive probability) and if all its states are ergodic (i.e. aperiodic and recurrent). We also allow the Markov chain to be inhomogeneous, with probabilities of transition varying over time. A simple and widely spread specification for inhomogeneous MS models is to have the probabilities being described by a logistic function of external regressors⁶. In our case, we want probabilities to vary with wind and solar penetration indices. Finally, the model to estimate is given by equations IV.7-IV.9 below (note that all the parameters of the model are estimated together via maximum likelihood):

$$\forall t \in \mathbb{N} \quad Price_t^* = \beta_0(t) + \beta_1(t) \frac{Wind_t}{Load_t} + \beta_2(t) \frac{Solar_t}{Load_t} + \beta_3(t) RLoad_t + \varepsilon_t \quad (\text{IV.7})$$

⁶It would also be possible to use another specification, for example a probit one as in Kim et al. (2008), but we think that a logit specification allows to interpret the coefficients more easily, and should not fundamentally change the results, as it is usually the case for discrete choice models.

where $RLoad = Load - Wind - Solar$ is the residual load, $Price^*$ is the transformed price, and:

$$\forall t \in \mathbb{N} \begin{cases} \beta(t) = \beta^{(1)} \times \mathbb{1}(S_t = 1) + \beta^{(2)} \times \mathbb{1}(S_t = 2) \in \mathbb{R}^4 \\ \varepsilon_t \rightsquigarrow \mathcal{N}(0, (\sigma_1)^2 \times \mathbb{1}(S_t = 1) + (\sigma_2)^2 \times \mathbb{1}(S_t = 2)) \end{cases} \quad (\text{IV.8})$$

$$\forall t \in \mathbb{N} \quad \text{logit}(p_{i1}(t)) = \ln \left(\frac{p_{i1}(t)}{1 - p_{i1}(t)} \right) = \alpha_0^{(i)} + \alpha_1^{(i)} \frac{Wind_t}{Load_t} + \alpha_2^{(i)} \frac{Solar_t}{Load_t} \quad (\text{IV.9})$$

$$\Leftrightarrow p_{i1}(t) = \frac{1}{1 + \exp \left(-\alpha_0^{(i)} - \alpha_1^{(i)} \frac{Wind_t}{Load_t} - \alpha_2^{(i)} \frac{Solar_t}{Load_t} \right)} \quad (\text{IV.10})$$

$$\Leftrightarrow p_{i2}(t) = 1 - p_{i1}(t) = \frac{1}{1 + \exp \left(\alpha_0^{(i)} + \alpha_1^{(i)} \frac{Wind_t}{Load_t} + \alpha_2^{(i)} \frac{Solar_t}{Load_t} \right)} \quad (\text{IV.11})$$

It is also possible to compute the expected duration of each state. This is done numerically for an inhomogeneous model, while for an homogeneous models the expected duration of regime $i \in \{1, 2\}$ has the following closed-form expression:

$$\mathbb{E}\tau_i = \sum_{k=1}^{+\infty} k \mathbb{P}(\tau_i = k) = \sum_{k=1}^{+\infty} k p_{ij} p_{ii}^{k-1} = \frac{1}{p_{ij}} = \frac{1}{1 - p_{ii}} \quad (\text{IV.12})$$

For an homogeneous ergodic Markov chain, one can also compute the stationary distribution $\pi = (\pi_1, \pi_2)$, with $\pi_1 + \pi_2 = 1$, which by definition is the probability distribution of states that does not change in time. These probabilities can be interpreted as the mean proportion of (or the unconditional probability of being in) each regime:

$$\pi P = \pi \Leftrightarrow \pi_1 = 1 - \pi_2 = \frac{p_{21}}{p_{12} + p_{21}} = \frac{\mathbb{E}\tau_1}{\mathbb{E}\tau_1 + \mathbb{E}\tau_2} \quad (\text{IV.13})$$

An ergodic Markov chains has a unique stationary distribution, and if it is homogeneous it is also the equilibrium (or limiting) distribution, i.e. it is reached asymptotically:

$$\lim_{n \rightarrow +\infty} P^n \underset{\text{not.}}{=} P^\infty = \begin{pmatrix} \pi_1 & \pi_2 \\ \pi_1 & \pi_2 \end{pmatrix} \quad (\text{IV.14})$$

For an inhomogeneous Markov chain these values have usually no closed-form expressions, but can nevertheless be estimated numerically, which is done with the estimation.

6 Results and discussion

Let us now present the estimation results, before discussing more in depth the interpretation of the regimes in a second subsection. Then, we will derive (average) marginal effects from the model, as the interpretation of the coefficients is not straightforward. Lastly, we will examine the impact on the structure of the regimes, and in particular their expected duration.

6.1 Estimation results

The estimation results are presented in tables IV.4 and IV.5 below. All coefficients are highly significant and significantly different from a regime to another (Wald tests were performed to test this). It is surprising at first sight that the coefficients associated with the relative shares of wind and solar productions are positive. However, we will show in subsection 6.3 that we can indeed deduce negative marginal effects of wind and solar productions. This is due to the fact that these productions are also present in the residual load variable⁷.

Furthermore, we conducted several robustness checks. Indeed, the possible multicollinearity between the three covariates could lead the estimates to be either non-significant or numerically unstable (Belsley et al., 2005). The estimation results show that the coefficients are statistically significant, which rules out the first issue. Regarding numerical stability, we have realised 50 additional estimations after adding noise to the data. We also estimated the model after removing the first and last four days from the sample (192 hours in total, i.e. roughly 1% of the whole sample). We found that in all cases the estimates were little affected by these operations, and we thus consider that multicollinearity is not an issue here.

Concerning the transition matrix parameters, $\alpha_1^{(i)}$ and $\alpha_2^{(i)}$ are both positive, i.e. the probability of staying in or switching to regime 1 (resp. regime 2) is an increasing (resp. decreasing) function of the relative shares of wind and solar productions. Figure IV.9 shows the evolution of the modelled probabilities of transition with the relative shares of wind and solar. This graph reveals two particular features: firstly, the influence of the wind energy output is much stronger than the influence of the solar one; secondly, the impact on p_{11} (and hence on p_{12}) is quite limited, compared to the impact on p_{21} (and p_{22}).

Table IV.5 below shows that the mean probabilities of transition are also significant, hence justifying the switching mechanism. Additionally, we showed using Wald tests that p_{11} and p_{21} (and thus also

⁷We could have chosen a specification whose coefficients could be more easily interpreted, but the chosen modelling was the only one with lowest information criteria and residual variance, which converged, and which was able to distinguish the two regimes properly.

