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THÈSE DE DOCTORAT

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Flexibilité sur le marché du gaz naturel

Flexibility in natural gas markets

Soutenue par

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À mon père

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Résumé en français

La question de la flexibilité a en réalité toujours accompagné le marché du gaz naturel. Elle reflète en tant que telle la nature même de la commodité : une demande largement inélastique (surtout résidentielle) sujette aux aléas climatiques et une offre qui ne réagit pas toujours aux signaux prix compte tenu des lourds investissements en infrastructure de production, transport et stockage. Ce besoin de flexibilité a essentiellement été associé à un enjeu de volume pour des producteurs de gaz naturel devant limiter les risques d'insécurité d'approvisionnements. Une myriade d'outils de flexibilité a pu se développer pour ainsi équilibrer offre et demande de gaz, sous la forme d'instruments physiques et d'arrangements contractuels. Parmi eux, les installations de stockage y jouent un rôle pivot tant pour la gestion des variations saisonnières que pour répondre à des changements abrupts de la demande et dans certains cas d'interruptions de la production. En injectant du gaz en été lorsque la demande est faible et le soutirant en hiver lorsque celle-ci augmente, ces dernières permettent d'éviter des coûts d'extraction et de transport démesurés tout en limitant les fluctuations de prix excessives. Les systèmes gaziers ont également eu recours aux *line-pack* pour contrecarrer les variations horaires de la demande en augmentant la pression dans les gazoducs afin d'y accroître la capacité de stockage. Le stockage dans les terminaux de gaz naturel liquéfié (GNL) est aussi envisagé lorsque les conditions géologiques offrent des options de stockage limitées. D'autres mécanismes d'équilibrages sont centrés sur la demande à travers par exemple des contrats d'interruptibilité qui se font sur la base de critères mutuellement consentis.

Ces stratégies de résilience se sont adaptées aux évolutions du marché gazier. La donne posée par les vagues de libéralisation des marchés électriques et gaziers en a constitué la clé de voûte.¹ L'abolition des monopoles d'états et des concessions exclusives pour le transport et

¹Le marché gazier américain est précurseur en la matière, passant d'un marché fortement réglementé à un

la distribution de gaz a permis l'émergence de *hubs* de gaz où se sont développés de nouveaux services gaziers. Ils sont des zones d'interconnexions entre pipelines, idéalement à proximité d'infrastructures de stockage et de centres de consommation, assurant une facilité de transport et un équilibrage à court terme de l'offre et la demande de gaz. Les marchés spot et futures viennent quant à eux offrir une nouvelle source de flexibilité aux acteurs de ce marché pour se couvrir contre les risques de prix et profiter d'opportunités d'arbitrages. Le gaz s'y échange comme toute autre commodité mais plus important encore, les outils de flexibilité sont devenus des services échangeables à part entière avec une valeur de marché. Le recours au stockage est très représentatif de cette tendance : il est passé d'un outil de gestion physique apportant de la flexibilité lors d'épisodes de pics de demande, à un service indépendant de *trading* combinant une couverture physique à l'exploitation d'opportunités d'arbitrages (Cretì et al., 2009).

Figure emblématique de la notion de flexibilité, l'industrie du GNL a connu une reconstruction substantielle de son modèle économique. Matière première initialement complexe à transporter, le processus de liquéfaction du gaz naturel sous -160 degrés Celsius permet de réduire son volume de 600 fois. Le commerce de GNL s'est plus rapidement développé durant la période 2000-15 que durant les 35 années de son histoire. Devenu un élément clé des marchés gaziers à l'échelle mondiale, le GNL contourne une propriété physique majeure du gaz naturel - celle d'être 1000 fois moins dense que le pétrole sous des conditions atmosphériques normales - et permet d'atteindre des marchés inouïs en évitant les risques de tensions géopolitiques qu'inflige le transit de gaz par pipeline. Le secteur est sur un sentier de croissance important avec une hausse substantielle des capacités d'exportation. Le nombre de pays exportateurs a plus que doublé depuis le début des années 2000 assignant au GNL un rôle de flexibilité et de sécurité d'approvisionnement notable. Au cœur de cette dynamique, la libéralisation des marchés de l'énergie, l'accès des tiers aux infrastructures de regazéification, l'augmentation substantielle de la flotte de navires méthaniers et l'augmentation du nombre d'acheteurs ont été déterminants (Corbeau and Ledesma, 2016). De surcroît, les développements récents du secteur ont conduit à une profonde reconfiguration de la structure contractuelle encadrant le commerce de GNL.

marché libéralisé sous le "Natural Gas Policy Act" de 1978. A l'échelle européenne, il a fallu attendre les directives gazières de 1998 (98/30/CE) et 2003 (2003/55/CE) du Parlement européen pour définir les règles communes de transport, distribution, approvisionnement et stockage de gaz naturel sous un cadre concurrentiel.

Fonctionnant initialement comme un *business* de point à point via des terminaux dédiés, scellés sous des contrats de long-terme largement inflexibles sur la destination et les volumes, l'industrie a aujourd'hui pris un tout autre tournant. La révolution américaine du gaz et pétrole de schiste, combiné à la forte demande asiatique au lendemain de la catastrophe de Fukushima en 2011, a exacerbé les écarts de prix régionaux, encourageant les décisions de détournement des navires de leurs destinations initiales. Avec des modèles économiques fondamentalement différents, les volumes mis à disposition par les projets américains récents sont exempts de clauses de destination et incluent des formules de tarification basées sur une indexation sur les prix *hubs*.²

A l'heure du dérèglement climatique, d'inéluctables inter-flexibilités se dessinent entre le marché des énergies renouvelables et celui du gaz naturel. La transition vers une économie décarbonée a permis aux énergies renouvelables d'émerger comme une source importante dans le mix énergétique mondial. En 2018, 28% de l'électricité mondiale est issue de sources d'énergies renouvelables, dont la plupart (96%) est produite à partir de technologies hydroélectriques, éoliennes et solaires (EIA). Les politiques de soutien à ces énergies combinées à la baisse substantielle des coûts technologiques expliquent largement la tendance. De manière concomitante, le gaz naturel a connu des développements sans précédent durant la dernière décennie. Ce dernier est considéré comme l'énergie fossile la plus respectueuse de l'environnement ; sa combustion émettant deux fois moins de CO₂ que le charbon. La révolution du pétrole et gaz de schiste américain a également ravivé le potentiel économique gazier sur les marchés énergétiques mondiaux. Mais plus important encore, il est au cœur des problématiques posées par le recours aux énergies renouvelables et en particulier les enjeux liés à leur intermittence. En effet, la capacité du gaz naturel à compléter la production d'énergie renouvelable presque instantanément pour assurer une alimentation ininterrompue en cas d'absence de vent ou d'approvisionnement solaire, pose la question d'une véritable synergie. En agissant comme des unités de pointes ou d'équilibrages, les centrales électriques au gaz serviraient de pont vers une production d'énergie

²Néanmoins, du côté asiatique, une période de transition vers une structure de marché plus flexible est attendue. En effet, les volumes de GNL importés par l'Asie n'étaient flexibles qu'à 5% en 2016 (IEA/OECD, 2016) et la perspective commune dans l'industrie du GNL prévoit une période de transition de cinq à dix ans pour voir les marchés d'importation de GNL achever leurs processus de libéralisation et établir un *hub* disposant de liquidités suffisantes pour construire un prix de référence crédible pour le commerce asiatique de GNL.

décarbonée.

Les perspectives de recherches menées au cours de cette thèse ont été largement dictées par ces évolutions. Pour rendre compte du contexte dans lequel opèrent les mécanismes de flexibilité, un premier chapitre est consacré à la question de la flexibilité de destination dans les contrats de long terme de GNL. La période de transition que traverse le secteur rend la question d'autant plus opportune. A moyen terme, de nouveaux contrats continueront d'adosser des clauses de destination, des formules de prix indexés au prix du pétrole et un recours limité au marché spot (IEA/OECD, 2016). Par ailleurs, la flexibilité des marchés du GNL en tant que métrique des évolutions actuelles du marché, découlera des contrats eux-mêmes dans les années à venir. Même si la flexibilité du marché pourrait provenir des approvisionnements de GNL qui ne sont pas sous contrat, des gestionnaires de portefeuille ou encore des détournements des approvisionnements de GNL; en réalité, seule la troisième option offre effectivement de la flexibilité. En effet, pour ce qui concerne les gestionnaires de portefeuille, leur impact en termes de flexibilité s'est avéré ambigu puisque le GNL acheté sur les marchés spot a tendance à être vendu à des clients sous des contrats de GNL indexés sur les cours du pétrole (Rogers, 2017). Quant aux approvisionnements de GNL qui ne sont pas sous contrat, des volumes limités devraient entrer en service au cours des prochaines années, ce qui signifie que la propension de la production de GNL à répondre à un choc potentiel de demande est très limitée (IEA/OECD, 2016). Nous nous attachons ainsi à assigner une valeur économique à l'option de flexibilité de destination dans les contrats de long-terme à travers l'étude de scénarios de détournement des cargaisons de GNL basée sur une approche par options réelles couplée à de l'économétrie non linéaire.

Un second chapitre se penche sur l'enjeu majeur de la financiarisation des marchés gaziers et la flexibilité apportée par l'émergence des *hubs* gaziers. A cet égard, l'environnement institutionnel des marchés européens du gaz naturel a connu un changement significatif au cours de la dernière décennie. Les *hubs* gaziers britanniques (National Balancing Point) et hollandais (Title Transfer Facility) ont considérablement gagné en popularité (Heather, 2016). De manière concomitante, la pratique d'indexation au prix du pétrole dans les contrats de long terme de gaz naturel a progressivement été remplacée par l'indexation aux prix *hub*, pour une meilleure représentation de la dynamique des fondamentaux. Nous posons alors la question de savoir si l'efficacité informationnelle sur ces marchés est atteinte. Nous nous appuyons sur la méthode de

traitement du signal des ondelettes (Maximum Overlap Discrete Wavelet Decomposition) pour décomposer les données quotidiennes des marchés spot et futures de gaz naturel Américain (Henry Hub), Britannique (NBP) et Néerlandais (TTF) pour différentes maturités. Cette décomposition fréquentielle nous permet ensuite d'étudier les phénomènes de causalité linéaire et non linéaire à la Granger en multi-résolution mais aussi d'effectuer des tests de marche aléatoires pour rendre compte du degré de prévisibilité des cours des futures.

Enfin, un troisième chapitre entend rendre compte de l'inter-flexibilité qui se dessine aujourd'hui entre le marché du gaz et celui de l'électricité. Des données au niveau Américain nous permettent de voir si la relation entre le prix du gaz naturel et les investissements dans les capacités solaires et éoliennes est non linéaire. Plus précisément, nous cherchons à vérifier si pour des niveaux de production renouvelables relativement bas, les deux modes de production sont des substituts et si lorsqu'un seuil de volume de production est atteint, les deux deviennent complémentaires. Un modèle de régression à la Markov Switching a permis de rendre compte du compromis entre deux caractéristiques majeures de ces modes de production : le degré élevé de flexibilité de la production d'électricité utilisant le gaz naturel comme intrant et le faible coût marginal des sources d'énergies renouvelables.

Chapitre I - Flexibilité de destination dans les contrats de long-terme de GNL

L'archétype du schéma contractuel dans l'industrie du GNL a longtemps été celui d'un producteur mettant sous contrat la totalité ou une partie substantielle de la production d'une usine de liquéfaction à des acheteurs pour une moyenne de 25 ans ou plus et pour un prix indexé sur le pétrole brut. Ces contrats incluaient également des clauses dites "*take or pay*" selon lesquelles le vendeur garantit que le gaz soit mis à disposition de l'acheteur, qui en retour garantit le paiement d'une quantité minimale d'énergie, qu'il en prenne livraison ou non. Pendant longtemps, l'indexation des prix s'est faite avec des variations géographiques: le prix du gaz se fixe en fonction des prix des énergies concurrentes sur chaque marché considéré. Ces clauses dites *netback* ne pouvaient être appliquées que si le gaz était effectivement vendu sur le marché qu'il lui été destiné. Toute possibilité de revente du gaz sous contrat pour l'approvisionnement

de marchés adjacents était exclue, rendant quasi inexistantes les opportunités d'échanges entre distributeurs de différents pays ou différents marchés nationaux. Cette structure contractuelle a connu une profonde reconfiguration au cours de la dernière décennie. La révolution américaine du gaz et pétrole de schiste combinée à la forte demande asiatique au lendemain de la catastrophe de Fukushima en 2011 a exacerbé les écarts de prix régionaux, encourageant les décisions de détournement des navires de leurs destination initiales. Représentatifs d'une tendance globale, les volumes mis à disposition par les projets américains récents sont exempts de clauses de destination et incluent des formules de tarification reposant sur l'indexation des *hubs* gaziers. Du côté asiatique, une période de transition vers une structure de marché plus flexible est en revanche attendue durant les prochaines années.

Ce premier chapitre réexamine la question de la flexibilité de destination dans les contrats de long-terme de GNL en prenant en compte les évolutions récentes du marché et les incertitudes susceptibles d'affecter sa dynamique. Pour donner une valeur économique à la flexibilité de destination dans les contrats de GNL, nous combinons une approche par les options réelles telle que proposée par (Yepes Rodríguez, 2008) à de l'économétrie non linéaire. Nous évaluons la rentabilité d'un routage flexible des cargaisons de GNL en fonction du degré d'incertitude sur le marché pour un producteur de gaz situé aux États-Unis, en Europe ou en Asie. Cette étude s'inscrit dans un domaine de recherche relativement vaste qui a considéré l'impact de la reconfiguration du marché du GNL sur les pratiques contractuelles (Von Hirschhausen, 2008; Ruester, 2009; Hartley, 2015) et les conséquences sur la question de l'intégration régionale du marché du gaz naturel (Siliverstovs et al., 2005; Neumann, 2009). Des études récentes se concentrent sur les efforts des marchés asiatiques pour créer des *hubs* et modifier les termes des contrats en vue de la suppression des clauses de destination et l'adoption de formules d'indexation aux prix *hubs* (Shi and Variam, 2016).

Méthodologie

La méthodologie retenue peut être décomposée en deux étapes successives. Premièrement, nous examinons et modélisons les interdépendances dynamiques complexes entre les prix du gaz naturel observées dans les trois principales régions consommatrices (Japon, Europe et États-Unis). Puis, des simulations de Monte-Carlo du modèle empirique obtenu sont effectuées pour

générer un échantillon de trajectoires de prix futures. Ces trajectoires sont à leur tour utilisées pour déterminer les décisions optimales d'expédition de GNL et leur rentabilité. D'un point de vue empirique, la stratégie de modélisation retenue considère la nature éventuellement non linéaire des interdépendances dynamiques entre les prix dans les trois régions. A cet effet, un modèle VAR à seuil (Threshold Vectorial Auto Regressive) est estimé dans une approche similaire à celle de Balke (2000), dans laquelle la volatilité des prix du pétrole joue le rôle de propagateur non linéaire des chocs sur les marchés régionaux du GNL. Le modèle VAR à seuil combiné à des fonctions de réponses impulsionnelles non linéaires possède un certain nombre de caractéristiques intéressantes. Premièrement, un tel modèle fournit un moyen assez simple de capturer des dynamiques non linéaires telles que les réponses asymétriques aux chocs, les changements de régime et les équilibres multiples. De surcroît, la variable par laquelle différents régimes sont définis peut elle-même être endogène et inclure dans le VAR. Enfin, il nous permet d'enrichir les analyses existantes sur la relation pétrole-gaz, dans un cadre où le système bascule entre des régimes élevés et faibles de volatilité des prix du pétrole en réponse à des chocs sur d'autres variables. L'utilisation de la volatilité des prix du pétrole comme propagateur de chocs non linéaires prend appui sur plusieurs pratiques: l'utilisation persistante de formules de prix indexées sur le pétrole dans les contrats de GNL à moyen terme, en particulier pour le principal importateur (Japon); le comportement des gestionnaires de portefeuille qui ancre sensiblement la dynamique des prix du pétrole à celle du gaz naturel dans les contrats à court terme; et le lien bien reconnu des fluctuations des prix du pétrole avec les incertitudes sur l'activité économique mondiale.

Résultats et interprétations

Les résultats ont généralement mis en évidence une valeur significative de l'option de flexibilité de destination. De surcroît, cette dernière s'est avérée considérablement plus importante dans un scénario de forte volatilité du prix du pétrole. Cela signifie que, plus le marché (asiatique notamment), est apte à se repositionner rapidement vers une reconfiguration plus flexible, impliquant finalement la dissolution des clauses de destination et l'utilisation d'une tarification marché dans ses termes contractuels, plus les acteurs de cette industrie seront enclins à s'engager et à profiter d'opportunités d'arbitrage. À cet égard, nos résultats sont en parfait accord avec

ceux de Shi and Variam (2016) qui appellent à privilégier la question de la flexibilité de destination dans le cas asiatique.

L'implication de ces résultats est multiple. Premièrement, du point de vue de l'industrie, le manque à gagner pour un producteur qui serait contraint en termes de destination est considérable. L'option de destination constitue également une source de profit importante pour les acteurs en position d'arbitrage. Deuxièmement, au cœur du vif débat sur l'intégration potentielle des marchés régionaux, cette analyse montre que l'aspect contractuel de cette industrie est susceptible de constituer une sérieuse barrière au commerce mondial de GNL. Nous concluons qu'il est trompeur de s'attendre à une intégration des marchés du gaz naturel uniquement par l'effet de l'appropriation des meilleures rentabilités lorsque les fournisseurs peuvent choisir leur destination finale. Le manque à gagner des producteurs géographiquement restreints met plutôt en évidence les avantages d'une plus grande dépendance future au marché spot, car même les partenaires engagés dans des contrats à long terme pourraient bénéficier d'une participation au marché spot, augmentant ainsi la liquidité de ce dernier. S'il fonctionne en coordination avec une indexation plus faible aux prix du pétrole, alors, dans ce cas précis, on pourrait s'attendre à une éventuelle "convergence". Enfin, la liberté de destination du GNL jouera un rôle pivot en termes de résilience aux événements imprévus. De ce point de vue et compte tenu du besoin constant de gérer l'incertitude de la demande de gaz, la valeur de la flexibilité de la destination dépasse la valeur optionnelle calculée dans cette étude par rapport aux conséquences possibles d'un choc imprévu.

Chapitre II - Efficience informationnelle des hubs gaziers

Malgré de profondes disparités entre les pays de l'Union européenne, la part de la concurrence dite gaz-gaz est passée de 15% en 2005 à 70% en 2017 (IGU, 2018) et semble devenir le mécanisme dominant de formation des prix. Néanmoins, l'Europe n'est pas encore parvenue à créer un marché du gaz complètement concurrentiel requérant la mise à disposition d'informations sur le marché qui soient non discriminatoires, fiables et opportunes (Garaffa et al., 2019). Dans le contexte de réserves éparses et d'un nombre limité de fournisseurs, le potentiel d'arbitrage élevé, en particulier à court terme, reste inexploité par les acteurs du marché en raison d'un accès limité aux infrastructures, d'une insuffisance d'informations fiables et de coûts

de transaction élevés (Stronzik, Rammerstorfer, and Neumann, 2009). La question de l'efficience au sens informationnel des *hubs* gaziers européens se pose donc et suscite des inquiétudes quant à leur capacité à constituer un support important pour la gestion des risques financiers des portefeuilles gaziers et l'équilibrage physique.

Ce contexte nous a conduit à examiner l'efficience informationnelle des deux plus grands marchés européens du gaz naturel (UK NBP et Dutch TTF) en établissant un parallèle avec le Henry Hub américain via une approche de décomposition en ondelettes, faisant l'objet d'un second chapitre. L'enjeu d'efficience sur les marchés à terme européens du gaz naturel et leur rôle dans l'élaboration de stratégies de couverture s'inscrit dans un domaine de recherche limité. La majorité des travaux sur le sujet s'est concentrée sur le marché nord-américain (Herbert (1995), Susmel and Thompson (1997), Dincerler, Khokher, and Simin (2005) ou encore Serletis and Shahmoradi (2006)). Cette question fait écho aux travaux originaux de Cootner (1964) tels que formalisés par Fama dans les années 1960 qui suppose que les prix observés sur un marché efficient devraient refléter instantanément toutes les informations disponibles. À tout moment, les prix sont censés être représentatifs des événements passés et futurs et des attentes des agents sur ce marché. Implicitement, l'information est censée être accessible à faible coût pour un grand nombre d'opérateurs qui ne peuvent pas à eux seuls exercer une influence notable sur les prix ou contrôler systématiquement le marché.

Méthodologie

Nous nous appuyons sur la méthode de traitement du signal des ondelettes (Maximum Overlap Discrete Wavelet Decomposition) pour décomposer les données quotidiennes des marchés spot et futures de gaz naturel Américain (Henry Hub), Britannique (NBP) et Néerlandais (TTF) pour différentes maturités. Nos séries temporelles sont transformées en domaine fréquentiel sans perte d'informations dans le domaine temporel. Nos données sont ainsi analysées à plusieurs échelles de temps et nous permet de ne pas négliger l'aspect saisonnier de la dynamique des marchés du gaz naturel. Une fois décomposées, elles sont utilisées pour effectuer des tests de causalité linéaires et non linéaires en s'appuyant sur le test de Diks and Panchenko (2006). Nous effectuons également plusieurs tests de robustesse pour nous assurer que nos résultats se maintiennent sous différentes configurations en répétant l'analyse pour les contrats à terme de

deux et trois mois et en nous appuyant sur différents filtres selon la méthodologie en ondelettes. Enfin, nous mesurons l'efficacité informationnelle des marchés futurs à court et à long terme en appliquant des tests de marche aléatoires aux résidus des rendements des séries des futures pour mesurer leur capacité à refléter instantanément toutes les informations de prix disponibles.

Résultats et interprétations

Pour tous les marchés considérés, nous obtenons de solides preuves en faveur d'une relation de cointégration entre les marchés spot et futures. De surcroît, la conduite de tests de causalité a montré que pour les trois marchés, les informations disponibles circulent entre les marchés spot et futures. En revanche, pour certaines échelles de temps, les marchés à terme jouent un rôle plus important dans la découverte des prix pour les *hubs* gaziers européens. Enfin, l'efficacité informationnelle des trois *hubs* gaziers n'est atteinte que sur le long terme; l'hypothèse nulle de marche aléatoire étant rejetée sur des horizons court et moyen termes.

Ces résultats permettent d'établir une évaluation des *hubs* en fonction de leur capacité à fournir des prix de référence fiables pour les quantités de gaz sous contrat. En matière de découverte des prix, les résultats du *hub* gazier américain se sont avérés robustes à toutes les échelles de temps considérées, contrairement aux marchés européens. Nous attribuons ce résultat à leurs divergences structurelles. En effet, les plateformes d'échange de gaz physiques et virtuels ont des configurations différentes : animées par des activités de transport entièrement privatisées et compétitives aux États-Unis, elles fonctionnent sous l'égide d'une réglementation par les gestionnaires de réseaux de transport au niveau européen. Le rôle crucial de la liquidité et de la capacité de stockage dans les *hubs* de gaz naturel est discuté et appelle à une augmentation significative du nombre de transactions physiques européennes entre les marchés, nécessaire pour réduire les goulets d'étranglement dans les réseaux de transport et les points d'interconnexion.

Chapitre III- Inter-flexibilités entre le marché de l'électricité et du gaz naturel

L'hypothèse d'une stricte substitution entre des sources stables de production d'électricité et des sources intermittentes telles que l'énergie éolienne ou solaire s'est vue tempérée dans la littérature. Alors qu'elles constituent des compléments stratégiques lorsque la production re-

nouvelable est défavorable, ces énergies peuvent demeurer des substituts à l'équilibre (Bouckaert et De Borger, 2014). Les capacités renouvelables pourraient également être considérées comme un substitut aux technologies de base et complémentaires aux technologies de pointe (Garcia, Alzate, and Barrera, 2012). Dans l'arène politique, Lee et al. (2012) soutiennent l'idée d'une relation complémentaire en considérant le contexte technique, économique, environnemental et politique. Les technologies renouvelables et le gaz naturel sont supposés avoir des profils de risque différents qui offrent des options de portefeuille complémentaires ; comme le suggère l'importante volatilité des prix du gaz naturel par rapport à un coût de combustible nul pour les énergies renouvelables ou encore les faibles coûts initiaux pour les usines de gaz naturel par rapport à la moindre compétitivité des projets d'énergie éolienne et solaire.

Lorsqu'il est question de cibler les moteurs essentiels à une large pénétration des énergies solaires et éoliennes, la littérature ne parvient à offrir une combinaison unanime entre par exemple, la baisse des coûts des technologies renouvelables, l'impact des politiques climatiques ou encore la disponibilité du stockage. Comme le soulignent Bistline and Young (2019), les structures des modèles retenus et les hypothèses d'entrée peuvent expliquer de telles différences, mais la principale raison tient au fait que la plupart d'entre elles se concentrent sur quelques facteurs pris isolément. Par exemple, Rodríguez et al. (2015) ont étudié l'effet des politiques publiques sur l'investissement privé dans les énergies renouvelables et ont constaté que, contrairement aux régimes basés sur des quotas, les régimes de soutien basés sur les prix sont positivement corrélés avec les contributions financières privées. Dans le même esprit, Criscuolo et al. (2014) ont examiné le rôle des différentes mesures de politique environnementale (par exemple, les tarifs de rachat, la réduction de la TVA et le soutien direct aux investissements en capital par le biais de subventions et incitations fiscales) pour induire un financement à un stade précoce. Íşlegen and Reichelstein (2011) examinent également la question d'un prix des émissions de carbone à l'équilibre qui propulserait les technologies de séquestration et de stockage du carbone. Sous le spectre des politiques climatiques, Shearer et al. (2014) soutiennent que l'abondance du gaz naturel diminuera l'utilisation des technologies du charbon et des énergies renouvelables.

Cette analyse qui fait l'objet d'un troisième chapitre s'est donné pour dessein de relier ces volets de la littérature dans un cadre cohérent capable d'évaluer de manière exhaustive le potentiel économique de la pénétration de l'éolien et du solaire sous un angle multifactoriel

et y explorer le degré de substituabilité / complémentarité entre le gaz naturel et les énergies renouvelables. En ce sens, nous nous intéressons au même problème que celui discuté par Bistline and Young (2019) et Baranes, Jacqmin, and Poudou (2017).

Méthodologie

D'un point de vue empirique, la stratégie de modélisation retenue dans ce chapitre considère la nature éventuellement non linéaire de la dynamique des énergies renouvelables. Plus spécifiquement, nous testons la présence d'un effet de régime en estimant un Modèle à changement de régime Markovien (MCRM) basé sur des données de janvier 2010 à décembre 2019 de production d'électricité éolienne et solaire et des variables explicatives potentielles couvrant le marché de l'électricité, les risques de politique carbone, les coûts technologiques ainsi que la santé économique mondiale. Une caractéristique majeure de ce modèle est telle que le mécanisme de basculement entre régimes est contrôlé par une variable d'état non observable qui suit une chaîne de Markov d'ordre 1. Le processus peut basculer entre les régimes à plusieurs reprises sur l'échantillon et nous sommes en mesure d'estimer les probabilités associées à chaque état. Nous évitons les erreurs de spécification encourues lorsque l'estimation de l'échantillon est simplement divisée en différents sous-échantillons pour tester la présence d'une rupture structurelle. Quatre MCRM alternatifs sont estimés. Chacune des quatre régressions examine les déterminants des capacités investies dans l'éolien et le solaire pour mieux saisir le potentiel économique de la pénétration des énergies renouvelables sous cinq moteurs potentiels. Plus précisément, nous comparons des modèles qui ajoutent progressivement des variables d'information pour évaluer leur impact relatif et explorer l'étendue de la substituabilité avec le marché du gaz naturel.

Résultats

Concernant la relation entre la production renouvelable intermittente et le coût du gaz naturel, nous apportons des preuves en faveur d'une interdépendance significative entre ces deux modes de production. Plus important encore, nos résultats soutiennent l'hypothèse que cette relation est non linéaire, basculant entre un régime élevé et un régime faible de production d'électricité renouvelable. Ce résultat implique que, pour un niveau de production relativement élevé via les énergies renouvelables, une augmentation marginale des prix du gaz tend à augmenter la part de la production renouvelable. Cette relation de substituabilité ne tient plus

lorsque nous passons à un régime de production plus faible, étant donné qu'une augmentation marginale du prix du gaz génère une baisse de la part de la production d'énergies renouvelables. Par ailleurs, notre modèle laisse présager une probabilité plus élevée d'être dans un régime élevé de production d'énergie éolienne et un faible régime de production d'énergie solaire. La probabilité de rester dans le régime faible de production d'énergie solaire est d'environ 95% en moyenne et la probabilité de passer d'un régime bas à un régime élevé de production d'énergie éolienne varie entre 39% et 46%, selon le modèle considéré. De surcroît, les résultats ont montré que le gaz naturel et les énergies éoliennes sont plus prompts à être des substituts alors que le gaz naturel et le solaire exhibent un terrain plus propice à la complémentarité. Le degré possible de substitution de l'énergie éolienne par le gaz naturel dépendra considérablement du facteur technologique capable de promouvoir une gamme d'innovations telles que celles du pétrole et du gaz de schiste et pose la question cruciale du rôle du stockage dans le déploiement de ces technologies pour contrer le problème de l'intermittence.

L'approche retenue dans cette analyse fait écho à celle suivie par Baranes, Jacqmin, and Poudou (2017) mais l'enrichit et le complète de plusieurs manières. Premièrement, nous examinons non seulement les différences dans l'impact de nos variables explicatives selon le régime considéré, mais nous livrons également la probabilité associée au régime de production renouvelable élevé ainsi qu'au régime de faible production, la probabilité de transiter de l'un à l'autre et les durées attendues. Deuxièmement, nous examinons la relation entre le coût du gaz et celui de la production d'électricité à partir d'énergies renouvelables sous un angle multifactoriel où la non-linéarité est testée pour toutes les variables informatives intégrées dans le modèle : les changements de régime peuvent émaner de facteurs liés au marché de l'électricité, au risque de politique carbone, à la santé économique mondiale et aux coûts des technologies renouvelables.

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Introduction

The question of flexibility has actually always been part of the natural gas industry. It reflects the very nature of the commodity: demand is not particularly flexible (especially residential) and supply does not always react to price signals in view of the heavy required investments in production, transport and storage infrastructure. The new situation posed by the electric demand for natural gas serving as a back-up to the intermittency of renewable energies and envisaged more and more as a storage solution poses enormous technical, physical, organizational and regulatory challenges. In this context, the supply and demand for flexibility is the result of a complex interaction between several factors: among them the development of natural gas trading hubs, renewable electricity production levels, the availability of cargoes of liquefied natural gas (LNG) or the development of floating storage.³ It is from this perspective that this thesis seeks to analyze the issues that call for flexibility on the natural gas market by considering recent developments in this market .

The archetypal contractual scheme used in the LNG industry is that of a producer that contracts either the entire output or a substantial portion of the output of a liquefaction plant to buyers for an average of 25 years or more for a price indexed to crude oil. In most cases, buyers are mid-stream utilities that sell gas and electricity to end customers. A typical contract also includes the so-called "take or pay" clauses according to which the seller guarantees the gas will be made available to the buyer, who in return guarantees the payment of a minimum quantity of energy, that he takes delivery or not. For a long time, price indexation was done with geographical variations: the price of gas was fixed according to the prices of competing energies on each market considered. These "netback" clauses could be applied only if the gas was indeed sold on

³See e.g. Cornot-Gandolphe (2002), IEA/OECD (2016) and IGU (2017).

the market for which it was intended. This clause excluded any possibility of resale of contracted gas to supply in adjacent markets. There was therefore no opportunity for trade between distributors in different countries, nor for trade-offs between the different national markets. Security of supply and investment has been claimed as reasonable reasons to introduce these traditional “dedicated contracts” with a predefined destination of the cargoes (Glachant and Hallack, 2009) even if it clearly constitutes a roadblock to a “gas-to-gas competition”.⁴ Recent developments have led to a deep reconfiguration of the contractual structure governing the LNG trade. The waves of market liberalization, third-party access to regasification infrastructures, the substantial increase of the fleet of LNG vessels and the rise in the number of buyers have been crucial (Corbeau and Ledesma, 2016). The American shale gas revolution combined with strong Asian demand in the aftermath of the Fukushima disaster in 2011 have exacerbated regional price differentials, further encouraging diversion decisions. In this context, long-term contracts experienced fundamental changes in comparison with their former structure : the contract duration substantially decreased and hub pricing is increasingly replacing oil-indexed prices (Hartley, 2015).¹⁶ Asia is still experiencing a transition period toward more flexible market structure. Indeed, LNG volumes imported by Asia were only flexible at 5% in 2016 (IEA/OECD, 2016) and the common prospect among the LNG industry foresees that it will take five to ten years to see LNG import markets complete their liberalization processes and establish a hub with sufficient liquidity to build a credible reference price for Asian LNG trade. In the meantime, Asian buyers are showing their support for a change in oil price indexation for new long-term contracts.

Against this background, the persistent need to resort to long-term contracts in the LNG industry leaves open the issue of destination flexibility that remains unresolved in Asian markets. The transition period toward a more flexible repositioning independent of oil indexation needs time to be completed and is accompanied by strong uncertainties over the medium-term horizon of the LNG market. To take this into account, we have adopted in the first chapter the only approach that has gave an economic value to the diverting option in the LNG market (Yepes Rodríguez, 2008) by connecting a real option approach to two literature strands: one on the

⁴See among others Creti and Villeneuve (2004), Ruester (2009), Neumann, Siliverstovs, and Hirschhausen (2006) and Massol and Tchong-Ming (2010).

integration of regional natural gas markets where little research has been investigated since the post-2010 gas price differentials and the other one on the persistent influence of oil prices on the dynamics of the gas markets. More specifically, the profitability of an LNG cargo shipment is examined for a single supplier taking into account the uncertainty in the medium-term dynamics of the gas markets. The natural gas price trajectories in Asia, America and Europe are modeled using a threshold VAR representation (Threshold Vectorial Autoregressive Model) in which the dynamics of the system switches back and forth between a regime of high and low uncertainty on oil prices. A real option approach is then used to give an economic value to this flexibility of destination of LNG supplies via Monte-Carlo simulations of our empirical model. The calculation of the flexibility option made it possible to determine for each possible trajectory of a producer located in the United States, Asia or Europe the optimal destination decisions and the associated profitability. Our results point to an important source of profit for the sector and reveal the future movements of the vessels. Finally, they shed light on the question of the conditional impact of flexibility of destination on the question of the global integration of natural gas markets.

The abolition of state monopolies and exclusive concessions for the transport and distribution of gas has led to the emergence of gas hubs where new gas services have developed. These interconnection zones between pipelines, ideally near storage infrastructures and consumption centers, ensure ease of transport and short-term balancing of gas supply and demand. The spot and future markets offer a new source of flexibility to market players to hedge against price risks and take advantage of arbitrage opportunities. Gas is traded like any other commodity but more importantly, flexibility tools are provided as tradable services with market value. The use of storage is very representative of this trend: it has gone from a physical management tool providing flexibility during episodes of demand peaks to an independent trading service combining physical hedging with the exploitation of arbitrage opportunities. Over the past decade, the institutional environment for European natural gas markets has changed significantly. In this regard, British (National Balancing Point) and Dutch (Title Transfer Facility) gas hubs have grown considerably in popularity (Heather, 2016). Concomitantly, the practice of indexing to oil prices in long-term natural gas contracts has gradually been replaced by hub indexation for a better reflection of the dynamics of fundamentals.

In this context, a second chapter focuses on a major issue of the financialization of gas

markets by examining the question of the informational efficiency of natural gas hubs. We rely on Maximum Overlap Discrete Wavelet Decomposition to decompose the daily data of the spot and future markets of American (Henry Hub), British (NBP) and Dutch (TTF) natural gas for different maturities. This frequency decomposition then allows us to study linear and non-linear Granger-like causality phenomena in multi-resolution but also to perform random walk tests to account for the degree of predictability of future prices. Causality tests show that the Henry Hub market exhibits strong bidirectional causality between the spot and futures markets. The results are less unanimous for the European markets with inconsistencies in the direction of causal relationships across time scales and maturities of futures contracts. Finally, for the three futures markets considered, information efficiency is only achieved in the long term. The results made it possible to establish an evaluation of the three hubs considered in terms of capacity to provide reliable reference prices for the quantities of gas under contract through a discussion on the crucial role of liquidity and storage capacity.

Against the backdrop of climate change and global warming, inevitable inter-flexibilities are emerging between the renewable energy market and the natural gas market. The transition to a low-carbon economy has enabled renewable energy to emerge as an important source in the global energy mix. In 2018, 28% of the world's electricity came from renewable energy sources, most of which (96%) was produced from hydroelectric, wind and solar (EIA) technologies. Support policies for these energies combined with the substantial drop in technological costs largely explain the trend. Concomitantly, natural gas has experienced unprecedented developments over the past decade. The American shale oil and gas revolution has rekindled the economic potential of gas in the global energy markets. The latter is considered to be the most environmentally friendly fossil fuel; its combustion emitting half as much CO₂ as coal. But more importantly, it is at the heart of the issues raised by the use of renewable energies and in particular the issues related to their intermittency. Indeed, the ability of natural gas to complement the production of renewable energy almost instantaneously to ensure uninterrupted supply in the event of absence of wind or solar supply poses the question of a real synergy.

The hypothesis of a *stricto sensu* substitution between reliable source of electricity production and intermittent sources such as wind or solar power have been tempered in the literature. They might be strategic complements when renewable generation is unfavorable, remaining substitutes

at the equilibrium (Bouckaert and De Borger, 2014). Renewable capacity could also be seen as a substitute to baseload technologies and complementary to peak generation technologies (Garcia, Alzate, and Barrera, 2012). In the policy arena, Lee et al. (2012) support the idea of a complementary relationship by considering technical, economic, environmental and political context. Moreover, the economic literature disagree as to which combinations of a plethora of potential drivers will allow for a wide penetration of wind and solar technologies (e.g. declining renewable costs of conventional technologies, climate policies, energy storage availability). For example, Rodríguez et al. (2015) investigated the effect of government policies on private finance investment in renewable energy and found that, in contrast to quota-based schemes, price-based support schemes are positively correlated with private finance contributions. In the same vein, Criscuolo et al. (2014), examined the role of different environmental policy measures (e.g. feed-in-tariffs, tradable renewable certificates, sales tax or VAT reduction, and direct capital investment support through subsidies, grants, rebates, and tax incentives) in inducing early-stage financing.

The third chapter aims to connect these strands of literature in a consistent framework able to comprehensively assess the economic potential of wind and solar penetration under many prospective drivers and explore in the same vein the degree of gross substitutabilities/ complementarities between natural gas and renewable energy. In this sense, we are interested in the same problem to the one discussed by Bistline and Young (2019) and Baranes, Jacqmin, and Poudou (2017). From an empirical perspective, the modeling strategy retained in the present paper considers the possibly non-linear nature of the renewable energy dynamics. More specifically, we test for the presence of regime effect by estimating a Markov Regime-Switching Model (MRSM) based on monthly data from January 2010 to December 2019 of wind and solar electricity generation and potential explanatory variables spanning from electricity market, carbon policy risks to global economic health. Four alternative MRSMs are estimated. Each of the four regressions looks at the determinants of invested wind and solar capacities by adopting a “from specific to general” strategy to better grasp the economic potential of renewables penetration under five prospective drivers. In this context, we compare models that gradually add information variables to comprehensively assess their relative magnitude and explore thoroughly the extent of substitutabilities with the natural gas market. First, our results support the hypothesis that renewable electricity generation dynamics is non-linear, switching between a high regime and a

low regime of production. Second, results portend a higher probability of being in a high regime of wind power generation and a low regime of solar power generation. Thirdly, natural gas and wind energies are more prompt to be substitutes whereas natural gas and solar energies exhibit more scope for complementarity. We discuss the crucial role of storage in the deployment of such technologies.

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Chapter 1

What can be learned from the free destination option in the LNG *imbroglio?*

Foreward

This first chapter is my first contribution as a PhD student. It's the culmination of reflexions and dicussions with Anna Creti and Olivier Massol, who coauthored the final paper published in Energy Economics (Baba et al., 2020). I wish to thank the anonymous referees for their constructive comments. I am also grateful to the participants of the CEMA conference at Sapienza University, Rome in June 2018, the FAEE workshop at Mines de ParisTech in July 2018 and the doctoral Energy Workshop at the University Paris Dauphine in September 2018 for constructive comments and suggestions. Iam also indebted to Marc Joëts for his very constructive review.

Abstract

We examine the profitability of flexible routing by LNG cargoes for a single supplier taking into account uncertainty in the medium-term dynamics of gas markets. First, we model the trajectory of natural gas prices in Asia, Northern America, and Europe using a Threshold Vector AutoRegression representation (TVAR) in which the system's dynamics switches back and forth between high and low regimes of oil price volatility. We then use the generalized impulse response functions (GIRF) obtained from the estimated threshold model to analyze the effects of volatility shocks on the regional gas markets dynamics. Lastly, the valuation of destination flexibility in LNG supplies is conducted using a real option approach. We generate a sample of possible future regional price trajectories using Monte Carlo simulations of our empirical model and determine for each trajectory the optimal shipping decisions and their profitability. Our results portend a substantial source of profit for the industry and reveal future movements of vessels. We discuss the conditional impact of destination flexibility on the globalization of natural gas markets.

1.1 Introduction

The 21st century imperative of flexibility has not spared the liquefied natural gas (LNG) industry. Reaching a historic high in 2016 with 258 million tons (Mt) of traded LNG volumes (IGU, 2017), global LNG trade is set to be fostered by projections of strong growth of global gas supplies mainly driven by the US shale advent and the arrival of new liquefaction capacities from Australia. In terms of additional capacities, the emergence of new actors not only has a major impact but it also provides a key contribution to flexible contracted volumes. With fundamentally different business models, volumes made available by US projects are sold free on board (FOB) and include pricing formulas that rely on hub-indexation. The growing flexibility wisdom is part of a more generalized movement that has led to an increase of spot and short-term LNG trade and fewer long-term binding contracts with decreased duration, relaxed inflexible clauses (e.g., take-or-pay obligations), fewer destination constraints¹ and an increasing reliance to hub-indexation allowing for gas-to-gas competition (Ruester, 2009; Hartley, 2015).²

However, this shift remains progressive. A transition period with new contracts that still includes destination clauses, oil indexation pricing formulas and limited reliance on spot trade is expected on the medium-term horizon (IEA/OECD, 2016). This transitional phase primarily involves Asia as the focal point of action in the coming years. The common prospect in the LNG industry foresees that it will take five to 10 years to see LNG imports markets complete their liberalization process and establish a hub with sufficient liquidity to build a credible reference price for Asian LNG trade.

Meanwhile, flexibility in LNG markets, as a good metric of the current market evolutions, will stem from contracts themselves in the coming years. Yet market flexibility could come from uncontracted LNG supplies, portfolio players³ and diverted LNG supplies. However, only the

¹The US shale gas revolution and the aftermath of the Fukushima disaster in 2011 have exacerbated regional price differentials, further encouraging buyers to re-sell/divert LNG cargoes to third-party destinations.

²Among the market developments that have prominently contributed to this reconfiguration, the waves of market liberalization, the end of destination clauses in Europe, the substantial increase in the number of buyers, third-party access to regasification terminals, the large growth of LNG fleet and the regional gas price differentials post-2010 have been crucial.

³They aggregate supplies from diverse projects and re-sell to different customers.

third option effectively provides flexibility.⁴

Our paper aims at putting contract flexibility into the perspective of medium-term market evolution based on market forecast. To determine the value of destination flexibility in LNG contracts, we follow and extend the real option approach proposed by Yepes Rodríguez (2008) by evaluating the profitability of flexible routing of LNG cargoes for a single supplier according to the degree of uncertainty in the market. That methodology can be decomposed into two successive steps. First, one has to examine and model the intricate dynamic interdependences among the prices of natural gas observed in the three main consuming regions (Japan, Europe, and United States). Then, Monte Carlo simulations of the obtained empirical model are conducted to generate a sample of future price trajectories that are consistent with the observed price dynamics. These trajectories are in turn used to determine the optimal LNG shipping decisions and their profitabilities.

From an empirical perspective, the modeling strategy retained in the present paper considers the possibly non-linear nature of the dynamic interdependences among these prices to meet the following three requirements. The first is to exploit the inter-relationships between the three markets by moving beyond of the generally used linear cointegrating framework as in Neumann (2009), Brown and Yücel (2008) and Kao and Wan (2009). In this vein, Siliverstovs et al. (2005) analyzed the relationship between international natural gas market prices through principal components analysis and Johansen likelihood-based cointegration procedure.⁵ Their most important result is that the natural gas markets across the Atlantic were not integrated with limited opportunities for arbitrage between either side of the Atlantic. This finding implies that the contractual structures and the dynamics of fundamentals remained intrinsically different.⁶

⁴Indeed, concerning portfolio players, their impact in terms of flexibility has been found to be ambiguous as the flexible LNG purchased tend to be sold to customers with oil-indexed LNG contracts (Rogers, 2017). As for the uncontracted LNG supplies, limited volumes are expected to come on stream over the next few years meaning that the extent to which LNG production would be able to respond to a potential demand shock is very limited (IEA/OECD, 2016).

⁵Both of them show a high level of natural gas market integration within Europe, between the European and Japanese markets as well as within the North American market.

⁶The rise in Henry Hub prices in the early 2000s has triggered the construction of major regasification terminals that the shale gas revolution finally converted into liquefaction units. On the other side of the Atlantic, Europe has experienced a gradual decoupling of natural gas prices from those of oil since 2009 in a context of limited

The second is to consider the presence of nonlinearities: linear models may not correctly capture transaction costs, market power (Ritz, 2014), asymmetry of the economic cycle, extreme events, regulations and inherent rigidity in the market. All these factors may cause non-linear effects such as unexpected changes, structural breaks or asymmetric responses to news.⁷ Thirdly, we need to recognize the uncertainties that may affect the dynamics of natural gas markets. The current context especially highlights the uncertainty weighing on the Asian demand, the extent to which Europe will maintain its role of balancing the market and on the pace at which the transition to market-related pricing mechanisms will take place, particularly in Asia, to replace oil indexation pricing in long-term contracts.

Our paper breaks new ground by estimating a threshold vector autoregressive model (TVAR) in a similar approach to that of Balke (2000), in which oil price volatility⁸ plays the role of non-linear propagator of shocks in the regional LNG markets. The Threshold VAR model combined with nonlinear impulse response functions has a number of interesting features that make it attractive for our purpose. First, a TVAR model provides a fairly simple way to capture non-linear dynamics such as asymmetric responses to shocks, regime-switching and multiple equilibriums. Moreover, the variable by which different regimes are defined can itself be endogenous and included in the VAR.⁹ More interestingly, the impulse response functions are no longer linear as they depend on the sign and the size of the shock but also on initial conditions; they are derived as conditional forecasts at each period of time. Therefore, it becomes possible to analyze time-variance in responses to shocks not only across regimes, but also within regimes.¹⁰

regasification capacities across the region. Compared to the US and European gas markets that are mainly supplied by local producers or pipeline imports, Japan is highly dependent on LNG imports. In this market, the Fukushima disaster in 2011 brought a turning point in the LNG price dynamics.

⁷Cremer and Cremer (2014) applied Brownian Distance Correlation tests for non-linearity to one-month forward futures of natural gas from the NYMEX and found significant non-linear relationships. This is also confirmed by Matilla-García (2007) based on the generalized Brock-Dechert-Scheinkman and Kaplan's test.

⁸Measured as the sample standard deviation of adjusted log price changes by using WTI spot prices.

⁹This is not the case within the framework of Markov-switching models where regime shifts evolve according to a Markov chain with a state variable not directly observable, or nonlinear logistic smooth transition VAR models where regime changes are determined by the asymmetric and dynamic interactions of all the variables.

¹⁰This feature makes a threshold VAR a convenient alternative to time-varying parameter (TVP)-VAR that imposes a priori structure and will allow us to analyze the impact of shocks according to different regimes of oil price volatility in the European, Japanese, and US markets.

Finally, the TVAR allows us to exploit the oil-gas relationship as the system switches back and forth between high and low regimes of oil price volatility in response to shocks to other variables. The use of that variable is supported by several practices: the persisting use of oil-indexed price formulas in long-term LNG contracts over the medium-term horizon, especially for the major importer (Japan); the behavior of portfolio players that will substantially anchor the oil price dynamics to that of the natural gas in contracts with short-term expiration dates;¹¹ and the well-recognized linkage of oil price fluctuations with uncertainties about the global economic activity.