Variable	Coefficient	Std. Error	z-Statistic	p-value
Regime 1				
Intercept	-7.171284	0.056058	-127.9269	0.0000
Wind/Load	1.271735	0.064171	19.81791	0.0000
Solar/Load	1.530959	0.064736	23.64942	0.0000
RLoad	0.000114	1.19e - 6	95.71098	0.0000
σ_1	0.581968	0.006004	96.93304	0.0000
Regime 2				
Intercept	-3.416402	0.089319	-38.24955	0.0000
Wind/Load	1.569330	0.135748	11.56058	0.0000
Solar/Load	2.242196	0.126642	17.70505	0.0000
RLoad	0.000106	1.40e - 6	75.80216	0.0000
σ_2	0.695252	0.008222	84.56472	0.0000
Transition Matrix Parameters				
$\alpha_0^{(1)}$	1.109705	0.059471	18.65958	0.0000
$\alpha_1^{(1)}$	5.306012	0.345166	15.37235	0.0000
$\alpha_2^{(1)}$	4.464573	0.414828	10.76247	0.0000
$\alpha_0^{(2)}$	-2.762521	0.069484	-39.75780	0.0000
$\alpha_1^{(2)}$	6.971012	0.392717	17.75075	0.0000
$\alpha_2^{(2)}$	1.483876	0.441446	3.361400	0.0008

Table IV.4 – Coefficient estimates

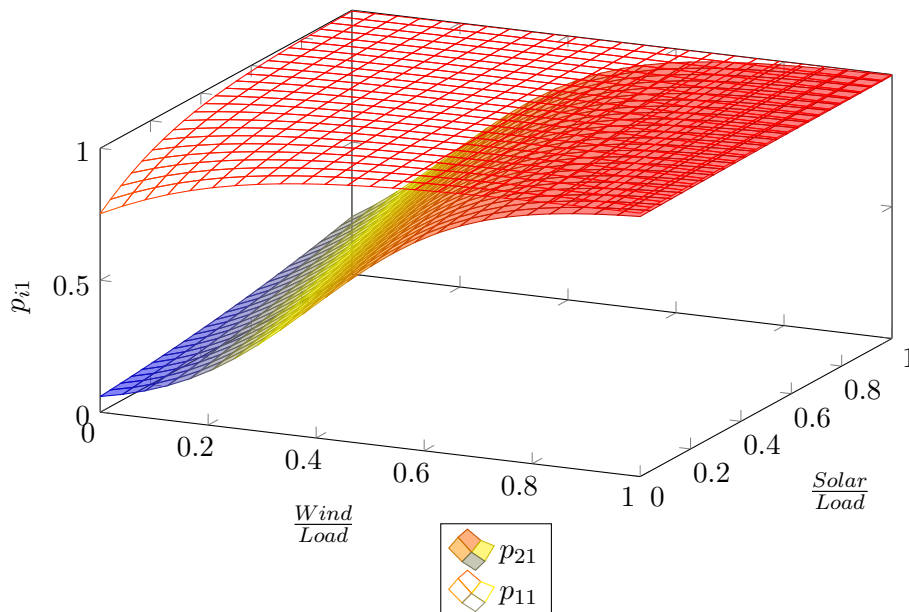


Figure IV.9 – Probabilities of transition

p_{12} and p_{22}) were significantly different from one another. This proves that the switching mechanism is indeed Markovian, at the opposite of a “simple” switching model, for which the probability of being in a given regime would be unconditional (i.e. $p_{11} = p_{21}$ and $p_{22} = p_{12}$).

Time-varying transition probabilities $p_{ij}(t)$:			
		1	2
Mean	1	0.876859	0.123141
	2	0.182783	0.817217
		1	2
Std. Dev.	1	0.060346	0.060346
	2	0.150465	0.150465
Time-varying expected durations:			
		Regime 1	Regime 2
Mean		12.64588	8.048185
Std. Dev.		13.72816	3.877061

Table IV.5 – Time-varying transition probabilities and expected durations

Finally, let us comment the time-varying expected durations: although regime 1 is on average 4.6 hours longer than regime 2, it is also much more variable. Also, one should not be surprised that the sum of the mean expected durations does not equal 24 hours. In particular, this means that there can be more than one regime change during a single day.

6.2 Regime visualisation

In this subsection, we now associate the regimes with the levels of prices and other variables. Fortunately, the estimation procedure computes for each time step the probability of being in each regime. In fact three kind of probabilities are computed by the algorithm:

- one-step probabilities: $\mathbb{P}(S_t = i | S_{t-1})$;
- filtered probabilities: $\mathbb{P}(S_t = i | S_{t-1}, \dots, S_1)$;
- smoothed probabilities: $\mathbb{P}(S_t = i | \{S_t\}_{t \in [1; T]})$.

Filtered or smoothed probabilities are often used to attribute the regimes to each time step. We will use smoothed probabilities, but there is almost no difference with the filtered probabilities in the regime attribution. In practice, the probabilities are very close to 1 or 0, so that the choice between a regime or another is unambiguous.

Dynamic visualisation

A very common and useful way to visualise the switching process is shown in figure IV.10 below. From this short sample (first week of September 2014), we clearly see that as expected, the regimes are associated to a price mode: prices are higher in regime 2 than in regime 1. Also, these regimes seem to be quite correlated to the hours of the day. This is normal since prices are strongly seasonal, as already explained in subsection 4.4. However, there are some exceptions, that the MS model is able to take into account, as we can see in this example. We find this week to be rather representative, as it presents the usual daily and weekly seasonalities of electricity demand and prices while showing the influence of the variable RES production on prices. Also, as can be seen later in figure IV.11 and IV.12, there difference in the attribution of the regimes is much more driven by the type of day than by the season.

These graphs contain a lot of information, and hence need to be analysed. First of all, we notice the very regular pattern followed by the load, with a peak at 11am and very low demand during the night and the weekend. During the first two days, wind and solar production is rather low, and the regimes seem to be driven by load only: regime 2 coincides with high demand and high prices, from 6am to 10pm, so roughly during daytime. On Wednesday and Thursday however, wind and solar generation increases. This incurs a change in regime with a decrease in price, respectively from 12pm to 5pm and 3pm. On Friday, the wind energy output is rather low, but solar production reaches its week peak at 1pm, and there is a slight and quick change of regime ($\mathbb{P}(S = 1) = 0.66$). Finally, the load decrease during the weekend, associated with a still strong solar generation, keeps the prices low.

Seasonality analysis of the regimes

Let us now look at the the frequency of occurrence of regime 1 for each hour, per type of day⁸ (figure IV.11) and season⁹ (figure IV.12). We observe as expected that night hours are mainly during the low-price regime (1), for all types of day and seasons. The morning peak hours (8-10am) are more associated to high prices (regime 2), but only for working days. Evening peak hours (6-8pm) are associated with high prices for all types of days (but less during week-ends), and particularly in autumn.

During working days, the middle of the day is less associated with a specific regime, except during spring in which prices are relatively lower. Indeed, although the type of day seems to be the main driver for the level of prices, the frequency of occurrence of regime 1 differs a lot among months, reaching

⁸We do not consider holidays in this analysis, but we believe that it would not change the results much, and that the pattern would be rather similar to the one observed for weekends.

⁹For simplicity, we considered that winter was running from December to February, spring from March to May, etc.