We then generate Monte Carlo simulations of the future price series and the subsequent shipping decisions to get the distribution of values for the option of diverting cargoes. The mean value over 10,000 possible future price trajectories in the three alternative destination markets is considered in each scenario. By taking into account the freight route costs, we have considered several configurations of an LNG supplier based either in Australia, Africa, the Middle-East, or North America. A base case where the supplier is committed to send its LNG cargoes to a unique destination (Europe, Japan or North America) is compared to a free destination case where LNG could be flowed to one of three alternative markets to maximize the profits obtained from the sale of that cargo on a monthly basis.

Results have generally highlighted a significant value of the flexibility option. Moreover, the option of free destination has been found to be substantially larger in the high case scenario suggesting that the more the market, particularly in Asia, swiftly repositions to a more flexible reconfiguration, ultimately involving the dissolution of destination clauses and the use of a hub-pricing in contractual terms, the more the players of this industry will be inclined to commit and take advantage of arbitrage opportunities. In this respect, our results are in perfect agreement with those of Shi and Variam (2016) that call for a prioritization of the destination issue over oil-indexation in East Asia .

This paper fits into a relatively large research area that considers the impact of the LNG market reconfiguration on the contractual practices (Von Hirschhausen and Neumann (2008), Ruester (2009), Hartley (2015)) and the consequences on the issue of regional NG market integration (Siliverstovs et al. (2005) and Neumann (2009)). Recent studies focus on East Asian

¹¹They tend to buy gas-indexed volumes and resell with oil-indexed formulas (IEA/OECD, 2016).

markets efforts in creating hubs and changing contract terms toward a removal of destination clauses and the adoption of hub indexation (Shi and Variam, 2016). The debate over whether the Asian premium in NG trade is due to price discrimination or market fundamentals is also considered (Zhang, Shi, and Shi, 2018). Concerning the specific question of destination restriction in long term LNG contracts, YepesRodríguez (2008) is the only study that exclusively focuses on this issue. Our paper enriches this literature as no existing study re-examined this issue by taking into account recent developments in the LNG market and the uncertainties that may affect its dynamics.

We extend Yepes Rodríguez (2008) in several ways. First, instead of describing the evolution of NG prices with Brownian motions which have the drawback of moving far away from their initial point, we rather consider a threshold modeling strategy based on a non-linear econometric approach (Balke, 2000). To the best of our knowledge, this is the first modeling analysis that takes into account the role of oil price volatility as a non-linear propagator of shocks to provide a new understanding of the link between regional natural gas price references. It hence fills the gap in the literature about gas market integration as the issue has been neglected since 2010¹² and also the one related to the more complex evolving relationship between oil and gas markets. Secondly, our model allows the value of the free destination option to be associated to a level of uncertainty in the market: these scenarios expand the scope of the valued option to the increasingly complex outlook of LNG. This is an other line of improvement regarding the hypothesis of constant prices volatility assumed in the Yepes Rodríguez (2008) approach as regional prices dynamics in our model switch back and forth between a high and low regime of oil price volatility. Thirdly, we have assumed the possibility to benefit from arbitrage opportunities on a monthly basis as a way to strengthen Yepes Rodríguez (2008) results that have suggested an important share of the destination flexibility option in the LNG value chain on a yearly basis. Finally, by taking into account spatial considerations, we have extended the calculation of the flexibility option to suppliers based in five countries and have estimated the profitability from diverting their cargoes to an alternative market.

Our results have useful implications. First, from the industry standpoint, not only the

¹²To the best of our knowledge, there has been are no econometric study on the degree of integration of intercontinental gas markets since 2011.

shortfall for a producer who would be constrained in terms of destination by a long-term contract could be conveyed by the destination option but also the important source of value for profit motive actors who are in a position to arbitrage. In this respect, the recent arrival of trading houses in this market would be prominent in terms of flexibility and market diversification; and the present work should help to understand how to value and manage these participants' businesses. Secondly, at the heart of the vivid debate over the potential integration of regional markets, this paper shows that the contractual aspect of this industry is capable of constituting a serious barrier in global LNG trade. The required cautious interpretation of the impact of the destination option on natural gas price convergence debate has been discussed. We conclude that expecting an integration of NG markets only via the effect of appropriation of best netbacks when suppliers can choose their ultimate market destination is misleading. The shortfall of geographically constrained producers rather highlights the benefits of greater future spot market reliance as even partners engaged in long-term contracts could profit from a participation in the spot market, thus increasing the liquidity of the latter. If it works in tandem with a lower indexation of oil prices and the market forces driving movements of vessels then, in this exact case, one would expect a possible "convergence". Finally, from a security of supply standpoint, with relatively low physical flexibility from the LNG export infrastructure and high utilization of liquefaction plants that tend to be base load (IEA/OECD, 2016), making it possible for the contracting parties to supply additional LNG or shifting the destination of LNG delivery, would play a pivotal role in terms of the resiliency to unforeseen events. From this perspective and in view of the steadfast need to manage gas demand uncertainty, the value of destination flexibility far outweighs the optional value calculated in this paper compared to the possible consequences of an unforeseen shock.

The remainder of the paper is organized as follows. The next section presents a brief overview of the existing theoretical and empirical studies surrounding the contractual aspect of the LNG industry and the question of destination flexibility. Sections 3 and 4 describe the real option model for the valuation of destination flexibility option and the model underlying LNG prices forecasts. Sections 5 and 6 present the results. Sections 7 and 8 discuss and conclude the paper.

1.2 Background

In the following, we present an overview of the contractual aspects of the natural gas industry and the issue of destination clauses that we contextualize in the new LNG market environment.

1.2.1 Long-term commitments and LNG trade

The pivotal question of destination flexibility is above all a matter of contract. Long-term commitments have always been an inherent component of the LNG business and the economics literature has extensively grasped the issue by flaunting the merits of these contractual imperatives on the one hand and analyzing their impact on NG trade on the other. Williamson (1979)'s seminal work helps us to understand the irrepressible need for long-term contracts via transaction costs economic theory. The durable transaction-specific and infrastructure-related nature of NG investments not only call for long-term contracts to support high investment costs but it also exposes the parties to hold-up risk. More specifically, it assumes the possibility of ex-post opportunistic behavior and strategic bargaining by the trading partners that suggest we move beyond the picture of an impersonal market and perceive the idiosyncrasy of contractual relations. Klein, Crawford, and Alchian (1978) described it as "appropriable quasi rents" that substantially explain decisions to vertically integrate. Entering into long-term contracts is then seen as an efficient tool to minimize transaction costs in view of the limited rationality of the players adding the issue of asymmetric information. Masten (1998)'s study refers to several works that aimed at analyzing contracts duration and design. Pirrong (1993) concludes that long-term arrangements prevail in specialized markets and reputation and repeat transactions are not enough to prevent strategic behavior without formal commitments. In this respect, the capital intensity of infrastructures in the gas industry has paved the way for several analyses on the sector from both a theoretical and an empirical point of view (see, among others, Gray (1978), Hubbard and Weiner (1986), Crocker and Masten (1988) and Klein, Frazier, and Roth (1990)). Creti and Villeneuve (2004) provide empirical and theoretical insights on long term contracts by examining the role of take-or-pay clauses and price indexation and opening up the discussion on the impact of regulation in the optimal contract duration. In Neuhoff and Hirschhausen (2006), they studied the role of long-term contracts under the liberalization point of view. In the same vein, Von Hirschhausen and Neumann (2008) focused on factors affecting

the duration of contracts by examining 311 long-term contracts between natural gas producers and consumers between 1964 and 2006. Contract duration is found to be shorter for deliveries in the US and UK markets and contracts related to investment in specific projects are of longer duration (see Ruester (2009)). Massol and Tchong-Ming (2010) underline that these rigid contractual structures result in a cost-inefficient organization of LNG shipping that could be rationalized. Price convergence within regional markets has also been studied (Serletis (1997); Walls (1994), and Neumann, Siliverstovs, and Hirschhausen (2006)). Few researches have investigated the potential integration of gas markets from a global perspective. Siliverstovs et al. (2005) obtain mixed results from a cointegration technique with evidence of market integration between European and Japanese markets but no integration between North America and Japan. Over the period 1999 to 2008, Neumann (2009) finds increased convergence of gas spot prices between North America and Europe and Barnes and Bosworth (2015)'s results suggests that the international NG market is less regional overall due to increased trade in LNG via a gravity model.

1.2.2 Destination flexibility

The archetypal contractual scheme used in the LNG industry is that of a producer that contracts either the entire output or a substantial portion of the output of a liquefaction plant to buyers for an average of 25 years or more for a price indexed to crude oil. In most cases, buyers are mid-stream utilities that sell gas and electricity to end customers. A typical contract also includes the so-called "*take or pay*" clauses according to which the seller guarantees the gas will be made available to the buyer, who in return guarantees the payment of a minimum quantity of energy, that he takes delivery or not. For a long time, price indexation was done with geographical variations: the price of gas was fixed according to the prices of competing energies on each market considered. These "netback" clauses could be applied only if the gas was indeed sold on the market for which it was intended.¹³ This clause excluded any possibility of resale of contracted gas to supply in adjacent markets. There was therefore no opportunity for trade between distributors in different countries, nor for trade-offs between the different national markets. Security of supply and investment has been claimed as reasonable reasons to introduce

¹³More specifically, final destination clause made it possible to base the formula for calculating the price in "netback".

these traditional “dedicated contracts” with a predefined destination of the cargoes (Glachant and Hallack, 2009) even if it clearly constitutes a roadblock to a “gas-to-gas competition”.

Nevertheless, even when long-term contracts do not entail destination restrictions, the incoterms may be such as to hinder market flexibility. In this respect, the Delivered Ex Ship (DES) contracts require that the gas exchange takes place at the port of destination and that any redirection of LNG cargoes prior to arrival at the agreed port requires some negotiation between buyers and sellers. On the other hand, Free on Board (FOB) contracts suggest that the exchange of LNG is done at the port of loading thus leaving more room for maneuver to divert the cargoes from their original destination.¹⁴ When FOB deliveries are concerned, “destination flexibility” actually refers to the fact of being able to divert a shipment of LNG according to its original destination; for a DES contract, one speaks about “right of diversion” to designate this phenomenon (Corbeau and Ledesma, 2016). Beyond these contractual considerations, buyers under the aegis of a long-term contract may come to demand the diversion of their cargo to an alternative market for operational reasons such as technical issues, insufficient demand, limited storage capacity at unloading terminals or force majeure. These so-called “cargo swaps” represent only a tiny fraction of the LNG trade and are often seen as an effective means of reducing navigation distances when both counterparts are able to receive LNG in two different destinations.¹⁵

When it comes to commercial reasons underpinning the diversion decision, the contractual landscape becomes complex. As highlighted by the survey on LNG trades by the Japan Fair Trade Commission (2017), there are some contracts providing that diversion “shall not be due to buyer’s commercial reasons” or “diversion is not for resale to seller’s other customers” or that “diversion shall be due to only seller’s direct sales to a third party, who owns or manages an unloading terminal”.

¹⁴In the DES contracts, the seller is responsible for the delivery of LNG and assumes the costs of transport and insurance contrary to FOB contracts where the buyer must bear these costs.

¹⁵Additional costs must be taken into account in the event of a diversion decision: transport costs, port charges, insurance fees, additional costs of the replaced LNG in the initial market and regasification fees in the alternative market.

1.2.3 LNG markets' growing flexibility

Recent developments have led to a deep reconfiguration of the contractual structure governing the LNG trade. The waves of market liberalization, third-party access to regasification infrastructures, the substantial increase of the fleet of LNG vessels and the rise in the number of buyers have been crucial (Corbeau and Ledesma, 2016). The American shale gas revolution combined with strong Asian demand in the aftermath of the Fukushima disaster in 2011 have exacerbated regional price differentials, further encouraging diversion decisions. In this context, long-term contracts experienced fundamental changes in comparison with their former structure : the contract duration substantially decreased and hub pricing is increasingly replacing oil-indexed prices (Hartley, 2015).¹⁶ Asia is still experiencing a transition period toward more flexible market structure. Indeed, LNG volumes imported by Asia were only flexible at 5% in 2016 (IEA/OECD, 2016) and the common prospect among the LNG industry foresees that it will take five to ten years to see LNG import markets complete their liberalization processes and establish a hub with sufficient liquidity to build a credible reference price for Asian LNG trade. In the meantime, Asian buyers are showing their support for a change in oil price indexation for new long-term contracts.¹⁷ Shi and Variam (2016) examined the potential impact of East Asia's efforts in creating hubs and changing contract terms toward a removal of destination clauses and the adoption of hub indexation. Using the Nexant World Gas Model, their findings suggest that the removal of the destination clause in long-term LNG contracts should be the priority over indexation issues for two reasons. First, this does not imply liberalizing the market, which can be very costly in terms of time. Secondly, importing countries have all the sovereignty to forbid firms to sign contracts with oil indexation (Cogan Jr, 2006).

Against this background, the persistent need to resort to long-term contracts in the LNG industry leaves open the issue of destination flexibility that remains unresolved in Asian markets. The transition period toward a more flexible repositioning independent of oil indexation needs

¹⁶This result is also related to the elimination of destination clauses in European contracts that were found to be anticompetitive by the European Commission in 2011. Such restrictions were considered as price discrimination by maintaining the seller's prices in different markets.

¹⁷The share of oil indexed contracted LNG and pipeline gas in East Asia was 88% higher than the global average of 65% (IGU, 2016).

time to be completed and is accompanied by strong uncertainties over the medium-term horizon of the LNG market. To take this into account, we have adopted the only approach that has gave an economic value to the diverting option in the LNG market (Rodríguez, 2008)¹⁸ by connecting a real option approach to two literature strands: one on the integration of regional NG markets where little research has been investigated since the post-2010 gas price differentials¹⁹ and the other one on the persistent influence of oil prices on the dynamics of the gas markets (section 1.4.3 explains in detail the transmission mechanisms at play).

1.3 Real option model for the valuation of the free destination

We develop a model to evaluate the opportunity of flexible routing of LNG cargoes for a single supplier. Our approach can be decomposed into three successive steps. First, we model the interactions among the price series observed in the three main importing regions using a threshold VAR specification. In a second step, we use that empirical model to conduct a series of Monte Carlo simulations aimed at generating a large number (10,000) of future price trajectories over a 36-month horizon. By construction, these trajectories are consistent with the observed dynamics. Third, we evaluate, for each of these trajectories, the stream of future net revenues obtained by an LNG exporter under two cases depending on whether the destination of its shipments is kept fixed or flexible.

By construction, the net present value of the exporter's stream of future revenue depends on the location of the exporter's liquefaction plant. Hence, we successively consider several possible locations in Oceania (Australia), Middle-East (Qatar), North America (USA - Atlantic), North Africa (Algeria), West Africa (Nigeria) where the LNG is committed to a unique destination (Europe, Japan or North America) as a base case (hereafter, labeled reference case). We will then compare it to the free destination case where LNG can flow to one of the three alternative markets to maximize the profits obtained from the sale of that cargo. Depending on the location of the supplier and its alternative destinations, the extra transportation costs would reflect, among others, the fuel oil cost, the vessel charter rate, the ship size, the trip length, and

¹⁸Results suggested that the free destination option is highly likely to improve the value of long-term LNG supplies by between 6% and 43% .

¹⁹International price correlations should have declined compared to the mid/late 2000s with the Fukushima accident representing a structural break.

other fundamental elements of the full-blown shipping market. Benefiting from an arbitrage opportunity will then occur in those months in which the price differentials between the initial and alternative market destination would be large enough to counterbalance the incremental shipping costs of diversion.²⁰ Following Yepes Rodríguez (2008), the value of a destination flexibility option for a unit production capacity in a given month m :

$$v(m) = \text{Max}(p_{\text{alternative}}(m) - p_{\text{preference}}(m) - \Delta t(m); 0) \quad (1.1)$$

with $p_{\text{alternative}}$: the average price of LNG in a future month m in the three possible alternative markets (Europe, Japan, and the US) and $p_{\text{preference}}$ the average price of LNG in the initial market in a future month m .

The value $v(m)$ has to be compared with the value of LNG supply without destination flexibility:

$$\bar{v}(m) = \text{max}(p_{\text{preference}}(m) - t_{\text{reference}}(m); 0) \quad (1.2)$$

The results of each scenario are presented in terms of the monthly average unit of $v(m)$ for a supply period T of 36 months. We let V denote the average value of destination flexibility for this medium-term period for a unit production capacity as the discounted sum of $v(m)$ over the supply period of T months:

$$V = \frac{\sum_{m=1}^T v(m) \cdot \delta^m}{\sum_{m=1}^T \delta^m} \quad (1.3)$$

where δ the risk-free discount factor.²¹ The value V is compared to \bar{V} the average unit value obtained in case of a project with an inflexible shipping policy:

²⁰The additional costs arising from diversion include: honoring the LNG volumes initially granted to the original destination market, access fees to regasification terminals in the alternative market and extra maritime costs.

²¹We assume a discount factor δ of 0,99 as a reasonable risk-free discount factor when considering a long-term supply period, T , of 25 years. As emphasized by Yepes Rodríguez (2008), a lower value δ would affect the calculation of the value of the free destination option as it will give more weight to the first years of the supply period and hence increasing the sensitivity of the results to the initial market prices. .

$$\bar{V} = \frac{\sum_{m=1}^T \bar{v}(m) \cdot \delta^m}{\sum_{m=1}^T \delta^m} \quad (1.4)$$

1.4 Empirical strategy

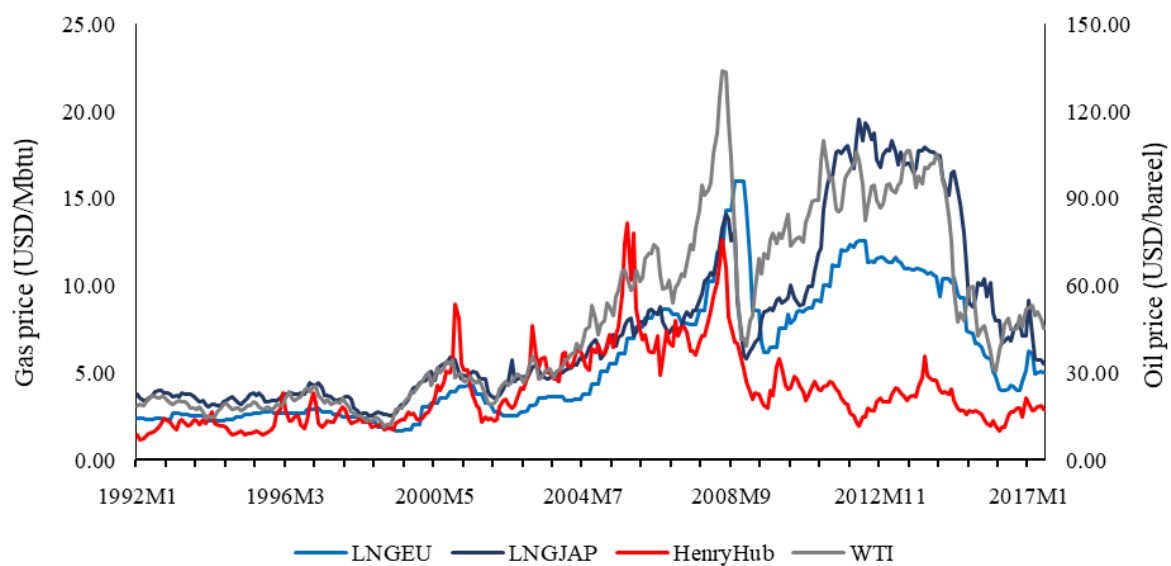
1.4.1 Data

The data consists of monthly prices of NG for the three major gas-consuming regions worldwide, namely Continental Europe, Japan, and the US. Henry Hub natural gas spot price, Japan LNG import price from Indonesia and Russian natural gas border prices in Germany are used to proxy the LNG price in US, Japan, and Europe. These prices were collected from January 1992 to June 2017. Data has been gathered from the IMF Primary Commodity prices. The prices are denominated in US\$ /MMBtu. The model also includes a measure of oil price volatility calculated from the weekly spot prices of WTI. Given the purpose of the study, we opted for a monthly frequency of the data with the aim of exploiting the possibility of monthly arbitrage opportunities between the three regions upon which the destination flexibility option will be based, which is a reasonable assumption with regard to shipping considerations.

A preliminary overview of the data in Figure 3.8 shows a reaction of markets to major exceptional events, e.g., the Californian crisis of 2000, the upward trend in natural gas prices following the soaring oil prices in the 2000s, the global financial crisis of 2007-2008 or the Fukushima disaster in 2011. The global picture underlying the price dynamics displays the following main facts: the rise in Henry Hub prices in the early 2000s (spiking in 2005 and 2008) that triggered the construction of major regasification terminals that the shale gas revolution finally converted into liquefaction units. Besides, on the other side of the Atlantic, Europe has experienced a gradual decoupling of natural gas prices from those of oil since 2009 in a context of limited regasification capacities across the region. Compared with the US and European gas markets that are mainly supplied by local producers or pipeline imports, Japan is highly dependent on LNG imports. In this context, the Fukushima disaster in 2011 brought about a turning point of the LNG price dynamics. The following period of a tight market pushed LNG prices in long-term contracts to be completely guided by oil prices. The subsequent rise

was also felt in Asian spot prices which are linked to the Japanese oil-indexed average price. The resulted regional price differentials enhanced the incentive to redirect LNG cargoes initially destined for Europe as the latter had the ability to rely on pipeline gas imports. Finally, the drop in oil prices in 2014 marked the end of the « boundless Asian premium », leading to a new LNG environment affected by the strong growth in global gas supply.²²

Figure 1.1: Natural gas import prices from the three main consuming regions and WTI crude oil price



1.4.2 Preliminary analysis of time series

Table 1.1 reports some descriptive statistics of the prices in first-logarithmic difference. The skewness and kurtosis coefficients indicate a non-normal distribution for all prices with a higher probability of extreme values. The highly likely occurrence of extreme values and the asymmetric nature of distributions calls for a non-linear specification. The Jarque-Bera (1980) statistics confirmed the non-normality at the 5% and 1% level. To check the stationarity properties of the series, we used Perron (1989), Augmented Dickey-Fuller (1979) and Philipps-Perron (1988) tests. The series are all integrated of order 1 according to all test results. In the sequel, all

²²Driven by the US shale gas revolution and the arrival of new liquefaction capacities from Australia and other regions all over the world.

variables are transformed into their first-logarithmic difference form.

Table 1.1: Descriptive statistics of the prices in first-logarithmic difference.

	<i>Natural gas</i>			<i>Oil</i>
	US	Europe	Japan	WTI
<i>Descriptive statistics</i>				
Observations	305	305	305	305
Mean	0.002	0.002	0.001	0.002
Median	-0.001	0.000	50.008	0.011
Maximum	0.479	0.405	0.258	0.214
Minimum	-0.429	-0.288	-0.368	-0.331
Std. Dev.	0.133	0.063	0.068	50.082
Skewness	0.057	0.281	-1.057	-0.657
Kurtosis	3.930	11.695	7.746	4.484
Jarque-Bera	11.178	964.806	342.997	49.937
Probability	0.003	0.000	0.000	0.000

1.4.3 Testing and Estimation of the TVAR model

The Threshold Vector Autoregression (TVAR) approach²³ used in this paper is similar to that of Balke (2000) who examined whether credit conditions act as a non-linear shock propagator. This propagation takes the form of regime change when credit conditions cross a critical threshold.

The TVAR model combined with nonlinear impulse response functions has a number of interesting features that make it attractive for our purpose. First, a TVAR model provides a fairly simple way to capture non-linear dynamics such as asymmetric responses to shocks, regime-switching and multiple equilibriums. Moreover, the variable by which different regimes are defined can itself be endogenous and included in the VAR.²⁴ More interestingly, the impulse

²³See Tong (1990) for the general structure of non-linear autoregressive models.

²⁴This is not the case within the framework of Markov-switching models where regime shifts evolve according to a Markov chain with a state variable not directly observable, or nonlinear logistic smooth transition VAR models

response functions are no longer linear as they depend on the sign and the size of the shock but also on initial conditions; they are derived as conditional forecasts at each period of time. Therefore, it becomes possible to analyze time-variance in responses to shocks not only across regimes, but also within regimes.²⁵ Finally, the TVAR allows us to exploit the oil-gas relationship as the system switches back and forth between high and low regimes of oil price volatility in response to shocks to other variables.²⁶

Threshold vector autoregression model can be specified as follows:

$$Y_t = A^1 Y_t + B^1(L) Y_{t-1} + (A^2 Y_t + B^2(L) Y_{t-1}) I[s_{t-d} > \gamma] + U_t \quad (1.5)$$

where Y_t is a vector containing the endogenous stationary variables namely the logged first-difference of Japan LNG prices, Europe LNG prices, US Henry Hub, and a measure of oil price volatility. s_{t-d} is the threshold variable that determines the volatility regime that prevails in the system²⁷ and I is an indicator function that takes the value one when the transition variable exceeds the threshold value γ and 0 otherwise. $B^1(L)$ and $B^2(L)$ are lag polynomial matrices and U_t is the vector of orthogonalized error terms. Shocks to the three regional LNG prices and also to the volatility variable will identify whether the market is in a regime of high volatility. A^1 and A^2 represent the contemporaneous relationships in both regimes of volatility²⁸ and are supposed to have a recursive structure with the causal ordering of US LNG prices, Japan LNG prices, European NG prices and the variable of uncertainty conditions;²⁹ implying that the volatility variable would respond contemporaneously to all variables in the system.

When estimating TVAR models, we are confronted with the endogeneity issue as the threshold variable is allowed to endogenously respond to natural gas price shocks. To overcome this issue, the common approach is to consider that the threshold variable switches across regimes with a delay. Also, the TVAR literature suggests defining the threshold variable as a moving average where regime changes are determined by the asymmetric and dynamic interactions of all the variables.

²⁵This feature makes a threshold VAR a convenient alternative to time-varying parameter (TVP)-VAR that imposes a priori structure and will allow us to analyze the impact of shocks according to different regimes of oil price volatility in the European, Japanese, and US markets.

²⁶The model is estimated using WinRATS and the dedicated estimation procedure provided by Nathan Balke.

²⁷By being an element of Y_t , the threshold autoregressive model hence reflects both the evolution of Y_t and the volatility regimes.

²⁸Which are also likely to vary according to the volatility regime considered (idem for the lag polynomials).

²⁹The choice of a threshold structure is not affected by other orderings.

ing average process needing some persistence in the variation of the threshold variable before shocks cause regime switching. Altogether, to thoroughly address the endogeneity issue, we have combined these two approaches by considering a three-period moving average of the two-month-lagged threshold variable. Robustness checks have shown that results are robust to different lag specifications.

An important question is whether the estimated TVAR model is statistically significant relative to a linear VAR. As the threshold value is unknown and needs to be estimated, the threshold model is estimated by least squares for all possible thresholds values. For each possible value of the threshold, we test the hypothesis that the coefficients of the model are equal across regimes, that is $A^2 = B^2(L) = 0$, by using a multivariate extension of the linearity test by Hansen (1999) and Lo and Zivot (2001).

Before testing for a threshold effect in the vector autoregression representation of the data, we estimate a linear VAR in order to select the optimal lag order that has been set to three in compliance with Akaike (AIC) and Hannan-Quinn (HQ) information criterions.³⁰

Choice of the transition variable

To better grasp the price dynamics that lay ahead in the LNG markets, we have chosen to consider volatility scenarios by exploiting the oil-gas relationship. More specifically, we have retained the oil price volatility,³¹ found to be a significant predictor of natural gas returns (Pindyck, 2004), as a non-linear propagator of shocks in the LNG markets. A plethora of elements may explain this choice:

First, if oil price volatility matters when looking at the future of LNG markets, this could be explained by the historic relationship between the two commodities.

In this regard, Serletis and Herbert (1999) and Brown and Yücel (2008) find that crude oil or refined products and US gas prices exhibit a high correlation and are cointegrated. Villar and Joutz (2006) results suggest the existence of a long-run relationship in which the price of WTI is weakly exogenous to the price of natural gas at the Henry Hub; meaning that the price of natural gas adjusts to deviations in the long-run evolving relationship but these deviations do not affect

³⁰For all variables except the volatility measure, we have used the first difference of natural logarithm transformation.

³¹Measured as the sample standard deviation of adjusted log price changes by using WTI spot prices.

the oil price. Substitution and competition are not the only driving forces of such a trend. Legislations or technological changes have also been found to be crucial (Hartley, Medlock III, and Rosthal, 2007).

The energy industry has long tried to relate natural gas prices to those of oil via rules of thumb (Brown and Yücel, 2008), but the failure of these rules to explain differential trajectories of oil and natural gas prices in long periods has contributed to the emerging idea of a decoupling of natural gas from the crude oil prices. Brown and Yücel (2008) argued that the relationship has complex short-term dynamics because of factors that affect market fundamentals such as extreme weather events, level of storage or disruption of production, but is quite stable in the long run.³² Their empirical work calls for a continuum of market links as a result of more complex market forces. Empirical studies have examined this issue by testing for the presence of structural breaks and investigating a non-linear relationship between oil and natural gas prices. Ramberg and Parsons (2012) find evidence for structural breaks in 2006 and 2009 in the cointegrating relationship. Along this line, Brigida (2014) modeled structural breaks in the relative pricing relationships as switches between cointegrating regimes and finds that the decoupling was a temporary shift in regime. Using Student-t copulas to model the non-linear links between crude and natural gas prices, Grégoire, Genest, and Gendron (2008) find evidence of extreme co-movement as well. Theoretical and empirical insights suggest a non-linear price transmission as most of the energy commodities exhibit non-linear behavior because of, among others, recessions, unforeseen extreme events, transaction costs, market power, geopolitical tensions, asymmetric information or stickiness in prices. The difference of the market structure also matters: as the oil market is global and responds more quickly to global factors whereas natural gas prices respond more to the regional dynamics of the markets.

Secondly, over a medium-term horizon, LNG markets will still experience a transition period during which oil-indexation, especially for the major importer (Japan), will still underpin contracts with limited reliance on spot trade.³³ The long road towards a liquid trading hub in

³²Erdős (2012) finds that oil and gas prices are close substitutes and should form a long-run equilibrium level close to the thermal parity around which they switch in the short run.

³³Oil indexation in Asia is expected to slightly decrease, moving from 78% in 2016 to 69% in 2022 (Rogers, 2017).

Asia (requiring 5 to 10 years) and the enigmatic role of portfolio players who buy gas-indexed volumes and resell with oil-indexed formulas (IEA/OECD, 2016) will substantially anchor the oil price dynamics to that of the natural gas in the near future.

The implications of the above findings are twofold. First, there is a strong correlation between oil and gas prices, and this relationship has to be modeled as non-linear.

Last but not least, oil price uncertainty has direct effects on global economic activity. This question has been studied by a huge strand of the economics literature pointing out different transmission channels. For instance, Elder and Serletis (2010) find that uncertainty over the price of oil had a negative and significant effect on real gross domestic products (GDP), durables consumption, several components of fixed investment and industrial production. In the same vein, theories of investment under uncertainty and real options suggest that an asymmetric relationship between uncertainty and economic activity tends to postpone firm's decision-making when committing irreversible investments by creating an option value to wait and see. Such micro decisions are likely to affect the macro-level dynamics by creating cyclical fluctuations: as explained by Bernanke (1983), this could be the result of an economic system that is not sufficiently diversified or a misperception about the duration of the shock by agents under imperfect information who tend to extend in time the effects of a temporary shock.³⁴

Oil price volatility

Oil price volatility, found to be a significant predictor of natural gas returns (Pindyck, 2004), is measured as the sample standard deviations of adjusted log price changes by using weekly WTI spot prices. Following Chen and Hsu (2012), the monthly volatility of WTI spot prices is considered:

$$wtivol_t = \sqrt{\left(\frac{1}{N-1}\right) \sum_{t=1}^N \left(r_t - \frac{1}{N} \sum_{t=1}^N r_t\right)^2} \quad (1.6)$$

$$r_t = \log(wti_t^w) - \log(wti_{t-1}^w) \quad (1.7)$$

³⁴The uncertainty over the future path of oil has also been found to be a decreasing factor of international trade flows (Chen and Hsu, 2012).

with r_t the weekly oil price returns and N the number of trading weeks during the t month. Several reasons explain this choice: First, as highlighted by Pindyck (2004), spot prices represent the best single statistic for market conditions when considering their capacity to reflect the volatility of current and future values of production, consumption and inventory demand. Secondly, by using a standard deviation as a measure, we attribute the same weight to the observations used in the estimation. Campbell et al. (2001) emphasize the benefit of such an approach that does not require any parametric model to describe the evolution of volatility over time. It also provides unbiased estimators of the underlying latent volatility (see Fleming, Kirby, and Ostdiek (2001) and Radchenko (2005)).

Lastly, an interesting result from Ewing, Malik, and Ozfidan (2002) consolidates our choice. By empirically modeling time-varying conditional variances of returns calculated from natural gas and oil indexes in a multivariate GARCH frame, they find that volatility persistence is less important in the oil market than in the gas market meaning that the return of volatility to its long-run level is faster in the case of oil returns. This result suggests that the unconditional variance of the series would yield a good forecast of the future volatility.

Hence, the approach we have retained to deal with the latency nature of return volatility enable us to imbed the oil price volatility in the VAR system as a function of its lagged value and values of the natural gas prices returns in US, Japanese and European markets and will act as a non-linear propagator of shocks in those markets.

1.4.4 Non-linear impulse responses

In the class of non-linear models, some properties of linear models no longer hold namely the impulse responses can no longer be directly derived from the estimated coefficients, the responses are no longer symmetrical in terms of sign and size to structural shocks and, above all, impulse responses are no longer constant since the variance-covariance matrix of the residuals depends on the considered regime.³⁵ The non-linear impulse response function (NIRF) is the change in the conditional expectation of Y_{t+k} as a result of knowing the value of an exogenous shock:

$$E[Y_{t+k}|\Omega_{t-1}, u_t] - E[Y_{t+k}|\Omega_{t-1}] \quad (1.8)$$

³⁵See Gallant, Rossi, and Tauchen (1993) and Koop, Pesaran, and Potter (1996).

where Y_{t+k} is a vector of variables at horizon k , Ω_{t-1} is the information set available at time $t-1$ and u_t is a particular realization of exogenous shocks. Besides, the calculation of the impulse response functions for the non-linear model requires a specification of the size and sign of shocks and the initial condition. We proceed by simulating the model conditional on an initial condition Ω_{t-1} and a given realization of u_t .³⁶

1.4.5 Simulation-Based Forecasting

As the multivariate forecast errors are asymptotically normally distributed with covariance matrix, the forecasts of Y_{t+h} are simulated by generating multivariate normal random variables with mean zero and covariance matrix from the residuals of the estimated TVAR. More specifically, we generate Multivariate Monte-Carlo Simulations to get the future LNG prices paths for each regime of volatility as the TVAR model is linear within each regime and the subsequent shipping decisions to obtain the distribution of values for the diversion option. This choice is empirically supported by the results of the Andersen-Darling normality test applied to the TVAR model residuals distribution in each regime.

1.5 Regime-dependent volatility transmission

1.5.1 Tests for TVAR and estimation of the threshold value

Table 1.4 presents results of the test of a linear VAR model against the alternative threshold effect. To test the null hypothesis of linearity (1 regime) against the alternative of nonlinearity (with 2 or 3 regimes), we relied on a multivariate extension of the linearity test of Hansen (1999) and Lo and Zivot (2001). The LR test statistic is calculated in the following way:

$$LR_{01} = T(\ln(\det(\hat{\Sigma}_0)) - \ln(\det(\hat{\Sigma}_1))) \quad (1.9)$$

with $\hat{\Sigma}_0$ the estimated covariance matrix of the model under the null hypothesis of linearity and $\hat{\Sigma}_1$ the estimated covariance matrix under the alternative hypothesis of a threshold specification. The p -values are calculated by simulation.³⁷ Three tests are computed. The both two first (panel A and B in Table 1.2) can be considered as linearity tests whereas the third (Panel

³⁶The employed algorithm for GIRFs computation is described in Appendix B.

³⁷Based on 500 replications, the bootstrap distribution is obtained by resampling the residuals from the null hypothesis model, estimating the threshold parameter and then computing the test.

Table 1.2: LR test results for a VAR(3)

LR test results	
Panel A: LR test for linearity against 2 regimes	
LR statistic	154.774
<i>p-value</i>	[0.008*]
Estimated threshold	0.0386
Panel B: LR test for linearity against 3 regimes	
LR statistic	276.6101
<i>p-value</i>	[0.0300**]
Estimated thresholds	0.0386 0.0502
Panel C: LR test for 2 regimes against 3 regimes	
LR statistic	121.836
<i>p-value</i>	[0.404]
Estimated threshold	0.0386 0.0502

Note: The response of LNG prices to changes in volatility context is supposed to occur with a delay d of 2 months. P-values based on Hansen's (1996) procedure method of inference with 500 replications are between brackets. *, ** denote the rejection of the null hypothesis at 1% and 5% respectively.

C in Table 1.4) can be seen as a specification test to check whether one or two thresholds are preferable. Results consolidate the choice of a threshold specification with two regimes of volatility that have one threshold. A better overview of this threshold effect is depicted in Figure 1.3 in Appendix A which represents the evolution of the uncertainty measure and the threshold estimated value above which the market toggles to the highest regime. It shows that oil prices react to major exceptional events: such as the 1997 Asian financial crisis, 2005 Hurricane Katrina, Global financial crisis of 2007-2008, the Fukushima disaster in 2011, and oil price slump in 2014. The uncertainty generated by these episodes of high volatility represents nearly 35% of the observations. The remainder is attributed to relatively low volatility regimes.

1.5.2 Non-linear impulse response functions

Figures 1.4 to 1.6 in Appendix B illustrate the estimated impulse response of liquefied natural gas returns to positive and negative shocks from oil price volatility in high regime (HR) and low regime (LR) configuration.³⁸ Overall, the non-linear impulse responses suggest that oil price volatility has a negative effect on natural gas returns in the three regions regardless of the regime. As discussed before, this result is with respect to the increased uncertainty of current and future oil price trajectories, consumption and inventory demand that will give credence to the option value to wait of investments, thereby delaying the consumption. More importantly, for all the regional price returns, the impact of oil price volatility shocks exhibits an asymmetrical phenomenon as it is more significant in the high case scenario: a result that consolidates the choice of the threshold specification with the oil price volatility as a non-linear propagator of shocks.

As one could expect, disparate impacts are wielded by oil price volatility shocks in the three regional markets. This result could mainly be explained by the differences in the oil dependence scheme and the natural gas market structures. Asian gas returns are the most responsive (in period 1) to a positive oil price volatility shock regardless of the considered regime. This result directly echoes the oil dependence of the country and the huge recourse to the oil-indexation in the LNG contracting structure.

Concerning the European market, there are some lag effects (period 3) in the gas returns

³⁸Four lines are displayed, corresponding to positive and negative nonlinear impulse response functions (IRFs) under high and low volatility states following a two-standard-deviation oil price volatility shock.

response to a positive shock from oil price volatility when the market is already in a high regime of volatility. This lag effect might be explained by the relatively large share of domestic gas production and pipeline import, the hybrid system of price formation and the competition with other energy sources that tend to postpone the effect of oil price volatility. Whatever the sign and the considered regime, there is a persistence effect in the European response to shock from oil price volatility with a slow return to the pre-shock values.

In the highest regime, North American gas returns have experienced a quick redirection toward their pre-shock values: the transitory nature of this response is indicative of the partial influence of oil prices dynamics in the US gas market, as the latter widely responds to its own supply and demand issues, storage level considerations, etc. This result is supported by the slightest difference between the response of gas returns in the high and low regime of volatility which is indicative of the reliance on the derivatives products to manage their risks.

1.5.3 Robustness checks

Overall, our results are found to be robust to different specifications of the threshold VAR model and the variables. More specifically, our conclusions are robust to variations in the number of lags in the TVAR system, to different delays d of the transition variable, and different orders of the moving average process.³⁹ Moreover, results are also robust to a threshold variable measured by using daily WTI spot prices to calculate the sample standard deviations of adjusted log price changes.⁴⁰ Finally, we have considered an other proxy of uncertainty to test the robustness of the model to another transition variable. Following Bloom (2009), we retained the Chicago Board of Exchange VXO stock market volatility measure constructed using the implied volatilities on S&P 500 index options.⁴¹ The latter is reputed to provide a measure of financial market uncertainty and shows the market's expectations of 30-day volatility and is hence primarily forward-looking. As it turns out, this alternative threshold variable makes little difference in terms of our testing

³⁹Tables 1.11.6, 1.7 and 1.11.6 in Appendix F present tests of a linear VAR against a threshold alternative. Three tests are computed: sup-Wald, avg-Wald and exp-Wald, which respectively represent the maximum, average and function of the sum of exponential Wald statistics over all possible threshold values (See Hansen (1996) for the simulation method used here to conduct inference).

⁴⁰See Table 1.4 and Figures 1.15 to 1.17 in Appendix E.

⁴¹The number of lags in the VAR was set to three.

of a threshold specification and also in terms of conclusions of the impulse response functions.⁴²

1.6 Destination flexibility option

1.6.1 Regime-dependent LNG prices paths

We will associate the high scenario to an increased uncertainty about the use of oil-indexation in long-term LNG contracts. An increasing oil price volatility could affect their duration and give a significant impetus to the willingness of Asian markets to push forward gas-to-gas competition. This could lead to a situation where buyers would tend to not renew their expiring contracts and would choose to enter into shorter spot indexed contracts. We will associate the low scenario with a persisting high reliance on oil-indexation and a relatively slow beginning of large US LNG volumes being exported to the global gas market.

1.6.2 Free destination option

To capture the dynamics of future flows by 2020 and determine the adapted shipping decisions, we have chosen to calculate the value of the free destination option for producers located in the US, Australia, Africa, and Middle East. Table 1.3 gathers the result for all tested configurations. Figures 1.9 to 1.14 in Appendix D depicts the cumulative frequency distribution throughout the 10,000 Monte Carlo simulations of monthly unit value of the free destination option in low and high regime of volatility for producers involved in transatlantic arbitrages with a map in Figure 1.2.

Australia As the looming prospect of large new LNG supplies by 2020 is partly coming from Australia, analyzing the spread-responsive LNG cargo movements from this region should be instructive. We consider four case scenarios and each one is related to the above described high and low regimes of volatility. In the first one, we compare a base case in which an Australian supplier could flow LNG only to Japan (the most reasonable destination in terms of shipping costs)⁴³ and a free destination case that allows for diverting LNG cargoes toward the European markets. Following the methodology described above, the monthly average unit value of destination flexibility in this case is found to be equal to \$0.02 per MMBtu in the highest regime

⁴²See Table 1.5 and Figures 1.18 to 1.20 in Appendix E.

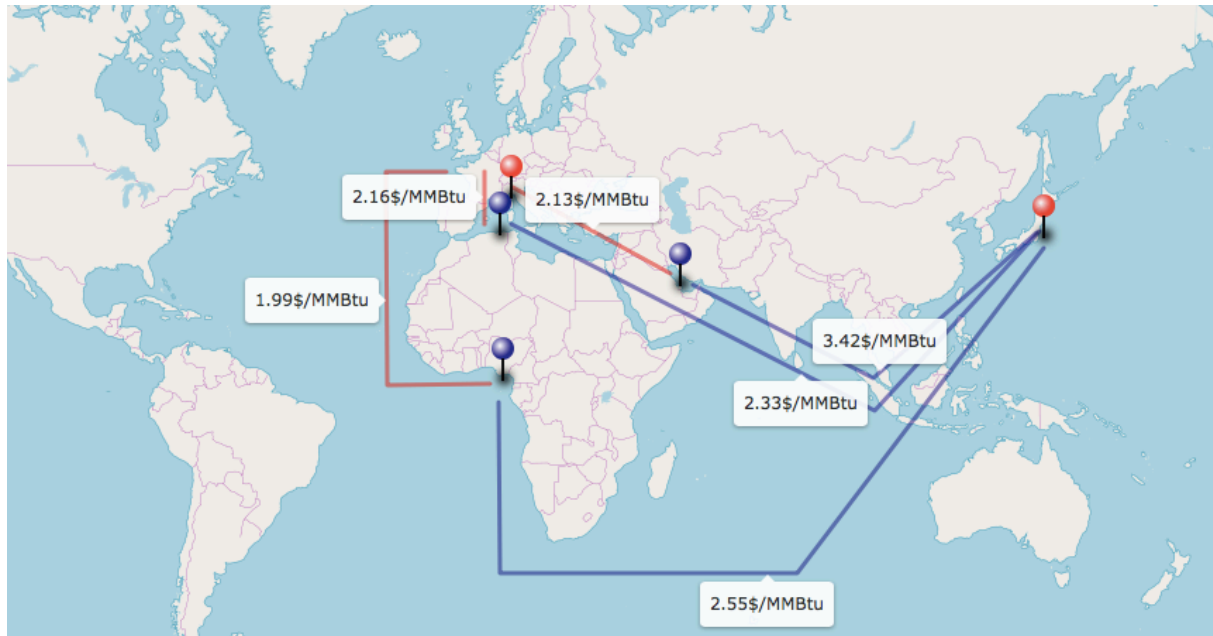
⁴³See Appendix C.

Table 1.3: Expected values of the free destination option in a high and low regime of volatility

Supplier	Initial	Alternative	Volatility Regime	Flexibility option	Gain
<i>Most profitable studied cases</i>					
Qatar	US	Japan	High Regime	3.42\$/MMBtu	172%
			Low Regime	1.55\$/MMBtu	156%
Algeria	US	Japan	High Regime	2.33\$/MMBtu	70%
			Low Regime	0.94\$/MMBtu	62%
Nigeria	US	Japan	High Regime	2.55\$/MMBtu	103%
			Low Regime	1.06\$/MMBtu	85%
<i>Transatlantic arbitrages</i>					
Qatar	US	Europe	High Regime	2.13\$/MMBtu	109%
			Low Regime	0.90\$/MMBtu	90%
Algeria	US	Europe	High Regime	2.16\$/MMBtu	82%
			Low Regime	0.93\$/MMBtu	70%
Nigeria	US	Europe	High Regime	1.99\$/MMBtu	81%
			Low Regime	0.84\$/MMBtu	67%
<i>Japan / Europe arbitrages</i>					
Australia	Japan	Europe	High Regime	0.02\$/MMBtu	1%
			Low Regime	0.00\$/MMBtu	0%
US	Europe	Japan	High Regime	1.07\$/MMBtu	25%
			Low Regime	0.41\$/MMBtu	20%
Qatar	Japan	Europe	High Regime	0.32\$/MMBtu	6%
			Low Regime	0.06\$/MMBtu	2%
Algeria	Europe	Japan	High Regime	0.84\$/MMBtu	18%
			Low Regime	0.27\$/MMBtu	12%
Nigeria	Europe	Japan	High Regime	1.06\$/MMBtu	24%
			Low Regime	0.38\$/MMBtu	18%

Note: "Initial" refers to the agreed destination in the long-term LNG contract, "Alternative" is the diverting option and the "Gain" column features the flexibility option/inflexible project value ratio.

Figure 1.2: Expected value of free destination option when suppliers are initially committed to serve US in the high regime



Note: Blue spots represent the suppliers locations, Red spots are the European and Japanese alternative markets, Red (Blue) lines represent the derouting of LNG toward the European (Japanese) market and the associated value of the free destination option.

and \$0.00 per MMBtu in the low case scenario. Here, the flexibility to respond to market price signals does not improve the expected value of an LNG project compared to an inflexible project as there is little chance to see a supplier from Australia engage in this physical arbitrage when transportation costs differentials are threefold. The optimization of LNG flows saliently explains this interpretation as the low oil and gas price environment has prominently tightened margins, not counting the additional costs incurred when the diversion option is exercised. Altogether, whatever the level of uncertainty that weighs on Japanese and European demand and the pace at which the transition toward a more flexible LNG market will move away from oil indexation, the looming new LNG supply from Australia would remain in the region when original contracts plan to send LNG to Japan. As the portfolio of Australian LNG supply could be diversified, we have also studied three other cases by comparing a base case in which an Australian LNG supplier is initially committed to the US market and a free destination case where LNG is able to be diverted either to Europe or Japan or both. The contingency of these situations has to

be considered as a way to widen the sphere of possibilities in terms of shipping decisions in a portfolio perspective rather than an exclusive optimization of shipping distances. It appears that the price spread stimuli between the markets in the US and Europe/Japan leads to the option of destination flexibility to be exercised regardless of sizeable extra maritime costs. For instance, the ability to respond to European market price signals allows for an 89% improvement in a high case scenario and for a 74% improvement in the lowest regime.

US Arbitrage decisions underpinned by the new wave of US LNG are equally of paramount importance.⁴⁴ Two cases are analyzed here: the first one embodies an American supplier which is committed to flowing LNG to Europe and evaluates the possibility to redirect its cargoes to Japan as an alternative destination. To give more support to the latter shipping decision, a second case exemplifies an American supplier which is initially involved in a long-term contract with Japan and sees in the European market a way to benefit from arbitrage opportunities. In terms of extra maritime costs, it is about twice as expensive for an American supplier to ship an LNG cargo to Japan as it is to Europe: this feature does not undermine the diversion decision of LNG cargoes in the first case. In this present instance, a \$1.07 per MMBtu is expected for the flexibility option in the high regime and \$0.41 per MMBtu in the low regime. In the adverse case, the value of free destination for a unit production capacity is expected to represent on average of \$0.16 per MMBtu in the low scenario case and \$0.56 per MMBtu in the high scenario case. More precisely, the distribution of the value of destination flexibility varies from zero to \$2.24 per MMBtu with a standard deviation of \$0.80 per MMBtu in the high case scenario and oscillates from zero to \$0.71 per MMBtu with a standard deviation of \$0.25 per MMBtu in the low case scenario. Hence, the Atlantic Basin is well positioned to take a turning point and become an important LNG arbitrage market by horizon of 2020 especially in a context of an increased uncertainties about the future path of LNG demand in Europe and Japan.

Middle-East The Middle East counts major players in the LNG industry. Even though some producers will see their export-oriented LNG production drop as Abu Dhabi or Oman, the stability of a key player such as Qatar will keep ensuring LNG flows from this region. The increase in capacity was phenomenal between 2009 and 2011 in Qatar, which resulted in large

⁴⁴The associated probability distributions of the free destination option are available upon request.

spare capacity that was able to significantly affect the dynamics of future LNG flows.⁴⁵ In a context of a producer initially engaged in the medium term on a contract with the United States,⁴⁶ the potential benefits of diverting LNG cargoes to Europe and Japan are both analyzed.

When the latter has to arbitrate between the US and Europe, it appears that the monthly average unit value of destination flexibility is calculated at \$2.13 per MMBtu in the high case scenario and \$0.90 per MMBtu in the low case scenario (see figures 1.9 and 1.10 in Appendix D). This is a significant value when reconsidering the relatively bleak outlook of LNG prices on the medium-term horizon. This decision turns out to be rational enough to be concretized as there is no huge extra-maritime cost (\$0.02 per MMBtu). Moreover, the decision to divert its LNG cargoes to the Japanese market is equally feasible: the monthly unit value of destination flexibility in this case totals \$1.55 per MMBtu in the low case scenario and \$3.42 per MMBtu in the high scenario case, the monthly average unit value of the destination flexibility option is about \$2.13 per MMBtu in the high case scenario and \$1.68 per MMBtu in the low case scenario.⁴⁷ The improvement provided by the flexibility option here is 1.72 times higher in a high scenario case and 1.56 higher in low scenario case compared with the case where the only destination alternative was the US.

Africa Finally, we have chosen to calculate the value of the destination flexibility option for a country in North Africa (Algeria) and in West Africa (Nigeria) whose production forecasts for 2020 are substantial (IGU, 2017). These countries have also shown by past diversions of LNG cargoes that they are very inclined to this type of practice. These two countries share in common their close link to the European market that receives LNG from these countries on a regular basis and have fairly comparable transportation cost differentials in that the Japanese market is far more laborious to reach than the European or US market.⁴⁸ As a first case, we then calculated the medium-term gains associated with a possible diversion of LNG cargoes

⁴⁵This production is mainly due to low production costs which explains the resilience of the latter to a low oil price environment.

⁴⁶A case that echoes the large production capacity that was intended to this market before the American shale gas revolution.

⁴⁷And with 90% probability, this value ranges from \$1.24 per MMBtu to \$1.64per MMBtu in the low case scenario and from \$1.77per MMBtu to \$7.38 per MMBtu in the low case scenario

⁴⁸See Table 1.8.

initially committed to Europe to the Japanese market. Whether from Algeria or Nigeria, the conclusions are unanimous: the free destination option has more chance of being exercised in the high regime. Nonetheless, whatever the considered volatility regime, the expected value of the option is found to be less profitable comparing to the transatlantic options (see Table 1.3). The end of the “boundless” Asian premium following the Fukushima disaster should give less rationality to this decision.

Two other cases are focused on Nigerian and Algerian suppliers who are initially committed to serve the US markets and study the possibility of diverting these cargoes to Europe or Japan (See Figures 1.11 to 1.14 in Appendix D). When Europe takes the role of alternative market, the monthly average unit value of destination flexibility is found to be equal to \$1.99 per MMBtu in the high case scenario and \$1.12 per MMBtu in the low case scenario for a Nigerian supplier and reaches \$2.16 per MMBtu in the high case scenario and \$0.93 per MMBtu in the low case scenario from an Algerian supplier point of view. These results reflect a high probability of exercising the option in the medium-term horizon as with 90% certainty, the value of the free destination option is about to vary from \$1.12 per MMBtu to \$3.02 per MMBtu in the high case scenario and from \$0.69 per MMBtu to \$0.99 per MMBtu in the low scenario case when a Nigerian supplier is free to divert its cargoes to Europe. The same improvement is expected on the Algerian side as the free destination option has the potential to bring an added value of around 82% in a high scenario case and 70% in a low scenario case compared to a geographically constrained project. In the same vein, when Japan is considered as the market destination of diverted LNG cargoes, the option of free destination is slightly less significant than in the European case for Algerian suppliers but increases from a Nigerian supplier point of view.

As part of our modeling, by increasing extra transportation costs to alternative markets from 10% to 50%, we find that for all suppliers involved in US-Japan and US-Europe arbitrages, the value of the free destination option turns out to be slightly more sensitive to extra-transportation costs when the market is under high volatility. By contrast, when the arbitrage decision hinges on the dynamics of the Japanese and European markets, it's not only the value of the option that is necessarily higher in the more volatile regime but also the sensitivity to the additional

maritime costs.⁴⁹ In all cases, given the weak oil and gas environment, particular attention will be paid to transportation costs which, combined with future price trajectories, will prominently drive diversion decisions.

1.7 Discussion

In comparison with the results obtained in the Yepes Rodríguez (2008) study, the value of the flexibility option remains a very important part of the value of LNG, and even more so on a monthly basis. Taking into account the volatility of oil prices, which is supposed to capture the pressure on the practice of oil indexation and partly the uncertainties related to global activity, three important points are to be emphasised.

First, the results described above show that the price differentials between the US and Europe/Asia will still be very significant in the coming years, creating considerable arbitrage opportunities. Indeed, our model has shown that for a producer located in Nigeria, Algeria or Qatar that must initially deliver the US market, it will always be profitable to exercise their right to diverge to Europe or Japan (see Figure 1.2).

Secondly, arbitrage opportunities are found to be more profitable in the highest regime of oil price volatility. Associated to an increased uncertainty about the practice of oil-indexation in long-term LNG contracts, this result echoes the study of Zhang et al. (2018) that sought to understand whether higher prices in Asia are due to pricing discrimination or simply reflect differences in the market fundamentals. From this point of view, our results suggests that oil indexation has probably had a significant impact on the Asian premium as the pressure on oil stability and thus the indexation process pushes Japanese prices to be more sensitive to uncertainties in fundamentals. This also means that the more the market swiftly repositions to a more flexible reconfiguration, ultimately involving the dissolution of destination clauses and the use of a hub-pricing in all contractual terms, the more the players of this industry will be inclined to commit and take advantage of arbitrage opportunities. Focusing on destination flexibility will

⁴⁹In a more relevant and exhaustive way, shipping market has to be considered here as a market itself. The latter is significantly affected by the economic business cycle, the ordering of new vessels and the subsequent balance of tanker supply and demand, on market expectations or on the lag between the start of liquefaction and the delivery of dedicated vessels.

thus be an effective way of giving some momentum to a quasi-inescapable transition period for the Asian markets. In this respect, our results are in perfect agreement with those of Shi and Variam (2016) who advocate a prioritization of the destination issue in the contractual terms of LNG sales.⁵⁰

Thirdly, our results suggest the end of the Asian premium with a tightening of price differentials between Europe and Asia, whatever the volatility regime considered (see Table 1.3). Indeed, in both high and low regime, producers from US, Algeria or Nigeria will probably not systematically exercise a diversion right to divert a shipment originally scheduled for Europe to Asia.

Finally, the low price environment for oil and gas industry and the subsequent tight margins are prominently calling for an optimization of LNG flows in the medium-term horizon. The greater the transport distances are, the greater the uncertainty that weighs on the days of travel, fuel costs and labor costs. From this point of view, the exercise of the valued options might give an indication of the direction of future LNG flows by 2020 that will depend on the two possible scenarios: a high case scenario under which the above described uncertainties about future LNG demand in Europe and Japan are exacerbated and where the transition to a more flexible LNG market away from oil indexation is occurring at a sustained pace and a low case scenario that does not really deviate from the current market configuration with a time-consuming transition. Thereby, one might expect that: US LNG would prominently go to Europe in both scenarios but is more likely to end up in Europe in a low case scenario; Australian and Middle Eastern LNG are expected to be moved toward the Japanese market and the European alternative would be profitable only when a producer in one of the two regions is initially committed to serving the US for both scenarios; and an African LNG will be found mainly in Europe with a higher probability of diverting an Algerian LNG to Japan than a Nigerian LNG given its lower sensitivity to extra maritime costs. As highlighted by Corbeau and Ledesma (2016), the high transaction cost LNG market is obviously not at a stage where LNG flows can be perfectly optimized. Logistical,

⁵⁰For two main reasons: the first being that a removal of destination clauses does not suggest the liberalization of the domestic market and would therefore be much easier to implement compared to a change of indexation; secondly, importing governments should have the sovereignty to prohibit firms under its competence to sign contracts with destination clauses, such as in the case of European Union.

operational and contractual bottlenecks are actually putting off the prime essence of the LNG industry: that of being a cargo business. For instance, the need for the compatibility of the offloading and the receiving infrastructure, the possible limited berth availability at terminals or the size restriction in accordance to the receiving liquefaction terminal show how the lack of standardization from an infrastructure point of view can pose significant barriers to LNG trade. And when considering the diversion decision, the additional costs can seriously deter the exercise of the option as it might imply that the supplier fulfills its commitments to the initial buyer by supporting all additional costs of the replaced LNG in addition to the question of rent-sharing which is also a government issue, bunker fuel costs, boil-off gas equivalent fees, charter costs, regas fees and costs to access to regasification terminals in the alternative market. All the complexity of these decisions is based on the fact that evolving physical, cost, and pricing aspects must be considered in tandem.

1.8 Conclusion

In fine, what could be learned from the destination flexibility option in the LNG markets? As mentioned above, LNG is a cargo business that makes the ability to move gas by sea over long distances the cornerstone for splitting natural gas markets from their regional dynamics. A speculation on the possibility of converging regional LNG prices requires a cautious interpretation of the valued destination flexibility option. Expecting an integration of natural gas markets by the only effect of appropriation of best netbacks when suppliers can choose their ultimate market destination could be misleading. Here, the shortfall of geographically constrained producers rather highlights the benefits of greater future market spotification as even partners engaged in long-term contracts could profit from a participation in the spot market, thus increasing the liquidity of the latter. If it goes in tandem with a lower indexation of oil prices and market forces driving prices and movements of vessels, then in this precise case, one would expect a possible "convergence". The transition to this state suggests looking closely at the process of liberalization of national gas markets, the pricing terms in forthcoming long-term contracts and the expansion of spot trade and its legitimacy in establishing itself as a reference for long-term LNG contracts. The question of the impact of destination flexibility would therefore have to

do with the time horizon considered. In the medium-term, it would be misleading to combine greater destination flexibility with a systematic price convergence mechanism as regional price formations remain intrinsically too divergent by responding to fundamentally different dynamics. At the limit, one could expect a convergence of regional prices. In the long run, if long-term contracts are able to completely get rid of oil indexation with an increased spot trade, these conditions would make flexibility destination a serious barrier in less to global LNG trade. Destination flexibility is one piece of the puzzle as global LNG trade is prone to remain strongly constrained by costly infrastructure challenges and logistical barriers. Nonetheless, the strong willingness for increased flexibility in the LNG market could bring new liquefaction technologies that will change the way to address the issue of flexibility in the destination, as evidenced by the Coral FLNG project in Mozambique.

Notwithstanding the value of our findings, our analysis can be extended in several directions. First of all, one could ambition to extend the analysis to incorporate the dynamics of the shipping market (i.e., the price formation and the volatility of the freight rates used for LNG tankers instead of the simple point estimates used in the present work). Indeed, the LNG market, historically stable, has been recently experiencing substantial changes over the last decade as the share of vertically integrated LNG trading companies owning tankers has declined whereas short-term chartering practices based on spot market rates are more and more frequent. However, to the best of our knowledge, this kind of investigation can hardly be conducted at present because of a lack of publicly available data. Should that limitation be slackened, an analysis incorporating that shipping dimension could offer an interesting avenue for future research. Another strand of research could also extend the geographical scope of our analysis by incorporating other LNG importing markets, such as the emerging ones in Latin America and Asia (e.g., China, India) where demand is expected to noticeably increase in the coming years.

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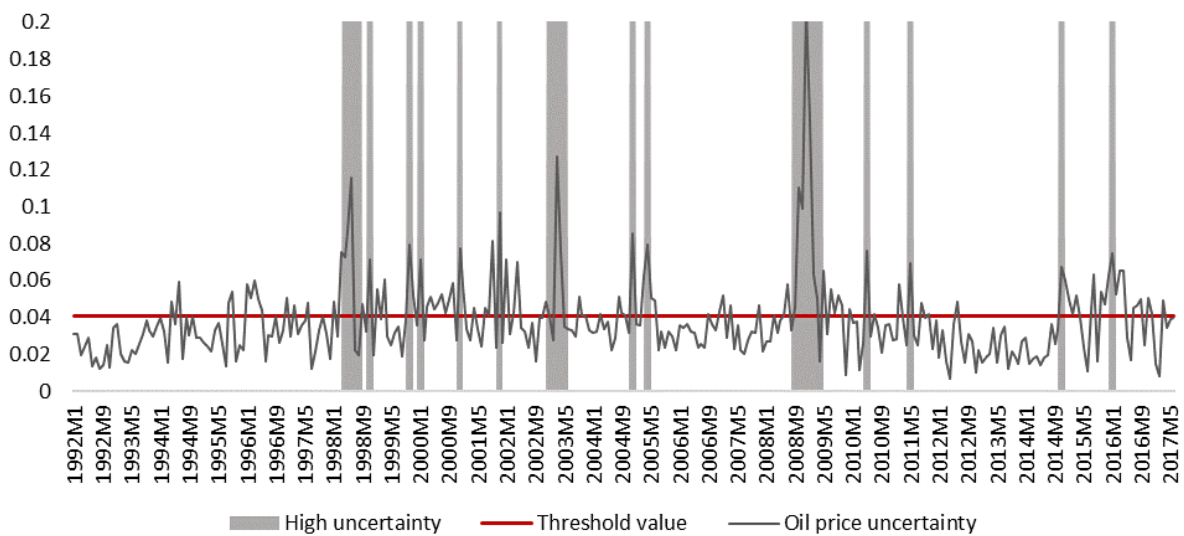
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Zhang, Dayong, Min Shi, and Xunpeng Shi (2018). “Oil indexation, market fundamentals, and natural gas prices: An investigation of the Asian premium in natural gas trade”. In: *Energy Economics* 69, pp. 33–41.

1.11 Appendices

1.11.1 Appendix A: Evolution of the uncertainty measure and the estimated threshold value

Figure 1.3: MA(3) of Oil Price Volatility and estimated threshold



1.11.2 Appendix B: Algorithm for GIRFs computation and their representation

The method for computing generalised impulse response functions follows Balke (2000). The employed algorithm is the following:

1. Pick a history Ω_{t-1}^r of all the lagged endogenous variables of the model at a particular date.
2. Pick a sequence of shocks from the covariance matrix by bootstrapping the estimated residuals of the TVAR model. The residuals are assumed to be jointly distributed.
3. Using this sequence of shocks, we produce forecasts conditional on initial conditions Ω_{t-1}^r by simulation.
4. We repeat step 3 by adding a new shock at time 0 equal to ± 1 or 2 SD.
5. We repeat steps 2 to 4 are B times (B=500).
6. We repeat steps 1 to 5 R times and compute the average impulse response function as the average difference between the forecast from step 3 and 4.

Figure 1.4: JAP LNG response from oil price volatility* shocks of +/- 2 SD

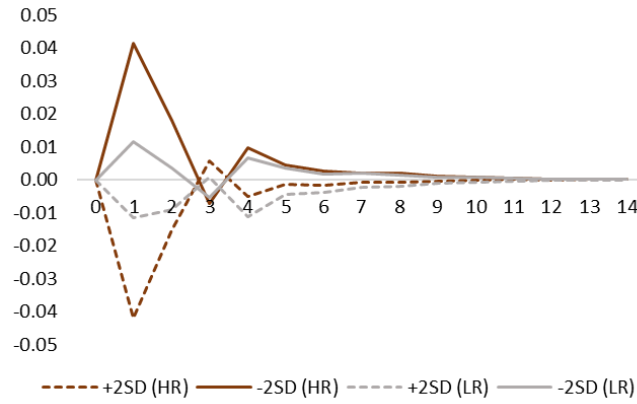


Figure 1.5: US LNG response from oil price volatility shocks of +/- 2 SD

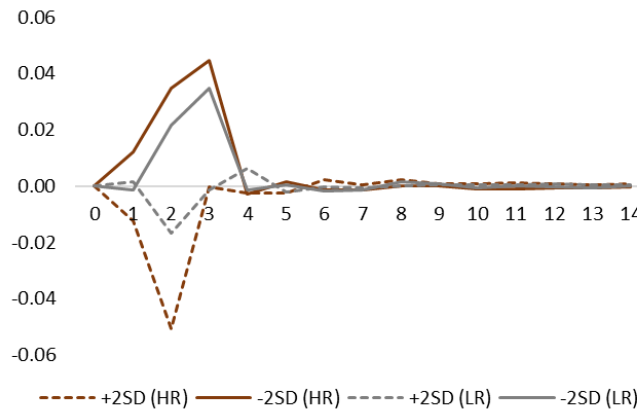
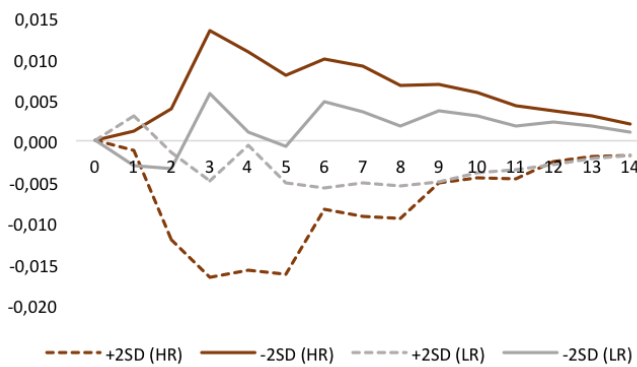


Figure 1.6: EU LNG response from oil price volatility shocks of +/- 2 SD



Notes: The x-axis corresponds to the months.

*: Oil price volatility calculation is based on weekly oil price returns.

1.11.3 Appendix C: Shipping considerations

Figure 1.7: Freight route costs

	Japan	South West Europe	North East US
Middle East	0.62	0.74	0.92
Australia	0.35	1.04	0.9
Nigeria	1.07	0.37	0.3
Algeria	1.23	0.08	0.19
US Gulf Coast	1.13	0.47	-

Source: Platts LNG Daily, 2016. Volume 13/ Issue 223.

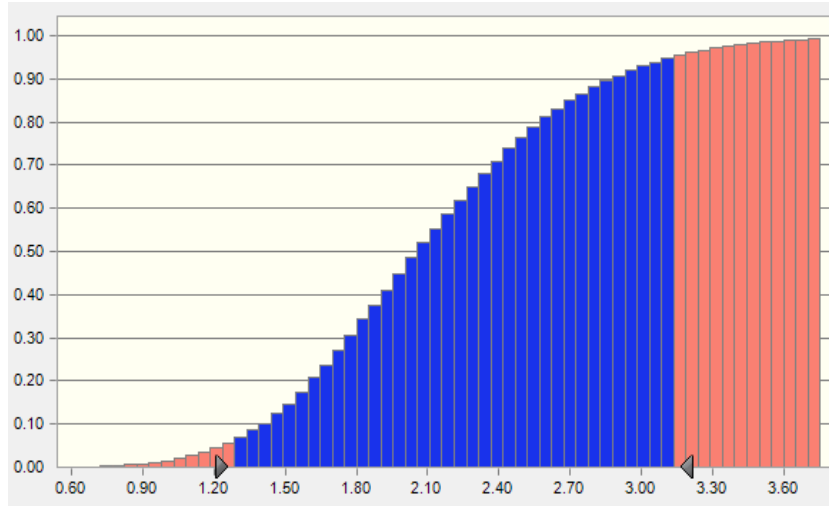
Figure 1.8: Shipping days

	Japan	South West Europe	North East US
Middle East	15	13*	22
Australia	8	21*	29
Nigeria	26	9	13
Algeria	24*	1	9
US Gulf Coast	2	12	-

Source: Platts LNG Daily, 2016. Volume 13/ Issue 223.

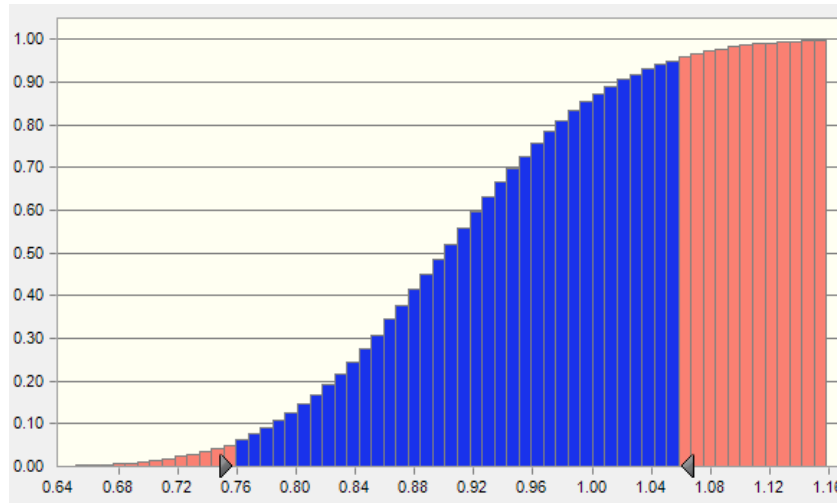
1.11.4 Appendix D: Cumulative probability distributions for 10.000 Monte-Carlo simulations with a 90% certainty level (\$ /MMBtu)

Figure 1.9: Value of flexibility - High Regime - QATAR



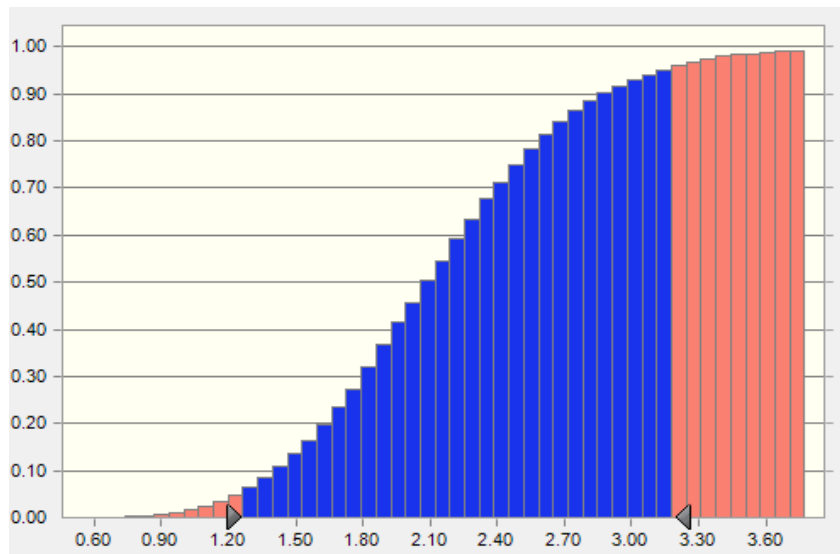
Expected value = 2.13\$ /MMBtu.
Lower limit value (10%) = 1.26\$ /MMBtu.
Upper limit value (90%) = 3.15\$ /MMBtu.

Figure 1.10: Value of flexibility - Low Regime - QATAR



Expected value = 0.90\$ /MMBtu.
Lower limit value (10%) = 0.76\$ /MMBtu.
Upper limit value (90%) = 1.06\$ /MMBtu.

Figure 1.11: Value of flexibility - High Regime - ALGERIA

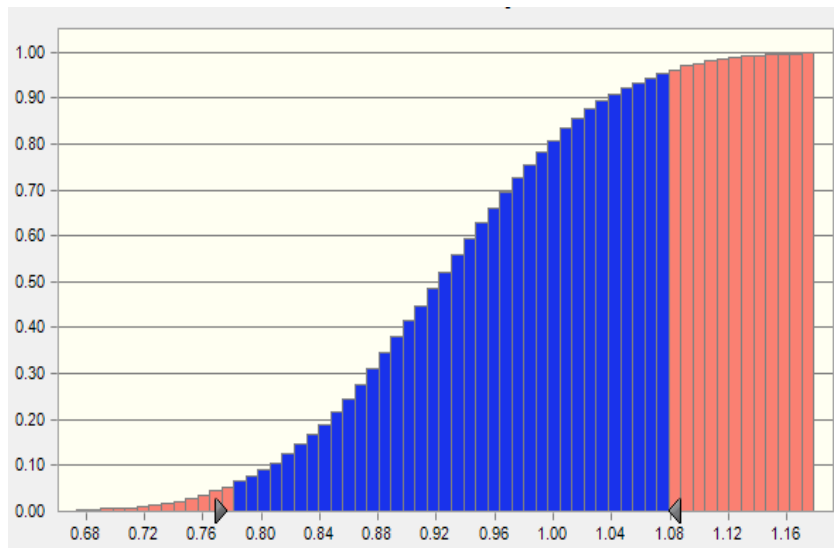


Expected value = 2.16\$ /MMBtu.

Lower limit value (10%) = 1.27\$ /MMBtu.

Upper limit value (90%) = 3.18\$ /MMBtu.

Figure 1.12: Value of flexibility - Low Regime - ALGERIA

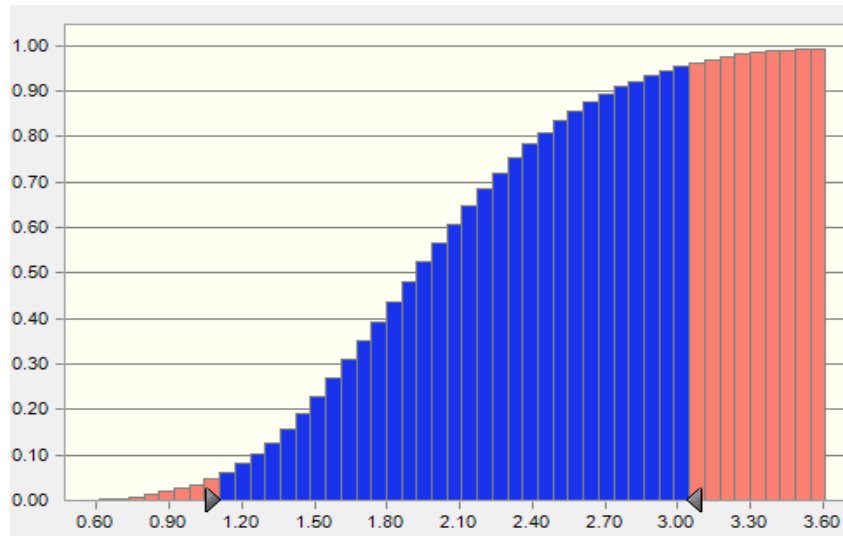


Expected value = 0.93\$ /MMBtu.

Lower limit value (10%) = 0.78\$ /MMBtu.

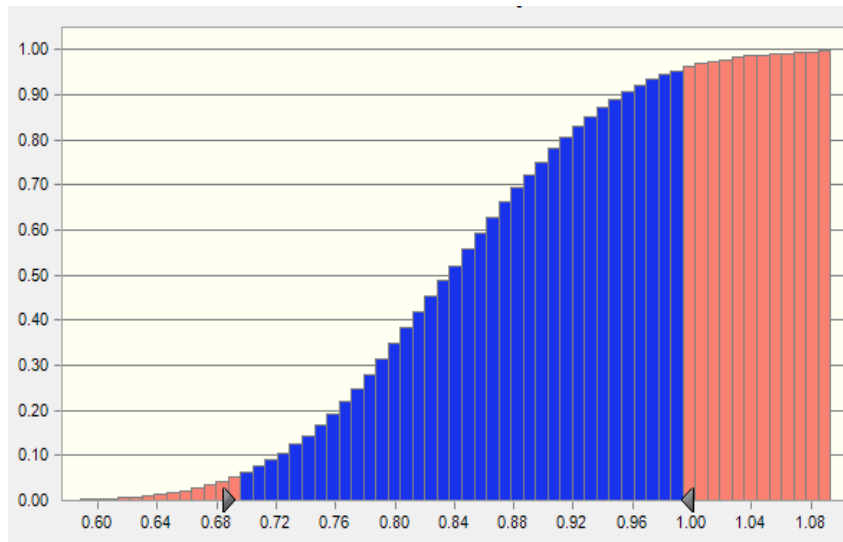
Upper limit value (90%) = 1.08\$ /MMBtu.

Figure 1.13: Value of flexibility - High Regime - NIGERIA



Expected value = 1.99\$ /MMBtu.
Lower limit value (10%) = 1.12\$ /MMBtu.
Upper limit value (90%) = 3.02\$ /MMBtu.

Figure 1.14: Value of flexibility - Low Regime - NIGERIA



Expected value = 0.84\$ /MMBtu.
Lower limit value (10%) = 0.69\$ /MMBtu.
Upper limit value (90%) = 0.99\$ /MMBtu.

1.11.5 Appendix E: Sensitivity to alternative threshold variables

Table 1.4: LR test results based on the VXO stock market volatility threshold

Panel A: LR test for linearity against 2 regimes

LR statistic 110.946

p-value [0.000*]

Estimated threshold 25.12

Panel B: LR test for linearity against 3 regimes

LR statistic 188.0672

p-value [0.000*]

Estimated thresholds 24.33 28.01

Panel C: LR test for 2 regimes against 3 regimes

LR statistic 77.121

p-value [0.500]

Estimated threshold 24.33 28.01

Note: The response of LNG prices to changes in volatility context is supposed to occur with a delay d of 2 months. P-values based on Hansen's (1996) procedure method of inference with 500 replications are between brackets. *, ** denote the rejection of the null hypothesis at 1% and 5% respectively.

Table 1.5: LR test results with volatility threshold based on daily oil price returns

Panel A: LR test for linearity against 2 regimes

LR statistic 115.198

p-value [0.000*]

Estimated threshold 0.0371

Panel B: LR test for linearity against 3 regimes

LR statistic 257.086

p-value [0.000*]

Estimated thresholds 0.0371 0.0447

Panel C: LR test for 2 regimes against 3 regimes

LR statistic 141.888

p-value [0.404]

Estimated threshold 0.0371 0.0447

Note: The response of LNG prices to changes in volatility context is supposed to occur with a delay d of 2 months. P-values based on Hansen's (1996) procedure method of inference with 500 replications are between brackets. *, ** denote the rejection of the null hypothesis at 1% and 5% respectively.

1.11.6 Appendix F: Robustness to different specifications of the TVAR model

Table 1.6: Test for Threshold VAR for different delays of the transition variable.

Delay of the transition variable	Best Threshold Value	Wald Statistics		
		<i>Sup-</i>	<i>Avg-</i>	<i>Exp-</i>
1	0.02987	746.7516 (0.000*)	712.2056 (0.000*)	712.0976 (0.000*)
2	0.03850	748.5684 (0.000*)	706.8801 (0.000*)	706.5793 (0.000*)
3	0.04055	745.6221 (0.000*)	705.5923 (0.000*)	705.1586 (0.000*)
4	0.02650	523.5905 (0.000*)	523.5905 (0.000*)	523.5905 (0.000*)
5	0.02676	523.5905 (0.000*)	523.5905 (0.000*)	523.5905 (0.000*)
6	0.02676	523.5905 (0.000*)	523.5905 (0.000*)	523.5905 (0.000*)
7	0.02676	523.5905 (0.000*)	523.5905 (0.000*)	523.5905 (0.000*)
8	0.02676	523.5905 (0.000*)	523.5905 (0.000*)	523.5905 (0.000*)

Note: P-values based on Hansen's (1996) method of inference with 500 replications are in parentheses. *,** denotes the rejection of the null hypothesis at 1 % and 5 % respectively.

Table 1.7: Test for Threshold VAR for different orders of the moving average process of the threshold variable.

Order of the MA process	Best Threshold Value	Wald Statistics		
		<i>Sup-</i>	<i>Avg-</i>	<i>Exp-</i>
1	0.04023	184.5802 (0.570)	145.3699 (0.482)	144.1165 (0.482)
2	0.03888	559.6944 (0.000)	509.5040 (0.000)	508.8447 (0.000)
3	0.03850	748.5684 (0.000)	706.8801 (0.000)	706.5793 (0.000)
4	0.04067	961.8254 (0.000)	903.9336 (0.000)	903.3456 (0.000)
5	0.03639	1031.256 (0.000)	992.858 (0.000)	992.476 (0.000)
6	0.03887	1085.520 (0.000)	1048.393 (0.000)	1048.162 (0.000)
7	0.03914	1165.940 0.000	1130.706 (0.000)	1130.492 (0.000)
8	0.03707	1235.725 (0.000)	1196.078 (0.000)	1195.901 (0.000)

Note: P-values based on Hansen's (1996) method of inference with 500 replications are in parentheses. *,** denotes the rejection of the null hypothesis at 1 % and 5 % respectively.

Table 1.8: Test for Threshold VAR for different lags of the VAR.

TVAR lags	Best Threshold Value	Wald Statistics		
		<i>Sup-</i>	<i>Avg-</i>	<i>Exp-</i>
1	0.02558	503.3623 0.000*	503.3623 0.000*	503.3623 0.000*
2	0.03850	733.0622 (0.000*)	687.4937 (0.000*)	687.1522 (0.000*)
3	0.03850	748.5684 (0.000)	706.8801 (0.000*)	706.5793 (0.000*)
4	0.03850	799.9046 (0.000)	750.4848 (0.000*)	750.2539 (0.000*)
5	0.03850	810.6776 (0.000*)	764.8100 (0.000*)	764.5587 (0.000*)
6	0.03850	831.0653 (0.000*)	789.2654 (0.000*)	789.0786 (0.000*)
7	0.03850	867.0831 (0.000*)	827.2700 (0.000*)	827.0429 (0.000*)
8	0.03850	918.2078 (0.000*)	863.4365 (0.000*)	863.1159 (0.000*)

Note: P-values based on Hansen's (1996) method of inference with 500 replications are in parentheses. *,** denotes the rejection of the null hypothesis at 1 % and 5 % respectively.

Figure 1.15: JAP LNG response from oil price volatility* shocks of +/- 2 SD

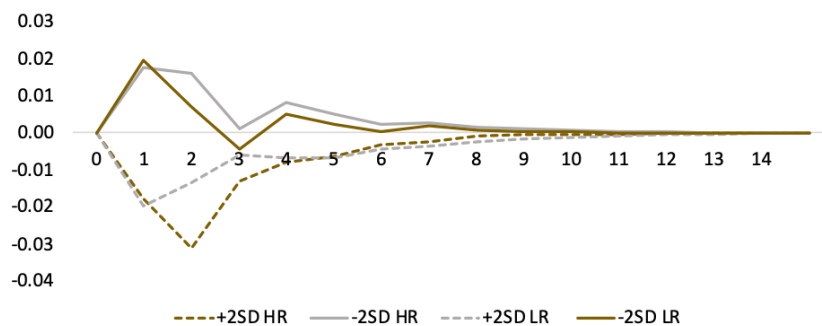


Figure 1.16: US LNG response from oil price volatility shocks of +/- 2 SD

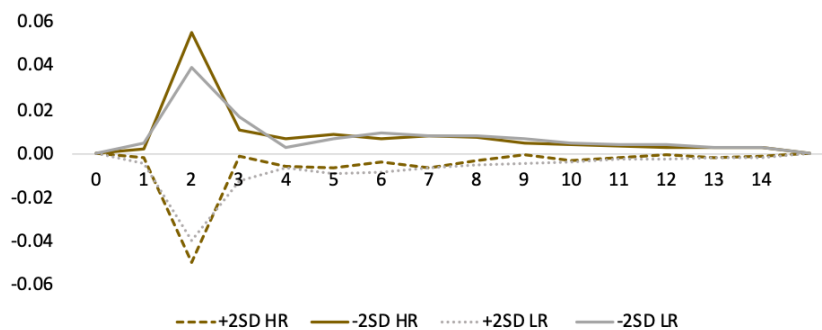
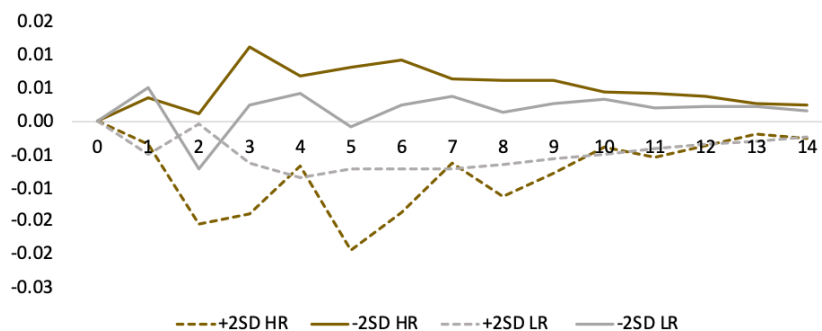


Figure 1.17: EU LNG response from oil price volatility shocks of +/- 2 SD



Note: The x-axis corresponds to the months.

*: Oil price volatility calculation is based on **daily** oil price returns

Figure 1.18: JAP LNG response from CBOE VXO volatility shocks of +/- 2 SD

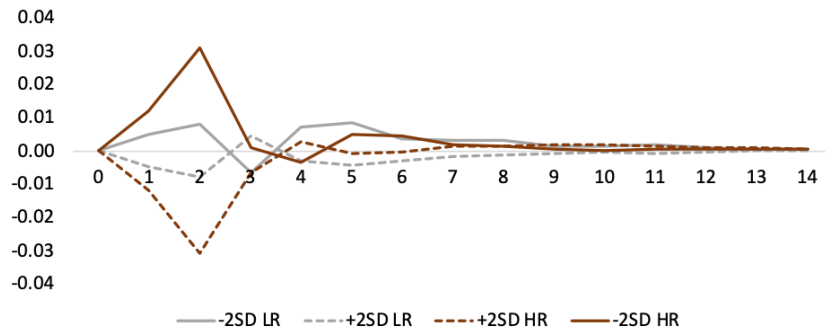


Figure 1.19: US LNG response from CBOE VXO volatility shocks of +/- 2 SD

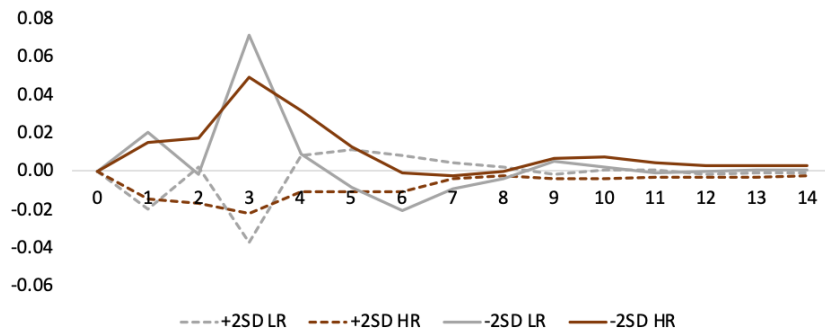
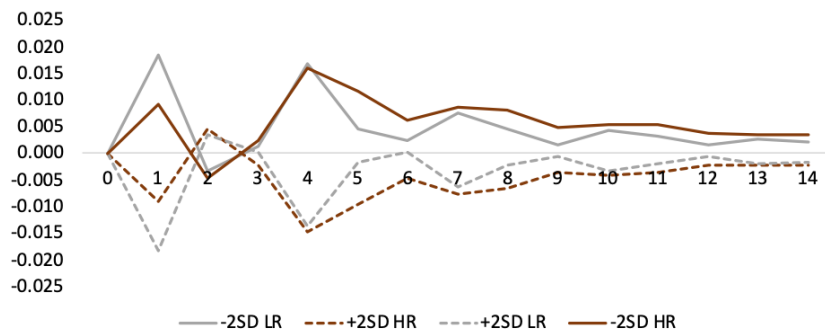


Figure 1.20: EU LNG response from CBOE VXO volatility shocks of +/- 2 SD



Note: The x-axis corresponds to the months.

Chapter 2

How efficient are natural gas markets in practice? A wavelet-based approach

Foreward

This chapter is the fruit of lengthy discussions and reflexions with Anna Creti and Sana Ben Kebaier at the laboratory of Economics of Dauphine (LEDa) who coauthored the final paper. I had the opportunity to present and discuss this paper at the second International Conference on the Economics of Natural Gas in June 2019 and the Paris Dauphine Finance workshop in May, 2019. I am grateful to the participants for their constructive comments and suggestions.

Abstract

This paper is the first attempt to provide a comprehensive account of pricing and informational efficiency of the US and EU natural gas markets. We rely on Maximum Overlap Discrete Wavelet decomposition (MODWT) of daily data of US Henry Hub, British NBP and Dutch TTF natural gas physical and futures returns at different maturities between 2013 and 2019. Multiscale linear and nonlinear Granger causality and random walk testing are investigated. We find that futures prices and spot prices of Henry Hub, NBP, and TTF are cointegrated. Moreover, multiscale causality testing shows that Henry Hub markets exhibit strong bidirectional causality between spot and futures markets. EU markets are globally efficient in terms of pricing despite some inconsistencies on the causality direction across time scales and maturities of the futures contracts. Finally, for the three selected futures markets, informational efficiency is reached only in the long-run. The results make it possible to establish an evaluation of the hubs in terms of their capacity to provide reliable reference prices for the quantities of gas under contract through a discussion on the crucial role of liquidity and storage capacity.

2.1 Introduction

The institutional environment of the European natural gas markets has experienced a significant change in the last decade. Trading at the British National Balancing Point (NBP) and the Dutch Title Transfer Facility (TTF) gas hubs has significantly gained traction (Heather and Petrovich, 2017).¹ Concomitantly, the anchored practice of oil indexation in long-term natural gas contracts has progressively been replaced by the hub indexation for a better reflection of fundamentals dynamics. Gas-to-gas competition's share increased from 15 % in 2005 to 70% in 2017 (IGU, 2018) and seemed to become the dominant price formation mechanism despite some deep disparities between the European Union countries.²

Nevertheless, Europe has not entirely created a truly competitive gas market yet that requires non-discriminatory, reliable, and timely market information (Garaffa et al., 2019). In the context of scattered reserves and a limited number of suppliers, high arbitrage potential, especially in the short-term, remains unexploited by market participants because of limited access to infrastructure, insufficient reliable and timely information, and high transaction costs (Stronzik, Rammerstorfer, and Neumann, 2009).³

The question of efficiency of European traded gas hubs is hence questionable and raises concerns about their ability to constitute an important support for financial risk management of gas portfolios and physical balancing. As derived from the original work of Cootner (1964) and formalized by Fama in the 1960s, prices observed in an efficient market should instantly reflect all available information. At all times, prices are supposed to be representative of past and future events and the expectations of agents in this market. Implicitly, the information is supposed to be accessible at no cost to a large number of operators that cannot on their own exert a significant influence on prices or systematically control the market.

In this context, this paper investigates the weak form pricing and informational efficiency

¹See also Heather (2016).

²These disparities suggest a path of development towards a more established integration of gas markets at the European scale, though growing (Neumann and Cullmann, 2012).

³These questions are in the cross-hair of the European Commission in ensuring sufficient liquidity to reduce price uncertainty and transactions costs associated with natural gas trade and to strengthen market integration across the continent.

of the two largest European natural gas markets (UK NBP and Dutch TTF) by drawing a parallel with the US Henry Hub (HH) through a wavelet decomposition approach.⁴ Following Rong and Zheng (2008), we consider pricing efficiency as the no-arbitrage prices depending on whether arbitrage strategies could be utilized and informational efficiency as the reaction of futures prices to new information. First, the pricing efficiency is tested by investigating the existence of a potential cointegrating relationship between spot and futures prices of the three considered hubs. The step further is to examine the process of price discovery through linear and nonlinear causality analyses between spot and futures prices at different time scales. Finally, we examine the informational efficiency/rationality of futures markets in the short-term and long-term by applying random walk tests to the residuals of futures log returns, and hence measure their ability to reflect all available price information instantly.

Our analysis controls for major methodological problems that are likely to impact the nature of the results significantly. First, we gain insight from the time-scale decomposition of our data by applying a Maximum Overlap Discrete Wavelet Transformation (MODWT) decomposition to NBP, TTF and HH spot and futures price returns of one-month maturity. The wavelet methodology went through successive refinements of Fourier analysis to allow non-linear and non-stationary time series to be transformed into frequency domain without loss of time-domain information and have been considered as the best scaling method to deal with complex dynamics of economic and financial time series (Nicolau and Palomba, 2015). It avoids us the need to assume certain parametric models of the series and accounts for time-dependent volatility covariance and structural breaks. More importantly, it enables us not to neglect a major aspect of natural gas markets characterized by highly seasonal dynamics. Moreover, linear and nonlinear causality testing have been used to investigate the causality direction by relying on Diks and Panchenko (2006) test through a multiresolution approach. As gas market participants differ in their objective and investment horizons, the true dynamics and causal relationship between gas spot and futures prices can only be uncovered when we decompose gas prices into different time

⁴Wavelets are an increasingly popular alternative for analyzing time series thanks to their efficient computational algorithms. The multiresolution approach let us examine the time series at different time scales. For a complete literature review on the application of wavelets in the economic and finance sphere, see Ramsey (2002) and Crowley (2007).

scales or horizons. Longer scales resemble the horizons of non-financial traders (producers and consumers) while shorter scales resemble various speculators horizons.⁵ We also conduct several robustness checks to make sure our results hold under different configurations, repeating the analysis for two-months and three-months maturities futures contracts and relying on different filters under the wavelet methodology.

This paper fits into a limited research area that has investigated the question of efficiency on European natural gas futures markets and their role in developing hedging strategies. The majority have focused on the North American market. For instance, Herbert and Kreil (1996) have examined US natural gas spot and futures markets and found that the market was not only informationally inefficient with a systematic difference between spot and futures prices but this difference was also predictable.⁶ Susmel and Thompson (1997) analyzed the relationship between commodity price volatility and investment in US storage facilities during natural gas market deregulation. Their results suggest that investments in additional storage facilities are followed by an increase in volatility. Dincerler, Khokher, and Simin (2005) have focused on the mean reverting process to provide additional evidence for the dependency of commodity futures prices on storage levels, including natural gas. Serletis and Shahmoradi (2006) confirmed the predictions of the theory of storage in the US between 1990 and 2002. Gebre-Mariam (2011) study examined unit roots, causality, cointegration, and efficiency of the natural gas market using the Northwest US natural gas market. He found that the efficient market hypothesis holds only for contracts with only about a month to maturity.⁷

The emerging European markets are less studied in the literature with clearly not enough data to conduct empirical investigations able to account for their medium-term and long-term

⁵Non-financial traders such as gas producers and consumers are interested in the physical commodity and thus trade on the spot market while participating in the futures market as hedgers. On the other hand, financial traders such as market makers, hedge funds, mutual funds and swap dealers are interested in the changes in prices but not the physical commodity and thus participate mainly in the futures market.

⁶Transparency of gas and transport prices, idiosyncracies and industry practices were pointed out to distinguish the relatively new (at that time) volatile short-term futures and spot for natural gas from other markets.