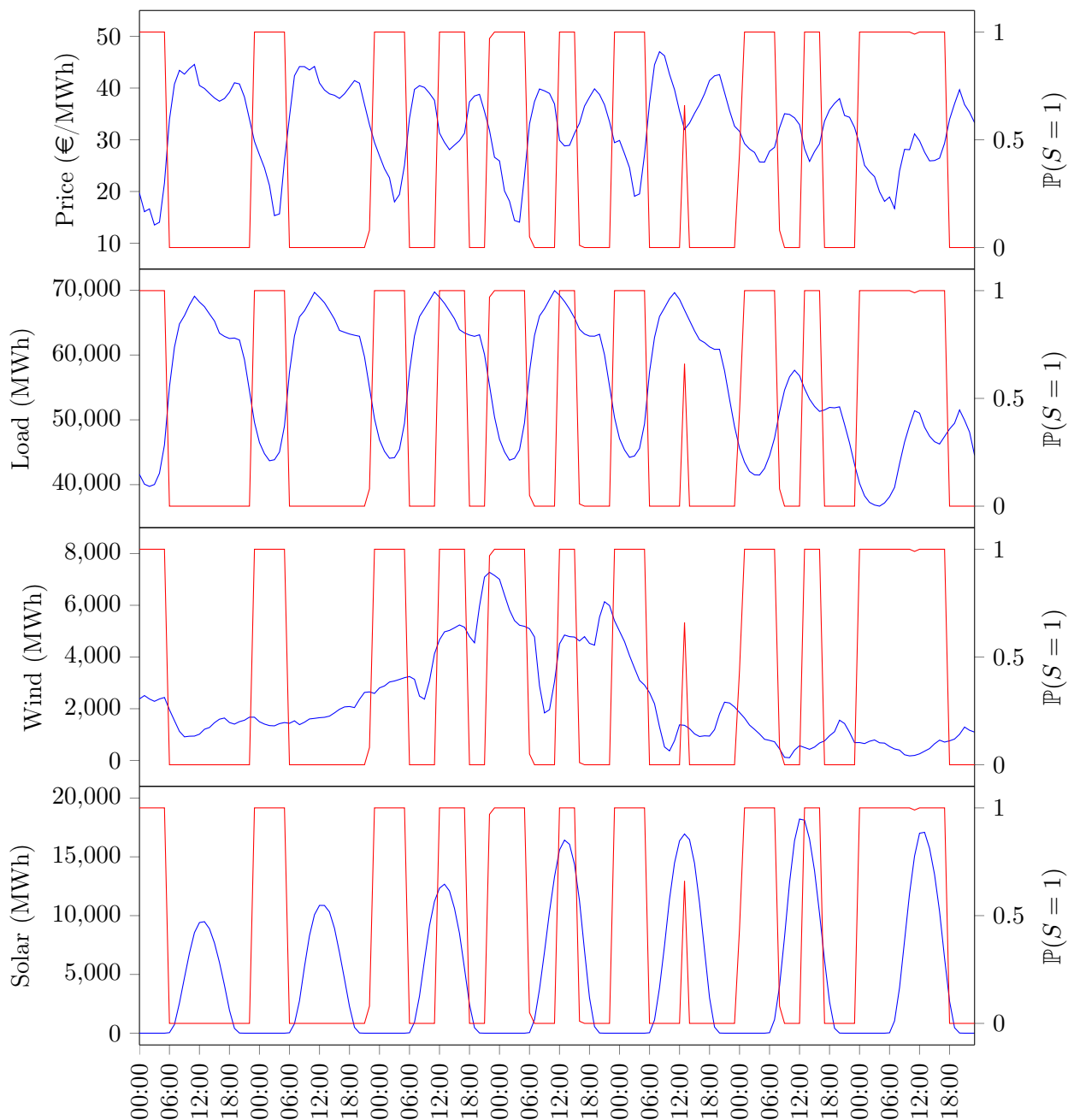


Figure IV.10 – Price, gross demand, wind and solar productions (blue, left axis) and probability of being in regime 1 (red, right axis), first week of September 2014

88.7% at 1-2pm in March while it is of only 41.7% in November. This confirms the fact that the model is indeed able to take the seasonality into account, while staying non-deterministic and hence more flexible.

Comparison of price and load regimes

We can also visualise the regimes thanks to 2D plots such as figure IV.13: (transformed) price vs. (logarithm of) load. On this graph the two regimes are easily identifiable. Also, this partly confirms

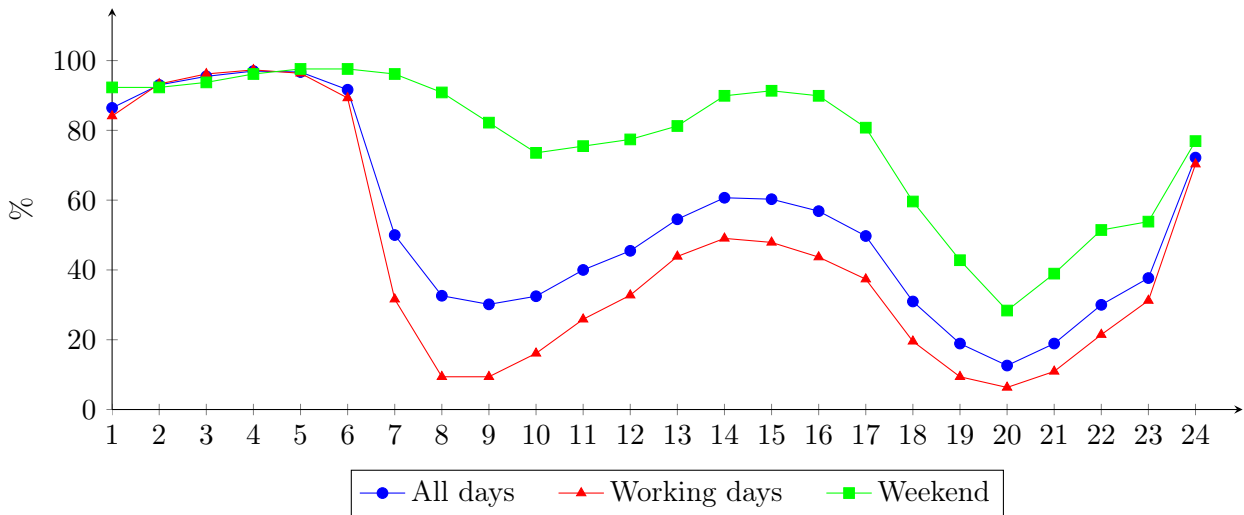


Figure IV.11 – Mean frequencies of occurrence of regime 1 for each hour of the day, for working days and weekends

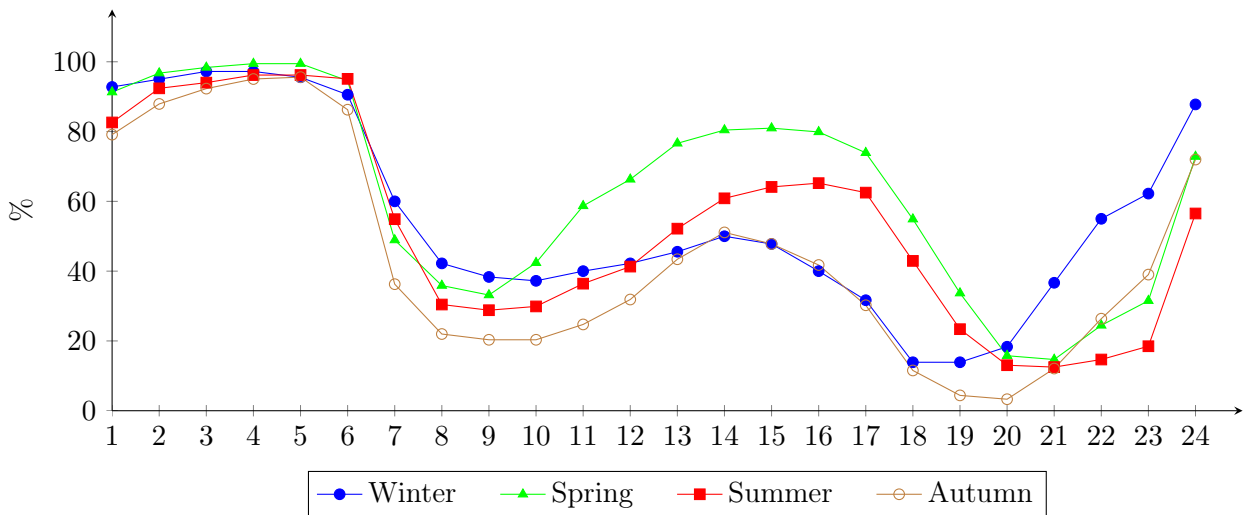


Figure IV.12 – Mean frequencies of occurrence of regime 1 for each hour of the day, per season

what we saw previously in figure IV.10, i.e. that price regimes are highly correlated with load regimes. When looking at the histograms of the transformed price for each regime (figure IV.14), we find that the two modes correspond to the previously identified ones in figure IV.7.