⁷More recently, Zhang and Liu (2017) explored the causal relationships between natural gas spot and futures prices in the New York Mercantile Exchange. Their results suggest that spot and futures prices are positive cross-correlated, the natural gas futures can linearly Granger cause spot price and there are bidirectional nonlinear causality relationships between natural gas spot and futures prices.

trends.⁸ At this stage, it is also important to note that in Europe, the process of change followed two very different courses: that of Britain's privatizations and Continental Europe's liberalization (Heather, 2016). It took 15 years for the UK market to complete its liberalization process (since the early 1980's). Today the NBP has reached maturity and constitutes a sufficiently liquid hub to provide support for financial risk management of gas portfolios for the British Isles. In Continental Europe, even if the transformation process dates from the end of the 1990s, real signs of change were not felt until the mid-2000s and only in western Europe. In this regard, a strong political commitment to make the Dutch TTF the pivotal point for European gas has fully contributed to its restructuring. Since 2003, the growing number of traders in other continental countries that rely on TTF hub to financially hedge and risk-manage their portfolios is fully representative of this trend.

We contribute to the literature in several ways. To the best of our knowledge, this is the first paper that investigates the issue of natural gas pricing and informational efficiency in European and American gas hubs using frequency domain approach. Indeed, most previous studies have ignored the possibility that direction, extent and strength of Granger causality may vary at different time scales. Furthermore, the literature of European natural gas futures prices is thin as the market is rather young compared to the North American experience. European markets have undergone such significant changes that a comprehensive approach was needed to analyze the two main functioning gas hubs. The question of their efficiency raises concerns about their ability to constitute an important support for financial risk management and to provide credible price creation, discovery and reference points, which could be used in medium and long-term gas contractual pricing terms. The question is all the more important when considering the European Commission's vision of a single energy market. Moreover, past studies neglected the nonlinearities governing energy commodities dynamics and mostly have considered linear causal effects between spot and futures prices. More recent empirical studies show the importance of considering nonlinearities of price dynamics in the study of causality effects because of, among others, recessions, unforeseen extreme events, transaction costs, market power, geopolitical ten-

⁸See e.g. Haff, Lindqvist, and Løland (2008) and Asche, Osmundsen, and Sandsmark (2006) that have examined the decoupling of natural gas, oil and electricity prices in the UK market.

sions, asymmetric information or stickiness in prices.⁹ Moreover, literature does not provide a clear consensus with respect to the direction of causality between natural gas spot and futures prices. These divergences stem from different specifications of volatility in the spot and futures markets, the periods considered and the employed methodologies. Finally, our results make it possible to establish an evaluation of the hubs in terms of their capacity to provide reliable reference prices for the quantities of gas under contract. We consider the subject very timely as long-term contracts are increasingly based on hub indexation and market participants are also effectively seeking to cover the risks associated with their physical gas portfolios efficiently.

Several outcomes are reached. First, all considered gas markets are found to be globally efficient in pricing with strong evidence of cointegrating relationships between spot and futures markets. Moreover, information flows between spot and futures markets although the futures markets play a leading role in price discovery at some time scales for NBP and TTF gas hubs. Furthermore, Henry Hub, NBP, and TTF gas hubs are found to be informationally efficient in the long run. For short-term and medium-term scales, the null hypothesis of futures acting as random walk is rejected.

The results make it possible to establish an evaluation of the hubs in terms of their capacity to provide reliable reference prices for the quantities of gas under contract. In terms of pricing efficiency, Henry hub showed the strongest and most robust results for all time scales considered. We attribute these results to structural divergences between European and American natural gas markets. Indeed, physical and virtual gas trading hubs have different set-ups to accommodate the different structures of their industries between fully privatized and competitive transport activities in the US versus regulated TSO in the European Union and respond to disparate objectives: if the US aims at facilitating trade, balancing trade is privileged in the European Union. The crucial role of liquidity and storage capacity in natural gas hubs are discussed and call for a significant increase in the number of European physical transactions between markets that is still required to reduce bottlenecks in transmission networks and interconnection points. Significant investments in transport infrastructure are required to extend the supply in the gas industry and the economic feasibility of these investments are highly dependent on pricing

⁹This has given rise to the use of nonlinear causality tests, including that of Baek and Brock (1992) or Diks and Panchenko (2006).

structure and predictability (Komlev, 2013).

Our results have useful implications. It can be argued that our findings shed some lights on the true nature of causality between natural gas spot and futures prices at European and American gas hubs. From an informational point of view, if all relevant information is incorporated into the prices, the allocation of capital would be all the more efficient as it would be attracted by the most productive producers. These findings have important implications for investors, producers, and policymakers.

The remainder of the paper is organized as follows. The next section presents a brief overview of the existing theoretical and empirical studies surrounding the question of efficiency. We describe the methodology of wavelet in section 2.3. The wavelet decomposed data and the resulted empirical evidence of pricing and informational efficiency are presented in section 2.4. We discuss our results in section 2.5 and conclude the paper in section 2.6.

2.2 Related literature

The causality relationship between futures and spot markets is and has been the subject of lively debates. Theoretical and empirical investigations on the subject did not reach a clear consensus on the causality direction. The theory of storage (Working, 1949) states that spot and futures markets for storable commodities have a long-term relationship through market players that perform intertemporal transactions in order to optimize their portfolio. Any deviation from the intertemporal equilibrium can lead to arbitrage activities by market players that benefit from substitutability between spot and futures markets. An alternative theory that has linked spot and futures markets is based on the efficient market hypothesis. The latter is the cornerstone of financial models and is derived from the original work of Cootner (1964) and was formalized by Fama in the 1960s. The theory of efficiency assumes that the price observed in the market instantly reflects all available information. At all times, the price is supposed to be representative of past and future events and the expectations of agents in this market. Implicitly, the information is supposed to be accessible at no cost to a large number of operators that cannot on their own exert a significant influence on prices or systematically control the market. It follows that price changes are only the result of unforeseeable events. This has brought the theory of efficiency closer to the random walk model and the martingale theory (Samuelson,

1965). Even though both theories recognize the existence of a long-term relationship between spot and futures prices, only the efficiency assumption suggests a potential sense of causality between the two markets.

Most of the empirical investigations that have addressed the issue of the relationship between spot and futures relied on cointegration techniques based on Johansen (1988) test and vector error correction model (VECM). For instance, Walls (1995) employed Johansen's cointegration methodology to test the efficiency of the US natural gas futures market with monthly data from June 1990 to January 1994 and found no statistically departures from the unbiasedness hypothesis (see also Herbert (1995)). De Vany and Walls (1993) tested for cointegrating relationships between price pairs between 20 locations and their results suggested that reforms have led to an increase of spatial integration. Serletis (1997) and King and Cuc (1996) have also analyzed the market integration for the North American market (US and Canada).¹⁰ Stronzik, Rammerstorfer, and Neumann (2009) investigated the application of the theory of storage to the European gas market using two indirect tests developed by Fama and French (1988) to study the overall market performance. Most of their findings do not confirm predictions of the theory of storage. Indeed, contrary to expectations, they found a positive correlation of inventory level with twelve-month maturity yields, and that natural gas price volatility correlates negatively with convenience yield approximations.¹¹ More recently, Chinn and Coibion (2014) found that futures prices are unbiased predictors of crude oil, gasoline, and heating oil prices but not of US natural gas prices. In Europe, Asche, Osmundsen, and Sandsmark (2006) have examined the decoupling of natural gas, oil, and electricity prices in the UK market.

Concerning the lead-lag relationship and the analysis of information flows between spot and futures markets under the process of price discovery, literature provides no consensus on the causality direction.¹² Doane and Spulber (1994) employed the Granger causality test to

¹⁰See also: Mohammadi (2011).

¹¹They attribute these results to possible obstacles concerning the appropriate use of storage in European natural gas market: limited access to infrastructure, insufficient information, missing secondary markets for unused capacities and high transaction costs.

¹²Garbade and Silver (1983) suggest that futures prices should lead spot prices in an efficient market because futures market are more responsive to new information than spot prices and represent a benchmark in arbitrageurs decision-making (Silvapulle and Moosa, 1999). Other researches support the idea that the spot market provides

assess US gas market integration prior to open access; their results have suggested Granger causality between only one of 20 pairs of gas prices from 5 regions. *A contrario*, open access has led to instantaneous bi-directional causality. In the same vein, Ghoddusi (2016) examined the integration between different types of physical (upstream/end use) and futures prices of natural gas in the U.S by applying cointegration tests and causality analysis. Based on monthly data from 1990 to 2014, results suggested that futures prices are cointegrated with wellhead, power, industrial, and city gate prices; futures prices Granger cause spot prices and finally shocks to futures prices have persistent effects on all physical prices.¹³ Gebre-Mariam (2011) found that spot prices in the market hubs exhibit bidirectional or two-way causal relationships, suggesting instantaneous response of price changes across markets.

Different areas of improvement emerge from this literature. First, most previous studies have ignored the possibility that direction, extent and strength of Granger causality may vary at different time scales. Secondly, among the studies that have analyzed the natural gas industry through the theory of storage, the majority have focused on the North American market (see e.g., Dincerler, Khokher, and Simin (2005) and Serletis and Shahmoradi (2006)). Thirdly, the empirical investigations of price discovery process are also rather thin for European markets and have neglected the nonlinearities governing energy commodities dynamics and mostly have considered linear causal effects between spot and futures prices. More recent empirical studies show the importance of considering nonlinearities of price dynamics in the study of causality effects because of, among others, recessions, unforeseen extreme events, transaction costs, market power, geopolitical tensions, asymmetric information or stickiness in prices. Fourthly, the literature does not provide a clear consensus about the direction of causality: these differences stem from the use of different methodologies and studied periods that need to be fortified.

In this context, we contribute to this literature by investigating the issue of natural gas efficiency from both a pricing and informational¹⁴ point of view in European (NBP and TTF) and

a potent benchmark underlying any future transaction (Moosa, 1996) or that bidirectional causality between the two markets is more sustainable.

¹³Futures markets are also found to cause fluctuations in spot prices (Brenner and Kroner, 1995).

¹⁴Following Rong and Zheng (2008), we associate pricing efficiency to the no-arbitrage prices depending on whether arbitrage strategies could be utilized and informational efficiency to the reaction of futures prices to new information. The first one is tested by investigating the relationship between spot price and futures prices, the

American (Henry Hub) gas hubs using a multi-scale analysis approach. More precisely, wavelet decomposition is applied to spot and futures prices to account for the intrinsic seasonality of natural gas markets when investigating linear and nonlinear causal relationships. We also rely on random walk testing to examine the informational efficiency of the natural gas hubs at different time scales.

2.3 Methodology

In this section, the retained Maximum Overlapped Discrete Wavelet Transformation (MODWT) methodology used to explore market efficiency on a multiresolution basis is described.¹⁵ First, wavelet decomposition is applied to spot and futures price returns to investigate multiscale linear and nonlinear causal relationships. We then rely on random walk testing via a variance ratio test applied both to raw data and wavelet details to examine the informational efficiency of the natural gas hubs.

2.3.1 Maximum overlapped discrete wavelet transformation

A crucial quality of wavelets is their ability to decompose the time series into details affiliated to different time scales characterized by increasing frequencies. In all wavelet's families, the wavelet is basically decomposed into two major functions. First, the father wavelet noted ϕ integrated to one $\int \phi(t) dt = 1$. The father wavelet represents the smooth component and the low frequencies of the signal; reflecting the time series general trend. It is represented by :

$$s_{j,k} = \int x(t) \phi_{J,k}(t) dt$$

Second, the mother wavelet noted ψ integrated to zero $\int \psi(t) dt = 0$. It represents the detail components which characterizes the deviations from the trend of the economic time series and describes the high frequency signals. The mother wavelet is represented by

$$d_{j,k} = \int x(t) \psi_{j,k}(t) dt, j = 1, 2 \dots, J.$$

second is tested by examining the residuals of futures log returns via random walk analysis.

¹⁵Wavelet decomposition is attractive from both the industry and the academic fields as investors, traders and policymakers seek to understand prices predictability and optimize investment decisions (see Zavadaska, Morales, and Coughlan (2018), Reboredo, Rivera-Castro, and Ugolini (2017), and Nicolau and Palomba (2015)).

where j is the maximum integer and 2^j must not exceed the length of the time series. $d_{j,k}$ is the increasing finer scale deviation from the flat trend $s_{j,k}$. Indeed, the decomposed time series $x(t)$ can be written as:

$$x(t) = S_{j,k}(t) + D_{j,k}(t) + D_{j-1,k} + \dots + D_1(t)$$

Where $S_{j,k}$ is the global smooth signal and $D_{j,k}(t) + D_{j-1,k} + \dots + D_1(t)$ are the details components. They can be defined as:

$$S_j(t) = \sum_k s_{j,k} \phi_{J,k}(t)$$

$$D_j(t) = \sum_k d_{j,k} \psi_{J,k}(t)$$

These coefficients measure the contribution of each component to the total signal. In order to decompose natural gas spot and futures prices, the maximum overlapped discrete wavelet transformation (MODWT) is used. The MODWT is considered as the best scaling method to deal with economic time series such as energy spot and futures prices (Nicolau and Palomba, 2015). It is suitable for any data size and overcomes the discrete wavelet transform difficulties such as the down sampling problem, in order to avoid information loss. Moreover, the variance estimator associated to MODWT is asymptotically more efficient compared to DWT. Indeed, MODWT enables the estimation of wavelet variance and covariance in the different time scale components.

The Daubechies filter of length eight is employed in time series decomposition. Daubechies is suitable for discrete wavelet analysis. Indeed, it conserves the energy of each detail and redistributes it into more bunched form. Besides, the filter width 8 is long enough to ensure the un-correlation between coefficients at the different scales and at the same time is short

enough to reflect fewer boundary condition (Daubechies, 1992). This decomposition level leads to eight details components (D1 to D8) in addition to the smooth component S8. The time-scale frequency is described in table 2.2. D1 is the highest frequency detail which reflects the short-term variations of the energy prices time series due to shocks occurring on a daily basis ($2^1=2$ days). D2 and D3 represent the weekly effects and variations on a time scale of $2^2=4$ days and $2^3=8$ days, respectively. D4 and D5 measure the variations on mid-term and reflects monthly variations with time scales from $2^4=16$ to $2^5=32$. Last, D6, D7 and D8 represent long term prices variations on time scales of 64 to 512 days. Finally, S8 measures the residue of the original time series and reflects the smooth movement of the original data.

2.3.2 Multi-scale analysis of correlation and cross correlation

To investigate the variability and dependence between energy spot and futures prices on a scale by scale basis, we use the multi-resolution analysis to calculate the correlation and cross correlation.

We consider a bivariate stochastic process $Y_t=(x_t,y_t)$, where x_t is the spot price and y_t is the futures price, and we consider $Z_t = (Z_{x,j,t}, Z_{y,j,t})$ as a scale, and w_j wavelet coefficient determined from Y_t . We apply the MODWT to each wavelet process of Y_t and we calculate the coefficient of each bivariate process. Once the coefficient is properly determined and finite, it is possible to calculate the time dependent wavelet variance σ_Y^2 for the scale w_j of the detail Y_t as follows:

$$\sigma_Y^2(w_j) = Var \left(\hat{Z}_{x,j,t} \right) \left(\hat{Z}_{y,j,t} \right)$$

Equivalently, we can calculate the wavelet covariance of the scale w_j as follows:

$$\gamma_{x,y}(w_j) = Cov \left\{ \hat{Z}_{x,j,t}, \hat{Z}_{y,j,t} \right\}$$

Consequently, the wavelet correlation coefficient is obtained by:

$$\rho_{x,y}(w_j) = \frac{\text{Cov} \left\{ \widehat{Z}_{x,j,t}, \widehat{Z}_{y,j,t} \right\}}{\left(\text{var} \left\{ \widehat{Z}_{x,j,t} \right\} \text{var} \left\{ \widehat{Z}_{y,j,t} \right\} \right)^{1/2}} = \frac{\gamma_{x,y}(w_j)}{\sigma_x(w_j) \sigma_y(w_j)}$$

The wavelet cross-correlation can be defined as a scale localized cross-correlation between two detail components. It helps understanding the similarity between two signals by shifting one relative to the other. Therefore, we consider a lag l in one of the time series when calculating the covariance, thereupon, we represent the wavelet cross-correlation as:

$$\rho_{x,y,l}(w_j) = \frac{\gamma_{x,y,l}(w_j)}{\sigma_x(w_j) \sigma_y(w_j)}$$

Furthermore, we calculate the confidence intervals for the nonlinear Fisher's z-transformation of the correlation coefficient using the asymptotic normality of $\rho_Y(w_j)$. Following Gençay, Selçuk, and Whitcher (2002), we present the Fisher's z-transformation correlation as $h\rho = \tanh(\rho)^{-1}$. Thus, for H independent gaussian observation, the estimated correlation $\widehat{\rho}$ verifies $\sqrt{H-3} [h(\widehat{\rho}) - h(\rho)] \sim N(0, 1)$. Hence, the $(1 - \alpha)$ confidence interval of the wavelet correlation and cross correlation can be represented by:

$$\tanh \left\{ h[\widehat{\rho}_{x,y}(w_j)] \pm \beta_{\frac{\alpha}{2}} \left(\frac{1}{\widehat{V}_j} - 3 \right)^{\frac{1}{2}} \right\}$$

Where \widehat{V}_j represents the number of MODWT coefficients of the scale w_j . $\beta_{\frac{\alpha}{2}}$ is a coefficient satisfying $P \left[-\beta_{\frac{\alpha}{2}} \leq U \leq \beta_{\frac{\alpha}{2}} \right] = 1 - \alpha$ and $U \sim N(0, 1)$.

2.3.3 Price discovery process

A linear and nonlinear Granger causality test is employed to understand the price discovery mechanism in gas markets. The corresponding section briefly describes the econometric methodology of the causal relationship between energy spot and futures prices applied to both original data and MODWT scales components. The linear causality is a standard Granger causality test (Granger (1969) and Engle and Granger (1987)). For the non-linear causal relationship, we adopted a modified version of Hiemstra and Jones (1994) developed by Diks and Panchenko (2006). Both methods are described in the following subsections 2.3.3 and 2.3.3, respectively.

Linear Granger causality test

The Granger causality is a bivariate test that provides the predictability of a future estimation of a time series using the historical information of another time series. Granger causality test between two time series x_t and y_t can be described as follows:

$$Ry_t = \gamma + \sum_{i=1}^a \alpha_i Ry_{t-i} + \sum_{j=1}^b \beta_j Rx_{t-j} + \varepsilon_t$$

where $Ry_t = \log(y_t) - \log(y_{t-1})$, and $Rx_t = \log(x_t) - \log(x_{t-1})$,

Ry_t and Rx_t denote the log returns of y_t and x_t , respectively. γ is a constant, a and b are the lag length of the time series, and ε_t is a white noise.

Consequently, the null hypothesis of no Granger causality can be defined by the equation: $\beta_1 = \beta_2 = \dots = \beta_b = 0$. To define the Granger causality, we use the Wald F-statistic as:

$$F = \frac{(RSS(a) - RSS(a, b)) / b}{RSS(a, b) / (N - b - a - 1)} \sim F(a, N - a - b - 1)$$

Where N is the number of observations, $RSS(a, b)$ is the sum of squared residuals of $Ry(t)$ respecting the lag order a .

However, according to Engle and Granger (1987), if the two series are cointegrated¹⁶, we rather use Granger causality test based on VECM model presented as:

$$Ry(t) = -a(y_{t-1} - \delta x_{t-1}) + \sum_{i=1}^a \alpha_i Ry_{t-i} + \sum_{j=1}^b \beta_j Rx_{t-j}$$

Where δ is the cointegration coefficient. The null hypothesis remains the same as the previous Granger causality based on VAR.

Nonlinear Granger causality

The economic literature assumes that energy commodity prices exhibit complex nonlinear dynamics and as such, linear causality may lead to inaccurate results when the tested variables display nonlinear structure. The first nonlinear causality test was proposed by Baek and Brock

¹⁶To test the cointegration, we adopted the Johansen (1991) test.

(1992) to investigate the relationship between stationary time series. This test was further developed by Hiemstra and Jones (1994) allowing the nonlinear causality testing between independent and identically distributed stationary time series. On this basis, Diks and Panchenko (2006) associated the Hiemstra and Jones (1994) test as a non-persistent test with the properties of Granger causality test and developed a new non-parametric test, able to investigate the Granger causality between two stationary time series. This test decreases the bias and reduces the risk of over rejection of the null hypothesis by using the estimated residuals of the vector autoregressive (VAR) model between energy spot and futures returns as input for non-parametric causality in order to escape any linear influence. Diks and Panchenko (2006) non-parametric test for causality is described as follows:

Consider x_t and y_t two stationary time series. x_t Granger causes y_t if x_t historical and current information are able to influence the future value of y_t . In addition, let's suppose that:

$X_t^{l_X} = (X_{t-l_X+1}, \dots, X_t)$ and $Y_t^{l_Y} = (Y_{t-l_Y+1}, \dots, Y_t)$ are the delay vectors, and $l_X, l_Y \geq 1$. The null hypothesis of the non-parametric causality test between two stationary time series considers a distribution of a vector $V_t = (X_t, Y_t, R_t)$, where $R_t = Y_{t+1}$ and $(l_X + l_Y + 1)$ is the dimension of the vector. Thus H_0 is described by:

$$H_0 : Y_{t+1} | (X_t^{l_X}; Y_t^{l_Y}) \sim Y_{t+1} | Y_t^{l_Y}$$

Which means that the historical observations of $X_t^{l_X}$ do not hold significant information of $Y_t^{l_Y}$ where \sim express the equivalence in distribution. We assume that $l_x = l_y = 1$ in order to respect the notation and to justify that H_0 is a statement about the invariant distribution of $(X_t^{l_X}, Y_t^{l_Y}, R_t)$. Consequently, with respect to the null hypothesis, we can assume that the conditional distribution of R under $(X, Y)=(x, y)$ equals the conditional distribution of R given $Y=y$. Hence, we can present the joint probability density function $f_{X,Y,R}(x, y, r)$ and the corresponding marginals as follows:

$$\frac{f_{X,Y,R}(x, y, r)}{f_Y(y)} = \frac{f_{X,Y}(x, y)}{f_Y(y)} \cdot \frac{f_{Y,R}(y, r)}{f_Y(y)}$$

According to Diks and Panchenko (2006), this means that X and R are independent conditionally on $Y=y$ for the fixed values of y . Thus, the null hypothesis could be reformulated as follows:

$$q = E [f_{X,Y,R}(x, y, r) f_Y(y) - f_{X,Y}(x, y) f_{Y,R}(y, r)] = 0$$

$f_v(V_i) = (2\varepsilon_n)^{-d_v} (n-1)^{-1} \sum_{jj \neq i} I_{ij}^V$ is the local density estimator of a d_v variate random vector V . Where $I_{ij}^V = I(\|V_i - V_j\| < \varepsilon_n)$ and $I(\cdot)$ is the indicator function and ε_n is the bandwidth of the non-parametric test. Given this indicator, the test statistic can be written as a scaled sample version of q as follows:

$$T_n(\varepsilon) = \frac{(n-1)}{n(n-2)} \sum_i \left(\hat{f}_{X,Y,R}(X_i, Y_i, R_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i) \hat{f}_{Y,R}(Y_i, R_i) \right)$$

The bandwidth choice depends on the sample size n . Following Powell and Stoker (1996), the test is consistent if the bandwidth is $\varepsilon_n = Cn^{-\beta}$ where C is a constant ($C > 0.1$ and $\beta \in]\frac{1}{4}, \frac{1}{3}[$, given if $l_x = l_y = 1$. In this case, if the vectors V_i are independent, the test statistic T_n is asymptotically normally distributed under suitable mixing factors taking into account the covariance between local density estimators Denker and Keller (1983) as follows:

$$\sqrt{n} \frac{(T_n(\varepsilon_n) - b)}{S_n} \rightarrow N(0, 1)$$

Where \rightarrow presents the convergence in distributions and S_n denotes the asymptotic variance of $T_n(\cdot)$.

Bandwidth choice

According to Diks and Panchenko (2006) and Bekiros and Diks (2008) the optimal $\beta = 2/7$. Thus, the optimal bandwidth which asymptotically provides the optimal estimator T_n characterized by the smallest mean squared error is $\varepsilon_n^* = C^* n^{-\frac{2}{7}}$, where

$$C^* = \left(\frac{18.3q_2}{4(E[s(V)])^2} \right)^{1/7}$$

To facilitate the calculation of C^* , Diks and Panchenko (2006) provide its' value for some specific processes. In our work, we followed Diks and Panchenko (2006) to select the optimal bandwidth depending on our data length. In our case, the data length is close to 2000 and consequently the bandwidth is equal to 1.

Informational efficiency and the random walk hypothesis

The idea of combining efficiency and random walk concept is a way of testing whether all subsequent price changes represent random departures from previous prices. More precisely, if information flows are not impeded and information is instantly reflected in prices, then tomorrow's price changes will only reflect tomorrow's news and are therefore independent of today's price changes.

We further tested the random walk of the natural gas futures prices for the US and European markets using Automatic Bootstrap variance ratio tests of Choi (1999) under conditional heteroskedasticity. The AVR test can be described as follows:

Consider Y_t as a stationary time series for the period ($t=1, \dots, T$), the statistic of the variance ratio is presented by;

$$VR(h) = 1 + 2 \sum_{t=1}^{T-1} m\left(\frac{i}{k}\right) \hat{\rho}(i)$$

Where $VR(h)$ is the ratio of $\frac{1}{h}$ times the variance of h-period return, $\hat{\rho}(i) = \frac{\sum_{t=1}^{T-i} (Y_t - \hat{\mu})(Y_{t+i} - \hat{\mu})}{\sum_{t=1}^T (Y_t - \hat{\mu})^2}$ and $\hat{\mu} = T^{-1} \sum_{t=1}^T Y_t$.

Moreover, $m(v) = \frac{25}{12\pi^2 v^2} \left[\frac{\sin\left(\frac{6\pi v}{5}\right)}{\left(\frac{6\pi v}{5}\right)} - \cos\left(\frac{6\pi v}{5}\right) \right]$ represents the quadratic spectral Kernel.

Let $f_Y(0)$ be the normalized spectral density of Y_t at a null frequency and $VR(h)$ is an efficient estimator for $2\pi f_Y(0)$. Consequently, the null hypothesis states that Y_t is serially uncorrelated:

$$H_0^B : 2\pi f_Y(0) = 1$$

$$AVR(h) = \frac{\sqrt{\frac{T}{h}} [VR(h) - 1]}{\sqrt{2}} \longrightarrow N(0, 1)$$

Choi (1999) used the data-dependent approach of Andrews (1991) to select the optimal lag length at the zero frequency for spectral density. In fact, the AVR test with optimal lag length is noted $AVR(\hat{h})$. We employed the wild bootstrap to the Lo-MacKinlay and Chow-Denning test to avoid any problem of heteroskedasticity according to the three following steps:

1. $Y_t^* = \tau_t Y_t$ ($t = 1, \dots, T$) where τ_t is a random variable that verifies $E(\tau_t) = 0$ and $E(\tau_t^2) = 1$
2. Compute the statistic of $AVR(\hat{h})$ obtained from $\{Y_t^*\}_{t=1}^T$
3. Repeat the first two steps K times until having a bootstrap distribution $\{AVR^*(\hat{h}^*; j)\}_{j=1}^K$

As a result, we have two-tailed p-values of the test verifying $|\{AVR^*(\hat{h}^*; j)\}_{j=1}^K| > |AVR(\hat{h})|$

2.4 Empirical strategy

2.4.1 Data and unit root tests

Argus provides the daily prices of natural gas spot and futures in UK and Netherlands. The sample ranges from 2nd January 2013 to 22th January 2019, consisting of 1532 observations. Futures contracts with three maturity lengths of one, two, and three months are considered. The US daily prices of natural gas spot and futures of one, two, and three months maturities are downloaded from the Energy Information Administration (EIA) website. Figure 2.1 shows the returns (i.e. first log-differenced) of natural gas spot and futures (one-month maturity) in the US, UK, and the Netherlands. We limit the starting date to 2013 to account for major changes in European natural gas markets to date in terms of market efficiency. Among them, the important change in price formation mechanisms (IGU, 2018) towards gas-on-gas competition, the progress in terms of market maturity, liquidity and integration as promulgated by the relevant regulatory authorities (see, e.g., ACER (2017) and ACER (2015)).

Table 2.1: Summary statistics

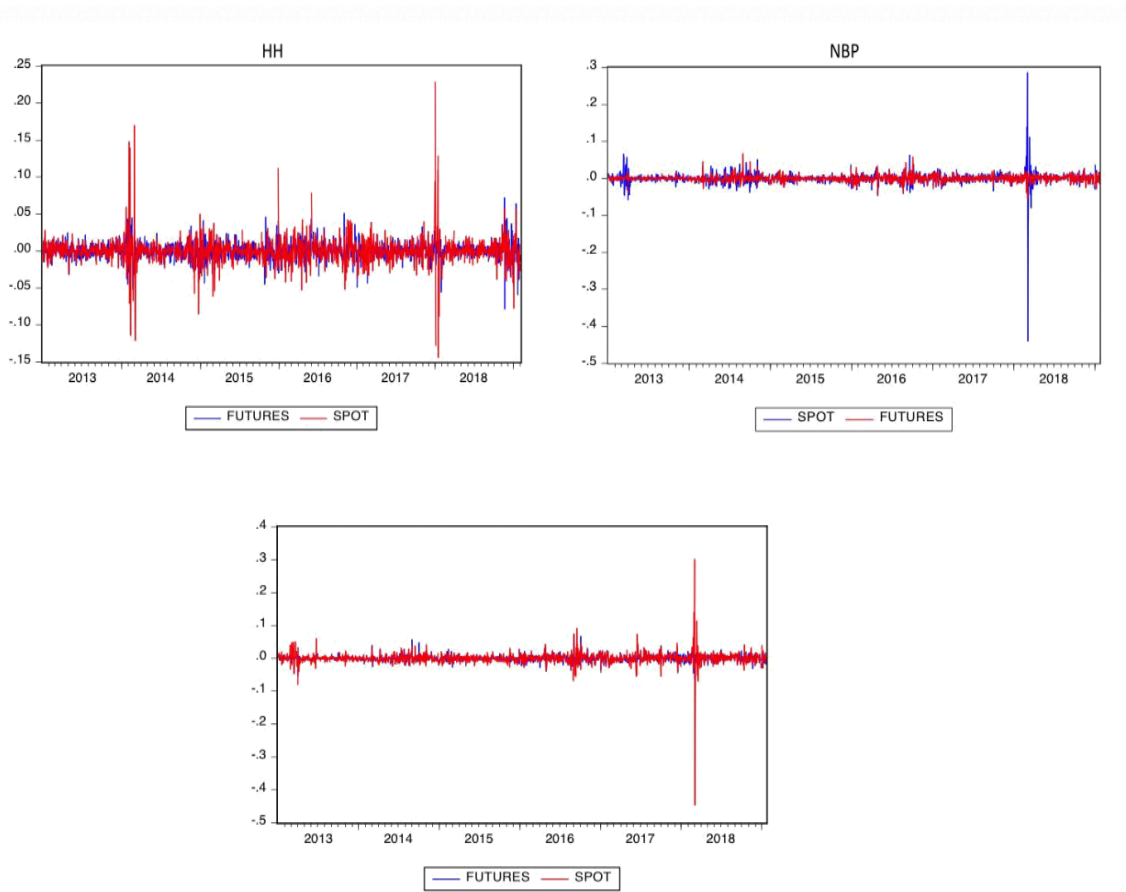
	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
HH Spot	3.211	2.990	8.150	1.490	0.822	1.188	6.803	1202.980*
HH Futures 1	3.189	2.980	6.149	1.639	0.729	0.581	3.203	83.521*
HH Futures 2	3.225	3.037	5.465	1.767	0.691	0.431	2.565	55.852*
HH Futures 3	3.265	3.085	4.846	1.867	0.668	0.378	2.406	55.381*
NBP Spot	50.138	48.600	230	20.475	13.988	1.714	20.360	19988.46*
NBP Futures 1	50.147	49.250	77.650	26.350	12.566	0.105	1.959	71.904*
NBP Futures 2	50.649	48.950	81.750	25.400	12.584	0.154	2.117	55.745*
NBP Futures 3	51.160	48.800	84.325	25.800	12.606	0.188	2.269	43.18*
TTF Spot	20.319	20.250	85	10.500	5.033	1.603	20.292	19745.3*
TTF Futures 1	20.189	20.037	29.250	10.650	4.525	0.018	2.060	56.414*
TTF Futures 2	20.383	20.150	29.525	11.125	4.500	0.012	2.011	62.400*
TTF Futures 3	20.521	20.200	29.650	11.050	4.481	0.019	2.005	63.274*

Notes: The following table summarizes the descriptive statistics of the daily spot and futures returns of the different natural gas markets.* reflects the significant level at 1 % .

Table 2.1 describes summary statistics for the US and the European natural gas spot and futures returns. The difference between spot and futures prices decreases when futures prices approach maturity. The data exhibits positive skewness and kurtosis which proves the significant asymmetry and heavy tails, further justified by the significant Jarque-Bera statistics.

The Augmented Dickey-Fuller (ADF), Phillips and Perron (1989) (PP) and Perron (89) unit root tests are used to check for the stationarity properties of our data (see Table 2.9 and 2.8 in Appendix A). We cannot reject the null hypothesis of unit root for all considered price series, suggesting non-stationarity. We hence apply a logarithmic first difference filter to work with stationary return series. Same results are yielded from the Perron (89) unit root test with a breakpoint (see 2.8 in Appendix A).

Figure 2.1: Natural gas spot and futures returns



Wavelet decomposition of daily natural gas returns

The first step of our approach is to decompose each of the daily spot and futures price returns via the Maximal Overlap Discrete Wavelet Transform (see Figure 2.2 to 2.7 in Appendix B). Contrary to tests performed at arbitrary time scales (e.g., daily, monthly or quarterly), here the wavelet decomposition avoids any loss of information since any information that is not captured on a scale is in the next scale.

Table 2.2: Frequency interpretation of MRD scale levels

Scale crystals	Daily frequency resolution
D1	1d-2d
D2	2d-4d
D3	4d-8d
D4	8d-16d
D5	16-32=4d-1wk 3d
D6	32-64 = 6wks 2d- 12wks 4d
D7	64-128= 12wks 4d- 25wks 3d
D8	128-256 = 51wk 1d - 102 wks 2d

This overlapping of information is enabled by the orthogonality property of the Daubechies (1992) and allows the wavelet decomposition to detect sudden regime changes and isolated shocks in the analysis of components of a non-stationary process (Ramsey, 2002). The MODWT is similar to the Discrete Wavelet Transform (DWT) but presents some advantages.¹⁷ In this paper, the original data have been transformed by the wavelet filter Symmlet [S(8)] up to time scale 8.¹⁸

Wavelet cross-correlation analysis

The wavelet cross-correlation is an intuitive way to measure the overall statistical relationships that might exist at different time scales among a set of observations on a bivariate random variable. To allow for more predictive interpretations of the data, a graphic representation (see Figure 2.8 to 2.10 in Appendix B) of wavelet cross-correlation is presented to indicate the type of correlation that exists within daily spot and futures natural gas returns, at different time

¹⁷First, the MODWT can handle any sample size while the DWT of level j restricts the sample size to 2^j . Also, MODWT is invariant to circularly shifting the time series, and the multiresolution details and smooth coefficients are associated with zero filters (Gençay, Selçuk, and Whitcher, 2002),(Percival and Mofjeld, 1997). Theses two properties do not hold for DWT. Finally, when it comes to calculating the wavelet correlations, the MODWT variance estimator is asymptotically more efficient than the same estimator based on DWT.

¹⁸Table 2.2 displays the frequency interpretation of the multiresolution decomposed scale levels.

scales, along with their confidence intervals and the lead and lag for each component. The red curves are the 95% confidence intervals. If the curve is significantly high, above the horizontal axis and skewed to the right, it means that there is a positive wavelet cross-correlation and the first variable leads, otherwise, the second variable leads.

Figure 2.8 in Appendix B displays the wavelet cross-correlation between Henry Hub spot and futures returns. It shows that there is no evidence of a clear lead across all the levels. Figure 2.9 in Appendix B represents the wavelet cross-correlation between NBP spot and futures returns. It shows that in level 8, the curve is right skewed, which means that spot lead-lag futures and in level 7 the curve is left skewed which means that the futures price lead-lag spot returns. from level 1 to 6, the curves do not reveal any leader.

Figure 2.10 in Appendix B shows a positive high correlation skewed to the left suggesting that futures prices lead spot prices in the TTF market for levels 8 to 3 (in the long and medium term). However, it decreases to reach low levels in the short run (levels 1 and 2). Only level 1 shows a centered curve.

Moreover, correlations are increasing with the time scale and reach almost 1 in the long-run. In other words, when periods exceed the year, the existence of a strictly linear relationship between spot and futures returns of the three natural gas markets considered cannot be rejected. It is worth noting that for the US case, correlations between spot and futures reach a high level faster than European ones.

2.4.2 Efficiency of intertemporal arbitrage: Johansen cointegration test on raw data

Before investigating the causal relationship between spot prices and futures prices, we first need to confirm the cointegration between natural gas spot and futures prices in the three considered hubs. Table 2.10 in Appendix C shows the results of the cointegration test based on both Johansen's maximum eigenvalues and the Trace test. We can reject in all cases the null hypothesis of no cointegration relationship between spot and futures prices at the conventional significance level of 5%, but we cannot reject the null hypothesis according to which at most one cointegration relationship exists for both American and European spot and futures natural

gas markets respectively.¹⁹ Therefore, results suggest the existence of a long-run relationship between Henry Hub spot and futures prices, NBP spot and futures prices, and TTF spot and futures prices. Results are robust to different maturities of futures contracts (one, two, and three months ahead contracts).

2.4.3 Price discovery process

Linear Granger causality test on raw and decomposed data

To determine the direction of Granger causality implied by the existence of a cointegrating relationship, we run a Vector Error Correction Model (VECM) which integrates an error correction term (EC) supposed to depict the adjustment process towards the long run relationship in the series. For comparison purpose, we also run Granger causality test based on unrestricted VAR. Results based on original data are quite comparable for NBP and TTF gas hubs as they suggest unidirectional Granger causality running from futures prices of one month and two months maturities to spot prices and no causality when three-months ahead futures contracts are considered. Henry Hub futures prices of two- and three-months maturities Granger cause spot prices. However, bidirectional causality is found when two-months ahead Henry Hub futures contracts are considered. After investigating the causality direction in the original series of price returns, we examine the time-scale components of the price return series based on wavelet transformation.²⁰ Table 2.3 shows that for most of the cases, there is bidirectional Granger causality between Henry Hub spot and futures price returns except for the 7th level for one-month ahead futures contracts and the 3rd level for two-month ahead futures contracts.

Concerning the UK gas hub NBP, results unveil bidirectional causality between spot and futures returns of 1- and 2-months maturities for most of the scale levels. Results are less unanimous when 3 months maturities contracts are considered. Indeed, inconsistency in causality direction when we go from one scale to another is found between TTF spot and futures re-

¹⁹Results are robust to three alternative models with different levels of restrictions: restricted intercept and no trend, unrestricted intercept and no trend, and unrestricted intercept and restricted trend. In all cases, the null hypothesis is rejected in favor of the existence of a cointegrating relationship between spot and futures prices for all considered gas hubs. Results are available upon request.

²⁰We test Granger causality between the time-scale components of spot and futures price returns in the three gas hubs based on an unrestricted VAR.

turns of two- and three-months maturities with an absence of causality from levels 1 to 3 and a bidirectional causality in the long run (levels 7 and 8).

Furthermore, as in the case where the original return series are considered, we find similarities between the TTF and NBP gas hubs where no causality is found between spot and two and three months ahead futures contracts suggesting lower visibility with longer futures contract maturities of market participants. Consequently, TTF and NBP can be considered as less informationally efficient than Henry Hub. Moreover, when unidirectional causality is found, it is almost exclusively running from futures to spot prices, emphasizing the explanatory power of futures for the next day spot price change. It corroborates the idea that futures markets tend to be used because they are more fluid and informative to adjust physical prices. This implies that the futures market discovers prices and spot market prices are influenced by the futures market prices. Consequently, futures markets have a stronger ability to predict subsequent spot prices. All in all, what can be learned from the linear Granger causality test is that:

- NBP and TTF spot and one-month maturity futures returns can be considered as efficient all along the considered time scales and only in the long run when two and three-months maturities contracts are considered.
- Bidirectional causality is clearly dominant for US gas hub suggesting instantaneous response of price change across markets and efficiency in short, medium and long term. More precisely, Henry Hub can be considered as efficient from intra-week to approximately annual period.

Nonlinear Granger causality test on original and decomposed data

Financial and commodity markets exhibit nonlinear dynamics because of, among others, transaction costs, unforeseen events, recessions, stickiness in prices, etc. To accommodate these nonlinearities in causality testing, Baek and Brock (1992) have proposed a nonparametric test for detecting nonlinear causal relationships based on the correlation integral, which is an estimator of spatial dependence across time. Hiemstra and Jones (1994) have provided an improved version that has been widely used in the economics literature. More recently, Diks and Panchenko (2006) found that these tests tend to over-reject the null hypothesis if it is accurate and proposed a non-parametric test that avoids over-rejection. Tables 2.4 to 2.6 present the results of nonlinear

Granger causality tests between spot and futures prices based on this test. The latter has been applied to both the time-scale components and original time series based on unrestricted VAR specification. The number of lags has been selected by relying on the Schwarz information criterion.

As displayed in Table 2.4, neither of the Henry Hub spot or futures markets seem to lead the other (with some exceptions where two- and three-months maturities futures prices seem to lead spot prices). In other words, both markets are efficient in terms of pricing, and the activity at the spot market is likely to affect prices as futures markets.

Concerning the case of the NBP (see Table 2.6), the results are not unanimous across the different wavelet details and vary between unidirectional causality from futures price returns to spot market price returns and bidirectional causality. When one-month ahead futures are considered, no market leads the other for all wavelet details except the level D8: suggesting that futures market plays a dominant role in price discovery on an annual basis. The same result is also found when two-months maturities contracts are considered as levels 2, 7 and 8 exhibit unidirectional causality from futures to spot prices while for all other frequencies, there is a feedback relationship between the two markets. The same is detected between spot and one-month ahead TTF futures except for an absence of causality for the 6th level. However, when two- and three-months maturities are considered, results are less unanimous with punctuated unidirectional causalities running from TTF futures prices to spot prices.

Futures markets providing price discovery for the spot market is noteworthy as the information sets in natural gas spot and futures markets are different (short-term influences, such as weather conditions or infrastructure outages are expected to have a significant impact on spot prices and a limited one on futures). Following Silvapulle and Moosa (1999) and Bohl and Stephan (2013), this is the result of the broader scope of market participants in the futures market where they have the opportunity to trade the commodity multiple time before maturity. The futures markets hence become attractive for hedgers and speculators without interest in the physical delivery of the underlying asset. It implies a greater informational efficiency of the market compared to the one of the spot. Futures markets hence play a dominant role in price discovery.

Table 2.3: Multiscale linear Granger Causality test based on VAR.

Henry Hub													
		Maturity 1				Maturity 2				Maturity 3			
		$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$	
Timescale (days)		F-test	P-value	F-test	P-value	F-test	P-value	F-test	P-value	F-test	P-value	F-test	P-value
Original level	Original	1.9297	0.1456	108.489	0.0000	7.4302	0.0000	60.3909	0.0000	0.8002	0.4495	62.7845	0.0000
Short scale	D1	5.0073	0.0000	18.2651	0.0000	3.7508	0.0002	3.7508	0.0002	11.5775	0.0000	21.9113	0.0000
	D2	1.8669	0.0613	15.4797	0.0000	1.0474	0.3980	14.0416	0.0000	8.7628	0.0000	32.4641	0.0000
Medium scale	D3	3.3204	0.0016	27.5350	0.0000	2.6833	0.0092	26.3501	0.0000	61.5653	0.0000	61.5653	0.0000
	D4	8.1115	0.0000	35.5340	0.0000	11.4122	0.0000	36.0752	0.0000	11.4122	0.0000	36.0752	0.0000
	D5	3.4713	0.0006	36.3207	0.0000	3.7335	0.0002	33.1086	0.0000	9.5163	0.0000	37.7405	0.0000
	D6	14.9722	0.0000	31.8082	0.0000	16.5630	0.0000	28.1400	0.0000	23.0441	0.0000	35.6345	0.0000
Long scale	D7	1.4331	0.1778	37.5900	0.0000	4.4100	0.0000	37.6928	0.0000	8.7873	0.0000	43.8998	0.0000
	D8	9.2195	0.0000	20.3114	0.0000	8.6360	0.0000	18.8043	0.0000	10.8266	0.0000	23.7487	0.0000
TTF													
		Maturity 1				Maturity 2				Maturity 3			
		$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$	
Timescale (days)		F-test	P-value	F-test	P-value	F-test	P-value	F-test	P-value	F-test	P-value	F-test	P-value
Original level	Original	1.6307	0.1349	13.9679	0.0000	0.9150	0.4007	4.6324	0.0099	1.0218	0.6000	3.4092	0.1818
Short scale	D1	1.5629	0.1312	2.4034	0.0141	0.7796	0.6208	1.0496	0.3963	0.7603	0.6381	0.9973	0.4361
	D2	2.2285	0.0231	4.0916	0.0001	1.3654	0.2160	0.9906	0.4362	1.0264	0.4137	1.5731	0.1280
Medium scale	D3	4.6372	0.0000	5.6445	0.0000	1.3654	0.2160	0.9906	0.4362	1.2759	0.2585	1.3512	0.2223
	D4	5.6826	0.0000	8.5633	0.0000	1.2906	0.2439	2.5901	0.0082	1.1791	0.3080	1.8356	0.0665
	D5	8.6640	0.0000	11.6771	0.0000	2.3582	0.0161	4.2395	0.0001	3.0187	0.0023	3.1162	0.0017
	D6	0.5486	0.7978	0.8508	0.5451	0.4230	0.8884	0.5813	0.7716	0.8364	0.5570	0.8364	0.5570
Long scale	D7	9.4265	0.0000	17.4629	0.0000	4.2382	0.0001	6.9044	0.0000	5.6698	0.0000	6.9619	0.0000
	D8	13.6710	0.0000	21.8379	0.0000	9.0826	0.0000	9.2583	0.0000	7.8678	0.0000	8.0394	0.0000
NBP													
		Maturity 1				Maturity 2				Maturity 3			
		$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$	
Timescale (days)		F-test	P-value	F-test	P-value	F-test	P-value	F-test	P-value	F-test	P-value	F-test	P-value
Original level	Original	2.0250	0.0594	14.2069	0.0000	2.13801	0.1439	11.8843	0.0006	1.0218	0.6000	3.4092	0.1818
Short scale	D1	1.9906	0.0442	1.8544	0.0633	2.0558	0.0371	1.0513	0.3951	1.4874	0.1568	1.2447	0.2690
	D2	1.2342	0.2749	3.5383	0.0005	1.1801	0.3073	2.0463	0.0381	1.0513	0.3951	1.4874	0.1568
Medium scale	D3	4.4352	0.0001	4.3790	0.0001	2.1833	0.0331	1.7329	0.0973	1.3347	0.2299	1.9786	0.0547
	D4	5.7843	0.0000	8.7505	0.0000	1.2318	0.2763	2.1833	0.0331	1.8283	0.0677	3.2113	0.0013
	D5	6.1356	0.0000	11.4883	0.0000	2.6655	0.0066	7.7813	0.0000	1.3163	0.2307	7.8749	0.0000
	D6	8.6921	0.0000	8.6921	0.0000	3.9076	0.0003	6.3413	0.0000	3.2045	0.0013	8.7322	0.0000
Long scale	D7	11.7638	0.0000	19.0803	0.0000	2.4395	0.0173	5.6855	0.0000	5.0945	0.0000	5.6790	0.0000
	D8	21.1932	0.0000	16.5408	0.0000	12.9411	0.0000	9.0093	0.0000	4.7637	0.0000	9.6151	0.0000

Notes: The results of the joint Wald test are reported in the table with associated p-values. A statistically significant result means the rejection of the null hypothesis of no Granger causality F refers to futures price returns and S to spot price returns. $F \rightarrow S$ means testing for a Granger cause from futures to physical price returns. $S \rightarrow F$ means testing for a Granger cause from the physical prices to the futures prices.

Table 2.4: Multiscale Nonlinear Granger Causality test, Henry Hub.

$Lx=Ly$	Maturity 1				Maturity 2				Maturity 3			
	$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$	
	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value
Panel A: Original data												
1	4.6740	0.0000	9.2420	0.0000	3.7160	0.0001	7.0910	0.0000	2.5860	0.0049	6.4410	0.0000
2	4.1560	0.0000	9.9840	0.0000	4.0110	0.0000	8.5970	0.0000	2.8350	0.0023	7.8420	0.0000
3	5.2670	0.0000	8.9570	0.0000	4.7010	0.0000	7.7410	0.0000	3.5400	0.0002	6.6170	0.0000
4	4.8200	0.0000	7.9390	0.0000	4.3070	0.0000	7.0350	0.0000	3.0550	0.0011	6.4850	0.0000
5	4.0820	0.0000	6.8440	0.0000	3.4480	0.0003	6.0280	0.0000	2.6290	0.0043	5.4340	0.0000
Panel B: D1												
1	5.7450	0.0000	6.6800	0.0000	5.4280	0.0000	7.1070	0.0000	4.7640	0.0000	6.3410	0.0000
2	5.6240	0.0000	5.5370	0.0000	4.3210	0.0000	6.0970	0.0000	3.2300	0.0006	5.6680	0.0000
3	5.2660	0.0000	5.6400	0.0000	4.3470	0.0000	5.9480	0.0000	3.0350	0.0012	5.5350	0.0000
4	4.9570	0.0000	4.8410	0.0000	3.9750	0.0000	5.3890	0.0000	2.8280	0.0023	5.0910	0.0000
5	4.7490	0.0000	4.1930	0.0000	3.6010	0.0002	4.9850	0.0000	2.6530	0.0040	4.8260	0.0000
Panel C: D2												
1	5.4770	0.0000	8.7480	0.0000	5.7020	0.0000	9.5180	0.0000	4.4990	0.0000	8.7460	0.0000
2	4.4940	0.0000	8.9140	0.0000	2.8950	0.0019	9.3130	0.0000	1.1380	0.1276	8.2460	0.0000
3	4.0880	0.0000	8.2180	0.0000	2.3750	0.0088	8.1450	0.0000	0.7430	0.2288	6.9520	0.0000
4	4.4340	0.0000	7.5660	0.0000	2.5620	0.0052	7.4560	0.0000	1.2650	0.1030	0.5420	0.0000
5	3.8280	0.0000	7.0950	0.0000	2.1300	0.0166	7.0700	0.0000	1.2330	0.1087	6.2000	0.0000
Panel D: D3												
1	2.7430	0.0000	8.9750	0.0000	2.2310	0.0128	9.3520	0.0000	-0.9810	0.8367	8.1970	0.0000
2	4.6990	0.0000	8.7580	0.0000	5.5680	0.0000	9.1120	0.0000	3.5130	0.0002	7.9140	0.0000
3	3.6480	0.0001	8.2510	0.0000	3.8110	0.0001	9.1910	0.0000	2.4500	0.0072	8.0950	0.0000
4	2.9700	0.0015	7.2140	0.0000	2.7240	0.0032	7.7640	0.0000	1.3230	0.0930	6.8330	0.0000
5	3.4350	0.0003	6.7840	0.0000	3.0040	0.0013	7.1210	0.0000	1.5070	0.0659	6.1940	0.0000
Panel D: D4												
1	-0.0020	0.5010	9.8490	0.0000	-3.7080	0.9999	12.0140	0.0000	-4.5940	1.0000	11.2690	0.0000
2	3.4380	0.0003	9.9240	0.0000	0.5900	0.2774	11.5570	0.0000	-0.5970	0.7248	10.8300	0.0000
3	5.9200	0.0000	9.5750	0.0000	4.8690	0.0000	11.0770	0.0000	3.5000	0.0002	10.3430	0.0000
4	6.0370	0.0000	8.9200	0.0000	5.4390	0.0000	10.1350	0.0000	4.3630	0.0000	9.6110	0.0000
5	5.4630	0.0000	7.9980	0.0000	4.5540	0.0000	9.0060	0.0000	3.4820	0.0003	8.6240	0.0000
Panel E: D5												
1	3.3690	0.0004	7.3890	0.0000	3.5000	0.0002	7.7970	0.0000	3.8960	0.0001	7.3140	0.0000
2	3.4000	0.0012	7.3060	0.0000	3.2990	0.0005	7.9100	0.0000	3.5680	0.0002	7.2800	0.0000
3	3.2400	0.0006	7.2260	0.0000	3.6070	0.0002	8.0460	0.0000	3.8770	0.0001	7.3880	0.0000
4	4.1060	0.0000	7.1850	0.0000	4.1480	0.0000	8.0210	0.0000	4.4620	0.0000	7.5840	0.0000
5	4.8600	0.0000	7.1810	0.0000	4.7720	0.0000	8.0700	0.0000	5.1630	0.0000	7.8570	0.0000
Panel F: D6												
1	4.4260	0.0000	5.4160	0.0000	2.7540	0.0029	5.4140	0.0000	2.2510	0.0122	4.9580	0.0000
2	4.1990	0.0000	5.3560	0.0000	2.5470	0.0054	5.2920	0.0000	1.9580	0.0251	4.8680	0.0000
3	3.9410	0.0000	5.2980	0.0000	2.4290	0.0076	5.2510	0.0000	1.7120	0.0435	4.8290	0.0000
4	3.6940	0.0000	5.2950	0.0000	2.3000	0.0107	5.3180	0.0000	1.5740	0.0577	4.8630	0.0000
5	3.5010	0.0000	5.2890	0.0000	2.3340	0.0098	5.4360	0.0000	1.5820	0.0568	4.9700	0.0000
Panel G: D7												
1	4.1080	0.0000	7.1510	0.0000	0.2550	0.3993	6.4780	0.0000	0.9690	0.1664	3.4580	0.0003
2	3.9820	0.0000	7.0760	0.0000	0.1990	0.4211	6.3560	0.0000	1.0730	0.1417	3.2880	0.0005
3	3.8500	0.0000	7.0050	0.0000	0.2210	0.4124	6.2250	0.0000	0.9510	0.1708	3.1700	0.0008
4	3.7310	0.0000	6.9310	0.0000	0.2160	0.4145	6.1190	0.0000	0.9480	0.1716	3.0460	0.0012
5	3.6090	0.0000	6.8600	0.0000	0.2400	0.4050	6.0360	0.0000	1.0000	0.1586	3.0320	0.0012
Panel H: D8												
1	7.2470	0.0000	3.8900	0.0000	8.3400	0.0000	4.1830	0.0000	7.7960	0.0000	4.9430	0.0000
2	7.1960	0.0000	3.8630	0.0000	8.3100	0.0000	4.0980	0.0000	7.7500	0.0000	4.8710	0.0000
3	7.1500	0.0000	3.8220	0.0000	8.2800	0.0000	4.0190	0.0000	7.7260	0.0000	4.8160	0.0000
4	7.1080	0.0000	3.8090	0.0000	8.2480	0.0000	3.9530	0.0000	7.6960	0.0000	4.7540	0.0000
5	7.0670	0.0000	3.7790	0.0000	8.2100	0.0000	3.8930	0.0001	7.6730	0.0000	4.6980	0.0000

Notes: The results of the Diks and Panchenko (2006) test are reported in the table with associated p-values. A statistically significant result means the rejection of the null hypothesis of no Granger causality. F refers to the futures price returns and S to spot price returns. $F \rightarrow S$ means testing for a Granger causality running from futures to physical price returns. $S \rightarrow F$ means testing for a Granger causality running from the physical prices to the futures prices.

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Table 2.5: Multiscale nonlinear Granger causality test- TTF returns

$Lx=Ly$	Maturity 1				Maturity 2				Maturity 3			
	$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$	
	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value
Panel A: Original data												
1	2.0370	0.0208	4.1760	0.0000	0.9920	0.1605	2.3910	0.0084	-0.9850	0.8378	0.8450	0.1989
2	2.476	0.0067	4.2760	0.0000	1.5750	0.0576	2.9770	0.0015	-0.710	0.7612	2.1310	0.0165
3	2.8530	0.0022	4.2830	0.0000	1.716	0.0431	2.7540	0.0029	-0.2940	0.6157	1.6170	0.0529
4	2.8900	0.0019	4.5910	0.0000	2.0260	0.0214	3.4930	0.0002	0.0930	0.4631	2.3630	0.0091
5	2.7410	0.0031	4.3250	0.0000	1.8690	0.0308	3.3700	0.0004	0.1340	0.4467	2.0760	0.0189
Panel B: D1												
1	2.1700	0.0150	4.5650	0.0000	1.5620	0.0592	3.1050	0.0010	-0.4560	0.6757	2.8200	0.0024
2	2.9710	0.0015	6.2170	0.0000	1.8830	0.0299	4.8360	0.0000	0.5010	0.3081	4.3480	0.0000
3	3.1570	0.0008	6.1830	0.0000	1.7380	0.0411	4.8240	0.0000	0.0930	0.4629	3.8750	0.0001
4	3.0690	0.0011	5.7840	0.0000	1.8820	0.0299	4.3010	0.0000	0.0630	0.4751	3.3250	0.0004
5	2.9660	0.0015	5.8490	0.0000	1.8050	0.0355	4.2170	0.0000	-0.0920	0.5365	3.1550	0.0008
Panel C: D2												
1	1.8920	0.0293	4.6560	0.0000	-0.8050	0.7897	2.9260	0.0017	-1.1100	0.8664	2.7490	0.0030
2	2.3000	0.0107	7.8640	0.0000	1.4700	0.0708	7.0000	0.0000	0.4650	0.3208	6.3320	0.0000
3	2.2840	0.0112	6.7810	0.0000	1.4010	0.0806	6.0880	0.0000	0.4800	0.3157	5.3420	0.0000
4	1.2270	0.1098	6.3150	0.0000	1.0440	0.1484	5.9230	0.0000	0.1450	0.4423	5.2900	0.0000
5	1.4240	0.0773	6.1030	0.0000	1.2110	0.1130	5.4990	0.0000	0.2450	0.4034	4.9750	0.0000
Panel D: D3												
1	2.1330	0.0164	8.2510	0.0000	0.0900	0.4640	6.5740	0.0000	-0.3030	0.6191	5.4860	0.0000
2	2.4080	0.0080	8.5480	0.0000	1.3950	0.0815	7.4240	0.0000	0.6890	0.2453	5.8880	0.0000
3	2.151	0.0157	8.4490	0.0000	0.7590	0.2239	7.8220	0.0000	1.2460	0.1064	6.4780	0.0000
4	2.0160	0.0219	6.9690	0.0000	0.7590	0.3525	6.6160	0.0000	1.2150	0.1121	5.3340	0.0000
5	1.966	0.0246	6.3790	0.0000	0.2580	0.3984	5.8690	0.0000	0.8950	0.1854	4.6490	0.0000
Panel D: D4												
1	4.1670	0.0000	5.7840	0.0000	4.1670	0.0000	5.7840	0.0000	1.0550	0.1457	4.3710	0.0000
2	4.047	0.0000	6.2150	0.0000	4.0470	0.0000	6.2150	0.0000	0.6350	0.2626	4.1600	0.0000
3	3.9660	0.0000	7.0700	0.0000	3.9660	0.0000	7.0700	0.0000	0.9390	0.1738	4.4820	0.0000
4	3.3980	0.0000	7.7090	0.0000	3.3980	0.0003	7.7090	0.0000	0.9070	0.1822	4.6140	0.0000
5	3.0690	0.0000	7.5280	0.0000	3.0690	0.0011	7.5280	0.0000	0.7540	0.2253	4.5940	0.0000
Panel E: D5												
1	4.6160	0.0000	6.434	0.0000	4.6160	0.0000	6.4340	0.0000	2.0410	0.0206	4.8760	0.0000
2	4.2240	0.0000	6.1710	0.0000	4.2240	0.0000	6.1710	0.0000	1.4730	0.0704	4.7940	0.0000
3	4.0770	0.0000	6.0340	0.0000	4.0770	0.0000	6.0340	0.0000	0.8340	0.2021	4.9030	0.0000
4	4.0520	0.0000	6.1530	0.0000	4.0520	0.0000	6.1530	0.0000	0.5240	0.3001	4.9100	0.0000
5	4.1050	0.0000	6.3110	0.0000	4.1050	0.0000	6.3110	0.0000	0.4960	0.3100	4.9080	0.0000
Panel F: D6												
1	0.4660	0.3206	0.2690	0.3940	0.4660	0.3206	0.2690	0.3940	0.3720	0.3548	0.7180	0.2364
2	0.3470	0.3642	0.4600	0.3227	0.3470	0.3642	0.4600	0.3227	0.4040	0.3432	0.8710	0.1920
3	0.2370	0.4063	0.7050	0.2404	0.2370	0.4063	0.7050	0.2404	0.4440	0.3287	1.0260	0.1524
4	0.1700	0.4324	0.8230	0.2054	0.1700	0.4324	0.8230	0.2054	0.4800	0.3156	1.0480	0.1472
5	0.0060	0.4975	1.1010	0.1356	0.0060	0.4975	1.1010	0.1356	0.6680	0.2520	1.2590	0.1040
Panel G: D7												
1	6.1650	0.0000	5.1330	0.0000	6.1650	0.0000	5.1330	0.0000	2.1380	0.0163	3.0860	0.0010
2	6.0890	0.0000	5.0600	0.0000	6.0890	0.0000	5.0600	0.0000	2.1520	0.0157	3.0350	0.0012
3	6.0250	0.0000	4.9950	0.0000	6.0250	0.0000	4.9950	0.0000	2.1720	0.0149	3.0020	0.0013
4	5.9630	0.0000	4.8940	0.0000	5.9630	0.0000	4.8940	0.0000	2.2150	0.0134	3.0760	0.0011
5	5.9070	0.0000	4.7980	0.0000	5.9070	0.0000	4.7980	0.0000	2.2510	0.0122	3.0370	0.0012
Panel H: D8												
1	4.2340	0.0000	7.6030	0.0000	4.2340	0.0000	7.6030	0.0000	-4.4840	1.0000	6.8720	0.0000
2	4.1770	0.0000	7.5550	0.0000	4.1770	0.0000	7.5550	0.0000	-4.5200	1.0000	6.8420	0.0000
3	4.0950	0.0000	7.5090	0.0000	4.0950	0.0000	7.5090	0.0000	-4.5580	1.0000	6.8140	0.0000
4	4.0090	0.0000	7.4740	0.0000	4.0090	0.0000	7.4740	0.0000	-4.4420	1.0000	6.7880	0.0000
5	3.9180	0.0000	7.4330	0.0000	3.9180	0.0000	7.4330	0.0000	-4.2470	1.0000	6.7540	0.0000

Notes: The results of the Diks and Panchenko (2006) test are reported in the table with associated p-values. A statistically significant result means the rejection of the null hypothesis of no Granger causality. F refers to the futures price returns and S to spot price returns. $F \rightarrow S$ means testing for a Granger causality running from futures to physical price returns. $S \rightarrow F$ means testing for a Granger causality running from the physical prices to the futures prices.

Table 2.6: Multiscale nonlinear Granger causality - NBP returns

$Lx=Ly$	Maturity 1				Maturity 2				Maturity 3			
	$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$		$S \rightarrow F$		$F \rightarrow S$	
	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value	T-stat	P-value
Panel A: Original data												
1	0.9420	0.1732	2.9840	0.0014	0.3400	0.3671	1.1320	0.1287	-0.8110	0.7912	0.0390	0.4845
2	1.0450	0.1480	3.2230	0.0006	0.5530	0.2901	1.5610	0.0593	-0.9390	0.8261	0.4320	0.3329
3	1.2490	0.1058	3.9710	0.0000	0.7600	0.2237	2.5340	0.0056	-1.0830	0.8605	1.5340	0.0626
4	1.7130	0.0433	5.0440	0.0000	0.6130	0.2698	3.1540	0.0008	-0.3110	0.6221	2.2950	0.0109
5	1.5420	0.0615	5.0890	0.0000	0.2380	0.4058	3.4970	0.0002	-0.3190	0.6250	-0.3190	0.6250
Panel B: D1												
1	1.7110	0.0435	4.4070	0.0000	2.0770	0.0189	3.6030	0.0002	0.7110	0.2386	2.5670	0.0051
2	2.1440	0.0160	6.0560	0.0000	2.3530	0.0093	5.2300	0.0000	1.2760	0.1009	3.7600	0.0001
3	2.0870	0.0184	6.3340	0.0000	2.0180	0.0218	4.6580	0.0000	1.0590	0.1447	3.7270	0.0001
4	1.7410	0.0408	5.5220	0.0000	1.7560	0.0396	4.0740	0.0000	1.1860	0.1179	3.8040	0.0001
5	1.8530	0.0319	5.3080	0.0000	1.7810	0.0374	3.8320	0.0001	0.7270	0.2336	3.4790	0.0003
Panel C: D2												
1	1.6590	0.0485	3.8920	0.0000	-0.3390	0.6327	2.3360	0.0098	-0.8860	0.8123	1.2730	0.1015
2	1.9170	0.0276	7.2040	0.0000	0.9960	0.1597	5.5220	0.0000	0.2070	0.4181	3.9320	0.0000
3	1.9640	0.0248	6.4820	0.0000	1.0080	0.1566	4.8410	0.0000	0.4870	0.3133	3.4480	0.0003
4	1.3070	0.0956	6.1600	0.0000	0.6610	0.2543	4.6070	0.0000	0.4590	0.3229	3.2350	0.0006
5	1.4290	0.0766	5.8030	0.0000	0.8730	0.1914	4.1180	0.0000	0.6100	0.2710	2.9470	0.0016
Panel D: D3												
1	2.9630	0.0015	7.6380	0.0000	1.9680	0.0246	5.9760	0.0000	0.8320	0.2027	5.1670	0.0000
2	3.9070	0.0001	7.7110	0.0000	2.4960	0.0063	6.6440	0.0000	1.4520	0.0733	5.2520	0.0000
3	3.0580	0.0011	7.6650	0.0000	1.7160	0.0431	7.1180	0.0000	1.5530	0.0602	6.2080	0.0000
4	2.6620	0.0039	5.9870	0.0000	1.1760	0.1197	5.8170	0.0000	1.1760	0.1198	5.2720	0.0000
5	2.4250	0.0077	5.3990	0.0000	0.9110	0.1810	5.2810	0.0000	0.7700	0.2205	4.7290	0.0000
Panel D: D4												
1	3.4990	0.0002	6.0840	0.0000	2.9530	0.0016	4.6000	0.0000	2.0900	0.0183	2.4350	0.0074
2	3.8660	0.0001	5.9580	0.0000	2.7550	0.0029	4.2190	0.0000	1.4980	0.0670	2.2820	0.0112
3	4.6370	0.0000	6.5240	0.0000	3.2390	0.0006	4.9110	0.0000	1.4020	0.0805	3.1410	0.0008
4	4.6500	0.0000	6.7630	0.0000	3.0460	0.0012	5.2450	0.0000	1.1810	0.1187	3.6540	0.0001
5	4.0920	0.0000	6.1840	0.0000	2.7360	0.0031	4.8700	0.0000	1.4020	0.0804	3.3130	0.0005
Panel E: D5												
1	3.7440	0.0001	5.8480	0.0000	3.1080	0.0009	3.6570	0.0001	1.8640	0.0312	3.5030	0.0002
2	3.4090	0.0003	5.5170	0.0000	2.7270	0.0032	3.4360	0.0003	1.5450	0.0612	3.3410	0.0004
3	3.2460	0.0006	5.3660	0.0000	2.4090	0.0080	3.5970	0.0002	1.2890	0.0988	3.4920	0.0002
4	3.2030	0.0007	5.3390	0.0000	2.2090	0.0136	3.8550	0.0001	1.2050	0.1141	3.7840	0.0001
5	3.4790	0.0003	5.4210	0.0000	2.2000	0.0139	4.3060	0.0000	1.2730	0.1014	4.1340	0.0000
Panel F: D6												
1	3.2280	0.0006	4.6380	0.0000	2.5370	0.0056	4.3390	0.0000	3.6690	0.0001	4.2830	0.0000
2	3.0530	0.0011	4.6700	0.0000	2.5490	0.0054	4.2380	0.0000	3.5590	0.0002	4.2020	0.0000
3	2.9510	0.0016	4.7240	0.0000	2.7110	0.0034	4.1500	0.0000	3.4870	0.0002	4.1220	0.0000
4	2.998,	0.0014	4.7770	0.0000	2.8550	0.0022	4.1000	0.0000	3.4110	0.0003	4.0450	0.0000
5	3.4670	0.0003	4.8340	0.0000	3.1820	0.0007	4.1420	0.0000	3.5050	0.0002	4.0160	0.0000
Panel G: D7												
1	5.3100	0.0000	5.2060	0.0000	1.2110	0.1130	3.8060	0.0001	-1.2530	0.8949	3.1630	0.0008
2	5.2050	0.0000	5.1140	0.0000	1.0920	0.1374	3.8330	0.0001	-1.2460	0.8936	3.1400	0.0009
3	5.0900	0.0000	4.9720	0.0000	0.9810	0.1632	3.8460	0.0001	-1.3060	0.9042	3.0870	0.0010
4	4.9720	0.0000	4.9120	0.0000	0.8270	0.2042	3.8320	0.0001	-1.3320	0.9086	3.0200	0.0013
5	4.8190	0.0000	4.8680	0.0000	0.7880	0.2152	3.8230	0.0001	-1.2210	0.8890	2.9430	0.0016
Panel H: D8												
1	-0.1270	0.5507	8.4400	0.0000	-6.0740	1.0000	8.2390	0.0000	-3.2400	0.9994	6.9540	0.0000
2	-0.2500	0.6018	8.4040	0.0000	-6.0790	1.0000	8.1930	0.0000	-2.5990	0.9953	6.9450	0.0000
3	-0.3790	0.6478	8.3600	0.0000	-6.0760	1.0000	8.1390	0.0000	-2.0730	0.9809	6.9500	0.0000
4	-0.524,	0.6999	8.3290	0.0000	-6.0650	1.0000	8.1060	0.0000	-1.5860	0.9436	6.9430	0.0000
5	-0.6480	0.7416	8.2990	0.0000	-6.1440	1.0000	8.0650	0.0000	-1.1160	0.8678	6.9410	0.0000

Notes: The results of the Diks and Panchenko (2006) test are reported in the table with associated p-values. A statistically significant result means the rejection of the null hypothesis of no Granger causality. F refers to the futures price returns and S to spot price returns. $F \rightarrow S$ means testing for a Granger cause from futures to physical price returns. $s \rightarrow F$ means testing for a Granger causality running from the physical prices to the futures prices.

2.4.4 Informational efficiency test

Table 2.7: Multiscale Automatic Bootstrap Variance Ratio Tests of HH, NBP and TTF futures returns of one-month maturity

	HH Futures 1		NBP Futures 1		TTF Futures 1	
	AB stat.	P-value	AB stat.	P-value	AB stat.	P-value
Original series	0.9610	0.22	0.5221	0.524	0.0805	0.814
Frequency bands						
D1	-13.3679	0.000	-13.446	0.000	-13.4471	0.000
D2	-10.6909	0.000	-10.7808	0.000	-10.7450	0.000
D3	-5.3826	0.004	-5.5527	0.000	-5.4916	0.000
D4	-3.1092	0.056	-3.3042	0.008	-3.2739	0.022
D5	-1.8128	0.190	-1.8008	0.200	-1.7907	0.194
D6	-0.7683	0.538	-1.0322	0.486	-0.9747	0.468
D7	-0.6422	0.578	-0.2970	0.700	-0.0065	0.980
D8	-0.3092	0.764	-0.3481	0.720	-0.2236	0.762

Note: AB stat is t-statistic of the Automatic Bootstrap variance ratio test. The corresponding P-value is the Bootstrap p-value for the Chow-Denning test.

The idea of combining efficiency and random walk concept is a way of testing whether all subsequent price changes represent random departures from previous prices. More precisely, if information flows are not impeded and information is instantly reflected in prices, then tomorrow's price changes should only reflect tomorrow's news.

We further tested the random walk hypothesis of the natural gas futures returns for the US and EU markets using Automatic Bootstrap Variance Ratio tests of Choi (1999). According to table 2.7, results for original data of futures returns of one-month maturity exhibit deviations from the random walk behaviors. As for the multiresolution nature of the informational efficiency allowed by the wavelet decomposed returns, the random walk test exhibits significance only at short and medium scales, that is from intra-week (D1), weekly (D2) and monthly (D4) scales.

It is fundamental to underline at this stage that the relation between random walk and informational efficiency is not an equivalence.²¹ Nevertheless, if these results are to be linked to the knowledge of the gas market and the literature which has strongly emphasized imperfect

²¹This echoes the problem inherent in any study of efficiency: while econometric tests can show predictability of returns from past values, proponents of efficiency argue that knowledge of this phenomenon does not put it into question; which has prompted various authors to test the efficiency hypothesis by working on higher horizons.

competition and high transaction costs of this industry, we are leaning towards a form of inefficiency of the market in the short and medium run. This result is certainly not systematic, but is very representative of the challenges intrinsic to the gas market where informational efficiency is significantly reached only in the long-run.

Several explanations can justify these findings and interpretations. First, market participants may exhibit low risk aversion levels in the short-run and consequently depend upon low risk premium (Gebre-Mariam, 2011). This behavior could be explained by the limited hedging advantages, low opportunities in making storage and transportation arrangements, and insufficient information across the market. Moreover, characteristics of natural gas, such as indivisibility and the required volume to ensure a transaction, make it harder to trade and less amenable for exchanges in small quantities.²² Furthermore, it is approved that news related to production and marketing of natural gas are not fully available to public (MacKinnon, Haug, and Michelis (1999), Mu (2007)). In other words, information and data on market fundamentals (e.g., demand, supply, production, imports, exports and prices of concurrent gas markets) are neither meticulous nor transparent, ultimately preventing the market to reach market efficiency in the short-run. It is only in the long run, when investors exhibit higher risk aversion and implement higher storage that the market is able to reach the efficiency from an informational point of view.

2.4.5 Robustness checks

Our previous findings are based on time-scaling decomposition via the Maximum Overlapped Discrete Wavelet Transformation (MODWT) using the Symlets filter. To make sure that our findings are not influenced by the choice of the wavelet transformation method, we repeated our analysis using the Discrete Wavelet Transformation method (DWT).²³ Results are found to be robust to this decomposition (See Appendix E). Moreover, the robustness of our specification to alternative wavelet transformation filter and length has also been investigated by considering the Daubechies Extremal Phase filter with different wavelet lengths from 2 to 6. Again, results proved to be robust and are available in the Appendix E.

²²For more details, please refer to the following link:<https://www.cmegroup.com/>.

²³DWT approach has several similarities compared to MODWT. This method, also, decomposes the energy spot and futures returns into dependent components.

2.5 Discussion

All considered gas markets are found to be globally efficient in pricing with strong evidence of cointegrating relationships between spot and futures markets implying that market participants can better anticipate price convergence by observing the deviations from the long-run relationships. Moreover, information flows between spot and futures market, although the futures markets play a leading role in price discovery at some time scales for NBP and TTF gas hubs.

Concerning informational efficiency, the null hypothesis of futures acting as a random walk is rejected for short and medium scales suggesting that Henry Hub, NBP and TTF gas hubs could be considered as informationally efficient only in the long run. Of course, the relation between random walk and informational efficiency is not an equivalence but knowledge of the gas market and the literature which has strongly emphasized imperfect competition and high transaction costs of this industry allows us to defend this hypothesis of short-term inefficiency. The multiresolution approach have greatly enriched the analysis by extending the view of our time series from time domain to frequency domain as when series of original log-returns are considered, we cannot reject the null hypothesis of the random walk. Considering this, the wavelet methodology sheds some light into the importance of taking into account the time horizon that has led to conflicting results in the literature. For instance, Poterba and Summers (1988) were unable to reject the null hypothesis of no serial correlation in returns even though their point estimates suggest a substantial degree of return predictability. This means that we avoid informational loss involved when long-horizons are investigated that ultimately alter the precision of the statistical inference.

Last but not least, in addition to depending on the time scales considered, information efficiency seems to be similar across the time scales in the three considered gas markets. In other words, in terms of informational efficiency, the US natural gas market is as efficient as TTF and NBP in the long-run. This result testifies a crucial breakthrough of the natural gas market known to be hampered by multiple logistical and transport barriers, making transactions in this industry both unclear and costly. Thirdly, the absence of informational efficiency in the short run is in line with the argument of Rong and Zheng (2008), according to which the pricing

efficiency is not necessarily consistent with the information efficiency.

The results make it possible to establish an evaluation of the hubs in terms of their capacity to provide reliable reference prices for the quantities of gas under contract. In terms of pricing efficiency, Henry hub showed the most reliable and most robust results at all time scales considered and for all considered maturities of futures contracts compared to the EU case. This comes from the conjunction of various elements regarding fundamentals development, hub structure and the respective role of liquidity and storage capacity in the considered gas hubs as developed hereafter.

Firstly, concerning wholesale gas market developments, European indigenous production does not make it possible to get rid of imports: the latter rose by 10% in 2017 compared to the previous year to cover for declined domestic gas production and growing consumption (ACER, 2017).²⁴ By 2030, the share of domestic production is expected to decrease to below 20%. This is mainly due to the lower cap on the extraction of gas from the Dutch Groningen field that has limited total domestic production to 24% of EU suppliers. On the other side of the Atlantic, the American gas landscape is characterized by strong growth in US natural gas production (IEA/OECD, 2016) and is schematically articulated around a complex set of production, transmission, storage, import/export and consumption associated with different nodes. The price of gas at different end-user nodes (e.g., commercial or residential points) shares a long-run equilibrium relationship with wholesale prices (Mohammadi, 2011). Henry Hub is also at a single point of junction of independent pipelines in a continental pipeline transport system that is completely competitive,²⁵ and sits on a vast network of 13 interstate and intrastate pipelines which allowed for non-interruptible and constant gas transportation with a very low risk of congestion and is located in a zone of conventional historical production.²⁶ Its role in futures markets could hence only be duplicated in parts of the world where pipeline systems have highly competitive transport (Makholm, 2016).

Secondly, a crucial distinction between US and EU gas markets lies on the fact that US

²⁴The gas supply portfolio of the EU mainly relies on imports from third countries via piped gas and LNG, accounting for 70% of total consumption, according to ACER (2015). 30% of European gas is imported from Russia followed by Norway and Algeria. Qatar is the major LNG supplier followed by Algeria.

²⁵Trading of Henry Hub futures started in 1990, while trading of TTF futures only took off in 2010.

²⁶50% of US gas production in the past was transferred via it (ACER, 2017).

Henry Hub (HH) is a physical trading hub setting the benchmark price for the entire North America trading area whereas, for the European Union, natural gas markets are integrated through the establishment of virtual (regional) trading hubs.²⁷ Physical and virtual gas trading hubs respond to a disparate structures of the gas industry: fully privatized in the United States *versus* regulated by the TSO in the European Union. Unique to natural gas markets and at the crossroads of different segments of the gas market between commodity markets, derivative financial markets, pipeline markets and regulatory policy environment, physical and virtual gas trading hubs object also differs in that it is more a means of facilitating trade in the United States and balancing in Europe.

Thirdly, the quality of the market is also a major factor in the explanation of our results: low liquidity is able to hamper intertemporal arbitrage between spot and futures markets and would be likely to increase the pressure exerted by trading activities on prices and hinder the development of gas hubs (Nick, 2016). In this regard, (Garaffa et al., 2019) have tested the hypothesis that asymmetric price responses in the continental European hubs derive from transaction costs. He concludes that, despite substantial efforts towards market integration, there remain concerns regarding the intensity of competition in European natural gas spot markets. In the same vein, De Menezes, Russo, and Urga (2019) have investigated the nature of transaction costs in European natural gas markets by focusing on the British case. More precisely, by drawing from the financial microstructure literature, their study was designed to capture tightness, depth and resilience of the one-month ahead NBP forward market from May 2010 to December 2014 for a comprehensive assessment of its liquidity in the period. Their results suggest that inventory costs and asymmetric-information costs represent 50.5% and 14.7% of the transaction costs, with the remaining 34.8% being attributable to order processing costs. They also found that 50% of the one-month-ahead NBP forward market's tightness is due to inventory costs.²⁸

²⁷A physical hub can be defined as a geographical point in the network where the price is set for natural gas delivered on that specific location. As for a virtual trading point, it is a non-physical hub associated with an entry-exit system from which gas can be transported to exit points by network users and is usually in a balancing area (see (Sieminski, 2013)).

²⁸They finally observed an increase in market tightness during 2014, which was coupled with low depth and resilience, decreasing number of transactions and higher variability in the average of volumes, which is a high concentration of the market at that time.

Last but not least, flexible storage capacity is crucial for efficient intertemporal arbitrage activity.²⁹ The US experience has shown that with a futures market at NYMEX, storage is not just dedicated to seasonal adjustments (Von Hirschhausen, 2008). There are about 123 natural gas storage operators in the United States, which control approximately 400 underground storage facilities. These facilities have a storage capacity of 4,059 Bcf of natural gas, and average daily deliverability of 85 Bcf per day. The issue of storage is widely debated among European regulators in order to counter supply disruptions. The access to storage facilities is often constrained: a strand of literature relied on game theory to analyze the strategic behavior of agents (see among others Maskin and Tirole (1988)). The effect of capacity constraints on collusion and market efficiency are also analyzed (e.g. Dechenaux and Kovenock (2003)). At the European level, the storage process responds to the seasonal consumption of gas in the face of a production that has less room for maneuver to adapt to it. The inventories are filled in summer to be used in winter. Storage levels below the seasonal standard tend to put upward pressure on prices, and conversely, storage levels above the seasonal standard tend to lower prices.

All in all, our results call for a significant increase in the number of physical transactions between European markets that are still required to reduce bottlenecks in transmission networks and interconnection points. Significant investments in transport infrastructure are required to extend the supply in the gas industry, and the economic feasibility of these investments are highly dependent on pricing structure and predictability (Komlev, 2013).

2.6 Conclusion

Gas hubs are actually at the crossroads of different segments of the gas market between commodity markets, derivative financial markets, pipeline market, and regulatory policy environment. Futures commodity exchange provides a centralized marketplace where market users can discover the prices of commodities for futures delivery and where risk-averse people can shift commodity price risk to others, who are willing to bear it. Ali and Bardhan Gupta (2011) highlight that the sustainability of commodity futures markets depends on the transparency and efficiency of its functioning in terms of price discovery, price risk management, flexible contract

²⁹Brennan (1958) and Fama and French (1987) work has allowed storage theory to link the impact of storage level on price differentials between spot and futures price

specification, controlling unfair speculation, commodity delivery system and coverage, infrastructural support, etc. As natural gas constitutes today a major commodity in the US and EU energy mix, examining the efficiency of the commodity futures market is of paramount importance to various stakeholders of commodities markets such as producers, traders, commission agents, commodity exchange participants, regulators and policymakers.

The present study empirically examines the direction of causality between the return series of futures and spot prices of US and European natural gas markets using frequency domain approach. We used daily data of physical and futures prices between 2013 and 2019. To the best of our knowledge, this is the first attempt to provide a comprehensive account of the connection between physical and futures market prices in European and US natural gas markets based on a multi-resolution approach through a wavelet decomposition of our data. Our analysis yielded interesting results. First, futures prices and spot prices of Henry Hub, NBP and TTF are cointegrated implying that market participants are able to better anticipate price convergence by observing the deviations from the long-run relationships. The existence of a cointegrating relationship enhances the capacity of physical market participants to hedge their exposure to market prices using futures prices. These results have potential implications for both firms hedging production risks using futures contracts and participants in natural gas trading. Secondly, nonlinear causality testing shows that neither of the Henry Hub spot or futures markets seems to lead the other (with some exceptions where two- and three-months maturities futures prices seem to lead spot prices). In other words, both markets are efficient in terms of pricing. The activity at the spot market is likely to affect prices as futures markets. This result reflects the adjustment process towards the long-run relationship (See Brenner and Kroner (1995)). Concerning NBP and TTF markets, results are not unanimous across the different time scales. Thirdly, the analysis shows evidence of limited informational efficiency of the three selected futures markets that cannot be concluded to be an unbiased predictor of prices at delivery in the short-term and medium-term. In contrast, informational efficiency is reached in the long-run.

Overall, it can be argued that the findings of this work shed some new light on the true nature of causality between the NG spot and futures prices contributing towards a better understanding of the existing interdependencies between the natural gas spot and futures markets. Investors

and other market participants can use our findings in order to develop more efficient investment strategies. For instance, the high-frequency components of futures contracts with one-month maturity can be utilized to realize excess returns in the spot market, while the low-frequency components of futures contracts with one-month maturity can be used to improve investors' ability to appraise the existing risk in the natural gas spot market.

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2.8 Appendices

2.8.1 Appendix A: Unit root tests

Table 2.8: Perron (89) Unit root test with a breakpoint

		Break Date	Constant and Trend	Constant
HH SPOT	Level	10/1/18	-6.015*** <0.01	-5.257*** <0.01
	Difference	12/1/18	-39.461*** <0.01	-39.464*** <0.01
HH FUT 1	Level	11/20/2014	-4.433 0.1552	-4.327* 0.0698
	Difference	11/1/13	-43.780*** <0.01	-43.792*** <0.01
HH FUT 2	Level	11/20/2014	-4.706104* 0.076	-4.628** 0.030
	Difference	8/1/13	-33.666*** <0.01	-33.675*** <0.01
HH FUT 3	Level	11/20/2014	-4.793* 0.0602	-4.762** 0.0198
	Difference	8/1/13	-32.618*** <0.01	-32.625*** <0.01
TTF SPOT	Level	1/07/2013	-6.428*** <0.01	-6.123*** <0.01
	Difference	8/1/13	-35.466*** <0.01	-35.476*** <0.01
TTF FUT 1	Level	3/12/13	-3.234 0.8313	-3.071 0.6445
	Difference	10/1/13	-39.845*** <0.01	-39.832*** <0.01
TTF FUT 2	Level	5/2/18	-3.368 0.7678	-3.141 0.6017
	Difference	1/14/2013	-39.2265 <0.01	-39.21665 <0.01
TTF FUT 3	Level	2/05/2018	-3.481 0.7034	-3.088 0.6341
	Difference	1/14/2013	-38.834*** <0.01	-38.828*** <0.01
NBP SPOT	Level	7/1/13	-5.974*** <0.01	-5.912*** <0.01
	Difference	8/1/13	-35.518*** <0.01	-35.527*** <0.01
NBP FUT1	Level	7/14/2017	-3.369 0.7669	-2.872 0.7517
	Difference	8/1/13	-29.305*** <0.01	-29.279*** <0.01
NBP FUT 2	Level	7/19/2017	-3.439 0.7284	-3.068 0.646
	Difference	1/17/2013	-40.018*** <0.01	-40.006*** <0.01
NBP FUT3	Level	11/26/2014	-3.730 0.545	-3.227 0.5512
	Difference	10/1/13	-39.242*** <0.01	-39.240*** <0.01

Note: Critical values are based on Vogelsong. *, ** and *** denote the rejection of the null hypothesis at 10 %, 5 % and 0 % respectively. Break selection is based on Dickey-Fuller t-statistic minimization. We have considered innovational outliers break type.

Table 2.9: Unit root tests results on spot and futures prices

	ADF test		PP test	
	Raw	Log-difference	Raw	Log-difference
NBP spot	-3.0687	-24.4436***	-5.6572	-96.6009
NBP Futures1	-0.5698	-40.3534***	-0.5454	-40.5723***
NBP Futures2	-0.5443	-40.0368***	-0.5381	-40.0525***
NBP Futures3	-0.5651	-39.2751***	-0.5663	-39.2766***
TTF spot	-3.2198	-24.3419***	-6.1266	-100.821***
TTF Futures1	-1.9231	-39.8554***	-0.7350	-39.9124***
TTF Futures2	-0.7324	-39.2309***	-0.7357	-39.2469***
TTF Futures3	-0.7705	-38.8262***	-0.7750	-38.8345***
HH spot	-2.4886	-20.5511***	-4.5584**	-45.2334***
HH Futures1	-2.3302	-38.8839***	-2.0855	-39.3399***
HH Futures2	-2.0255	-39.6721***	-2.0830	-39.6938***
HH Futures3	-1.9803	-39.6721***	-1.9803	-39.6797***

Note: Critical values are based on MacKinnon (1996). Associated P-values are in the underlines. The Schwartz information criterion is used for optimal lag selection in the ADF test. The truncation lags for PP are decided by Newey-West default.

2.8.2 Appendix B: MODWT of spot and futures returns and cross-correlation analysis

Figure 2.2: MODWT Henry Hub spot returns.

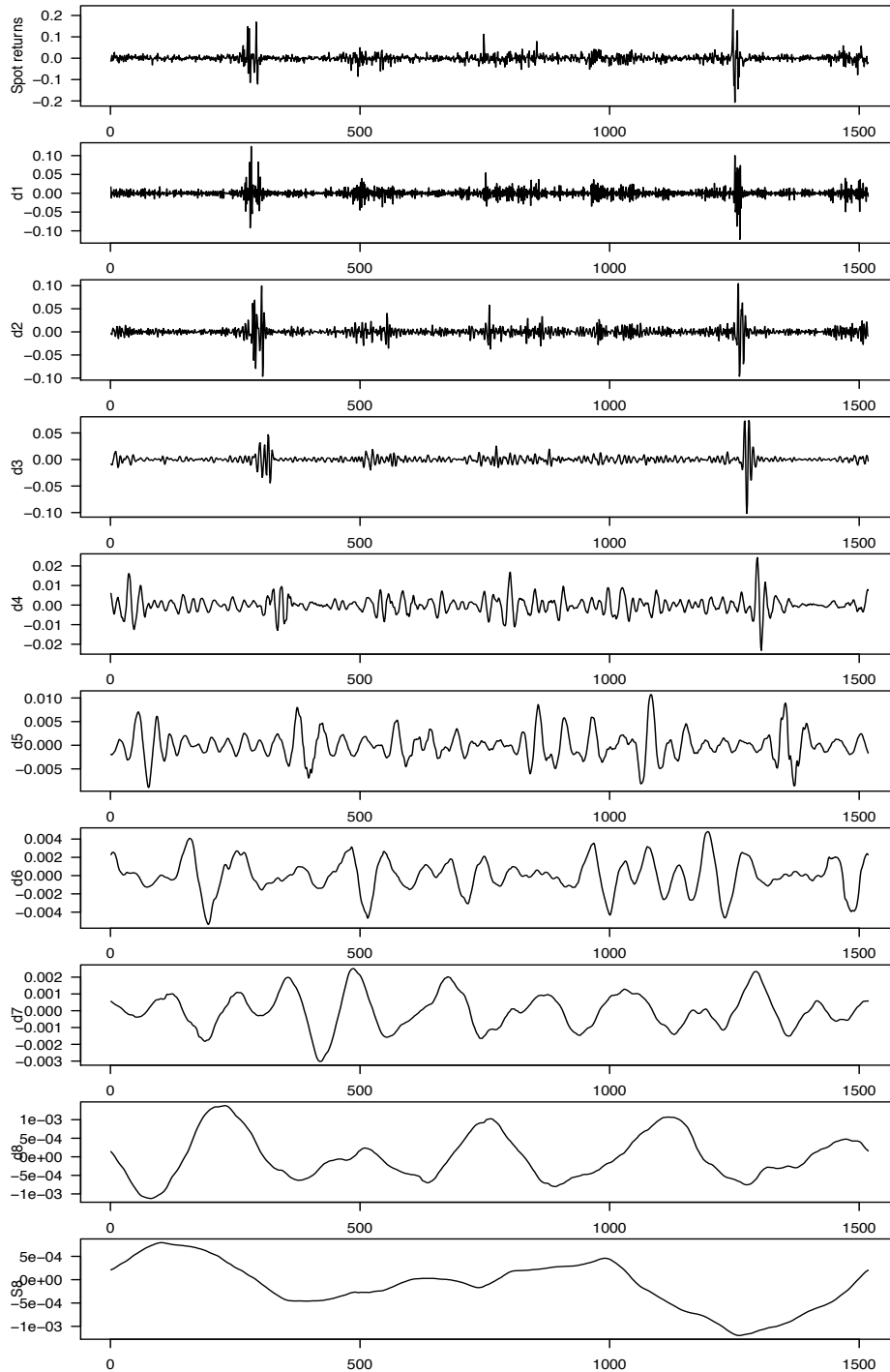


Figure 2.3: MODWT Henry Hub Futures returns (one-month ahead maturity).

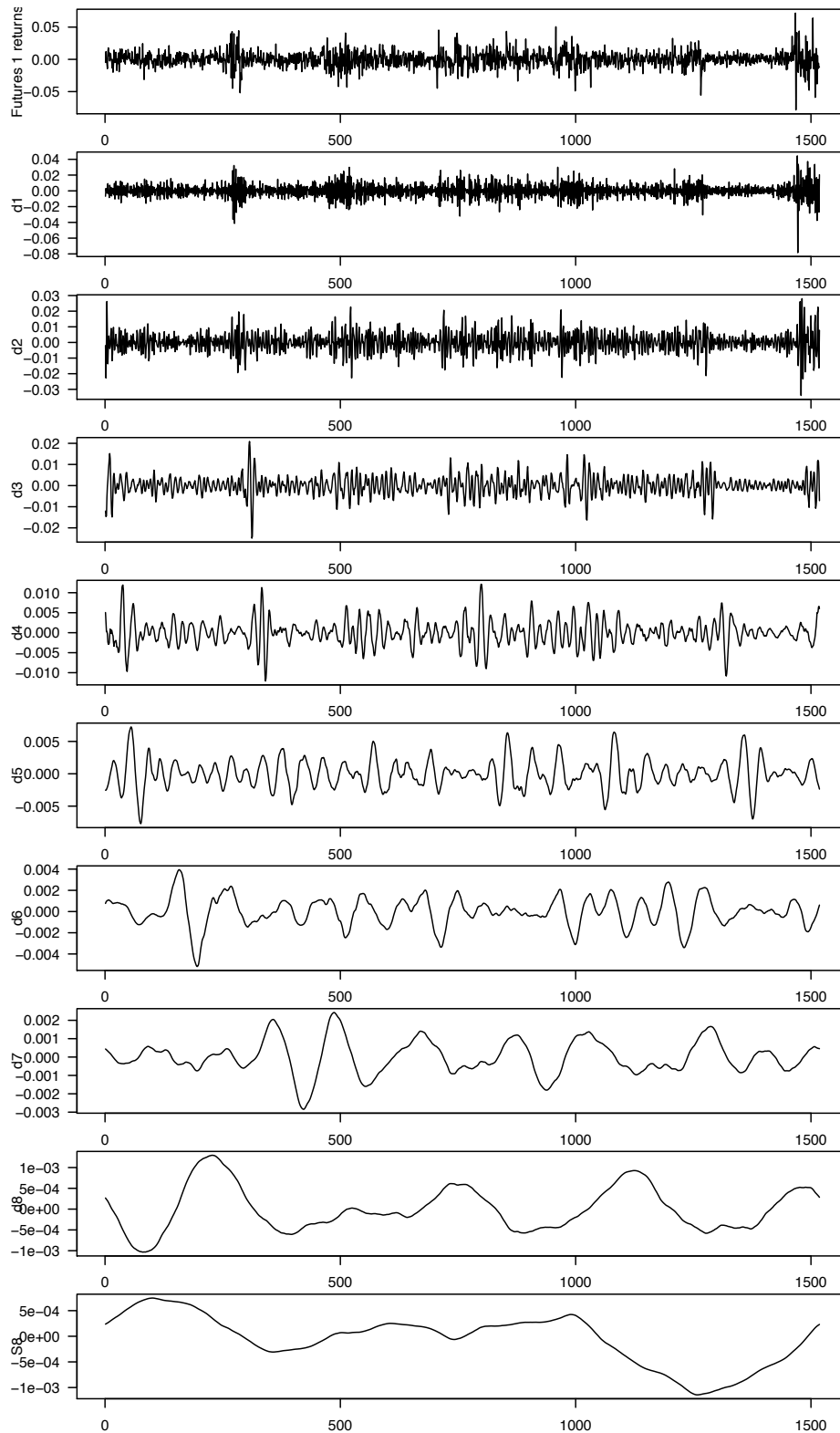


Figure 2.4: MODWT NBP spot returns.