However, we can see from the Price-Load graph that there exists a region for which the demand is high, while the price remains low. This is confirmed by taking a look at the histograms of load for each regime (figure IV.15): during regime 1 there is a (relatively small) proportion of “high” demand, whereas only a high-demand mode is present in regime 2.

Finally, if we plot the transformed price versus the residual demand (figure IV.16), this region disappears, and the relationship between the transformed price and the residual load appears to be rather linear within each regime, hence comforting the choice of the transformation and of the residual

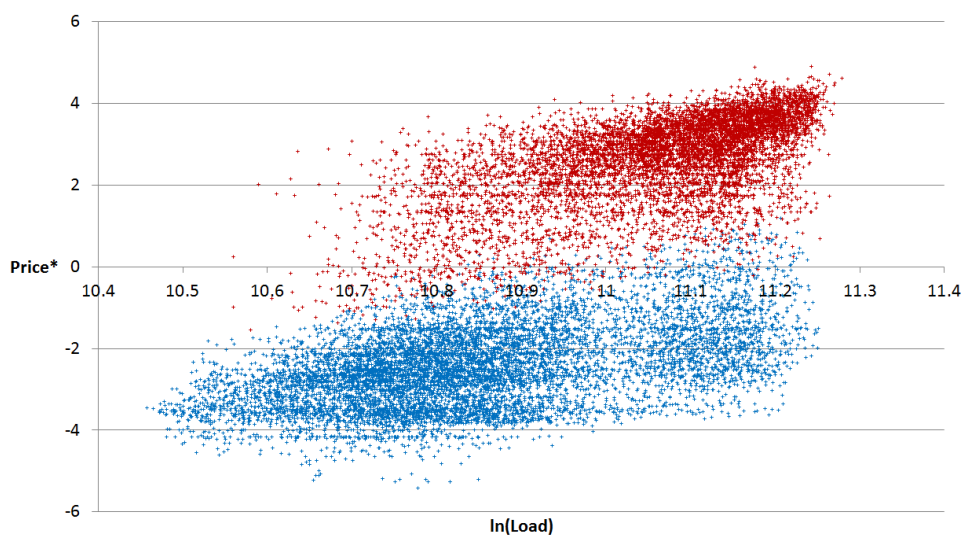


Figure IV.13 – Transformed price vs. logarithm of load for the two regimes (blue: regime 1, red: regime 2)

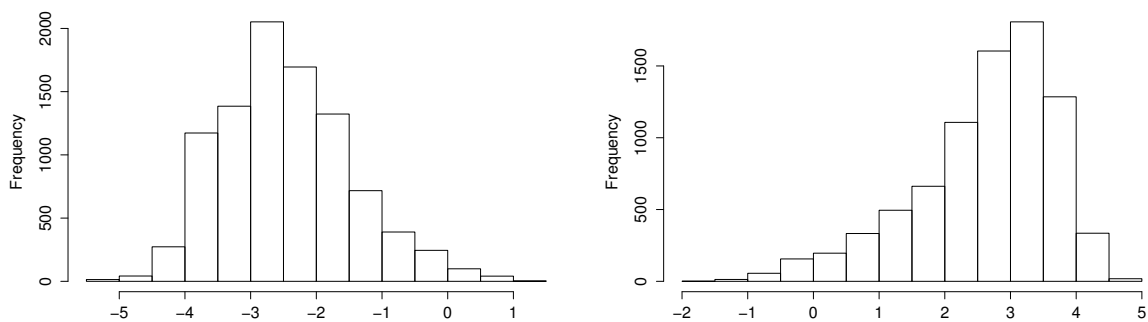


Figure IV.14 – Histograms of the transformed price for regime 1 (left) and 2 (right)

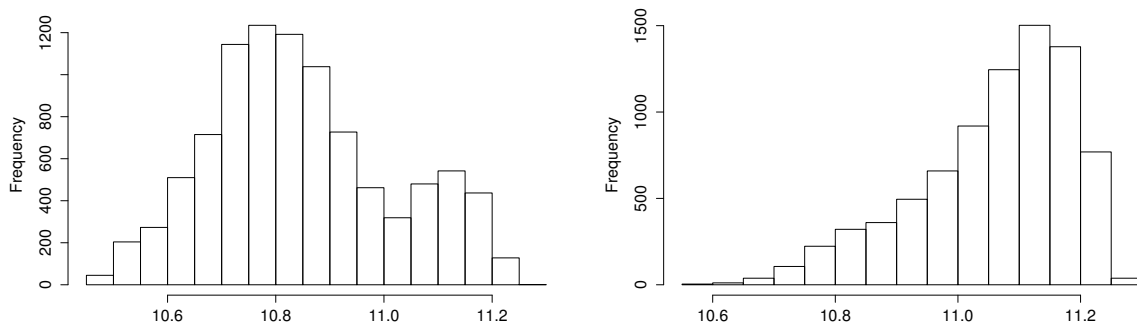


Figure IV.15 – Histograms of the logarithm of load for regime 1 (left) and 2 (right)

demand as covariate.

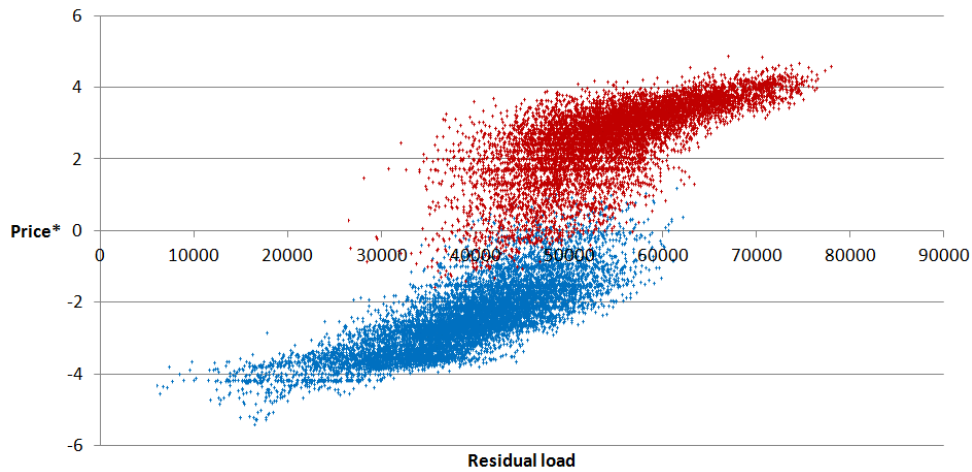


Figure IV.16 – Transformed price vs. residual load in regime 1 (blue) and 2 (red)

6.3 Effect on prices

Average marginal effects

Interpreting the coefficients can be difficult, since the price has been transformed and because we use wind and solar penetration indices as well as residual load. In particular, the coefficients associated with wind and solar productions are positive, which would mean at first look that they increase the price. However, when taking into account the effect of RES through the residual load coefficient we should find a negative effect. Hence, it is interesting to derive an expression for the average marginal effects (slopes), that would tell how much the decrease in price is when RES production and load increase. We do not compute elasticities, because they would be very high when prices approach zero, and would change sign whenever the price does. For clarity reasons, we put in appendix C the computations and the formal expressions of the average marginal effects (equations IV.26-IV.28), while we show the results here (table IV.6)¹⁰.