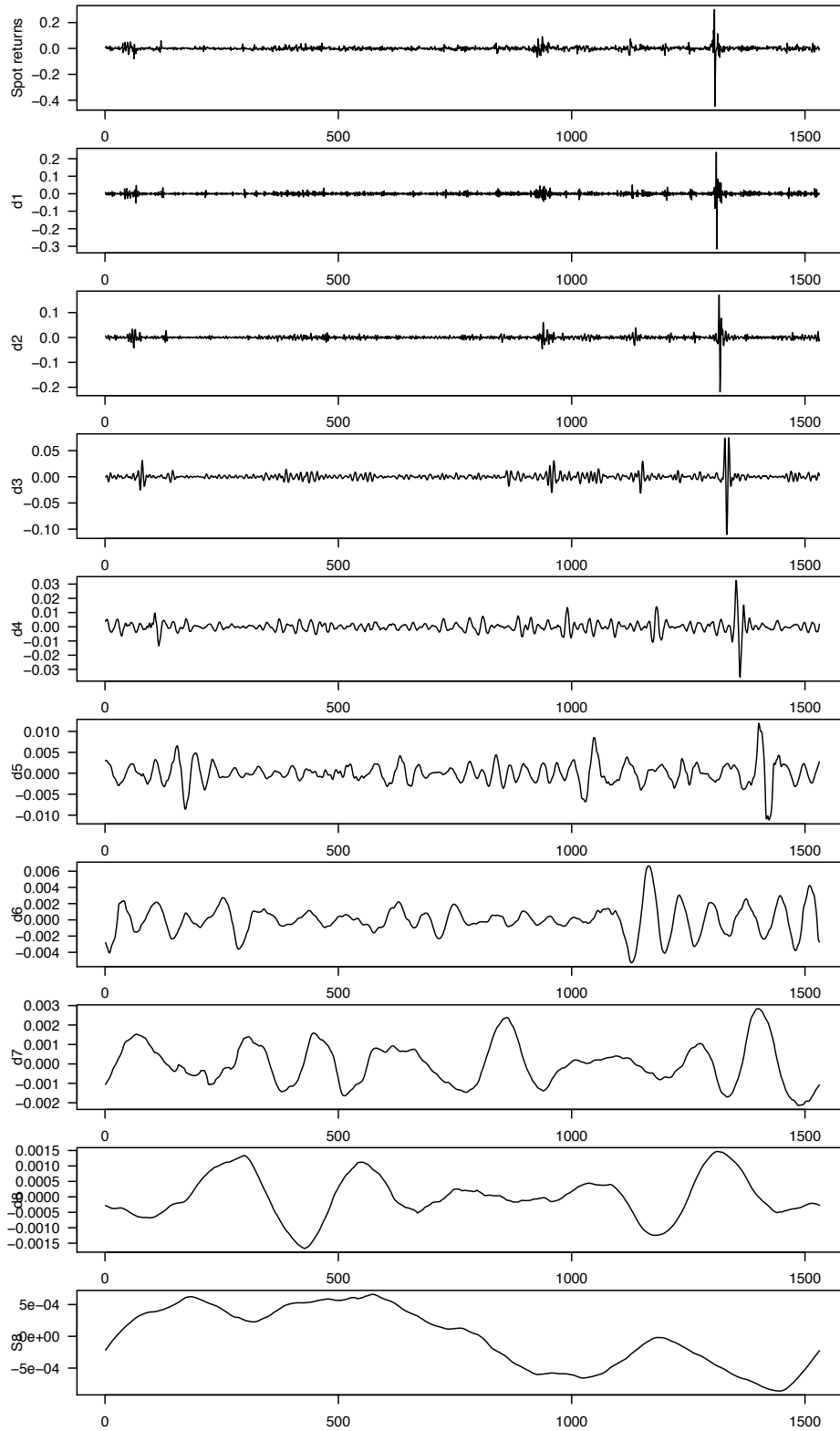


Figure 2.5: MODWT NBP futures returns (one-month ahead maturity).

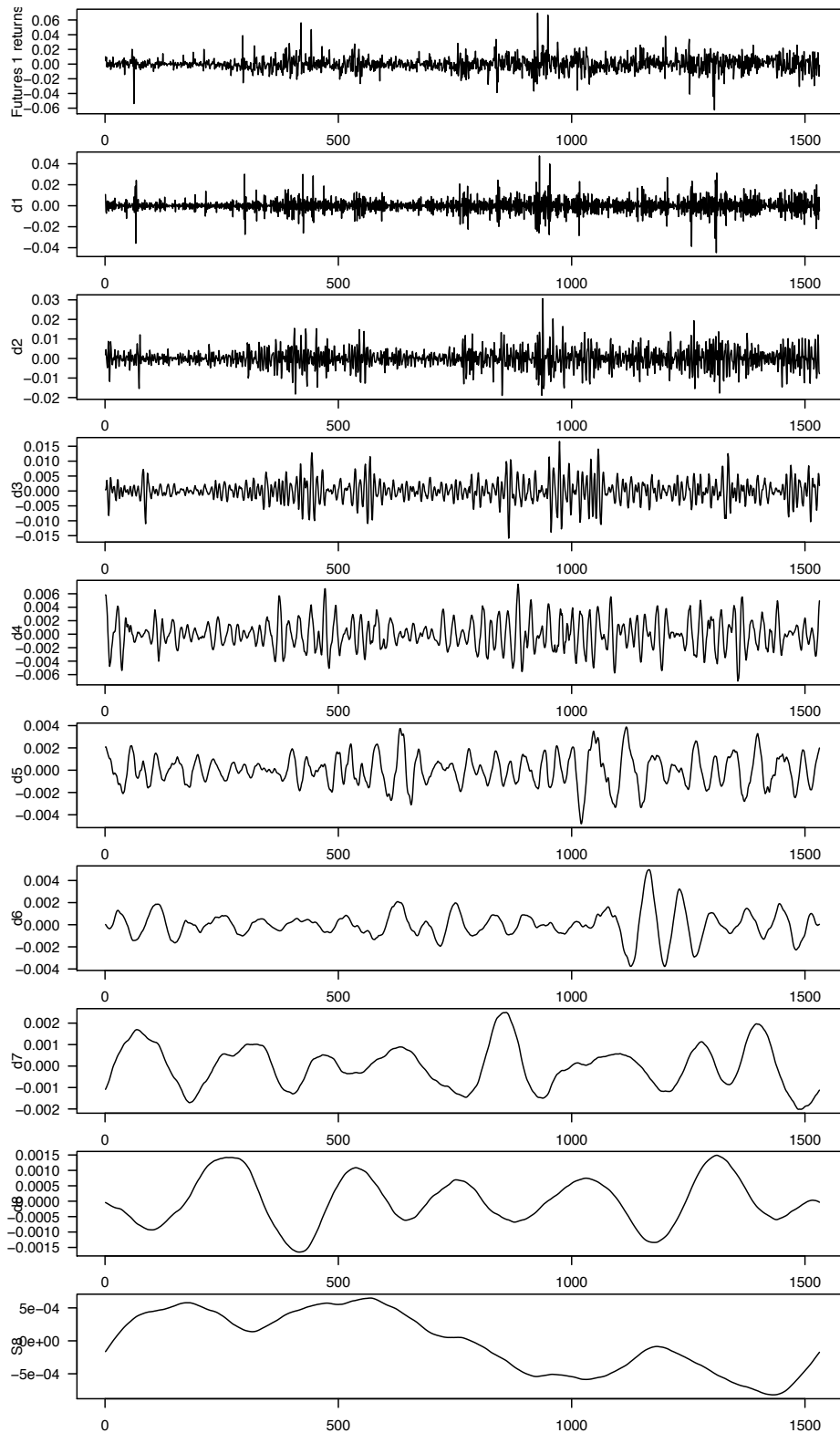


Figure 2.6: MODWT TTF spot returns.

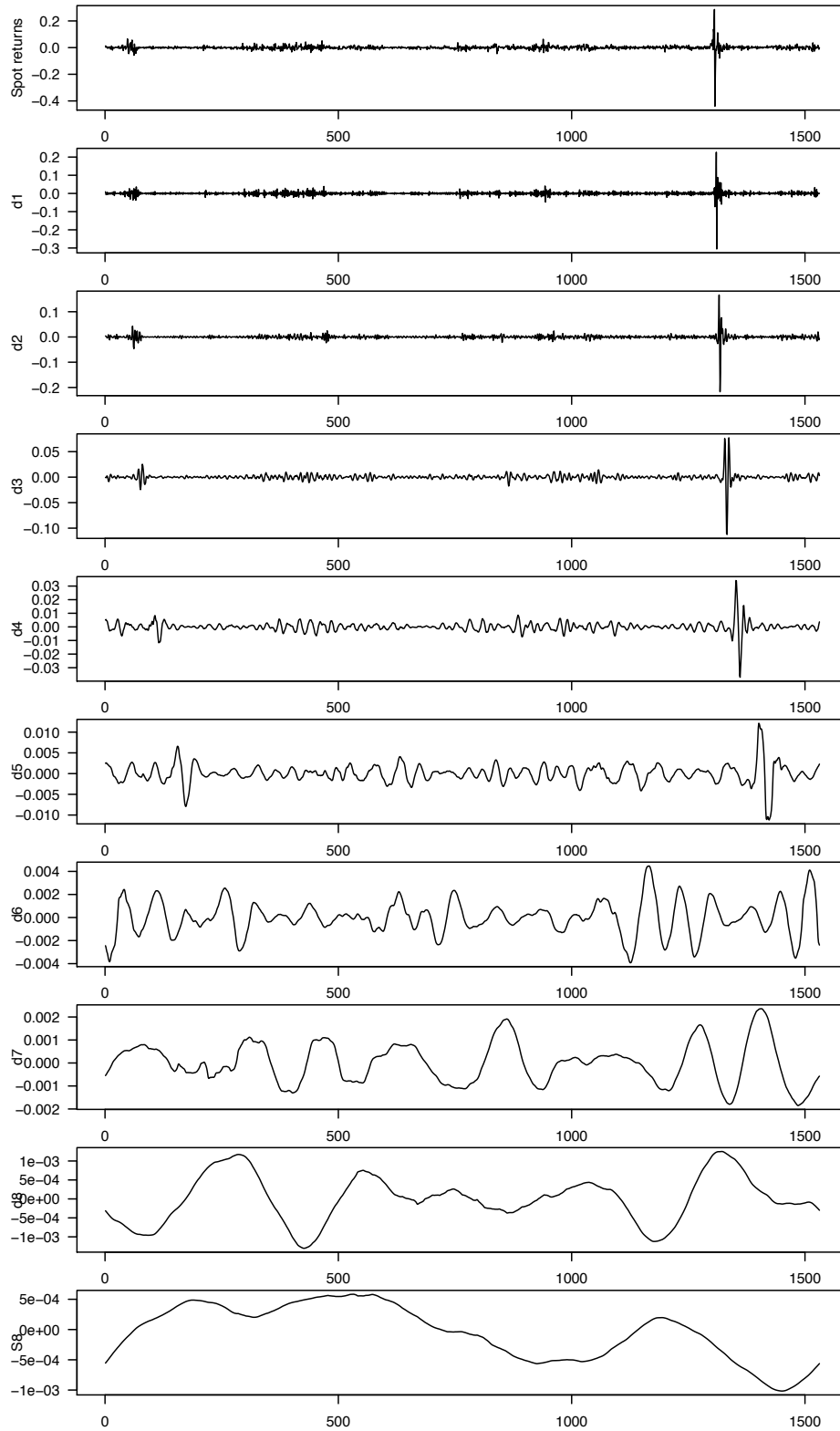


Figure 2.7: MODWT TTF Futures returns (one-month ahead maturity).

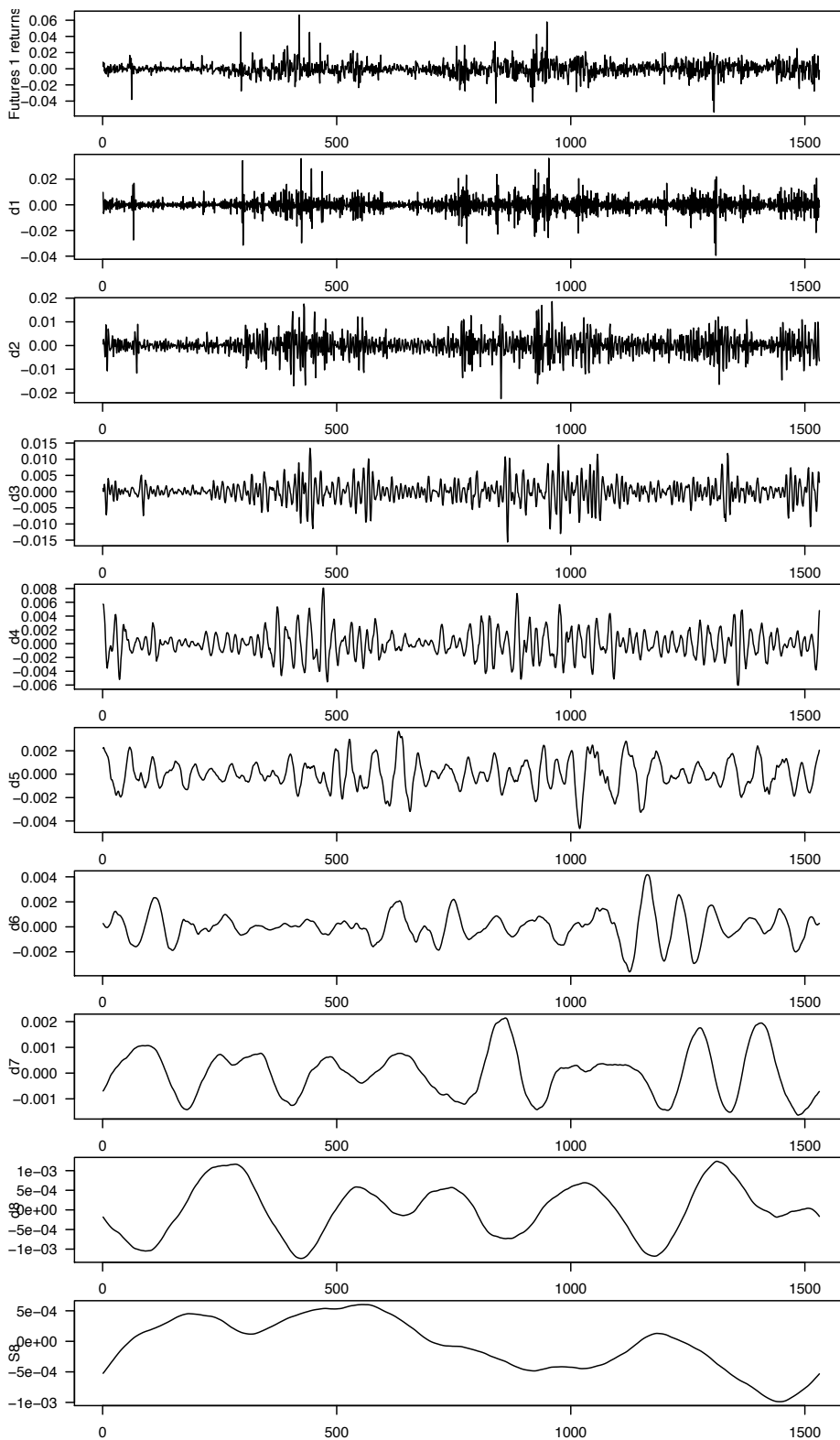


Figure 2.8: Wavelet cross-correlation between Henry Hub spot and futures1 returns.

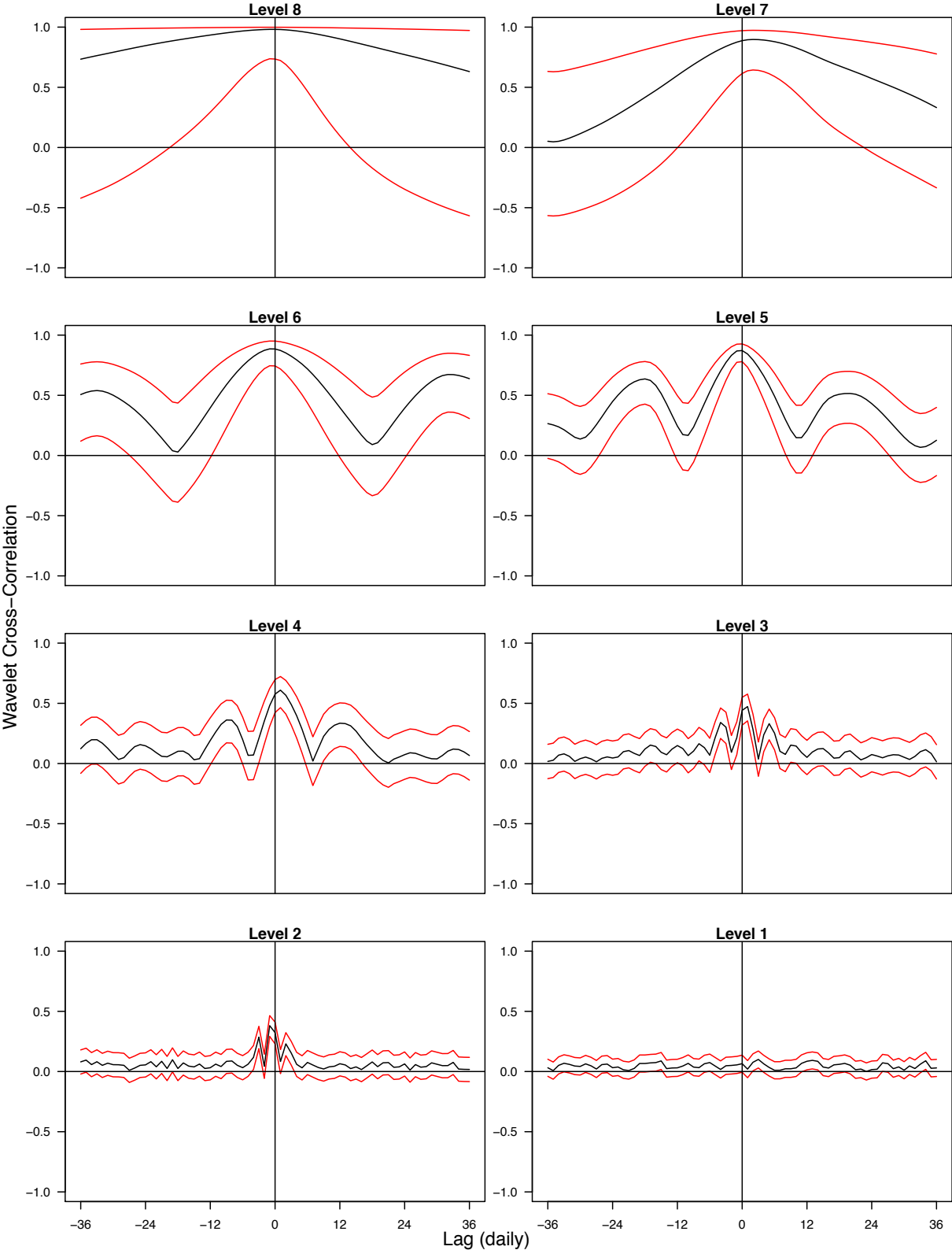


Figure 2.9: Wavelet cross-correlation between NBP spot and futures1 returns.

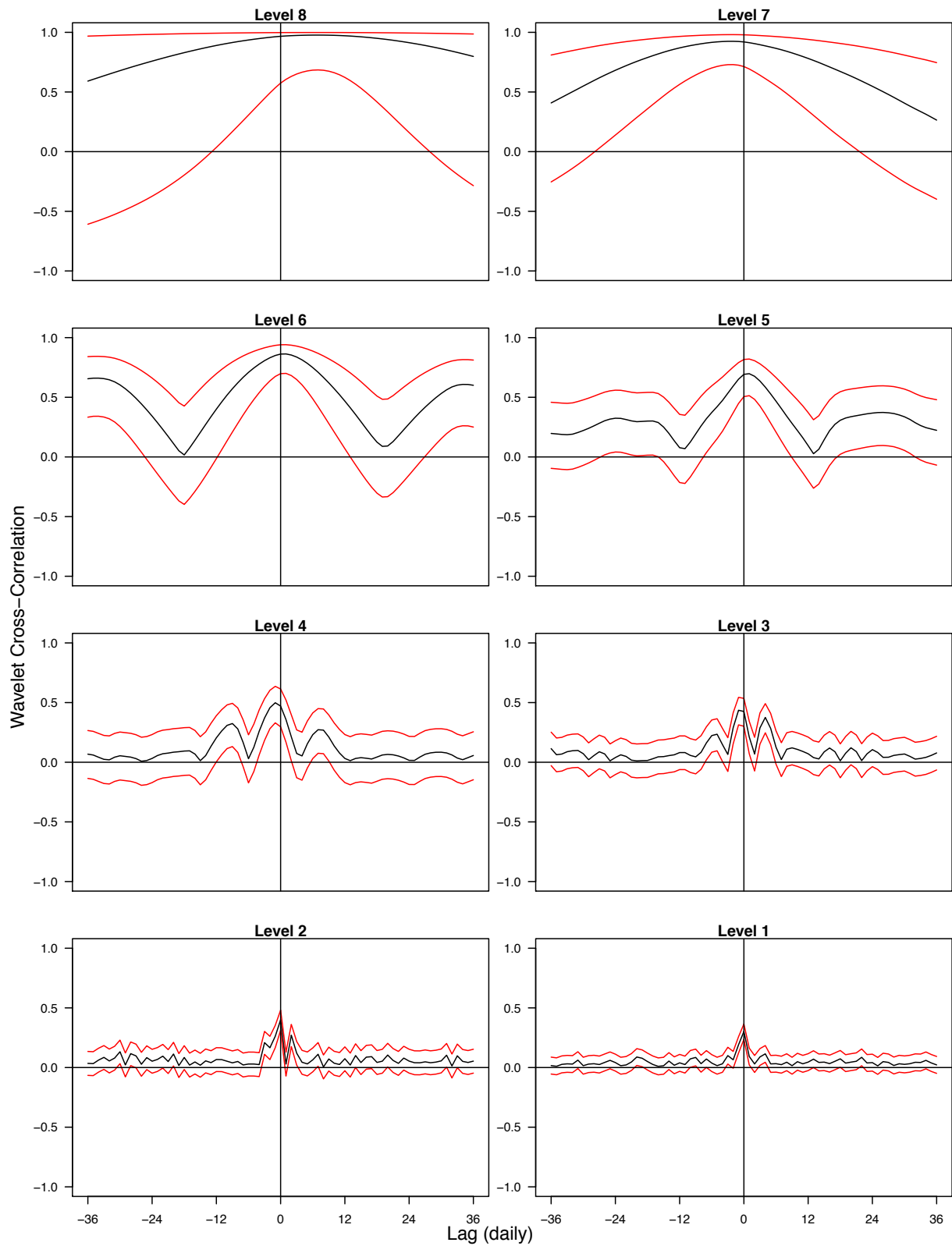
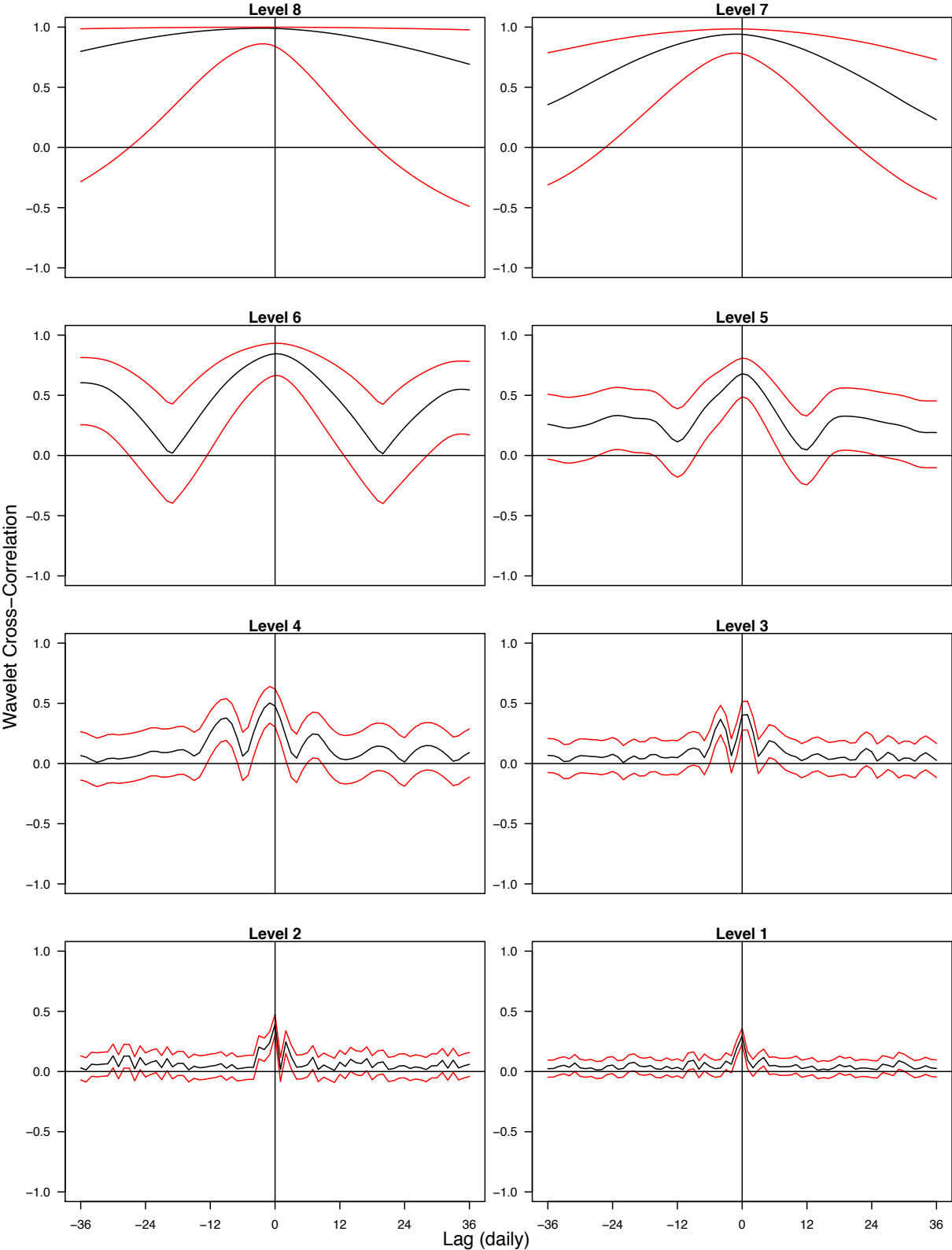


Figure 2.10: Wavelet cross-correlation between TTF spot and futures1 returns.



2.8.3 Appendix C: Johansen cointegration test between spot and futures prices.

Table 2.10: Johansen cointegration test between spot and futures prices.

No. of cointegrating eq.		<i>Maturity 1</i>			<i>Maturity 2</i>			<i>Maturity 3</i>		
		Eigen	Trace test	<i>P-value</i>	Eigen	Trace test	<i>P-value</i>	Eigen	Trace test	<i>P-value</i>
HH	None	0.0833	136.3405	0.0000	65.3736	20.2618	0.0000	0.0248	39.4988	0.0000
	At most one	0.0034	5.2028	0.2619	3.7744	9.1645	0.4467	0.0025	3.5727	0.4795
NBP	None	0.1381	230.9784	0.0000	0.07926	128.9045	0.0000	0.0583	94.3893	0.0000
	At most one	0.0022	3.4421	0.5015	0.0017	2.6397	0.6499	0.0015	2.40365	0.5245
TTF	None	0.1204	200.0916	0.0000	0.0922	151.3797	0.0000	0.0720	117.4782	0.0000
	At most one	0.0025	3.8696	0.4319	0.0022	3.3875	0.5109	0.0020	3.0964	0.5628

Note: Results of Johansen Cointegration test are reported in this table and * denotes the rejection of the null hypothesis at the 5 % significance level. Lag lengths have been selected using the Shwarz information criterion.

2.8.4 Appendix D: Linear Granger causality test based on VECM.

Table 2.11: Linear Granger causality test based on VECM.

Timescale	<i>Maturity 1</i>				<i>Maturity 2</i>				<i>Maturity 3</i>			
	<i>S → F</i>		<i>F → S</i>		<i>S → F</i>		<i>F → S</i>		<i>S → F</i>		<i>F → S</i>	
	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value
Original level												
HH	3.3199	0.1902	10.7588	0.0046	2.0899	0.1241	74.1299	0.0000	2.8417	0.0000	61.0687	0.0000
NBP	4.0015	0.1352	17.5930	0.0002	1.1367	0.5665	5.4910	0.0642	0.1477	0.9288	0.7275	0.6951
TTF	1.5945	0.4506	264.8163	0.0000	0.3515	0.8388	1.9614	0.3750	0.1477	0.9288	0.7275	0.6951

Note: Results of linear Granger causality test based on VECM of raw data are reported in this table and the lag lengths have been selected using the Shwarz information criterion.

2.8.5 Appendix E: Robustness check based on DWT

Table 2.12: Multi-scale linear Granger causality between natural gas spot returns and futures returns based on DWT

Henry Hub							
Linear Granger causality test based on VECM							
Timescale (days)	Series	Lag	Spot does not Ganger		Futures does not		Results
			cause futures	cause futures	Ganger cause spot	Ganger cause spot	
			Chi-sq	P-value	Chi-sq	P-value	
Original level	Original	5	3.319874	0.1902	10.758	0.004	Fut. \rightarrow <i>spot</i>
Multiscale linear Granger causality test based on VAR							
Original level	Original	2	1.929	0.145	108.489	1.E-44	Fut. \rightarrow <i>spot</i>
Short scale	D1	6	9.314	0.156	32.341	0	Fut. \rightarrow <i>spot</i>
	D2	4	3.174	0.529	5.939	0.203	No causality
Medium scale	D3	2	19.600	0.000	7.494	0.023	spot \leftrightarrow <i>Fut</i>
	D4	2	2.130	0.344	7.288	0.026	Fut. \rightarrow <i>spot</i>
	D5	2	8.784	0.012	3.343	0.187	No causality
Long Scale	D6	1	4.832	0.027	3.476	0.062	Fut. \rightarrow <i>spot</i>
	D7	1	0.164	0.684	1.486	0.222	No causality
	D8	1	22.173	0	22.826	0	spot \leftrightarrow <i>Fut</i>
NBP							
Linear Granger causality test based on VECM							
Timescale (days)	Series	Lag	Spot does not Ganger		Futures does not		Results
			cause futures	cause futures	Ganger cause spot	Ganger cause spot	
			Chi-sq	P-value	Chi-sq	P-value	
Original level	Original	2	4.001	0.135	17.593	0.000	Fut. \rightarrow <i>spot</i>
Multiscale linear Granger causality test based on VAR							
Original level	Original	6	2.025	0.059	14.206	0.000	Fut. \rightarrow <i>spot</i>
Short scale	D1	5	3.933	0.559	9.323	0.096	Fut. \rightarrow <i>spot</i>
	D2	3	4.392	0.222	7.215	0.065	Fut. \rightarrow <i>spot</i>
Medium scale	D3	2	8.578	0.013	15.836	0.000	spot \leftrightarrow <i>Fut</i>
	D4	1	0.800	0.371	0.357	0.549	No causality
	D5	1	0.003	0.955	6.997	0.008	Fut. \rightarrow <i>spot</i>
Long Scale	D6	1	1.343	0.2464	0.325	0.568	No causality
	D7	1	0.299	0.584	0.470	0.492	No causality
	D8	1	0.976	0.323	0.539	0.462	No causality
TTF							
Linear Granger causality test based on VECM							
Timescale (days)	Series	Lag	Spot does not Ganger		Futures does not		Results
			cause futures	cause futures	Ganger cause spot	Ganger cause spot	
			Chi-sq	P-value	Chi-sq	P-value	
Original level	Original	2	1.594	0.450	264.816	0.000	Fut. \rightarrow <i>spot</i>
Multiscale linear Granger causality test based on VAR							
Original level	Original	6	1.630	0.134	13.967	0.000	Fut. \rightarrow <i>spot</i>
Short scale	D1	5	8.681	0.122	15.175	0.009	Fut. \rightarrow <i>spot</i>
	D2	2	3.833	0.147	16.632	0.000	Fut. \rightarrow <i>spot</i>
Medium scale	D3	3	6.825	0.077	27.344	0.000	Fut. \rightarrow <i>spot</i>
	D4	1	0.283	0.594	0.776	0.378	No causality
	D5	1	0.037	0.846	4.648	0.031	Fut. \rightarrow <i>spot</i>
Long scale	D6	1	2.174	0.140	1.776	0.182	No causality
	D7	1	0.561	0.453	1.401	0.236	No causality
	D8	1	2.029	0.154	0.259	0.610	No causality

Notes: The results of the Diks and Panchenko (2006) test are reported in the table with associated p-values. A statistically significant result means the rejection of the null hypothesis of no Granger causality. F refers to the futures price returns and S to spot price returns. $F \rightarrow S$ means testing for a Granger cause from futures to physical price returns. $S \rightarrow F$ means testing for a Granger cause from the physical prices to the futures prices.

Table 2.13: Multi-scale nonlinear Granger causality test between NBP spot and futures returns based on DWT

Timescale (days)			Spot does not Ganger		Futures does not		Results
	$Lx=Ly$	T-test	P-value	T-test	P-value		
Henry Hub							
Original level							
Short scale	D1	6	2.218	0.013	2.708	0.003	spot \leftrightarrow <i>Fut</i>
	D2	4	2.980	0.001	3.528	0.000	spot \leftrightarrow <i>Fut</i>
Medium scale	D3	2	2.223	0.013	3.435	0.000	spot \leftrightarrow <i>Fut</i>
	D4	2	0.987	0.161	1.176	0.119	No causality
Long scale	D5	2	0.696	0.243	0.984	0.162	No causality
	D6	1	0.217	0.414	-0.399	0.655	No causality
	D7	1	-1.200	0.884	0.985	0.162	No causality
	D8	1	-1.195	0.884	-1.447	0.856	No causality
NBP							
Original level	Original						
Short scale	D1	5	0.663	0.253	1.516	0.064	Fut. \rightarrow <i>spot</i>
	D2	3	1.026	0.152	1.778	0.037	Fut. \rightarrow <i>spot</i>
Medium scale	D3	2	0.436	0.331	-0.791	0.785	No causality
	D4	5	1.113	0.132	-0.335	0.631	No causality
Long scale	D5	1	0.238	0.405	-0.144	0.557	No causality
	D6	1	-1.435	0.924	0.506	0.306	No causality
	D7	1	0.595	0.275	0.482	0.314	No causality
	D8	1	-1.452	0.915	-1.155	0.875	No causality
TTF							
Original level	Original						
Short scale	D1	5	0.926	0.177	1.884	0.029	Fut. \rightarrow <i>spot</i>
	D2	2	-0.020	0.507	2.565	0.005	Fut. \rightarrow <i>spot</i>
Medium scale	D3	3	-0.195	0.577	0.176	0.430	No causality
	D4	1	-0.772	0.779	0.876	0.190	No causality
Long scale	D5	1	-1.049	0.852	1.147	0.125	No causality
	D6	1	-0.914	0.819	-1.284	0.900	No causality
	D7	1	0.564	0.198	0.550	0.290	No causality
	D8	1	0.489	0.854	0.412	0.915	No causality

Notes: The results of the Diks and Panchenko (2006) test are reported in the table with associated p-values. A statistically significant result means the rejection of the null hypothesis of no Granger causality. F refers to the futures price returns and S to spot price returns. $F \rightarrow S$ means testing for a Granger cause from futures to physical price returns. $S \rightarrow F$ means testing for a Granger cause from the physical prices to the futures prices.

2.8.6 Appendix F: Robustness check based on different filter

Table 2.14: Multi-scale nonlinear Granger causality test between Natural gas spot and futures returns based on db4

Henry Hub							
Timescale (days)		Spot does not Ganger cause futures			Futures does not Ganger cause spot		Results
		$Lx=Ly$	T-test	P-value	T-test	P-value	
Short scale	D1	6	1.346	0.089	2.793	0.002	spot \leftrightarrow <i>Fut</i>
	D2	4	3.209	0.000	6.028	0.000	spot \leftrightarrow <i>Fut</i>
Medium scale	D3	2	5.786	0	10.306	0.000	spot \leftrightarrow <i>Fut</i>
	D4	2	5.524	0	9.353	0.000	spot \leftrightarrow <i>Fut</i>
Long scale	D5	2	3.035	0.001	7.172	0.000	spot \leftrightarrow <i>Fut</i>
	D6	1	3.703	0.000	5.078	0.000	spot \leftrightarrow <i>Fut</i>
	D7	1	0.763	0.222	7.114	0.000	Fut. \rightarrow <i>spot</i>
	D8	1	7.338	0	2.219	0.013	spot \leftrightarrow <i>Fut</i>
NBP							
Short scale	D1	8	2.213	0.013	3.400	0.000	spot \leftrightarrow <i>Fut</i>
	D2	10	2.052	0.020	3.395	0.000	spot \leftrightarrow <i>Fut</i>
Medium scale	D3	8	2.035	0.020	4.825	0.000	spot \leftrightarrow <i>Fut</i>
	D4	10	2.075	0.018	4.400	0.000	spot \leftrightarrow <i>Fut</i>
Long scale	D5	10	2.897	0.001	4.529	0.000	spot \leftrightarrow <i>Fut</i>
	D6	8	5.288	0	5.399	0.000	spot \leftrightarrow <i>Fut</i>
	D7	10	4.363	0.000	3.750	0.000	spot \leftrightarrow <i>Fut</i>
	D8	10	4.539	1.000	7.727	0.000	spot \leftrightarrow <i>Fut</i>
TTF							
Short scale	D1	8	2.459	0.006	3.076	0.001	spot \leftrightarrow <i>Fut</i>
	D2	8	1.552	0.060	4.757	0.000	spot \leftrightarrow <i>Fut</i>
Medium scale	D3	10	2.298	0.010	5.393	0.000	spot \leftrightarrow <i>Fut</i>
	D4	10	1.989	0.023	4.715	0.000	spot \leftrightarrow <i>Fut</i>
Long scale	D5	10	3.798	0.000	5.414	0.000	spot \leftrightarrow <i>Fut</i>
	D6	10	5.278	0.000	5.278	0.000	spot \leftrightarrow <i>Fut</i>
	D7	10	5.121	0.000	4.240	0.000	spot \leftrightarrow <i>Fut</i>
	D8	10	0.312	0.377	6.680	0.000	Fut. \rightarrow <i>spot</i>

Notes: The results of the Diks and Panchenko (2006) test are reported in the table with associated p-values. A statistically significant result means the rejection of the null hypothesis of no Granger causality. F refers to the futures price returns and S to spot price returns. $F \rightarrow S$ means testing for a Granger cause from futures to physical price returns. $S \rightarrow F$ means testing for a Granger cause from the physical prices to the futures prices.

Table 2.15: Multi-scale linear Granger causality between natural gas spot returns and futures returns based on db4

Henry Hub							
Linear Granger causality test based on VECM							
Timescale (days)	Series	Lag	Spot does not Ganger cause futures		Futures does not Ganger cause spot		Results
			Chi-sq	P-value	Chi-sq	P-value	
Original level	Original	5	3.319	0.190	10.758	0.0046	Fut. \rightarrow <i>spot</i>
Multiscale linear Granger causality test based on VAR							
Original level	Original	2	1.929	0.145	108.489	1.E-44	Fut. \rightarrow <i>spot</i>
Short scale	D1	6	12	37.226	159.333	0.000	spot \leftrightarrow <i>Fut</i>
	D2	4	8	18.760	123.656	0.000	spot \leftrightarrow <i>Fut</i>
Medium scale	D3	2	8	23.681	200.315	0.000	spot \leftrightarrow <i>Fut</i>
	D4	2	12	51.054	327.703	0.000	spot \leftrightarrow <i>Fut</i>
Long scale	D5	2	8	36.656	309.518	0.000	spot \leftrightarrow <i>Fut</i>
	D6	1	8	270.578	90.852	0.000	spot \leftrightarrow <i>Fut</i>
	D7	1	8	23.055	321.674	0.000	spot \leftrightarrow <i>Fut</i>
	D8	1	12	433.053	104.512	0.000	spot \leftrightarrow <i>Fut</i>
NBP							
Linear Granger causality test based on VECM							
Timescale (days)	Series	Lag	Spot does not Ganger cause futures		Futures does not Ganger cause spot		Results
			Chi-sq	P-value	Chi-sq	P-value	
Original level	Original	2	4.001	0.135	17.593	0.000	Fut. \rightarrow <i>spot</i>
Multiscale linear Granger causality test based on VAR							
Original level	Original	6	2.025	0.059	14.207	0.000	Fut. \rightarrow <i>spot</i>
Short scale	D1	8	14.868	0.062	15.748	0.046	spot \leftrightarrow <i>Fut</i>
	D2	12	30.063	0.003	50.447	0.000	spot \leftrightarrow <i>Fut</i>
Medium scale	D3	8	34.129	0.000	53.290	0.000	spot \leftrightarrow <i>Fut</i>
	D4	12	16.835	0.156	49.374	0.000	Fut. \rightarrow <i>spot</i>
Long scale	D5	12	55.619	0.000	123.339	0.000	spot \leftrightarrow <i>Fut</i>
	D6	8	50.073	0.000	94.069	0.000	spot \leftrightarrow <i>Fut</i>
	D7	12	84.268	0.000	123.003	0.000	spot \leftrightarrow <i>Fut</i>
	D8	12	232.890	0.000	195.163	0.000	spot \leftrightarrow <i>Fut</i>
TTF							
Linear Granger causality test based on VECM							
Timescale (days)	Series	Lag	Spot does not Ganger cause futures		Futures does not Ganger cause spot		Results
			Chi-sq	P-value	Chi-sq	P-value	
Original level	Original	2	1.594	0.450	264.816	0.000	Fut. \rightarrow <i>spot</i>
Multiscale linear Granger causality test based on VAR							
Timescale (days)			Spot does not Ganger cause futures		Futures does not Ganger cause spot		Results
			F-test	P-value	F-test	P-value	
Original level	Original	6	1.630	0.134	13.967	2.E-15	Fut. \rightarrow <i>spot</i>
Short scale	D1	8	12.399	0.134	19.228	0.014	Fut. \rightarrow <i>spot</i>
	D2	8	17.987	0.021	32.965	0.000	spot \leftrightarrow <i>Fut</i>
Medium scale	D3	12	40.150	0.000	50.672	0.000	spot \leftrightarrow <i>Fut</i>
	D4	12	24.524	0.017	59.214	0.000	spot \leftrightarrow <i>Fut</i>
Long scale	D5	12	70.627	0.000	115.015	0.000	spot \leftrightarrow <i>Fut</i>
	D6	12	74.121	0.000	144.793	0.000	spot \leftrightarrow <i>Fut</i>
	D7	12	77.726	0.000	116.461	0.000	spot \leftrightarrow <i>Fut</i>
	D8	12	264.458	0.000	168.496	0.000	spot \leftrightarrow <i>Fut</i>

Notes: The results of the Diks and Panchenko (2006) test are reported in the table with associated p-values. A statistically significant result means the rejection of the null hypothesis of no Granger causality. F refers to the futures price returns and S to spot price returns. $F \rightarrow S$ means testing for a Granger cause from futures to physical price returns. $S \rightarrow F$ means testing for a Granger cause from the physical prices to the futures prices.

Chapter 3

Natural gas at the energy-climate nexus: a bridge fuel or a barrier?

Foreward

Even if this work could not have been presented at conferences due to the health crisis, it benefited from fruitful discussions with Anna Creti and members of the Chair Economcis of Natural Gas. I also had the chance to disucuss this work with Peter Hartley and Jim Krane at the Rice University of Houston and participants of the USAEE workshop on the long term outlook for Natural gas and the French-American Chamber of Commerce of Houston workshop on the impact of climate risk on the energy investment industry in February 2020.

Abstract

Are natural gas and intermittent renewable sources of electricity competitors or rather provide some scope of complementarity? We propose to empirically assess the economic potential of wind and solar penetration in the U.S. electricity generation mix under a multi-factorial perspective. The modeling strategy considers the possibly non-linear nature of the renewable energy dynamics by estimating a Markov Regime-Switching Model (MRSMS) based on monthly data from January 2010 to December 2019 of wind and solar electricity generation. Four alternative MRSMSs are estimated. Each of the four regressions looks at the determinants of invested wind and solar capacities by adopting a “from specific to general” strategy to better grasp the economic potential of renewables penetration. First, our results support the hypothesis that renewable electricity generation dynamics is non-linear, switching between a high regime and a low regime of production. Second, results portend a higher probability of being in a high regime of wind power generation and a low regime of solar power generation. Thirdly, natural gas and wind energies are more prompt to be substitutes whereas natural gas and solar energies exhibit more scope for complementarity. We discuss the crucial role of storage in the deployment of such technologies.

3.1 Introduction

The frantic race for the U.S. most dominant source of electric power is passing a turning point. The sustained development of shale gas resources along with the shift in economics between existing coal-fired and natural gas-fired combined-cycle generators led to a significant drop in the rate of use of coal-fired power plants. In 2019, the average capacity factor of the U.S. coal-fired fleet was 48% compared with an average natural gas-fired combined-cycle capacity factor of 58% (EIA, 2020). Concomitantly, generating capacity fueled by renewable energy sources, especially solar and wind, has increased steadily (cf. Figure 3.1). EIA expects the U.S. electric power sector will add 19.3 GW of new utility-scale solar capacity in 2019 and 2020, a 65% increase from 2018 capacity levels. Notwithstanding the continued decline in the capital costs¹ for new wind and solar projects, these technologies would have not been able to compete without subsidies and mandates that have largely supported their growing share in the U.S. electric mix.

Focal point of debates on the reduction of greenhouse gas emissions, the above mentioned highly influential developments leaves open the question of whether renewable energies and natural gas technologies are competitors or rather provide some scope of complementarities. The quest of their true relationship has been grasped by the economic literature and the policy arena that largely regard them as substitutes, implying that increased fuel prices would ultimately lead to a rise of investments in renewable energies.² The theoretical literature mostly unravels the way choices of capacity between intermittent and conventional generation technologies are done. While Aflaki and Netessine (2017) investigate a strategic market-based rationale, others retained a social a point of view such as the general equilibrium in Schwerin (2013) or the partial equilibrium analysis in Ambec and Crampes (2010).

Nevertheless, the hypothesis of a *stricto sensu* substitution between reliable source of electricity production and intermittent sources such as wind or solar power have been tempered in the literature. They might be strategic complements when renewable generation is unfavorable,

¹See Figure 3.9 in Appendix C.

²The current natural gas dynamics with enhanced availability and low prices largely propelled by the shale oil and gas advent is believed to lead to a gas dominated electricity sector where renewable energy is muffled by a large surge of natural gas and coal is displaced (Small et al., 2014 ; Shearer et al., 2014).

remaining substitutes at the equilibrium Bouckaert and De Borger (2013). Renewable capacity could also be seen as a substitute to baseload technologies and complementary to peak generation technologies (Garcia, Alzate, and Barrera, 2012). Yuan et al. (2011) claim that “the wind generation capacity generally substitutes the investment in combined cycle gas turbine capacity but complements the investment in gas turbine units.” In the policy arena, Lee et al. (2012) support the idea of a complementary relationship by considering technical, economic, environmental and political context. Renewable technologies and natural gas are assumed to have different risk profiles and as such offer complementary portfolio options (e.g. high volatility of natural gas prices vs. zero fuel costs for renewables, low upfront costs for natural gas plants vs. hardly competitive wind and solar energy projects). As far as the empirical literature on the determinants of renewable energy generation is concerned, the latter largely focused on the impact of policy measures such as renewable portfolio standards or feed-in tariffs (see among others, Delmas and Montes-Sancho (2011), Hitaj (2013), Polzin et al. (2015), Marques, Fuinhas, and Manso (2010), Shrimali and Kniefel (2011)).

Beyond the above-mentioned extent of possible substitutabilities and complementarities between natural gas and renewable energy, the economic literature also disagree as to which combinations of a plethora of potential drivers will allow for a wide penetration of wind and solar technologies (e.g. declining renewable costs of conventional technologies, climate policies, energy storage availability)³. As emphasized by Bistline and Young (2019), the model structures and input assumptions can explain such differences, but the main reason lies to the fact that most of them focus on couple of drivers taken in isolation (e.g. Fell and Linn (2013) and Craig, Jaramillo, and Hodge (2018)). For example, Rodríguez et al. (2015) investigated the effect of government policies on private finance investment in renewable energy and found that, in contrast to quota-based schemes, price-based support schemes are positively correlated with private finance contributions. In the same vein, Criscuolo et al. (2014) examined the role of different environmental policy measures (e.g. feed-in-tariffs, tradable renewable certificates, sales tax or VAT reduction, and direct capital investment support through subsidies, grants, rebates, and tax incentives) in inducing early-stage financing. Their results suggest strong evidence for the role

³See e.g. MacDonald et al. (2016), Luderer et al. (2017), Bistline and Young (2019), Mai et al. (2018), Craig, Jaramillo, and Hodge (2018), and Sepulveda et al., 2018.

of such policy measures in allowing for increased levels of finance, especially for policy measures related to investment costs. The question of a break-even carbon emission price that would propel carbon capture and storage technologies is also examined by Íşlegen and Reichelstein (2011). Across a range of climate policies, Shearer et al. (2014) find that abundant natural gas will decrease use of both coal and renewable energy technologies in the future.