As expected, we find negative average marginal effects for RES generation, and a positive one for load, for each time step. Then on average, an increase of 1 GW of wind will decrease the price in regime 1 (resp. 2) by 0.77€/MWh (resp. 1€/MWh). The influence of solar is slightly weaker, as an extra gigawatt hour lowers the price of 0.73€/MWh in period 1, and 0.96€/MWh in regime 2. On the contrary, if the demand increases by 1 GW in regime 1 (resp. 2), the price increases on average by 0.93€/MWh (resp. 1.18€/MWh). Moreover, we performed Welch t-tests on the obtained coefficients to test whether their means are significantly different from one another (from a regime to another and for each variable within each regime), which seems to be the case.

¹⁰The standard deviations are computed directly from the time series generated by equations IV.26-IV.28

	Regime 1			Regime 2		
	Mean	S.D.	C.V.	Mean	S.D.	C.V.
$\frac{\partial Price}{\partial Wind}$ ((€/MWh)/(GW))	-0.77	0.73	0.94	-1.0	0.79	0.79
$\frac{\partial Price}{\partial Solar}$ ((€/MWh)/(GW))	-0.73	0.68	0.94	-0.96	0.76	0.79
$\frac{\partial Price}{\partial Load}$ ((€/MWh)/(GW))	0.93	0.84	0.90	1.18	0.92	0.78

Table IV.6 – Average marginal effect for each regime

Even though we cannot rigorously conclude about the statistical significance of the average marginal effects, many elements are consistent with the fact the the effect is negative. Indeed, the time series computed from equations IV.26-IV.27) are fully negative, and the estimated coefficients of the model are indeed statistically significant. Furthermore, we estimated a model using RES productions in level instead of their relative shares, which produced statistically significant negative marginal effects on the transformed price¹¹.

This analysis confirms the existence of different merit-order effects in high-price and low-price regimes. However, these slopes have very high coefficients of variation, which means that inside each regime the marginal effect can vary a lot. Nevertheless, these high variations are partly due to the reverse transformation that is needed to compute those slopes, and the estimated coefficients β are on the contrary very well determined, with rather low standard deviations. It is thus important to remember that these marginal effects are not equivalent to the model, which considers a non-linear transformation of the price, but only illustrate it in a linear framework. Additionally, when trying to estimate the MS model for the non-transformed price, we fail to disentangle the two regimes, which confirms the usefulness of the price transformation. Yet, the existence of different marginal effects for high and low prices confirms that the inverse supply curves are on average convex, as explained in the introduction. Similarly, the volatility was found to be higher in regime 2 than in regime 1, which is consistent with this hypothesis.

Non-marginal effects

Although the average marginal effects are of huge interest, they are only valid inside each regime, i.e. when there is no switching. Indeed, when there is a regime change, marginal effects are not defined

¹¹Unfortunately, this model could not converge when using time-varying probabilities, which is why we did not use it.

since the coefficients change. In particular, the predicted change of the transformed price conditionally on the previous period is:

$$\begin{aligned} \mathbb{E} [\Delta Price^* | S_{t-1} = i] = & p_{ii} \left[\beta_1^{(i)} \Delta \left(\frac{Wind}{Load} \right) + \beta_2^{(i)} \Delta \left(\frac{Solar}{Load} \right) + \beta_3^{(i)} \Delta RLoad \right] \\ & + p_{ij} \left[\Delta \beta_0 + \Delta \left(\beta_1 \frac{Wind}{Load} \right) + \Delta \left(\beta_2 \frac{Solar}{Load} \right) + \Delta (\beta_3 RLoad) \right] \end{aligned} \quad (IV.15)$$

We recognise in this expression a weighted average of a regime- i term and a regime- j switching term. The first term is the equivalent of the marginal effect, which is computed for an infinitesimal change of the covariates. This cannot be done with the second term, because of the switching coefficients. To have an idea of the importance of the switching term, the mean price in regime 1 is 23.5€/MWh, while it is 42.6€/MWh in regime 2, i.e. approximately the first and third quartiles Q1 and Q3.

6.4 Impact on the regimes

Odds ratios

Also of interest is the interpretation of the coefficients of the time-varying probabilities. We have already analysed the effect of the RES penetration indices on the probabilities through the sign of the coefficients, but we would also like to assess the impact more quantitatively. The first and natural idea is to look at odds ratios (e^α), which would tell how the odds of switching or staying in a regime vary with the shares of renewable production. This is given in table IV.7 below:

Variable	(1)	(2)
e^{α_0}	3.033463	0.06313241
$e^{\alpha_1/100}$	1.054493	1.072197
$e^{\alpha_2/100}$	1.045657	1.014949

Table IV.7 – Odds ratios of the logit model for the transition probabilities

From this table we can see for example that an increase of one percentage point of the relative share of wind energy output would increase the odds of staying in regime 1 by 5.4% while increasing the odds of switching from regime 2 to regime 1 by 7.2%. Similarly, an increase of one percentage point of the relative share of solar production would increase the odds of staying in regime 1 by 4.6% while increasing the odds of switching from regime 2 to regime 1 by 1.5%. These odds ratios show again that solar generation has a smaller impact than wind generation, especially when it comes to switching from high to low prices.

Impacts on regime durations

In addition, we would like to refer to more understandable variables than probabilities of transition, e.g. the expected duration of each regime $\mathbb{E}\tau_i$, or the stationary distribution π , as defined at the end of section 5. We have presented closed-form expressions for these variables in the homogeneous case, that are no longer valid in the inhomogeneous one. However, deriving closed-form expressions for marginal effects on these variables in the inhomogeneous case can give an idea of the magnitude of the impact, even though it is not mathematically rigorous. Since the expression of the stationary distribution involves both $\alpha^{(i)}$ coefficients, we will focus on the expected durations only. Also, we will only derive the impact of RES production (similar expressions can be derived for the load). We show in appendix C the following results:

$$\left\langle \frac{\partial (\mathbb{E}\tau_1 - 1)}{\partial Wind} \right\rangle \simeq \frac{\alpha_1^{(1)}}{\langle Load \rangle} \simeq 9.2 \text{ \%} \cdot \text{GW}^{-1} ; \left\langle \frac{\partial (\mathbb{E}\tau_2 - 1)}{\partial Wind} \right\rangle \simeq \frac{-\alpha_1^{(2)}}{\langle Load \rangle} \simeq -12 \text{ \%} \cdot \text{GW}^{-1} \quad (\text{IV.16})$$

$$\left\langle \frac{\partial (\mathbb{E}\tau_1 - 1)}{\partial Solar} \right\rangle \simeq \frac{\alpha_2^{(1)}}{\langle Load \rangle} \simeq 7.7 \text{ \%} \cdot \text{GW}^{-1} ; \left\langle \frac{\partial (\mathbb{E}\tau_2 - 1)}{\partial Solar} \right\rangle \simeq \frac{-\alpha_2^{(2)}}{\langle Load \rangle} \simeq -2.6 \text{ \%} \cdot \text{GW}^{-1} \quad (\text{IV.17})$$

Hence, $\frac{\alpha_1^{(i)}}{\langle Load \rangle}$ and $\frac{\alpha_2^{(i)}}{\langle Load \rangle}$ can be interpreted as the (absolute values of the) semi-elasticities of $\mathbb{E}\tau_i - 1$ with respect to wind and solar productions, respectively. The fact that $\mathbb{E}\tau - 1$ is considered instead of simply $\mathbb{E}\tau$ is due to the mathematical derivation of the expressions, but it also reminds us that the expected duration of a regime cannot be lower than 1, as long as it exists, but it can nevertheless be very rare. Furthermore, as $\mathbb{E}\tau$ is the expected duration of a regime conditionally on being in this regime, one could interpret $\mathbb{E}\tau - 1$ as the mean “remaining time” in the regime, as the current period is taken into account in the definition of $\mathbb{E}\tau$.

On average, when there is an additional GW of wind (resp. solar), $\mathbb{E}\tau_1 - 1$ increases by 9.2% (resp. 7.7%), while $\mathbb{E}\tau_2 - 1$ decreases by 12% (resp. 2.6%). As a reminder, the computed mean expected durations where $\mathbb{E}\tau_1 = 12.6$ h and $\mathbb{E}\tau_2 = 8.04$ h. The computed semi-elasticities are quite high (in absolute value), and it must be remembered that they are only approximate mean values. However, this confirms that RES generation not only affect electricity prices marginally, but also more globally, through the expected duration of each regime, but also their frequency (not derived here).

In the long run, with very high shares of renewable production, these estimates have no reason to stay valid. In particular, the price structure is expected to change, with on average lower prices and less episodes of high prices. With time, regime 2 as defined here is likely to shrink or disappear, while

regime 1 will become more and more predominant. In fact, recall that the regimes have more or less been “predefined”, as we chose the mean price as location parameter for the inverse hyperbolic sine transformation. Hence, as the mean is expected to decrease as well, a new transformation would have to be defined at some point. One could also think of including a dynamic modelling of the mean itself, but this would most certainly prove very difficult to achieve.

7 Conclusions and policy implications

We have assessed the impact of wind and photovoltaic productions on electricity prices, taking into account the intermittency of these power generating units. For this purpose, we developed a two-state Markov switching model that we estimated using data from the German market. We exhibited two regimes, of “low” (1) and a “high” (2) prices, which present intra and inter-regime temporal correlation. Within each regime, the marginal impact of RES production is shown to be negative, and significantly different from a regime to another. These results are in line with standard electricity markets theory: the higher the prices, the higher the merit-order effect, and the higher the volatility as well. This is due to the fact that (inverse) supply curves are on average convex, as peak power plants have a relatively high marginal cost but usually provide little capacity compared to base power plants. Also, while marginal effects are only valid inside each regime (i.e. when there is no switching), we show that is also a non-marginal switching effect, which is influenced by renewable generation through their impact on the transition probabilities. Indeed RES production, and especially the wind one, leads to more frequent and longer low-price episodes. As a consequence, although the regimes are partly deterministic (due to the strong seasonality of demand), there are many exceptions, i.e. episodes of low prices with high demand. From the estimation of the transition probabilities, we derived odds ratios as well as approximations of semi-elasticities for the expected remaining duration of each regime. These values confirm and help quantify the overall impact of RES production on the structure of prices.

Although we have only considered the effect of RES generation on electricity prices, there is necessarily an impact on the other units of production and on cross-border flows. Hence, we can also expect to have a differentiated effect on the conventional units, depending on the merit-order and on which plant is marginal. However, a more thorough analysis would be needed to numerically evaluate this impact. For example, using a different methodology, Graf and Marcantonini (2016) used panel data in Italy to show that RES generation effectively reduces CO₂ emissions while increasing the average plant emission factor. Furthermore, although we have only shown that the volatility is higher during

the high-price regime, intermittent RES production might influence it as well. This could be done for example using MS-GARCH modelling.

Finally, the policy implications of these results are diverse, but the first related issues are security of supply and support schemes for renewables. Indeed, since we expect RES production to decrease prices on average, we might also expect fewer episodes of very high prices. Unfortunately, these are essential to the profitability of peak power plants, who in turn suffer from “missing money”. This well known “failure” of the energy-only market has led several countries to adopt capacity remuneration mechanisms (CRMs), such as capacity payments, capacity obligations, or strategic reserves.

Yet this issue concerns other production facilities as well. In particular, renewables are expected to become competitive on energy markets (at least on the retail market, which is already the case today in some places). However competitiveness might not ensure profitability on the wholesale market, if prices become too low. Indeed, it might then be necessary to keep subsidising RES for longer than expected, while some conventional power plants could have to be subsidised as well, for example through CRMs¹², if they are valuable to the system as secure capacity. Indeed, it is often considered that security of supply is a public good, which can then be subsidised if it is not produced in sufficient quantity by the market (market failure), for example if prices are too low, or high enough on average but with very few occurrences of very high prices, i.e. with a lot of uncertainty. In the long run, electricity markets and support mechanisms would have to be redesigned to take into account all these specificities. Hopefully, dynamic retail pricing and electricity storage might help gain overall efficiency, but it is still uncertain whether they will be available soon and deliver their promises or not. In any case, it is necessary to start addressing the problem by thinking about future market design. In this context, this paper contributes to understanding the market impact of load and renewable production, by highlighting the non-linear relationship between electricity prices and these particular determinants. Consequently, policy makers will have to take into account these increasing interactions when designing future electricity markets.

Appendices

A Marginal shock on supply or demand: theory

Let us denote $D : p \mapsto D(p)$ (with $D' < 0$) and $S : p \mapsto S(p)$ (with $S' > 0$) the demand and supply functions for a certain time step, and let us derive the expression of the marginal effect on price for

¹²Note that CRMs are not necessarily subsidies, and that other means of subsidies could be used in the present case.

an infinitesimal change in supply $dRES$ or demand $dLoad$. At the equilibrium, price and quantity are jointly determined by equating supply and demand: $Q = D(p) = S(p)$. Suppose that there is a change in supply so that the equilibrium quantity writes $Q = S(p, s)$, and/or a change in demand so that $Q = D(p, d)$. Hence, as $Q = D(p, d) = S(p, s)$, when s and d change, p does too so that the equation continues to hold. We can then write the price as function of s and d : $p = p(s, d)$; and the equilibrium equation becomes: $D(p(s, d), d) = S(p(s, d), s)$. Differentiating then yields:

$$\frac{\partial D}{\partial p} \left(\frac{\partial p}{\partial s} ds + \frac{\partial p}{\partial d} dd \right) + \frac{\partial D}{\partial d} dd = \frac{\partial S}{\partial p} \left(\frac{\partial p}{\partial s} ds + \frac{\partial p}{\partial d} dd \right) + \frac{\partial S}{\partial s} ds \quad (IV.18)$$

For an additive change in supply only we simply have $S(p, s) = S(p) + s$ and $D(p, d) = D(p)$, so that:

$$\frac{\partial D}{\partial p} \frac{\partial p}{\partial s} = \frac{\partial S}{\partial p} \frac{\partial p}{\partial s} + 1 \quad (IV.19)$$

Rearranging and replacing s by RES gives:

$$\frac{\partial p}{\partial RES} = \frac{1}{\frac{\partial D}{\partial p} - \frac{\partial S}{\partial p}} < 0 \quad (IV.20)$$

Finally, considering an additive change in demand only we have $D(p, d) = D(p) + d$ and $S(p, s) = S(p)$.