The present research aims to connect these strands of literature in a consistent framework able to comprehensively assess the economic potential of wind and solar penetration under many prospective drivers and explore in the same vein the degree of gross substitutabilities/ complementarities between natural gas and renewable energy. In this sense, we are interested in the same problem to the one discussed by Bistline and Young (2019) and Baranes, Jacquemin, and Poudou (2017).⁴ From an empirical perspective, the modeling strategy retained in the present paper considers the possibly non-linear nature of the renewable energy dynamics. More specifically, we test for the presence of regime effect by estimating a Markov Regime-Switching Model (MRSM) based on monthly data from January 2010 to December 2019 of wind and solar electricity generation and potential explanatory variables spanning from electricity market, carbon policy risks to global economic health. Four alternative MRSMs are estimated. Each of the four regressions looks at the determinants of invested wind and solar capacities by adopting a “from specific to general” strategy to better grasp the economic potential of renewables penetration under five prospective drivers. More precisely, we compare models that gradually add information variables to comprehensively assess their relative magnitude and explore thoroughly the extent of substitutabilities with the natural gas market.

Our contribution lies to the estimation of a Markov Switching Regression Model (MRSM) that has a number of interesting features that make it attractive for our purpose.⁵ A MRSM provides a fairly simple way to capture more complex non-linear dynamic patterns such as asymmetries and regimes shifts of energy markets in a simple dynamic econometric model. A

⁴Our objective is to measure the relative magnitude of a range of potential drivers, spanning from policy support, electricity market factors, declining renewable costs, carbon policies and global economic growth to understand which factor or combination of factors foster or limit the wind and solar penetration.

⁵The seminal work of (Hamilton, 1989) suggested that quarterly real gross national product exhibits significant asymmetries stemming from the differences in the mean growth rates, in the transition probabilities between the two states, and in the unconditional expected duration of each state.

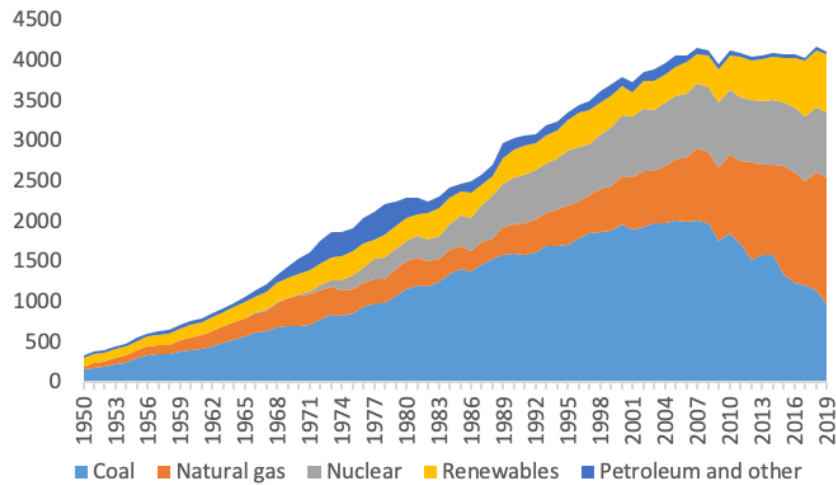


Figure 3.1: U.S. electricity generation by major energy source, 1950-2019

novel feature of the Markov switching model is that the switching mechanism is controlled by an unobservable state variable that follows a first-order Markov chain. The process can switch between regimes repeatedly over the sample and we are able to estimate the probabilities associated with each state. We avoid plausible model misspecification incurred when the sample estimation is simply splitted into different subsamples to test for the presence of a structural break.⁶ Also, MRSM admits only occasion and exogenous changes and are therefore suitable for describing correlated data that exhibit distinct dynamic patterns during different time periods. This aspect is important as our sample period incorporates several financial, economic and geopolitical events: between the new geopolitical world that is emerging from the US shale oil and gas revolution or the technological advances and falling costs of renewables energy sources.⁷ More importantly, states of investment in renewables are unobservable in essence: therefore, the Markov Regime Switching model is appropriate to capture unobserved regimes with an estimation of transition probabilities and expected durations for each regime. More interestingly, we have coupled the Markov Switching specification to a strategy that gradually add information variables to the model, so that the true determinants of renewable electricity penetration can

⁶Following this methodology, we have to accept the hypothesis according to which all parameters change at the same time and we need to define a priori break date (Boivin, 2006).

⁷It is important to note that these events are exogenous only with respect to triggering regime switch for the Markov process and not with respect to their impact on the US renewable invested capacity.

be observed.

Our results have useful implications. First, regarding the relationship between intermittent renewable generation and natural gas cost, we provide evidence in favor of a significant interdependence between these two modes of production. More importantly, our results support the hypothesis that this relationship is non-linear, switching between a high regime and a low regime of renewable electricity generation. This result implies that, for a relatively high level of production via renewables, a marginal increase in gas prices tends to increase the share of renewable production. This relationship of substitutability no longer holds when we switch to a lower production regime, given that a marginal increase in the price of gas generates a fall in the share of production of renewables. Secondly, our model portends a higher probability of being in a high regime of wind power generation and a low regime of solar power generation. The probability of remaining in the low regime of solar energy generation is around 95% on average and the probability to switch from a low regime to a high regime of wind energy generation varies between 39% and 46%, depending on the considered model. Thirdly, results have shown that natural gas and wind energies are more prompt to be substitutes whereas natural gas and solar exhibit more scope for complementarity. We discuss the possible degree of wind substitution by natural gas, emphasizing the technological factor able to promote a range of innovations such as those of shale oil and gas and put into perspective the crucial question posed by the role of storage in the deployment of these technologies to counteract the issue of intermittency.

The retained approach in this paper echoes the one followed by Baranes, Jacqmin, and Poudou (2017) but enriches and complements it in several ways. First, we are not only examining the differences in the impact of our explanatory variables according to the regime considered, but also deliver the probability associated with the high renewable production regime as well as with the lower production regime, the probability of transiting to each other and their expected durations.⁸ Second, we examine the relationship between the gas cost and that of electricity

⁸Starting from the premise that ranking states by the proportion of invested capacities in intermittent renewables energies could be misleading when the associated networks are characterized by a high level of trade in electricity, we have chosen to work on a federal level. For example, Hartley (2018) focused on the Texan ERCOT system because the latter has weak connections with its neighbors and could be considered as a standalone network.

production from renewable energy from a multifactorial angle where non-linearity is tested for all the informative variables integrated into the model. In fact, the degree of investment is non-linear with the cost of natural gas cost but not only: regime shifts can emanate from factors related to the electricity market, carbon policy risk, global economic health and renewable technologies costs. Thirdly, we have examined renewable production under two distinct spectra: that of wind and solar energies whose dynamics are not completely similar.

The structure of the paper is as follows: Section 2 describes methodology of Markov Regime Switching. Section 3 presents the used data and Section 4 yields estimation outputs of alternative Markov Regime Switching models. We discuss the results in Section 5 before providing concluding remarks in Section 6.

3.2 Empirical strategy

Hamilton (1989) pioneering work rests on the existence of regime changes that are not directly observable but for which a probabilistic inference would make it possible to know whether these regime changes took place and when they took place; all based on the observable behavior of the series in question. The major advantage of Markov-switching models lies in their ability to capture the non-linear asymmetry and persistence phenomena in extreme observations that are commonly observed in energy data. In this regard, regime switching models are used in the electricity prices modeling as a result of their empirical performance and their ability to deal with multiple equilibria in markets with repeated interactions (Fabra and Toro, 2005). See for example, Weron, Bierbrauer, and Trück (2004), Mari (2006), Karakatsani and Bunn (2008), Janczura and Weron (2010), and Sapio (2015). In the context of our paper, the use of this type of model is motivated by the desire to investigate the effect of various potential drivers on the penetration of renewable energies in the U.S. electric mix.

The Markov Regime-Switching model is widely used in the detection of business cycles by estimating so-called latent state variables. In this regard, Hamilton (1989) introduced the founding model of Markov Switching in order to detect American business cycles by comparing them to the estimated NBER cycles. An important literature has continued in this line of research: for example, Filardo (1994), Kim and Nelson (1998), Chauvet (1998) among others. All these analyzes allow Markov Switching models to constitute a real alternative to linear models

by authorizing changes in parameters via stochastic processes. Changes in volatility between periods of contraction and expansion are therefore detected through probabilistic inference. By authorizing regime changes to the time series generating process, Markov Switching models have been proposed as an alternative to constant parameter models, linear time series models which are part of the traditional modeling of Box and Jenkins (1970). The general idea behind these regime change models is such that the parameters of a vector time series process $\{ y_t \}$ of dimension K , depend on an unobservable state variable $s_t \in \{ 1 \dots ,M\}$, that represents the probability of being in a particular state of the world (Krolzig, 2000) such as:

$$p(y_t | (Y_{t-1}, X_t, s_t)) = \begin{cases} f(y_t | (Y_{t-1}, X_t, \theta_1)) & \text{if } s_t = 1 \\ \cdot & \\ \cdot & \\ \cdot & \\ f(y_t | (Y_{t-1}, X_t, \theta_M)) & \text{if } s_t = M \end{cases} \quad (3.1)$$

where $Y_{t-1} = \{y_{t-j}\}_{j=0}^{\infty}$ indicates the history of y_t , X_t represent exogenous variables and θ_m the parameter vector associated to regime m . The regime-generating process is a homogenous and ergodic first order Markov chain with a finite number of states defined by the transition probabilities:

$$p_{ij} = Pr(s_{t+1} = j | s_t = i), \sum_{j=1}^M p_{ij} = 1 \forall i, j \in \{1, \dots, M\} \quad (3.2)$$

The probability of transition from regime 1 to regime m at time period $t+1$ depends entirely on the regime at time period t .

In the seminal work of Hamilton (1989) , U.S. business cycles are modeled as switching regimes of the stochastic process generating the growth rate of real output Δy_t :

$$\Delta y_t - \mu(s_t) = A_1 (\Delta y_{t-1} - \mu(s_{t-1})) + \dots + A_p (\Delta y_{t-p} - \mu(s_{t-p})) + u_t \quad (3.3)$$

Where μ represent the mean growth rate of y_t and u_t is normally and independently distributed. Two regimes (expansions and contractions) are associated with different conditional distributions of the growth rate of real output where μ depends on the state s_t (Krolzig, 2000).

This general form has been extended to a multivariate framework as in Raymond and Rich (1997), Jeanne and Masson (2000), Frömmel, MacDonald, and Menkhoff (2005). In this line, the approach used in this paper refers to a dynamic multivariate Markov-Switching model, as described in equations 3.4 and 3.5, in order to investigate the drivers of wind and solar production in the U.S. and sharpen our knowledge on the relationship with the gas market.

$$WIND_t = \beta_{0,S_t} + \beta_{1,S_t} t + \sum_{i=2}^n \beta_{i,S_t} X_{i,t} + u_t \quad (3.4)$$

$$SOLAR_t = \beta_{0,S_t} + \beta_{1,S_t} t + \sum_{i=2}^n \beta_{i,S_t} X_{i,t} + u_t \quad (3.5)$$

$WIND_t$, $SOLAR_t$ are wind and solar electricity generation, S_t represents the regime at time t , and $X_{i,t}$ the explanatory variables i at time t and u_t the error term following a normal distribution. Parameters β_{0,S_t} , β_{1,S_t} , ..., β_{n,S_t} are regime-dependant time-varying parameters. Maximum likelihood methodology of MSM is employed in this paper in order to detect potential regime changes as explained in Hamilton (1989) by employing analytical derivatives of Feasible Sequential Quadratic Programming (SQPF) (see Lawrence and Tits, 2001).

We estimate equations 3.4 and 3.5 in the framework of two regimes then we derive the regression coefficients which are regime-dependent. Since the Markov chain is unobservable, the probability of being in a specific state is included in our estimation results. A Markov-Switching Regression Model is deemed to be good-fit when the smoothed probabilities are either close to zero or to one. In this context, we follow Ang and Bekaert (2002) approach to estimate the regime classification measure (RCM) that characterizes the accuracy of Markov-Switching Regression models.

$$RCM(S) = 100S^2 \frac{1}{T} \sum_{t=1}^T \prod_{j=1}^S p_{j,t} \quad (3.6)$$

RCM corresponds to the average of the product of smooth probabilities p and s , the number of states. The RCM can take values ranging from 0 to 100. Lower is the RCM value and better is the ability of the model to discriminate between regimes.

3.3 Data

3.3.1 Preliminary analysis of the data

Our dataset comes from the U.S. Energy Information Administration (via the Electric Power Monthly report) where monthly data on net generation of electricity from renewables⁹ (wind and solar), average cost of natural gas delivered for electricity generation and revenue from retail sales of electricity is available. We also rely on the Module Spot Price Index¹⁰ from Bloomberg New Energy Finance platform and the Nasdaq (NQ) wind index that tracks companies involved in the production of wind power to capture technological cost evolution of the wind and solar industry. As stringent carbon policies are prone to significantly impact renewable energy penetration if enacted by raising the costs of emissions-intensive generation, we also consider the S&P 500 Carbon Efficient Index as a carbon policy risk proxy. Finally, as energy technology is deemed to have a strong influence on, and is also strongly influenced by, economic growth, the Business Confidence Index¹¹, as published by the OECD website, allows us to take into account the macroeconomic anticipations surrounding the decision to invest in intermittent renewable capacities.

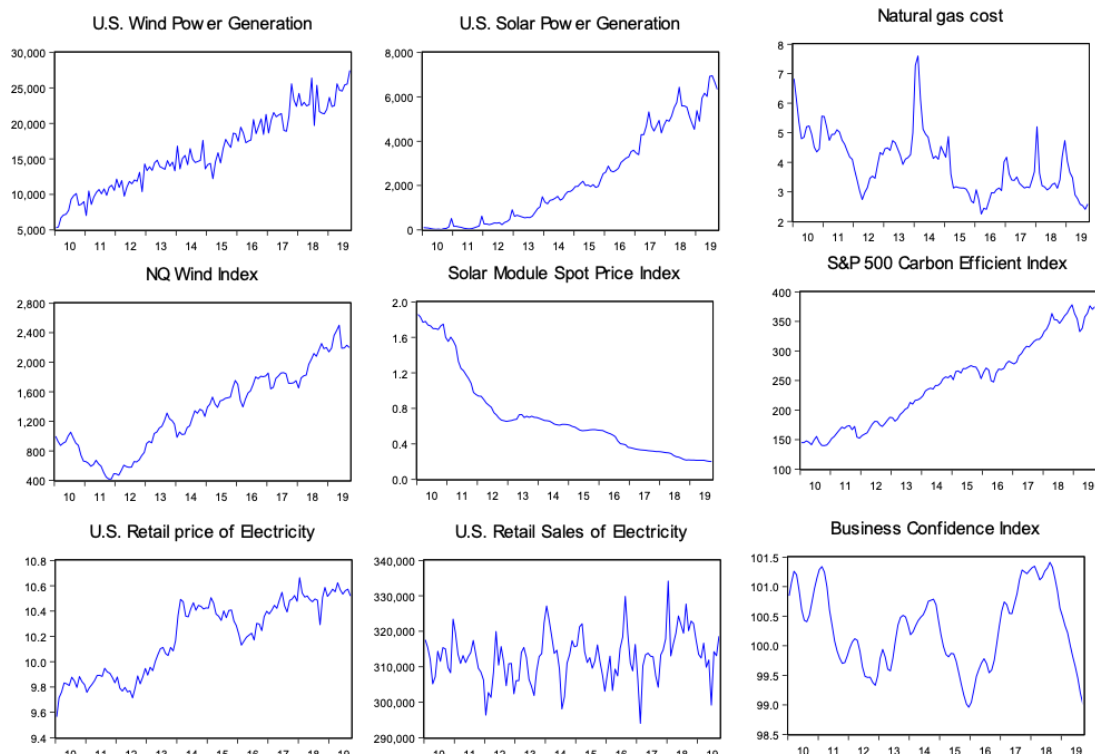
The monthly raw data of U.S. wind power generation, solar power generation, and the natural gas cost in the electricity generation variables are collected from EIA (*Electric Power Monthly*

⁹Supposed to capture the capacity investments dynamics as the latter is only available on a yearly basis.

¹⁰The Module Spot Price Index is surveying spot prices for the dominant technologies of crystalline silicon, thin film silicon, cadmium telluride and copper indium gallium selenide modules.

¹¹ It provides information on future developments, based upon opinion surveys on developments in production, orders and stocks of finished goods in the industry sector. The latter is used to monitor output growth and to anticipate turning points in economic activity. Numbers above 100 suggest an increased confidence in near future business performance, and numbers below 100 indicate pessimism towards future performance.

Figure 3.2: Historical evolution of the series (2010M1-2019-M9).



Notes: The monthly raw data of U.S. wind power generation, solar power generation, and the natural gas cost in the electricity generation variables are collected from EIA (Electric Power Monthly Survey Data). Monthly business confidence index (BCI) is sourced from OECD: numbers above 100 suggest an increased confidence in near future business performance, and number 100 indicate pessimism towards future performance. The solar module spot price index is extracted from the Bloomberg New Energy Finance platform. The monthly S&P 500 Carbon efficient index tracks multi-sectorial company's exposure to carbon emissions as a proxy of climate policy risk. The Nasdaq (NQ) wind index tracks companies involved in the production of wind power and is used to capture technological cost evolution of the wind industry.

Survey Data). Monthly business confidence index (BCI) is sourced from OECD: numbers above 100 suggest an increased confidence in near future business performance, and number 100 indicate pessimism towards future performance. The solar module spot price index is extracted from the Bloomberg New Energy Finance platform. The monthly S&P 500 Carbon efficient index tracks multi-sectorial company's exposure to carbon emissions as a proxy of climate policy risk. The Nasdaq (NQ) wind index tracks companies involved in the production of wind power and is used to capture technological cost evolution of the wind industry.¹² The sample period spans

¹²Table 3.1 provides a summary of used variables.

from January 2010 to September 2019, yielding a total of 117 observations. The plots (3.2 of solar electricity generation and wind electricity generation show a sharp increase during the last decade. A quick graphical intuition let us associate this trend to the concomitant effect of an increase of the carbon risk policy and a substantial decrease of renewable energy costs. As far as the natural gas cost variable is concerned, the dynamics of the latter is representative of the substantial increase in US natural gas supplies and the corresponding decrease in natural gas prices resulting from the development of shale gas.

Table 3.1: A summary of variables.

Variables	Meaning
WIND_GEN	U.S. Wind power generation
SOL_GEN	U.S. Solar power generation
REV_ELEC	Revenues from retail prices of electricity
NG_COST	Natural gas cost for electricity generation
NQ_WIND	NASDAQ Wind Index
SOL_MOD	Solar Module Spot Price Index
S&P_CEI	S&P Carbon Efficient Index
BCI	Business Confidence Index

Note: The variables NQ_WIND_t and SOL_MOD_t are used to proxy capital costs involved in wind and solar power generation. The S&P_CEI_t and BCI_t are used to proxy the carbon policy and economic environment under which investments in solar and wind energies are made.

3.3.2 Unit root tests

In order to further investigate the time series properties of the data¹³, three versions of unit root tests are conducted for each data series. We apply the DF-GLS (Elliott, Rothenberg, and Stock, 1992) that tests the null hypothesis of a unit root, the KPSS (Kwiatkowski et al., 1992) that tests the null hypothesis of stationarity and a breakpoint unit root test which allow for a

¹³Summary statistics are presented in Table 3.6 in Appendix A.

structural break in the trend process (Perron, 1989). The optimum lag length is based on Schwarz Information Criteria. For the first two unit root tests, two versions of each test are calculated: one with a constant and one with a linear trend. Results are shown in Table 3.2. Overall, they reveal stationarity among all variables with few exceptions. In the case of the KPSS test, we fail to reject the null hypothesis of stationarity in all instances (except for the Business Confidence Index variable when a model with constant is considered). When considering the DF-GLS test, the null hypothesis of a unit root is rejected at the 1% significance level for natural gas cost, revenues from retail sales of electricity (model with constant), carbon risk variable, Business Confidence Index (model with constant). Finally, breakpoint unit root test leads us to strongly reject the null hypothesis of a unit root for all variables. All in all, our data are integrated of order 1. To work with stationary time series, we apply a first logarithmic difference filter to our data series.

Table 3.2: Unit root tests on monthly first log-differenced data.

	Conventional URTs				Breakpoint URTs	
	DF-GLS (c)	DF-GLS (t)	KPSS (μ)	KPSS (τ)	TBs	T-statistics
DL.WIND.GEN	-12.913***	-12.239***	0.167	0.162	2015M06	-9.668*** [10]
DL.SOL.GEN	-12.449***	-12.939***	0.251	0.054	2014M01	-10.752***[8]
DL.REV.ELEC	-13.127***	-13.262***	0.052	0.051	2018M01	-13..969***[0]
DL.NG.COST	-7.128***	-8.315***	0.071	0.061	2014M01	-10.336***[1]
DL.NQ.WIND	-6.884***	8.852***	0.209	0.109	2016M02	-9.954***[0]
DL.MOD.SPOT	-1.722*	-3.886***	0.559	0.117	2012M10	-9.019***[9]
DL.BCI	-2.979***	-5.950***	0.109	0.106	2018M08	-8.079***[1]
DL.CEI	-9.102***	-9.296***	0.070	0.068	2016M04	-9.782***[0]

Notes: The DF-GLS (Elliot et al., 1996) tests the null hypothesis of a unit root. The KPSS (Kwiatkowski et al., 1992) tests the null hypothesis of stationarity. The Schwarz Information Criteria have been used to choose the optimal lag length. ***, **, * indicates the rejection of a unit root hypothesis at the 1%, 5% and 10% significance level respectively. The breakpoint unit root test tests the null hypothesis of a unit root. Lag length is selected following Schwarz criterion and the optimal lag is reported in brackets. Dickey-Fuller min-t method is used for the breakpoint selection.

3.3.3 BDS independance test

We also examine the distributional pattern of the monthly first log-differenced data by applying the BDS test proposed by Broock et al. (1996). This test is based on the concept of correlation integral, a measure of the frequency with which temporal patterns are repeated in the data. This is a broadly accepted test to detect the presence of non-linear structure and spatial dependence of a time-series. This test can also be applied to check whether increments to a data series is independent and identically distributes (*iid*).¹⁴ The test is asymptotically distributed as standard normal under the null hypothesis of independence. Table 3.3 reports the results. Overall, for almost all combinations of m parameter (which corresponds to the number of consecutive data points to include in the set) and ε values (which corresponds to the distance used for testing proximity of the data points), we can reject the null hypothesis of independent and identical distribution at the 1% significance level. Confronting these results to the plotted monthly variables in Figure 3.2 suggest the presence of a likely nonlinear structure of the considered data.

3.4 Results

By employing the monthly data of U.S. wind and solar PV power generation and potential explanatory variables from January 2010 to December 2019, four alternative Markov Regime Switching Models (MSMs) are estimated. Each of the four regressions looks at the determinants of invested renewables capacities by adopting a “from specific to general” strategy to better grasp the economic potential of renewables penetration under many prospective drivers. We hence compare models that gradually add information variables to comprehensively assess their relative magnitude. For each specification of the model outlined in Equation 3.4 and Equation 3.5, estimation results are presented in Table 3.4 and Table 3.5. The first columns of Table 3.4 and Table 3.5 (Panel A) feature the explanatory variables of U.S. renewables generation to be analyzed in alternative MSMs. Columns 2 to 5 of these same tables display estimations results of Markov Regime Switching Model 1 (MSM1) to Markov Regime Switching Model 4 (MSM4).¹⁵

¹⁴To perform the test, we first choose a distance, ε . We then consider a pair of points. If the observations of the series truly are iid, then for any pair of points, the probability of the distance between these points being less than or equal to epsilon will be constant.

¹⁵Estimated coefficients are on Panel A whereas transition probabilities and expected durations are on Panel B.

Table 3.3: BDS tests for monthly first log-differenced data.

	m	$\epsilon(1)$		$\epsilon(2)$		$\epsilon(3)$		$\epsilon(4)$	
DL_WIND_GEN	2	-5.131	(0.000)	0.682	(0.496)	0.844	(0.399)	0.063	(0.950)
	3	-1.518	(0.129)	3.742	(0.000)	1.459	(0.000)	2.989	(0.003)
	4	-6.736	(0.000)	3.393	(0.001)	2.233	(0.001)	4.293	(0.000)
	5	-4.128	(0.000)	4.404	(0.000)	2.502	(0.000)	4.455	(0.000)
	6	-2.822	(0.005)	7.883	(0.000)	2.571	(0.000)	4.350	(0.000)
DL_SOL_GEN	2	2.940	(0.003)	7.724	(0.000)	5.037	(0.000)	14.752	(0.000)
	3	2.325	(0.020)	10.270	(0.000)	6.027	(0.000)	13.525	(0.000)
	4	1.127	(0.260)	11.823	(0.000)	5.890	(0.000)	12.358	(0.000)
	5	-2.489	(0.013)	14.158	(0.000)	5.984	(0.000)	11.456	(0.000)
	6	-1.617	(0.106)	16.702	(0.000)	5.781	(0.000)	10.755	(0.000)
DL_REV_ELEC	2	30.950	(0.000)	43.119	(0.000)	2.258	(0.000)	3.105	(0.002)
	3	57.387	(0.000)	83.205	(0.000)	3.198	(0.000)	2.590	(0.010)
	4	165.026	(0.000)	187.142	(0.000)	5.306	(0.000)	-2.892	(0.004)
	5	413.889	(0.000)	427.316	(0.000)	6.941	(0.000)	-1.117	(0.264)
	6	1132.076	(0.000)	996.731	(0.000)	8.094	(0.000)	0.964	(0.335)
DL_NG_COST	2	2.875	(0.004)	3.726	(0.000)	3.286	(0.000)	2.575	(0.010)
	3	6.928	(0.000)	3.638	(0.000)	3.546	(0.000)	2.435	(0.015)
	4	16.468	(0.000)	4.952	(0.000)	3.219	(0.000)	2.142	(0.032)
	5	66.156	(0.000)	3.828	(0.000)	2.684	(0.000)	1.719	(0.086)
	6	282.916	(0.000)	4.025	(0.000)	2.152	(0.000)	1.356	(0.175)
DL_NQ_WIND	2	1.154	(0.249)	1.257	(0.209)	1.972	(0.209)	0.930	(0.352)
	3	1.058	(0.290)	1.501	(0.134)	1.749	(0.134)	0.350	(0.726)
	4	2.534	(0.011)	1.329	(0.184)	2.037	(0.184)	0.799	(0.424)
	5	-2.644	(0.008)	-1.453	(0.146)	1.931	(0.146)	1.150	(0.250)
	6	-1.756	(0.079)	-2.716	(0.007)	1.727	(0.007)	1.402	(0.161)
DL_MOD_SPOT	2	7.479	(0.000)	7.131	(0.000)	1.637	(0.000)	0.134	(0.893)
	3	8.611	(0.000)	8.764	(0.000)	1.575	(0.000)	-0.347	(0.729)
	4	18.276	(0.000)	12.992	(0.000)	1.807	(0.000)	-0.558	(0.577)
	5	38.960	(0.000)	18.777	(0.000)	1.819	(0.000)	-0.862	(0.388)
	6	125.717	(0.000)	31.501	(0.000)	1.956	(0.000)	-0.844	(0.398)
DL_CEI	2	2.073	(0.038)	1.194	(0.232)	1.595	(0.232)	0.449	(0.654)
	3	3.906	(0.000)	2.782	(0.005)	2.411	(0.005)	1.517	(0.129)
	4	0.839	(0.402)	2.623	(0.009)	2.400	(0.009)	1.291	(0.197)
	5	-2.244	(0.025)	3.293	(0.001)	2.733	(0.001)	1.391	(0.164)
	6	-1.583	(0.113)	1.617	(0.106)	2.452	(0.106)	0.933	(0.351)
DL_BCI	2	28.647	(0.000)	44.070	(0.000)	17.409	(0.000)	15.111	(0.000)
	3	61.466	(0.000)	60.120	(0.000)	14.841	(0.000)	12.341	(0.000)
	4	75.288	(0.000)	79.971	(0.000)	13.453	(0.000)	10.576	(0.000)
	5	65.641	(0.000)	108.841	(0.000)	13.151	(0.000)	9.897	(0.000)
	6	-4.469	(0.000)	147.579	(0.000)	12.961	(0.000)	9.497	(0.000)

Notes: BDS test statistics are reported with associated p-values within brackets. The m parameter is the embedding dimension with the epsilon values for close points (numerical values are not reported).

Inferences are based upon the hypothesis of two regimes.¹⁶ A number of features stand out.

It turns out that, for all considered models MSM1 to MSM4, there is a strong regime effect with changing directions of coefficients across regimes. Estimated coefficients associated to the state-dependant variables are statistically different and their magnitude changes significantly and economically. In other words, the sample effectively dichotomizes in phases of production decline and phases of production growth, which allows us to relate them to a high regime and low regime of intermittent renewable production.¹⁷ In what follows, we describe the results associated with each of the four retained specifications.

MSM1s employs, besides a constant term and a linear trend, independent variables of natural gas cost in electricity generation and revenues from retail sales. Positive impact of natural gas cost in the high regime (regime 1) turns out to be negative and statistically significant in the low regime (regime 2) suggesting that a one-unit increase of natural gas cost induces for instance an increase of 18% of wind energy production in the high regime and a seven-fold decrease of wind energy production in the low regime (Table 3.4). The downward impact in the low regime of wind production is hence much stronger in magnitude. The same pattern is observed in the case of solar but with a different magnitude: higher natural gas prices double solar production in the high regime while reducing it by 14% in the low regime. These results are consistent with prior expectation and empirical evidence of Baranes et al., (2017) of a non-linear relationship between natural gas prices and renewable capacity investments. When looking at the impact of the revenues from retail sales of electricity on renewable generation growth, one may notice that while the estimated coefficients are statistically significant at the 1% significance level and positive in the low regime (20.42 in the case of wind and 0.84 in the case of solar), they turn out to be negative in the highest regime (-0.15 in the case of wind and -4.91 in the case of solar). Here again, whether we consider wind or solar production, the signs of the estimated coefficients are similar but differ in magnitude. For instance, the increase of wind production induced by a raise of revenues from retail sales of electricity is significantly stronger than the one obtained in the case of solar generation.

¹⁶Given the sample of available data, it would not have been reasonable to consider more than two regimes of renewable generation growth.

¹⁷Note that for all regressed MSMs, the state 1 is associated with a high regime of renewable penetration and the state 2 is associated with a low renewable generation regime.

In comparison to MSM1s, MSM2s seek to evaluate the impact of an additional driver in connection with climate policy risk variable. Similar to MSM1, results show evidence of strong regime effect with changing directions of coefficients associated to natural gas costs and revenues from retail sales of electricity across regimes. Indeed, natural gas cost coefficients are statistically significant at the 1% level and negative in the low regime (regime 2) and turn out to be positive in the high regime (regime 1)¹⁸. As for MSM1s, the reverse holds true for the revenue variable. From this point, this specification is robust to the introduction of the policy risk variable. The latter does not show any regime change effect in the case of wind as coefficients are positive in both regimes. *A contrario*, it contributes toward improving solar energy penetration only in the low regime. Here again, estimated coefficients associated to the state-dependant variables are statistically different and their magnitude changes significantly and economically: in the case of solar, while the estimated coefficient of carbon policy risk variable is negative and significant in the high regime, it turns out to be positive in the lower one. In others words, when the penetration of solar energy is on a high path, results suggest that a more ambitious carbon policy would lead to a drop-in production. Conversely, when the latter is in a low regime, any policy that could lead to an increase of carbon price is found to boost investment in renewables. We will discuss the economic mechanisms underlying these results in the next section.

Our third specification, MSM3, goes further by including the renewable energy cost variable¹⁹ as additional regime-switching regressors. Previous results about the impact of revenues, natural gas costs, renewables costs and climate policy risk are robust to this specification.²⁰ The contribution of the MSM3 is to shed light on the impact of renewable energy costs which seem to be in favor of a state-dependant effect only in the case of wind.

Indeed, the estimated coefficients of the solar cost variable are not state-dependant: increasing capital costs by 1% leads to a 13% drop of solar production in the low regime and a four-fold decrease in the high regime. This absence of regime effect in the case of solar may testify an intensified sensitivity of the solar industry to incurred technological costs.

¹⁸It should be noted that in this case, the estimated coefficient associated with the costs of natural gas is borderline significant in the regime 1 (at the 10% significance level) in the case of wind (Table 3.4).

¹⁹With reference to the variables DL_NQ_WIND in the case of wind (Table 3.4) and DL_MOD_SPOT in the case of solar (Table 3.5).

²⁰Except for the case of the climate risk variable in the case of wind which exhibits a regime effect by having a positive and statistically significant impact in the low regime and a negative impact in the high regime.

Table 3.4: Markov Regime-Switching Models for U.S. wind electricity generation growth: 2010M11 - 2019M9

Panel A: Estimated coefficients									
		MSM1		MSM2		MSM3		MSM4	
Independent var.	State								
DL_NG_COST	1	0.176	(0.081)	0.181	(0.095)	0.074	(0.389)	0.162	(0.116)
	2	-7.194	(0.000)	-7.241	(0.000)	-1.836	(0.000)	-4.154	(0.000)
DL_REV_ELEC	1	-0.147	(0.761)	-0.206	(0.663)	-0.132	(0.769)	-0.115	(0.819)
	2	20.424	(0.000)	20.256	(0.000)	-7.489	(0.000)	6.815	(0.000)
Constant	1	0.001	(0.878)	0.000	(0.979)	0.002	(0.847)	0.001	(0.904)
	2	0.185	(0.000)	0.180	(0.000)	0.291	(0.000)	-0.033	(0.000)
Trend	1	0.000	(0.602)	0.000	(0.444)	0.000	(0.541)	0.000	(0.721)
	2	-0.002	(0.000)	-0.002	(0.000)	-0.004	(0.000)	0.000	(0.000)
DL_CEI	1			0.026	(0.931)	-0.539	(0.160)	-0.008	(0.982)
	2			0.517	(0.604)	6.463	(0.000)	8.341	(0.000)
DL_NQ_WIND	1					0.043	(0.784)	0.142	(0.326)
	2					-5.496	(0.000)	-1.902	(0.000)
DL_BCI	1							-4.040	(0.492)
	2							293.597	(0.000)
Sigma 1		0.037	(0.000)	0.037	(0.000)	0.037	(0.000)	0.037	(0.000)
Sigma 2		0.034	(0.000)	0.036	(0.000)	0.001	(0.000)	0.001	(0.000)
Log-Likelihood		185.857		185.140		203.074		208.617	
AIC		-3.231		-3.199		-3.563		-3.563	
SIC		-2.906		-2.849		-3.159		-3.113	
Linearity test		9.886	(0.000)	4.769	(0.000)	7.607	(0.000)	4.096	(0.002)
(Max Wald F-stat)									
Panel B: Transition probabilities and expected durations									
		MSM1		MSM2		MSM3		MSM4	
	P11	0.97		0.97		0.97		0.97	
	P12	0.03		0.03		0.03		0.03	
	P21	0.42		0.43		0.46		0.39	
	P22	0.58		0.57		0.54		0.61	
	DU1	30.61		30.16		28.82		32.91	
	DU2	2.38		2.33		2.16		2.56	
	RCM	4.36		4.38		1.02		0.60	

Notes: the dependant variable is the monthly wind electricity generation. State 1 (2) refers to the high (low) regime of wind power production. Regime-specific coefficients are reported with the associated p-values in brackets. Sigma refers to the standard deviation of each state. RCM is the regime classification measure. The transition probabilities are reported as p_{ij} . The expected duration of being in state i are reported as DU_i , i.e., DU_1 for state 1 and DU_2 for state 2.

Table 3.5: Markov Regime-Switching Models for U.S. solar electricity generation growth: 2010M1 - 2019M9

		MSM1		MSM2		MSM3		MSM4	
Independant var.	State								
DL_NG_COST	1	0.9996	(0.275)	0.892	(0.355)	0.086	(0.917)	0.427	(0.555)
	2	-0.135	(0.070)	-0.134	(0.072)	-0.134	(0.092)	-0.152	(0.089)
DL_REV_ELEC	1	(4.918)	(0.124)	-4.901	(0.196)	-2.589	(0.508)	-4.271	(0.369)
	2	0.840	(0.006)	0.742	(0.028)	0.776	(0.025)	0.801	(0.038)
Constant	1	-0.00831	(0.877)	0.002	(0.979)	-0.028	(0.656)	-0.001	(0.504)
	2	0.039	(0.000)	0.038	(0.000)	0.037	(0.000)	0.033	(0.000)
Trend	1	0.00000	(0.996)	0.000	(0.912)	0.000	(0.749)	0.000	(0.991)
	2	-0.00036	(0.000)	0.000	(0.000)	0.000	(0.001)	0.000	(0.509)
DL_CEI	1			-1.11860	(0.767)	-0.871	(0.779)	-0.342	(0.902)
	2			0.46773	(0.102)	0.477	(0.102)	0.754	(0.026)
DL_MOD_SPOT	1					-4.468	(0.243)	0.866	(0.787)
	2					-0.133	(0.654)	-0.520	(0.088)
DL_BCI	1							-35.268	(0.461)
	2							6.411	(0.303)
Sigma 1		0.101	(0.000)	0.101	(0.000)	0.092	(0.000)	0.097	(0.000)
Sigma 2		0.032	(0.000)	0.031	(0.000)	0.031	(0.000)	0.034	(0.000)
Log-Likelihood		204.613		206.113		206.983		195.202	
AIC		-3.379		-3.370		-3.351		-3.144	
SIC		-3.091		-3.034		-2.967		-2.760	
Linearity test		7.836	(0.000)	6.919	(0.000)	5.507	(0.000)	4.716	(0.002)

(Max Wald F-stat)

Panel B: Transition probabilities and expected durations

	MSM1	MSM2	MSM3	MSM4
P11	0.64	0.63	0.61	0.65
P12	0.36	0.37	0.39	0.35
P21	0.04	0.04	0.05	0.05
P22	0.96	0.96	0.95	0.95
DU1	2.75	2.70	2.54	2.88
DU2	25.77	24.81	20.51	19.22
RCM	10.55	10.49	14.42	17.38

Notes: the dependant variable is the monthly solar electricity generation. State 1 (2) refers to the high (low) regime of wind power production. Regime-specific coefficients are reported with the associated p-values in brackets. Sigma refers to the standard deviation of each state. RCM is the regime classification measure. The transition probabilities are reported as p_{ij} . The expected duration of being in state i are reported as DU_i , i.e., DU_1 for state 1 and DU_2 for state 2.

Finally, our fourth specification, MSM4, takes into account the macroeconomic environment supposed to affect agents' expectations during their investment decisions through the additional variable: Business Confidence Index (BCI). Results suggest that economic growth is relevant and statistically significant in at least one regime. More precisely, the associated coefficient is positive and statistically significant at the 1% significance level in the lower regime (regime 1) and turns out to be negative in the high regime (regime 2). The impact of the other variables remains robust to the addition of the BCI variable.

By gauging the significance, direction and magnitude of our estimated coefficients, we can, at this stage, note an obvious dichotomy effect of our sample, alternating between phases of decline in the production of renewables and phases of growth of production. This result consolidates our choice to work under a Markov-Switching regime regression. We are then dealing with two widely distinct regimes, where our explanatory variables; whether linked to the natural gas market, to carbon risk or to the health of global economy, generally exhibit a state-dependant impact. These results turn out to be completely robust to specifications that gradually integrate these different drivers.

All four MSM models seem to fit data well. Nevertheless, in the case of wind, Table 3.4 show that MSM4 fits the data the best, according to lowest AIC of -3.563 and highest log-likelihood of 208.616, among others, while the poorest fit is recorded for MSM2. Looking at the RCM values, we see that the Markov Switching model fits the MSM4 the best (smaller RCM value) while the poorest fits the data is recorded for MSM2. One may notice that MSM3 has the second lowest RCM, as well. When looking at the solar case in Table 3.5, MSM1 fits the data the best, according to lowest AIC of -3.379 and SIC of -3.091. MSM1 is the second best option when looking at the regime classification measure of RCM. If we rely on another indicator, that of variance, we notice that: the variance of Regime 1 chooses MSM1 whereas the variance of Regime 2 chooses MSM2. All in all, we can conclude that the four MS models fit well the data as they all reach strong convergence through SQPF using analytical derivatives from one part and exhibit no conflict in terms of significances and signs of our five potential drivers. Our progressive approach is justified by the fact that the higher is the number of estimated parameters, the riskier is to have poorer goodness of fit measurements or strong convergences. Finally, all MSMs conducting nonlinear estimations are preferred against their linear counterparts. Linearity tests in Table 3.4 and Table 3.5 show that the null hypothesis of linearity is strongly rejected for all models, at the 1% level

of significance.

Panel B of Table 3.4 and Table 3.5 presents results of transition probabilities from one regime to another and the expected durations. From MSM1 to MSM4, all four of them reveals that, when the current state of renewable production is in regime 1²¹ at time t , the probability of transiting from regime 1 to regime 2 at time $t+1$ is 3% on average in the case of wind and 36% on average in the case of solar. The results hence suggest a higher probability of transiting from a high regime to a low regime for solar than for wind. On the other side, when the current state of renewable production is at its low state (regime 2) at time t , the probability of transiting to the high regime at time $t+1$ is nine time higher in the case of wind (42.5% on average) than in the solar one (4.5% on average). Table 3.4 and Table 3.5 also yield the probability of staying in the highest regime (regime2) at time $t+1$: 0.97 in the case of wind and 0.36 in the case of solar. Therefore, one may claim that the cumulative effect of any shock in the system to renewable energy penetration whatever the regime considered is prompt to be persistent.

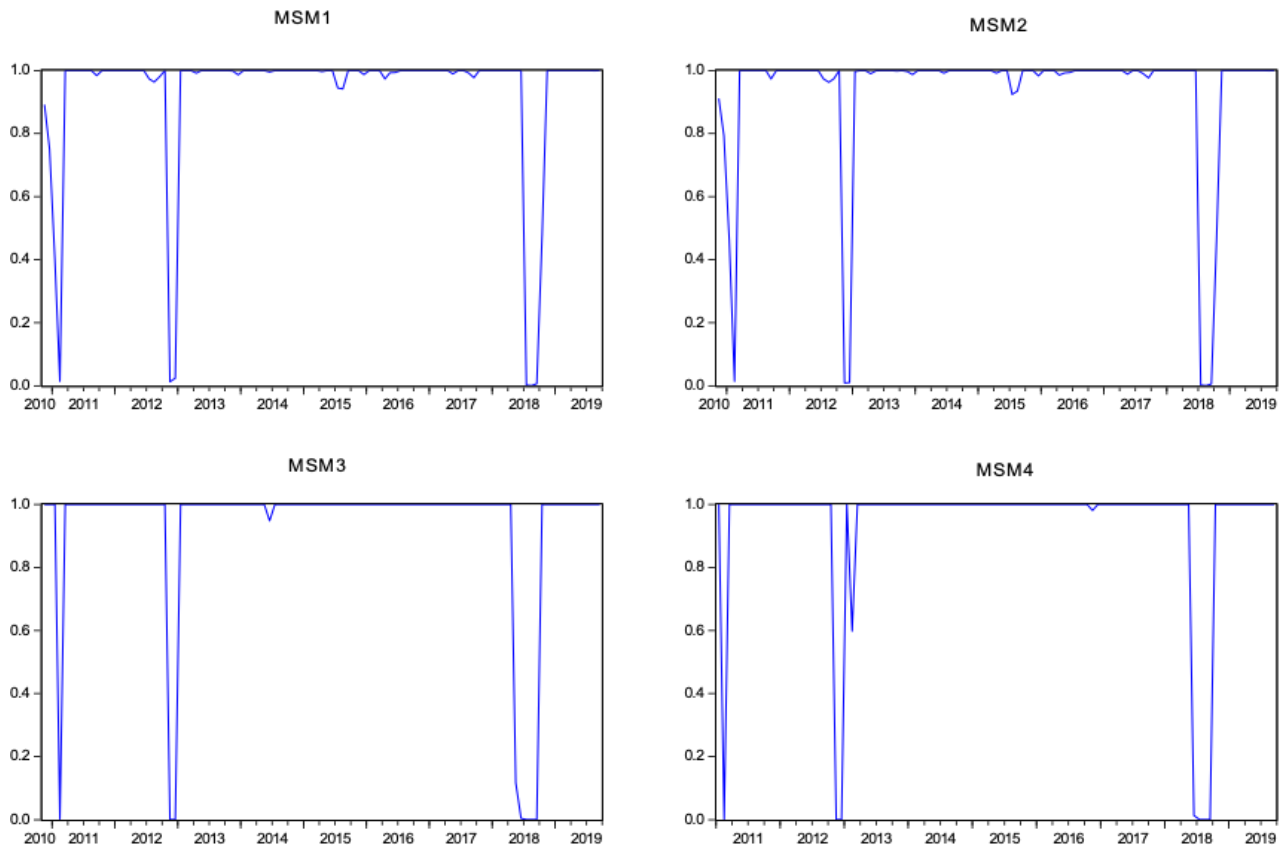
Notice also that the estimated coefficient on sigma is positive in each model and statistically significant in both regimes at the 1% significance level. Sigma refers to the standard deviation of each regime. It provides the magnitude of volatility (measured by the standard deviation) of each regime. The state with the largest estimated coefficient on sigma is the “high” volatility regime, while the state with the smallest coefficients on sigma is the “low” volatility regime. The estimated coefficients of sigma support this switching between high-and-low volatility regimes. Table 3.4 and Table 3.4, for example, shows that for MSM3 and MSM4, there is a strong distinction between a high-and-low volatility regime, where the conditional variance in the former is 37 times as large. For all MSMs, the estimated sigma value in state 1 is larger than the estimated sigma value in state 2 indicating that state 1 has more volatility. In the case of solar, MSM1 and MSM2 exhibit highest volatility coefficients in state 1.

Figures 3.3 and 3.4 that exhibit the smoothed probabilities of high regime of wind production and low regime of solar production derived from Markov Switching regressions with regime-specific variance error, highlight all the results discussed above. One may notice that the RCM values are in agreement with the plots of the smoothed probabilities. Smaller values of RCM correspond to a clearer pattern in switching between states. According to the RCM values, the MSM4 fits the best

²¹For all MSMs, regime 1 corresponds to the high state of renewable production and regime 2 to the low state of renewable production.

our data in the case of wind and MSM1 in the case of solar. These representations confirm our primary intuition of alternating between high and low regimes of renewable production, resulting from the interaction of a multitude of factors.