Replacing d by $Load$ then gives equation IV.1:

$$\frac{\partial p}{\partial Load} = \frac{-1}{\frac{\partial D}{\partial p} - \frac{\partial S}{\partial p}} = -\frac{\partial p}{\partial RES} > 0 \quad (IV.21)$$

B Statistical graphs and tests for the price time series

B.1 Statistical graphs

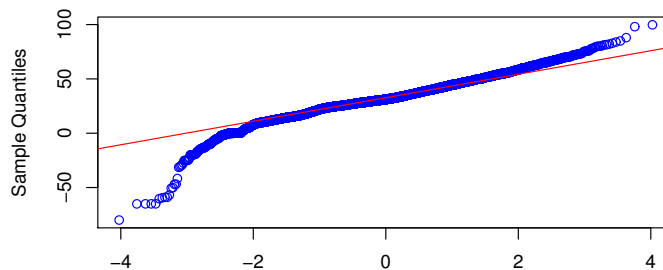


Figure IV.17 – Normal QQ-plot

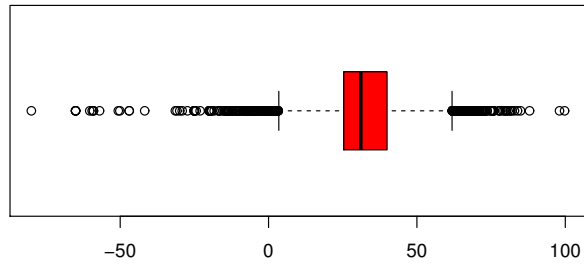


Figure IV.18 – Box-plot

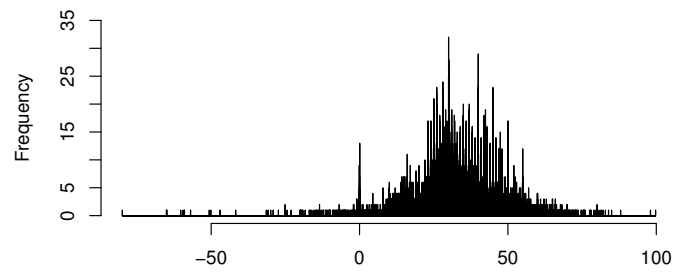


Figure IV.19 – “Complete” histogram

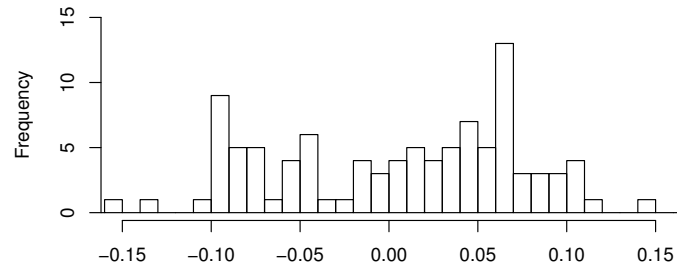


Figure IV.20 – Histogram around 0€/MWh

B.2 Statistical tests: unit roots and stationarity

Null Hypothesis: PRICE has a unit root
 Exogenous: Constant

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-17.13532	0.0000
Test critical values: 1% level	-3.430552	
5% level	-2.861513	
10% level	-2.566797	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: PRICE has a unit root
 Exogenous: Constant

	Adj. t-Stat	Prob.*
Phillips-Perron test statistic	-24.45028	0.0000
Test critical values: 1% level	-3.430551	
5% level	-2.861513	
10% level	-2.566797	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: PRICE is stationary
 Exogenous: Constant, Linear Trend

	LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.109461
Asymptotic critical values*: 1% level	0.216000
5% level	0.146000
10% level	0.119000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Table IV.8 – Unit root and stationarity tests without structural breaks for the price time series

C Mathematical expressions of the marginal effects

C.1 Marginal effects on price

We show here how to derive the expression for the marginal effects in each regime. For simplicity of presentation, we use the centred variable $X = Price - \langle Price \rangle$ (where $\langle \cdot \rangle$ is the temporal mean operator), we denote by $W = \frac{Wind}{Load}$ and $S = \frac{Solar}{Load}$ the relative shares of wind and solar productions, and we drop the index t . As the derivative of $x \mapsto \sinh^{-1} x$ is $x \mapsto (x^2 + 1)^{-1/2}$, we have the following computations¹³:

$$\sinh^{-1} X = \beta_0 + \beta_1 W + \beta_2 S + \beta_3 RLoad \quad (IV.22)$$

$$\Rightarrow \frac{dPrice}{\sqrt{X^2 + 1}} = \beta_1 dW + \beta_2 dS + \beta_3 dRLoad \quad (IV.23)$$

$$= \beta_1 \left(\frac{dWind}{Load} - \frac{Wind}{Load} \frac{dLoad}{Load} \right) + \beta_2 \left(\frac{dSolar}{Load} - \frac{Solar}{Load} \frac{dLoad}{Load} \right) \quad (IV.24)$$

$$+ \beta_3 (dLoad - dWind - dSolar) \quad (IV.25)$$

All other variables held constant, we obtain the following expressions for the marginal effects due to wind and solar productions and load:

$$\frac{\partial Price}{\partial Wind} = \sqrt{X^2 + 1} \left(\frac{\beta_1}{Load} - \beta_3 \right) \quad (IV.26)$$

$$\frac{\partial Price}{\partial Solar} = \sqrt{X^2 + 1} \left(\frac{\beta_2}{Load} - \beta_3 \right) \quad (IV.27)$$

$$\frac{\partial Price}{\partial Load} = \sqrt{X^2 + 1} \left(\beta_3 - \beta_1 \frac{Wind}{Load^2} - \beta_2 \frac{Solar}{Load^2} \right) \quad (IV.28)$$

Finally, we compute these marginal effects for each time step and take temporal their mean and standard deviation, as shown in table IV.6¹⁴.

C.2 Marginal effects on expected duration

As stated in section 6, the marginal effects computed below are not mathematically rigorous, since we use formulas for expected duration and stationary distribution that are only valid for homogeneous Markov chains. Nevertheless we hope that it will give an idea of the magnitude of the marginal effects.

¹³For simplification, we omit the error term and the regime indices: we consider in fact the expectation of X conditional on a regime and on the covariates

¹⁴The standard deviations are computed directly from the time series generated by equations IV.26-IV.28.

First, let us recall the aforementioned formulas:

$$\mathbb{E}\tau_i = \frac{1}{p_{ij}} = \frac{1}{1 - p_{ii}} \quad \text{and} \quad \pi_1 = 1 - \pi_2 = \frac{p_{21}}{p_{12} + p_{21}} \quad (\text{IV.29})$$

We inject the expression of the time-varying probabilities in the equation giving the expected durations, using W and S as before for the sake of simplicity:

$$p_{i1} = \frac{1}{1 + \exp\left(-\alpha_0^{(i)} - \alpha_1^{(i)}W - \alpha_2^{(i)}S\right)} \quad \text{and} \quad p_{i2} = \frac{1}{1 + \exp\left(\alpha_0^{(i)} + \alpha_1^{(i)}W + \alpha_2^{(i)}S\right)} \quad (\text{IV.30})$$

so that we have for the expected durations:

$$\mathbb{E}\tau_1 = 1 + \exp\left(\alpha_0^{(1)} + \alpha_1^{(1)}W + \alpha_2^{(1)}S\right) \quad (\text{IV.31})$$

$$\Rightarrow d\mathbb{E}\tau_1 = \alpha_1^{(1)} \exp\left(\alpha_0^{(1)} + \alpha_1^{(1)}W + \alpha_2^{(1)}S\right) dW + \alpha_2^{(1)} \exp\left(\alpha_0^{(1)} + \alpha_1^{(1)}W + \alpha_2^{(1)}S\right) dS \quad (\text{IV.32})$$

$$\Rightarrow \frac{d(\mathbb{E}\tau_1 - 1)}{\mathbb{E}\tau_1 - 1} = \alpha_1^{(1)} dW + \alpha_2^{(1)} dS \quad (\text{IV.33})$$

$$= \alpha_1^{(1)} \left(\frac{dWind}{Load} - \frac{Wind}{Load} \frac{dLoad}{Load} \right) + \alpha_2^{(1)} \left(\frac{dSolar}{Load} - \frac{Solar}{Load} \frac{dLoad}{Load} \right) \quad (\text{IV.34})$$

and

$$\mathbb{E}\tau_2 = 1 + \exp\left(-\alpha_0^{(2)} - \alpha_1^{(2)}W - \alpha_2^{(2)}S\right) \quad (\text{IV.35})$$

$$\Rightarrow d\mathbb{E}\tau_2 = -\alpha_1^{(2)} \exp\left(-\alpha_0^{(2)} - \alpha_1^{(2)}W - \alpha_2^{(2)}S\right) dW - \alpha_2^{(2)} \exp\left(-\alpha_0^{(2)} - \alpha_1^{(2)}W - \alpha_2^{(2)}S\right) dS \quad (\text{IV.36})$$

$$\Rightarrow \frac{d(\mathbb{E}\tau_2 - 1)}{\mathbb{E}\tau_2 - 1} = -\alpha_1^{(2)} dW - \alpha_2^{(2)} dS \quad (\text{IV.37})$$

$$= -\alpha_1^{(2)} \left(\frac{dWind}{Load} - \frac{Wind}{Load} \frac{dLoad}{Load} \right) - \alpha_2^{(2)} \left(\frac{dSolar}{Load} - \frac{Solar}{Load} \frac{dLoad}{Load} \right) \quad (\text{IV.38})$$

Finally, all other variables held constant, we can isolate the marginal effects and take their temporal mean:

$$\left\langle \frac{\partial(\mathbb{E}\tau_1 - 1)}{\mathbb{E}\tau_1 - 1} \frac{\partial(\mathbb{E}\tau_2 - 1)}{\partial Wind} \right\rangle = \frac{\alpha_1^{(1)}}{\langle Load \rangle} ; \left\langle \frac{\partial(\mathbb{E}\tau_2 - 1)}{\mathbb{E}\tau_2 - 1} \frac{\partial(\mathbb{E}\tau_1 - 1)}{\partial Wind} \right\rangle = \frac{-\alpha_1^{(2)}}{\langle Load \rangle} \quad (\text{IV.39})$$

$$\left\langle \frac{\partial(\mathbb{E}\tau_1 - 1)}{\mathbb{E}\tau_1 - 1} \frac{\partial(\mathbb{E}\tau_2 - 1)}{\partial Solar} \right\rangle = \frac{\alpha_2^{(1)}}{\langle Load \rangle} ; \left\langle \frac{\partial(\mathbb{E}\tau_2 - 1)}{\mathbb{E}\tau_2 - 1} \frac{\partial(\mathbb{E}\tau_1 - 1)}{\partial Solar} \right\rangle = \frac{-\alpha_2^{(2)}}{\langle Load \rangle} \quad (\text{IV.40})$$

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Résumé

Cette thèse s'intéresse à différents aspects relatifs à l'économie des énergies renouvelables (EnR) électriques. Celles-ci ont été choisies par de nombreux pays, désireux de réduire leur empreinte carbone, dans le cadre de la lutte contre le changement climatique.

N'étant la plupart du temps pas compétitives face aux moyens de production conventionnels, les EnR nécessitent des subventions publiques, à la fois nationales et locales, pour être rentables. J'analyse l'efficacité de ces aides dans le cas du photovoltaïque chez les particuliers français, en tenant compte des phénomènes de communication, qui participent fortement à la diffusion. Je montre combien ces derniers peuvent être un levier supplémentaire dans le développement des EnR.

Ensuite, j'étudie l'impact des schémas régionaux de raccordement au réseau des EnR, dans le cas de l'éolien terrestre en France. Ces schémas introduisent une différenciation spatiale des frais de raccordement. Cela permet de réorienter les investissements vers les régions dans lesquelles le réseau est moins contraint, ce que je quantifie.

Les réseaux jouent également un rôle dans le développement des EnR via leur tarification. Celle-ci est essentielle dans le cas de l'autoconsommation, qui fait peser des risques sur l'équilibre budgétaire du gestionnaire de réseau. Ainsi, je détermine notamment les prix à l'optimum économique de second rang dans le cas d'un tarif binôme énergie-puissance.

Enfin, j'analyse l'impact de la production renouvelable sur les prix de gros de l'électricité en Allemagne. Je montre que les EnR induisent une baisse des prix différenciée en fonction de l'équilibre offre-demande. Ceci pénalise les centrales de pointe nécessaires à la sécurité d'approvisionnement, ainsi que les EnR de demain, qui devront se passer de subventions.

Mots Clés

Énergies renouvelables ; réseaux électriques ; marchés de l'électricité ; subventions ; diffusion ; autoconsommation

Abstract

This thesis deals with several aspects of the economics of electric renewable energy sources (RES). These have been chosen by many countries, willing to reduce their carbon footprint, in order to fight climate change.

As RES are usually not competitive against conventional power plants, they rely on national and local subsidies in order to be profitable. I analyse the efficiency of such support schemes in the case of solar photovoltaics for residential households in France. Communication phenomena also take a huge part in the diffusion process. My work shows in how far these are an additional driver of RES development.

Then, I study the impact of regional network connection schemes for renewables in France, in the field of onshore wind energy. These schemes introduce a spatial differentiation of network connection charges. They enable to reallocate investments in regions in which the electricity network is less constrained, and I quantify this reallocation.

Electricity networks also play a role in the development of RES through their tariffication. The latter is fundamental in the case of self-consumption (or "prosumption"), that puts the budget balance of the network operator at risk. Thus, I derive second-best prices in the case of a two-part energy-capacity tariff.

Finally, I analyse the impact of renewable generation on electricity wholesale prices in Germany. I show that RES induce a decrease in prices, which depends on the supply-demand equilibrium. This penalises peaking power plants that are necessary to the security of supply, as well as future renewables, which shall progressively become profitable without subsidies.

Keywords

Renewable energy; electricity networks; electricity markets; subsidies; diffusion; self-consumption