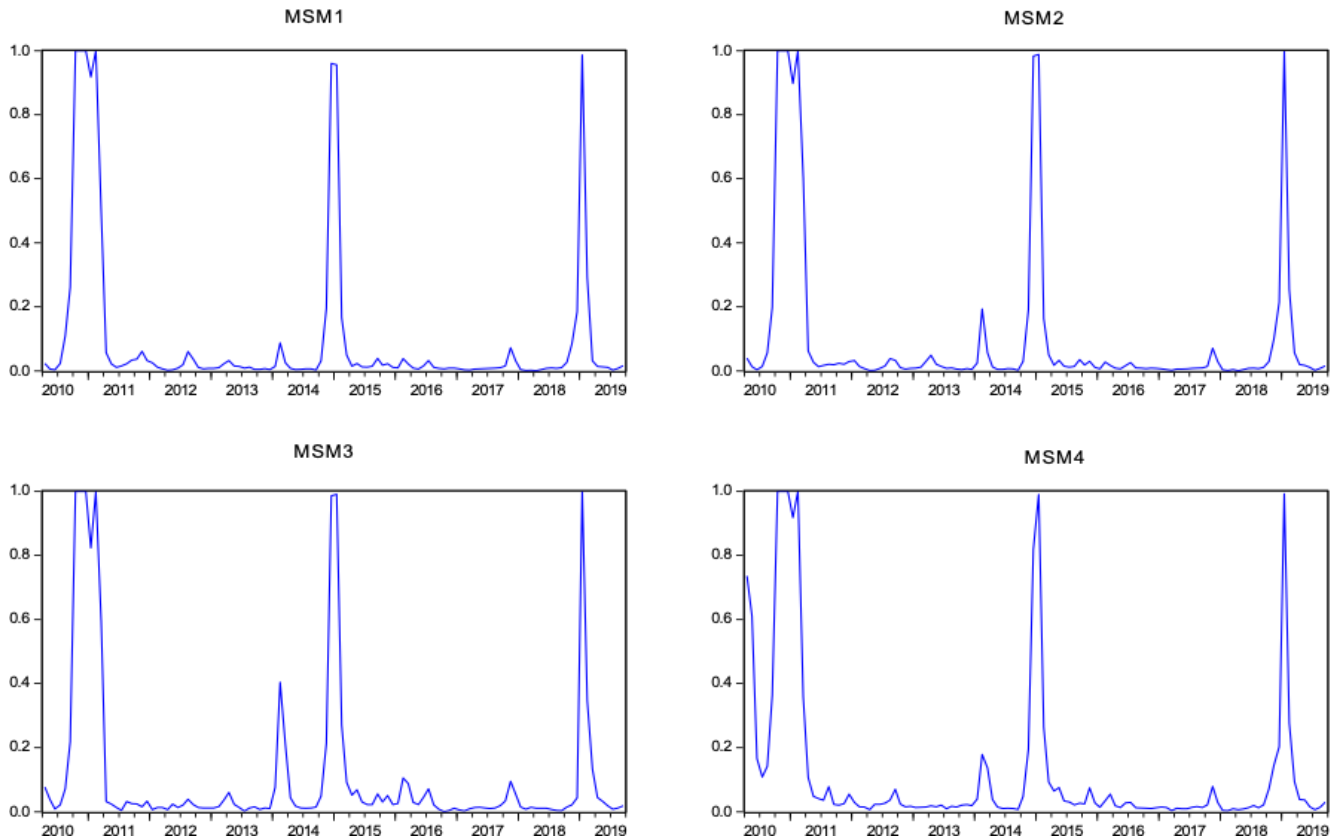
Figure 3.3: Probability of high wind generation regime smoothed from MSMs (fixed transition probabilities).



3.4.1 Robustness checks

Finally, we have tested the robustness of our empirical specification to a Markov Switching model with variable transition probability (MS-TVTP). Filardo (1994) and Diebold, Hahn, and Tay (1999) have extended the Markov-Switching model of Hamilton (1989) to a model that not only estimate the probabilities of transition among regimes, but allow also transition probabilities to vary with respect to chosen information variables. Researchers relied on MS-TVTP model to examine the dynamics of important economic variables such as interest rate or exchanges rates (see Gray (1996) and Diebold, Lee, and Weinbach (1993)). In our case, it turns out that the main results have proven to be completely robust to this specification (See reported results in Appendix

Figure 3.4: Probability of high solar generation regime smoothed from MSMs (fixed transition probabilities).



B).

3.5 Discussion

If we examine the results under the lens of the electricity generation from natural gas and intermittent renewable energies, this study provides strong evidence in favor of a significant interdependence between these two modes of production. Moreover, this relationship is found to be nonlinear, switching between a regime of complementarity and a regime of substitutability. This implies that, for a relatively high level of wind production through renewables, a marginal increase in gas prices tends to increase the share of renewable production. *A contrario*, this substitutability no longer holds when we switch to a low production regime, since a marginal increase in the price of gas generates a decrease in the share of production from renewables. Indeed, in all the regressions we carried out, the coefficients associated with the natural gas variables are

positive and statistically significant at the 1% in regime 1 (high regime), positive in the regime 2 (low regime).

Not only are these results corroborating those obtained by Baranes, Jacqmin, and Poudou (2017) but they also complement them in three ways. First, we are not only examining the differences in the impact of our explanatory variables according to the regime considered, but also deliver the probability associated with the high renewable production regime as well as with the lower production regime, the probability of transiting to each other and their expected durations. Second, we examine the relationship between the gas cost and that of renewable electricity from a multifactorial angle where non-linearity is tested for all the informative variables integrated into the model. In fact, the degree of investment in renewables is non-linear with the cost of gas but not only: regime shifts can emanate from factors related to the electricity market, to carbon policy risks, global economic health or renewable capital costs. Thirdly, we have examined renewable production under two distinct spectra: that of wind and solar energies whose dynamics are not completely similar. In this context, we have tested the robustness of our results by adopting a strategy that gradually take into account our chosen information variables to better grasp their contribution in enhancing intermittent renewables penetration. In what follows, we discuss the implications of these results made possible by these three key contributions, which we describe in detail and compare with a fairly broad spectrum of literature.

Concerning the first contribution, our model have exhibited two striking features of the renewable energy market: i) there is clearly a higher probability of being in a high regime of wind production and a higher probability of being in a low regime of solar production ²² and ii) natural gas and wind energy are more prompt to be substitutes whereas natural gas and solar energy present more scope for complementarity.

3.5.1 High wind regime vs. low solar regime

This first result is indicative of a more advanced level of U.S. wind power development compared to solar so far. The U.S. was one of the first leaders in wind electricity, with the world's largest wind investments in California in the 1980's (Richter, 1996). Solar still represents a tiny

²²The probability of moving from a low regime to a high regime varies between 39% and 46% in the case of wind, depending on the considered model. The probability of remaining the low regime of solar energy generation varies between 95% and 96% .

fraction of U.S. electric generation mix²³; though growing : solar installations represented 32% of all new U.S. electric generation capacity in 2019, just behind natural gas with 39.8% (see Figure 3.6). This state of fact interferes with a myriad of factors posing a certain number of challenges to the U.S. solar industry. When looking at the incurred cost of renewable technologies through the commonly used levelized cost of energy²⁴ (LCOE) estimate²⁵, the U.S. case exhibits two salient features in Figure 3.5. First, it is significantly cheaper to produce electricity from the wind energy than from the solar energy when compared to electricity generated from gas turbines.²⁶ Second, the cost difference with that of natural gas is significantly higher in the case of solar.²⁷ This result echoes the need of innovation-driven cost and performance improvements in module design and manufacturing (Chung et al., 2016). Denholm and Margolis (2016) raised issues regarding transportation challenges toward an efficient deployment of the grid-flexibility options²⁸; able to accelerate PV penetration by 25% .

The combined effect of these two cost structures is able to justify the lower probability of being on a sustained path of solar generation when comparing with the wind industry. But policy orientations are also of a great interest. The federal Production Tax Credit (PTC) and state Renewable Portfolio Standard (RPS) are important drivers of wind penetration. Initially supported by the Public Utilities Regulatory Policy Act (PURPA) and the Business Energy Tax Credits in

²³ In 2019, 17% of U.S. electricity have been generated thanks to renewables with solar and wind representing 1.8% and 7.3% of this part, respectively (EIA, 2020).

²⁴Levelized cost of electricity represents the average revenue per unit of electricity generated that would be required to recover the costs of building and operating a generating plant during an assumed financial life and duty cycle. Key inputs to calculating LCOE include capital costs, fuel costs, fixed and variable operations and maintenance (O& M) costs, financing costs, and an assumed utilization rate for each plant type (EIA, 2020). See also Figure 3.10 in Appendix C.

²⁵It quickly becomes a tricky exercise to make a strico sensu comparison of the costs incurred by the deployment of wind and solar PV technologies by relying on the commonly used levelized cost of energy (LCOE) estimate. The latter is not always successful in its enterprise to fully capture all the factors that contribute to actual investment decisions (EIA, 2020) but is still indicative of economic competitiveness between generation technologies in the capacity expansion.

²⁶This result must be linked to the fact that solar has not reached wind popularity at the utility scale level, but generally make more sense for residential energy production. Moreover, solar suffers from a lack of standardization from a quality point of view.

²⁷The extent of the solar cost range is partly related to the disparity of available solar technologies.

²⁸Through a better grid management, demand response and affordable energy storage technologies.

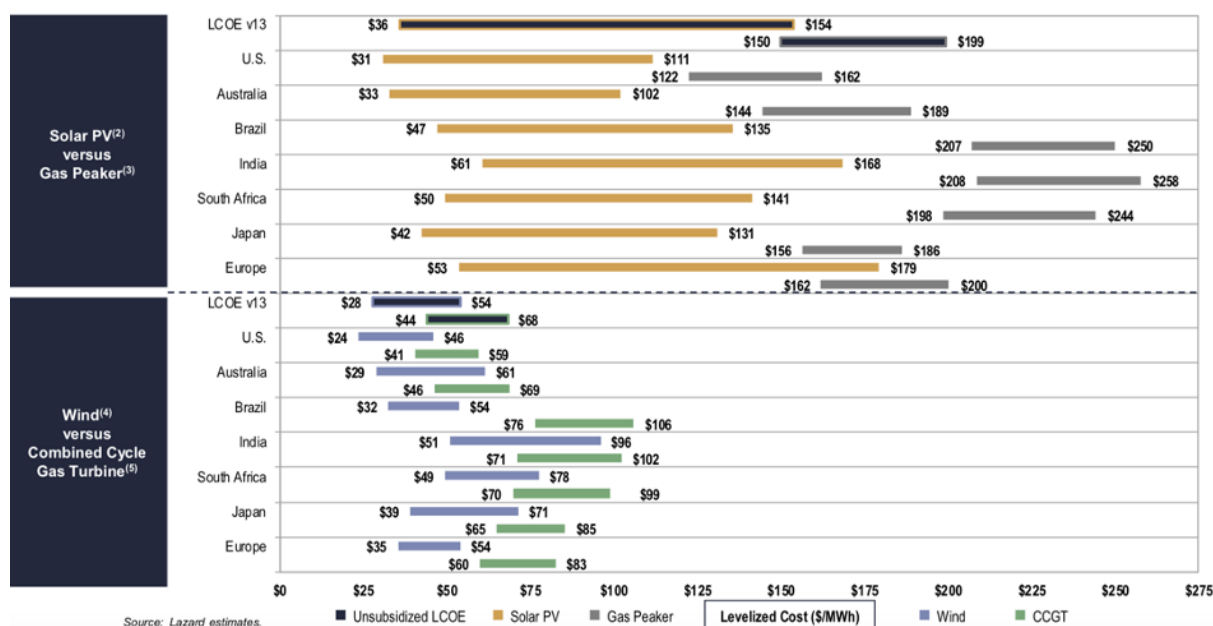


Figure 3.5: Levelized Cost of Energy Comparison

Source: Lazard estimates, 2019. Notes: (1) Low end assumes crystalline utility-scale solar with a single-axis tracker. High end assumes rooftop Commercial and Industrial (CI) solar. Solar projects assume illustrative U.S. capacity factors of 28%. (2) Wind projects assume illustrative capacity factors of 55%. (3) Assumes natural gas prices of \$3.45; capacity factors of 55% - 70% on the high and low ends, respectively.

the 1978 National Energy Act, the U.S. was one of the first leaders in wind electricity (Righter, 1996). Since the late 1990's, the federal Production Tax Credit (PTC) and state Renewable Portfolio Standard (RPS) policies have constituted the two major supporting policies of the U.S. wind electricity penetration. During the decades that follow, the PTC went through a succession of expirations and renewals including the Energy Policy Act of 2005 (Stokes and Breetz, 2018) and played a pivotal role in wind project financing combined with state RPS requirements. The RPS regulation requires electricity suppliers to produce a specified fraction of their electricity from renewable energy sources.²⁹ In reality, even if these regulations targeted several renewables energies including solar, wind, geothermal and biomass; in fact, they have mostly contributed to meet the RPS requirement of the wind energy, up to 68% (Barbose, 2016). As illustrated by the Texan

²⁹Since 2005, several states have adopted non-binding voluntary RPS policies (see Stokes and Breetz (2018) for a detailed analyze of policies supporting renewable deployment in the U.S.).

case, the U.S. extension of RPS to the case of solar³⁰ failed in the years that followed, gradually widening the disparities we observe today with wind energy dynamics (Stokes and Breetz, 2018).

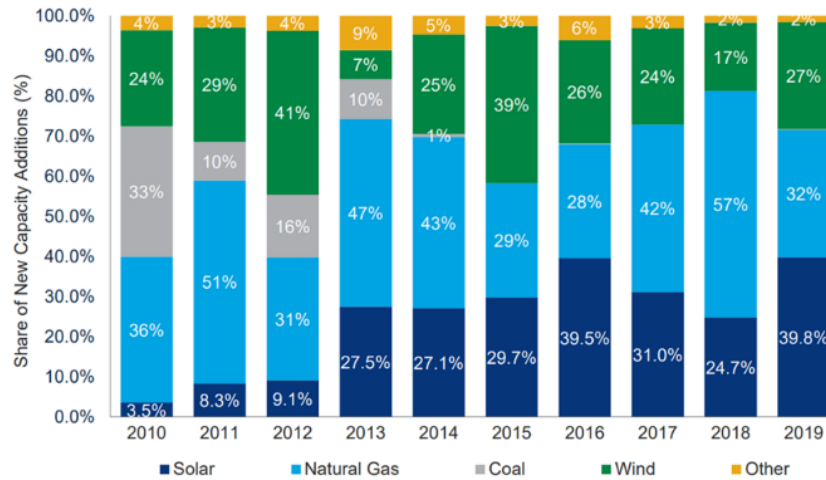


Figure 3.6: New U.S. electricity-generating capacity additions, 2010-19

Source: Wood Mackenzie U.S. Solar Market Insight 2019 year in review

3.5.2 Substitutability vs. complementarity

When facing the current market situation, we believe that the degree of substitution between wind energy and natural gas will depend on the technological factor. In other words, if a technology as important as that of hydraulic fracturing is brought to prove itself, the advent of the shale oil and gas could represent the first of a long series, threatening by the same token the penetration of renewables and especially the solar. In this respect, literature has sought to understand how unconventional gas development has changed the landscape of American energy in a very short time. Some forecast that increased availability and low prices will lead to a gas-dominated electricity sector, in which coal is displaced and loses its prominent share of the market—as is already occurring—and renewable energy is stifled by the large influx of natural gas (Krupnick et al. (2014); Shearer et al. (2014)). While fuel-switching from coal to natural gas may reduce greenhouse gas emissions, the potential for a decrease in renewable penetration into the generation

³⁰With less vigorous impetus compared to the dynamics known in Germany or Japan, U.S. solar technology benefits mostly from the federal Investment Tax Credit (ITC) and state level net energy metering (NEM) laws (Stokes and Breetz, 2018).

sector has led researchers to conclude that a gas-dominant generation portfolio will not be enough to prevent the 2-degree Celsius temperature rise limit associated with high risks of catastrophic climate change (Newell and Raimi, 2014).³¹

3.5.3 Regime effects

Concerning the second contribution, we examine the relationship between the gas market and that of electricity production from renewable energy from a multifactorial angle where non-linearity is tested for all the informative variables integrated into the model, and not only with the price of natural gas. The regime effects these variables have exhibited are discussed in the following three points.

- First, our model has shown that in a regime of low wind production, increasing costs generates a decrease in wind invested capacity but that in high regime, the reverse holds true: we believe this regime effect might be linked with a process that economists have called "valley of death". Norberg-Bohm (2000), one of the earliest authors to apply the valley of death notion to energy technologies, noted that the phrase is meant to reflect the common experience that many new technologies "die" before being successfully commercialized.

³¹Others raise concerns about that methane leakage associated with natural gas extraction, transport, and storage, may perpetuate climate change.

The scope of complementarity with natural gas as a support option providing flexible back-up power that can ramp up quickly may also be limited. Hartley and Medlock III (2017), argue that the price of energy is often insufficient to cover even the operating costs of renewable energy production, let alone provide a competitive rate of return to the capital employed. In fact, they show that the full long-run costs of renewable energy (including a competitive rate of return on capital) are not covered until sometime after fossil fuels are abandoned. Their model points to potential difficulties in financing investments in productive capital in the face of competition from fossil fuels.³² In the same vein, Esposito, Rupp, and Carley (2015) shows that the limited scope of complementarity can raise from the fact that, as the two sources of electricity are developed at the same time, the individual risks associated with developing these two different types of systems may interact, resulting in overall increased risks to the portfolio. The question of the effect of generation intermittency on investment in renewable capacity is also crucial. Wind blows neither continuously nor in concert with demand. And solar production is volatile due to the sensitivity to weather conditions, air pollution and other driving determinants of solar radiation intensity. Even if this variability can be partly programmed (e.g., absence of solar production at night), a significant uncertainty associated to the output of renewable energy remains.³³

She suggested that generating technologies may find it difficult to capture a market niche because the homogeneity of electricity as a product meant that it was not possible to use “quality improvements to charge higher prices to the lead adopters.” Uncertainty about competitiveness and government support (Murphy and Edwards, 2003) coupled with an inability to capture benefits external to the firm, including some benefits of learning-by-doing, learning-by-using and network externalities that limits the ability of new technology firms to attain the economies of scale that could lead to lower costs are identified as serious barriers to commercialization of renewable energies. These elements imply that, the longer the path to technological maturity, the greater the sensitivity of renewable production to the technological costs incurred.

Second, in perfect agreement with Afaki and Netessine (2017) our results showed that increasing the carbon price has two counteracting effects on investment in renewables. This result can be explained by two concomitant phenomena: on the one hand, increasing the carbon price improves the cost competitiveness of renewables relative to non-renewable technologies. On the other hand, renewables require back up generation, which typically comes from generators using fossil fuels; thus, an increase in the carbon price leads to an increase in the costs of reserves to cover intermittency. Often, it’s the older, more emission-intensive technologies that are used as backup. So, in stark contrast with intuition, increasing the carbon price may actually reduce the overall proportion of renewable generation. Drake, Kleindorfer, and Van Wassenhove (2016)) also suggest that increasing carbon prices might have an adverse effect on investment in the clean technology via carbon leakage i.e., increased dirty production in unregulated regions. In a context of liberalized markets, the negative effect of intermittency is amplified by the marginal cost pricing typical of such markets.

Third, in the face of growing demand for electricity, our results show a tendency to invest less during high regimes. We can see this through the revenue variable whose coefficient is both negative and statistically significant in the high regimes and positive in the low regimes. One possible explanation would be to consider that investing in these intermittent energies would not have the main leitmotiv of assuming a production in baseload. As a result, a revival in demand would make technologies offering a greater margin of flexibility

more eligible in the face of a security of supply objective. This result perfectly matches the one obtained by Baranes, Jacquemin, and Poudou (2017) who relied on a Panel Tobit model to look at this question at the state level using annual data from 1998 to 2015.

3.5.4 Storage: the ultimate solution?

Beyond the results obtained by the empirical approach retained in this article, it seems important to us to refocus the crucial issue that storage solutions represent in the penetration of renewable energies and that we did not take into account. In tune with the most advanced technological advances, they are often claimed as a quick fix in the industrial arena. They would make it possible to modify the production profile of renewable energies by charging when the production is high and the load low, and by discharging when the production level is low and the load high. However, these storage solutions are capital-intensive and may incur significant operational losses (high initial cost, safety concerns, not yet proven for cycle life or maintenance cost, significant environmental effects and sophisticated management). In that respect, Bistline and Young (2019) results suggest that low-cost energy storage would not induce a substantial increase of renewable penetration. Using their own words, “Low cost energy storage is neither necessary nor sufficient for higher wind and solar penetration, as storage can be valuable at lower variable renewable shares (e.g. for regions with high shares of inflexible generation and high gas prices) and is not economic under some conditions with higher shares (e.g. for wind-heavy mixes in areas with extensive transmission)”. They rather suggest how storage “is quite dissimilar from a hypothetical scenario with constant renewable output, as neither storage nor transmission surmount the hourly profile correlation challenges between intermittent renewable energy and load”.

In this vein, Balducci et al. (2018) and Arbabzadeh et al. (2019) suggest that it would be more reasonable to assign to the storage solution a role of facilitator to the penetration of renewable energies. It could pave the way to a modernization of the electrical networks by improving their flexibility and by limiting saturation periods through a range of services that go beyond the integration of intermittent energies. In addition, lower-cost storage options can help reduce the impact of declining incomes but do not solve the problem because the latter itself also exhibit deflation (Bistline and Young (2019), Mai et al. (2018)).

What would ultimately imply a large-scale penetration of renewable energies like solar or wind technologies for the electrical system? This article is intended to identify the real determinants and to take a closer look at the interdependence with the natural gas market. In this quest, we also implicitly put into perspective a question that is of great importance: what would be the cost of replacing fossil fuels? Hartley (2018) looked at the case of Texas to find out whether combining wind and storage would be the cheapest way to replace fossil fuels in power generation. The choice of this precise state is not trivial: it echoes the fact that it is one of the only ISOs to have very little exchange with neighboring electrical systems. This makes it all the more eligible to gauge system costs that would involve replacing fossil fuels with an increased reliance on wind power. Results suggest that wind plus storage has a higher cost than the nuclear plus storage. More interestingly, the level of storage required by these scenarios is “extraordinary” : it’s about 30% more than the current pumped storage capacity in all of the US in the nuclear case, and more than 2.5 times current US capacity in the wind case. He also found that an electricity system exclusively based on gas would be the least expensive option even when gas prices rise substantially. An implication is that a tax on natural gas use, or on CO2 emissions, would raise electricity prices substantially while doing very little to reduce gas use until the tax rate is high enough to trigger the entry of wind, or especially nuclear generation into the system.

3.6 Conclusion

In fine, the answer to the question of whether natural gas at the energy-climate nexus is rather a bridge fuel or a barrier: our model showed that it was difficult to talk about a strict substitutability or a pure complementarity. A regime swing as the result of a complex interaction of a multitude of factors is more reasonable. Nevertheless, our data showed a higher likelihood of a substitution relationship between natural gas and wind power technology in a high path regime and a complementary relationship with solar power in a lower regime of solar electricity generation. We associate this result to the more advanced level of U.S. wind power development compared to solar energy whose multiple challenges give direction for future political support. From a political ground, these increasing interrelationships show how important is for investments in renewable and non-renewable energy to be considered simultaneously.

Gas and renewables should not be left to compete? To answer this question, one must be aware of the full range of technologies that exist to generate electricity using natural gas. When greener technologies like fuels cells or micro-turbines are used, natural gas might become more attractive than a more expensive renewable alternative.

3.7 References

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3.8 Appendices

3.8.1 Appendix A: Data

Table 3.6: Descriptive analysis of first log-differenced data.

	DL_WIND_GEN	DL_SOL_GEN	DL_REV_ELEC	DL_NG_COST	DL_NQ_WIND	DL_MOD_SPOT	DL_CEI	DL_BCI
Observations	116	116	116	116	116	116	116	116
Mean	0.021	0.005	0.000	-0.004	0.003	-0.008	0.004	0.000
Median	0.020	0.005	0.000	-0.007	0.003	-0.006	0.006	0.000
Maximum	0.364	0.158	0.027	0.164	0.067	0.031	0.026	0.001
Minimum	-0.215	-0.124	-0.033	-0.156	-0.072	-0.052	-0.048	-0.002
Std. Dev.	0.063	0.049	0.010	0.046	0.029	0.012	0.012	0.001
Skewness	0.889	0.350	0.087	0.438	-0.351	-0.946	-1.140	0.038
Kurtosis	11.918	4.251	3.768	5.669	3.174	5.701	5.360	2.084
Jarque-Bera	399.65***	9.15**	2.99	38.14***	2.33	52.56***	52.06***	4.08

. Note: ***, ** denote the rejection of the null hypothesis at 1% and 5% respectively.

3.8.2 Appendix B: Robustness analysis

Table 3.7: Markov Regime-Switching Models for U.S. wind electricity generation growth: 2010M11 - 2019M9 with time-varying transition probabilities

Panel A: Estimated coefficients									
		MSM1		MSM2		MSM3		MSM4	
Independant var.	State								
DL_NG_COST	S1	0.185	-0.069	0.184	-0.073	0.175	-0.093	0.184	-0.087
	S2	-7.249	(0.000)	-7.256	(0.000)	-6.465	(0.000)	-6.373	(0.000)
DL_REV_ELEC	S1	-0.228	-0.638	-0.237	-0.631	-0.103	-0.835	-0.223	-0.693
	S2	20.775	(0.000)	20.796	(0.000)	20.098	(0.000)	21.216	(0.000)
Constant	S1	0.001	-0.906	0.001	-0.924	-0.001	-0.867	0.000	-0.996
	S2	0.190	(0.000)	-0.136	(0.000)	0.149	(0.000)	0.136	(0.000)
Trend	S1	0.000	-0.506	0.000	-0.509	0.000	-0.395	0.000	-0.573
	S2	-0.002	(0.000)	-0.002	(0.000)	-0.001	(0.000)	-0.001	(0.000)
DL_CEI	S1			0.046	-0.896	0.053	-0.881	0.075	-0.840
	S2			-0.136	(0.000)	0.892	-0.045	1.553	-0.226
DL_NQ_WIND	S1					0.095	-0.513	0.116	-0.445
	S2					1.889	(0.000)	1.942	(0.000)
DL_BCI	S1							-3.704	-0.547
	S2							4.237	-0.864
Sigma 1		0.037	(0.000)	0.037	(0.000)	0.037	(0.000)	0.037	(0.000)
Sigma 2		0.036	(0.000)	0.036	(0.000)	0.004	(0.000)	0.015	(0.000)
Log-Likelihood		186.039		186.051		196.142		191.264	
AIC		-3.216		-3.179		-3.361		-3.231	
SIC		-2.866		-2.779		-2.909		-2.729	
Panel B: Time-varying transition probabilities and expected durations									
		MSM1		MSM2		MSM3		MSM4	
P11	Mean	0.97		0.97		0.97		0.96	
	SD	0.03		0.03		0.01		0.04	
P12	Mean	0.03		0.03		0.03		0.04	
	SD	0.03		0.03		0.01		0.04	
P21	Mean	0.38		0.38		0.39		0.36	
	SD	0.18		0.18		0.14		0.15	
P22	Mean	0.62		0.62		0.61		0.64	
	SD	0.18		0.18		0.14		0.15	
DU1	Mean	47.27		47.84		35.32		46.53	
	SD	42.65		43.90		9.22		43.83	
DU2	Mean	3.78		3.81		2.98		3.48	
	SD	4.33		4.41		1.73		2.45	
RCM		4.19		4.13		0.31		4.23	

Notes: the dependant variable is the monthly wind electricity generation. State 1 (2) refers to the high (low) regime of wind power production. Regime-specific coefficients are reported with the associated p-values in brackets. Sigma refers to the standard deviation of each state. RCM is the regime classification measure. The transition probabilities are reported as p_{ij} . The expected duration of being in state i are reported as DU_i , i.e., DU_1 for state 1 and DU_2 for state 2.

Table 3.8: Markov Regime-Switching Models for U.S. solar electricity generation growth: 2010M11 - 2019M9 with time-varying transition probabilities

Panel A: Estimated coefficients										
		MSM1		MSM2		MSM3		MSM4		
Independant var.	State									
DL_NG_COST	S1	1.261	(0.224)	0.872	(0.389)	0.274	(0.703)	0.049	(0.968)	
	S2	1.261	(0.362)	-0.140	(0.074)	-0.158	(0.043)	-0.249	(0.004)	
DL_REV_ELEC	S1	0.072	(0.988)	-0.265	(0.957)	-2.603	(0.514)	-2.793	(0.565)	
	S2	-0.183	(0.649)	-0.226	(0.542)	0.832	(0.016)	1.053	(0.006)	
Constant	S1	-0.001	(0.979)	0.021	(0.789)	0.002	(0.983)	-0.226	(0.542)	
	S2	0.039	(0.000)	0.038	(0.000)	0.036	(0.000)	0.021	(0.789)	
Trend	S1	0.000	(0.722)	0.000	(0.854)	0.000	(0.881)	0.000	(0.979)	
	S2	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	0.000	(0.389)	
DL_CEI	S1			-1.708	(0.697)	-2.617	(0.584)	0.470	(0.894)	
	S2			0.614	(0.037)	0.501	(0.073)	0.692	(0.023)	
DL_SOL_MOD	S1					-3.263	(0.342)	-3.584	(0.549)	
	S2					-0.176	(0.549)	-0.959	(0.001)	
DL_BCI	S1							-2.866	(0.971)	
	S2							6.658	(0.208)	
Sigma 1		(2.221)	(0.000)	0.116461446	(0.000)	-2.365	(0.000)	0.100	(0.000)	
Sigma 2		-3.438	(0.000)	0.031861783	(0.000)	-3.504	(0.000)	0.033	(0.000)	
Log-Likelihood		201.794		202.719		211.022		202.839		
AIC		-3.294637		-3.276		-3.38635		-3.243		
SIC		-2.959		-2.892		-2.954		-2.811		
Panel B: Transition probabilities and expected durations										
			MSM1		MSM2		MSM3		MSM4	
P11	Mean		0.682896		0.646028		0.733069		0.649122	
	SD		0.278		0.030		0.370		0.479	
P12	Mean		0.317		0.354		0.267		0.351	
	SD		0.278		0.030		0.370		0.479	
P21	Mean		0.042		0.043		0.046		0.056	
	SD		0.023		0.000		0.076		0.076	
P22	Mean		0.958		0.957		0.954		0.944	
	SD		0.023		0.000		0.076		0.076	
DU1	Mean		272.371		2.846		1.97000		NA	
	SD		1869.139		0.255		1.87000		NA	
DU2	Mean		28.812		23.519		61.868		41.696	
	SD		14.091		0.263		114.842		64.520	
RCM			11.962		12.008		8.256		8.455	

Notes: the dependant variable is the monthly wind electricity generation. State 1 (2) refers to the high (low) regime of wind power production. Regime-specific coefficients are reported with the associated p-values in brackets. Sigma refers to the standard deviation of each state. RCM is the regime classification measure. The transition probabilities are reported as p_{ij} . The expected duration of being in state i are reported as DU_i , i.e., DU_1 for state 1 and DU_2 for state 2.

Figure 3.7: Probability of high wind generation regime smoothed from TVTP-MSMs.

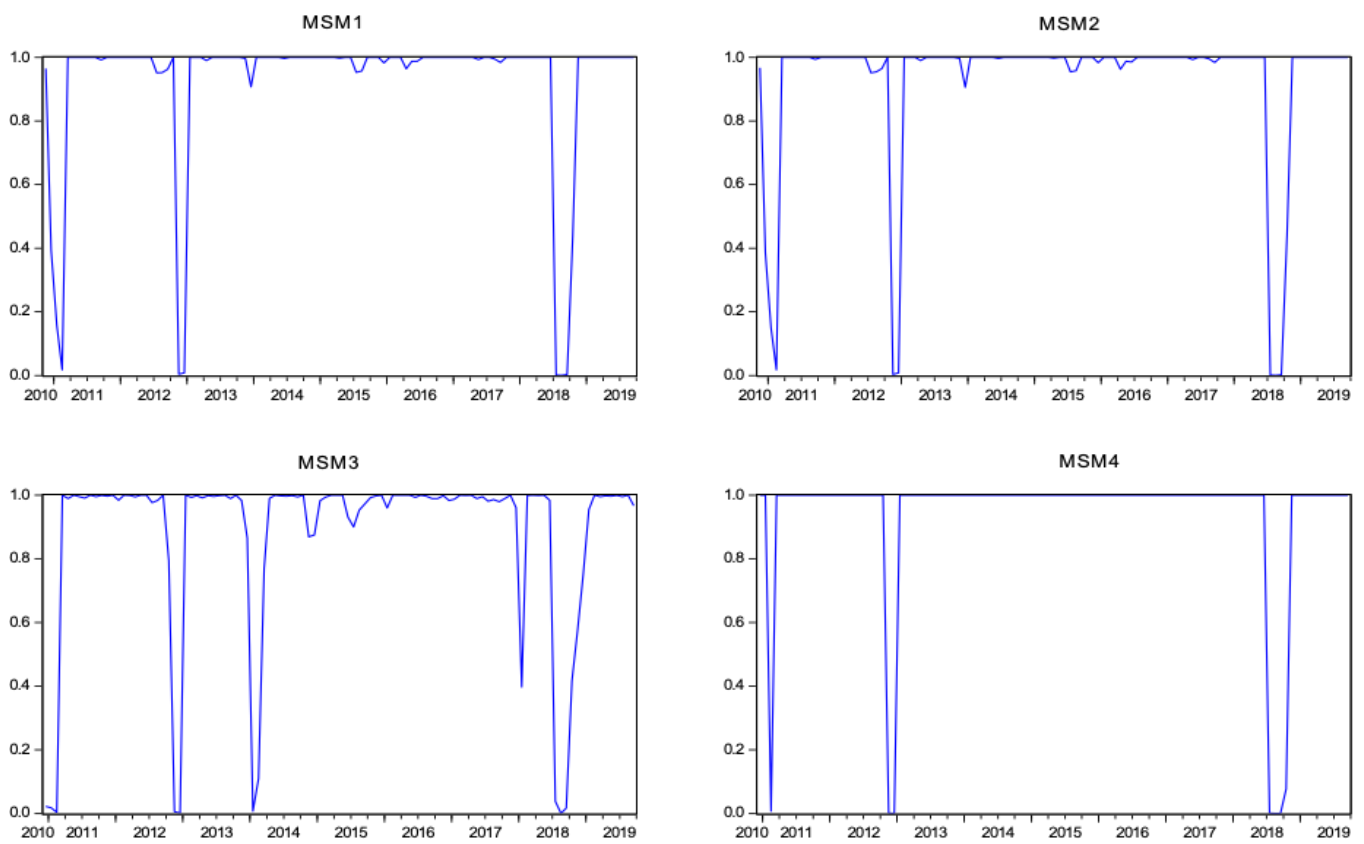
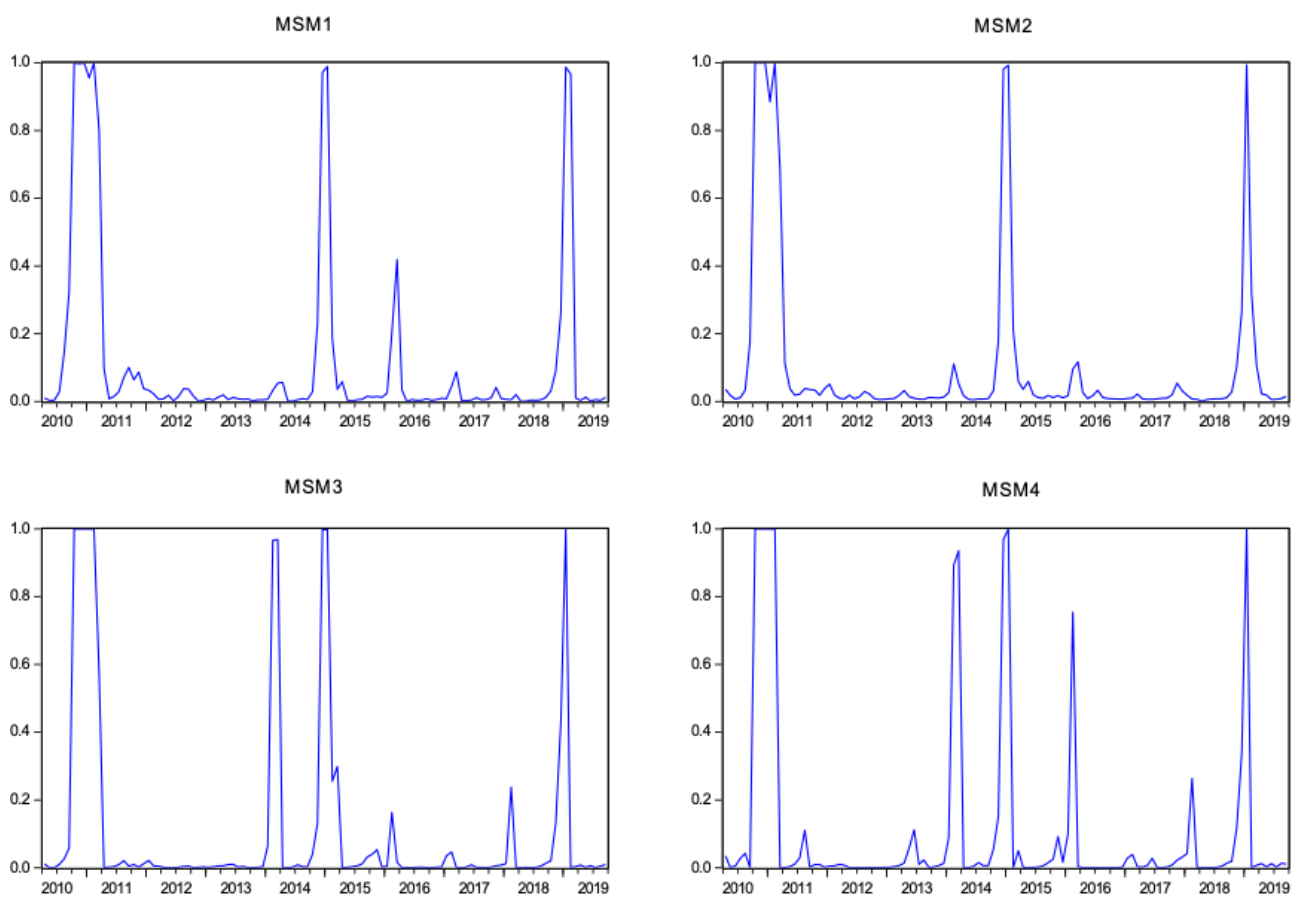
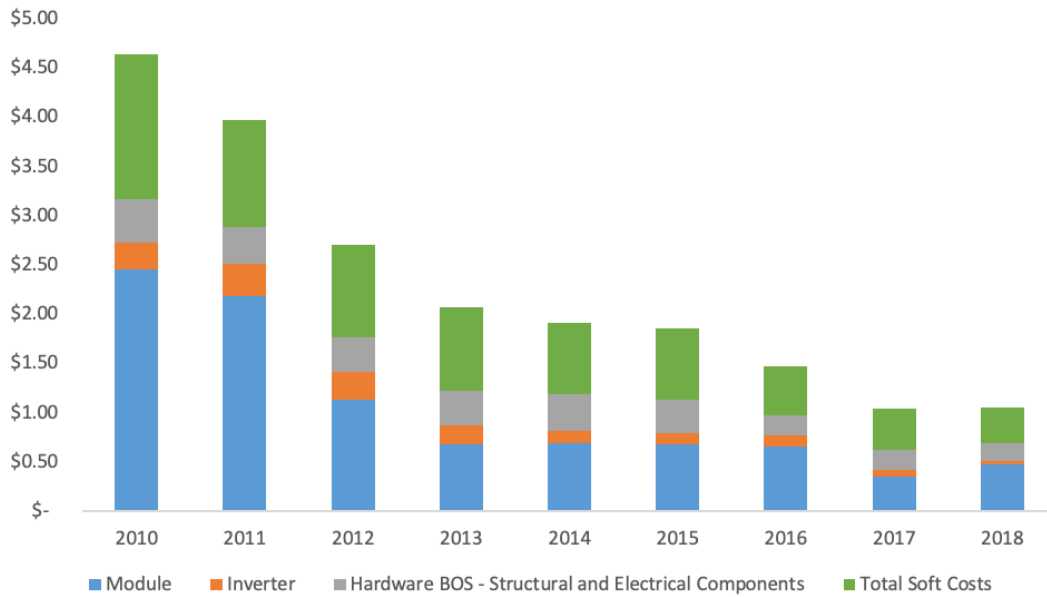


Figure 3.8: Probability of high solar generation regime smoothed from TVTP-MSMs.



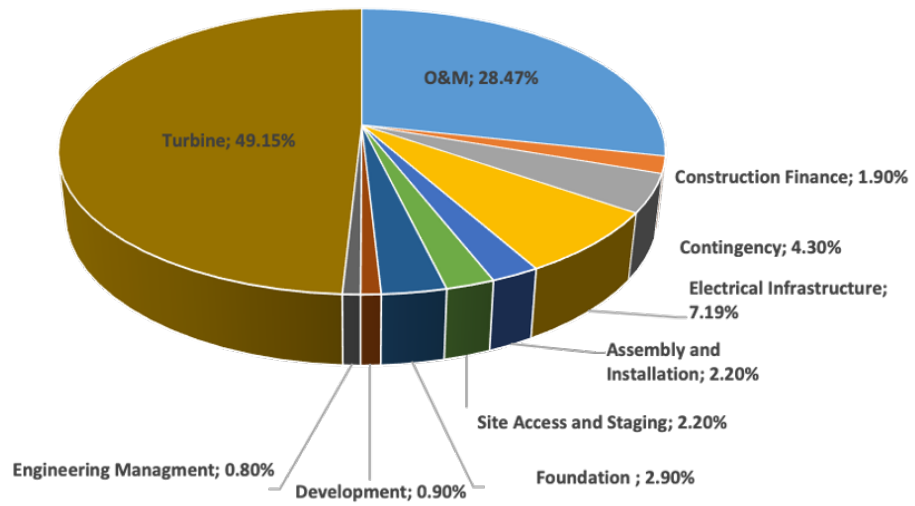
3.8.3 Appendix C: Renewable cost benchmark

Figure 3.9: NREL PV system cost benchmark (inflation adjusted), 2010-18.



Source: U.S. Solar Photovoltaic System Cost Benchmark: Q1 2018. Golden, CO: NREL.

Figure 3.10: U.S. component-level LCOE contribution for the 2018 NREL land-based wind reference project.



Source: 2018 Cost of Wind Energy Reviews, NREL (Stehly et al., 2018)

Conclusion

Overall, this thesis made it possible to refocus the issue of flexibility under the prism of recent developments in the natural gas market. The three chapters studied have shown that it remains a fully contractual issue when it comes to LNG trade, that it brings to the fore the question of the efficiency of gas hubs in view of their increasing financialization and finally that it becomes imminently dependent on the dynamics of the electricity markets. Under a resolutely applied framework, the analysis that were carried out considered the non-linear features of natural gas dynamics in an attempt to fill the gaps in an emerging empirical literature.

The first chapter aimed at putting contract flexibility into the perspective of medium-term market evolution based on market forecast. The retained modelling strategy moved beyond of the generally used linear cointegrating framework to be able to capture transaction costs, market power, asymmetry of the economic cycle, extreme events, regulations and inherent rigidity in the market. Results have generally highlighted a significant value of the flexibility option. Moreover, the option of free destination has been found to be substantially larger in the high case scenario of oil price volatility suggesting that the more the market, particularly in Asia, swiftly repositions to a more flexible reconfiguration, ultimately involving the dissolution of destination clauses and the use of a hub- pricing in contractual terms, the more the players of this industry will be inclined to commit and take advantage of arbitrage opportunities.

From the industry standpoint, not only the shortfall for a producer who would be constrained in terms of destination by a long-term contract could be conveyed by the destination option but also the important source of value for profit motive actors who are in a position to arbitrage. In this respect, the recent arrival of trading houses in this market would be prominent in terms of flexibility and market diversification; and the present work should help to understand how

to value and manage these participants' businesses. Moreover, at the heart of the vivid debate over the potential integration of regional markets, this first chapter showed that the contractual aspect of this industry is capable of constituting a serious barrier in global LNG trade. The required cautious interpretation of the impact of the destination option on natural gas price convergence debate has been discussed. We concluded that expecting an integration of NG markets only via the effect of appropriation of best netbacks when suppliers can choose their ultimate market destination is misleading. The shortfall of geographically constrained producers rather highlights the benefits of greater future spot market reliance as even partners engaged in long-term contracts could profit from a participation in the spot market, thus increasing the liquidity of the latter. If it works in tandem with a lower indexation of oil prices and the market forces driving movements of vessels then, in this exact case, one would expect a possible "convergence". Finally, from a security of supply standpoint, with relatively low physical flexibility from the LNG export infrastructure and high utilization of liquefaction plants that tend to be base load, making it possible for the contracting parties to supply additional LNG or shifting the destination of LNG delivery, would play a pivotal role in terms of the resiliency to unforeseen events. From this perspective and in view of the steadfast need to manage gas demand uncertainty, the value of destination flexibility far outweighs the optional value calculated in this chapter compared to the possible consequences of an unforeseen shock.

The second chapter poses the question of efficiency of European traded gas hubs that raises concerns about their ability to constitute an important support for financial risk management of gas portfolios and physical balancing. More precisely, pricing and informational efficiency of the two largest European natural gas markets (UK NBP and Dutch TTF) have been investigated by drawing a parallel with the US Henry Hub through a wavelet decomposition approach. We contribute to the literature in several ways. To the best of our knowledge, this is the first study that investigates the issue of natural gas pricing and informational efficiency in European and American gas hubs using frequency domain approach. Indeed, most previous studies have ignored the possibility that direction, extent and strength of Granger causality may vary at different time scales. Furthermore, the literature of European natural gas futures prices is thin as the market is rather young compared to the North American experience. The question of their efficiency raises concerns about their ability to provide credible price creation, discovery

and reference points, which could be used in medium and long-term gas contractual pricing terms. The question is all the more important when considering the European Commission's vision of a single energy market. Moreover, past studies neglected the nonlinearities governing energy commodities dynamics and mostly have considered linear causal effects between spot and futures prices.

Several outcomes are reached. First, all considered gas markets are found to be globally efficient in pricing with strong evidence of cointegrating relationships between spot and futures markets. Moreover, information flows between spot and futures markets although the futures markets play a leading role in price discovery at some time scales for NBP and TTF gas hubs. Furthermore, Henry Hub, NBP, and TTF gas hubs are found to be informationally efficient in the long run. For short-term and medium-term scales, the null hypothesis of futures acting as random walk is rejected. From a policy standpoint, our results call for a significant increase in the number of physical transactions between European markets that are still required to reduce bottlenecks in transmission networks and interconnection points.

Are renewable and natural gas technologies competitors or rather provide some scope of complementarities? To answer this question, the third chapter aimed to connect different strands of the literature in a consistent framework able to comprehensively assess the economic potential of wind and solar penetration under many prospective drivers and explore in the same vein the degree of gross substitutabilities/ complementarities between natural gas and renewable energies. From an empirical perspective, we have tested for the presence of regime effects by estimating a Markov Regime-Switching Model (MRSW) based on US monthly data of wind and solar electricity generation and potential explanatory variables spanning from electricity market, carbon policy risks to global economic health. Compared to the literature on the subject, we are not only examining the differences in the impact of our explanatory variables according to the regime considered, but also deliver the probability associated with the high renewable production regime as well as with the lower production regime, the probability of transiting to each other and their expected durations. Furthermore, we have examined renewable production under two distinct spectra: that of wind and solar energies whose dynamics are not completely similar.

The answer to the question of whether natural gas at the energy-climate nexus is rather

a bridge fuel or a barrier: our model showed that it was difficult to talk about a strict substitutability or a pure complementarity. A regime swing as the result of a complex interaction of a multitude of factors is more reasonable. Nevertheless, our data showed a higher likelihood of a substitution relationship between natural gas and wind power technology in a high path regime and a complementary relationship with solar power in a lower regime of solar electricity generation. We associate this result to the more advanced level of U.S. wind power development compared to solar energy whose multiple challenges give direction for future political support. From the political ground, these increasing interrelationships show how important is for investments in renewable and non-renewable energy to be considered simultaneously.

Notwithstanding the value of our findings, we do not claim to answer all questions requiring flexibility in the natural gas market and this work can be extended in several directions. One could ambition to extend the analysis on destination flexibility to incorporate the dynamics of the shipping market or widen the geographical scope of the analysis by incorporating other LNG importing markets, such as the emerging ones in Latin America and Asia (e.g., China, India) where demand is expected to noticeably increase in the coming years. Also, apart from the British and Dutch cases, what about the rest of Europe in terms of the informational efficiency of gas hubs? Are they able to provide valid price signals? To what extent would the results obtained on the growing inter-flexibility with renewable energies be sensitive to the regional specificities of American electricity markets? These fundamental questions constitute avenues for future research on the flexibility mechanisms in natural gas market.

RÉSUMÉ

La question de la flexibilité sur le marché du gaz naturel reflète la nature même de la commodité: la demande n'est pas particulièrement flexible (surtout résidentielle) et l'offre ne réagit pas toujours aux signaux de prix au vu des lourds investissements en infrastructure de production, transport et stockage requis. La nouvelle donne posée par la demande électrique de gaz naturel servant de *back-up* à l'intermittence des énergies renouvelables et envisagé de plus en plus comme une solution de stockage pose d'énormes défis techniques, physiques, organisationnels et réglementaires. Dans ce contexte, l'offre et la demande de flexibilité est le fruit d'une interaction complexe entre plusieurs facteurs: parmi eux le développement des *hubs trading* de gaz naturel, des niveaux de production d'électricité renouvelable, de la disponibilité des cargaisons de gaz naturel liquéfié (GNL) ou encore du développement du stockage flottant. Cette thèse s'intéresse aux enjeux qui font appel aux mécanismes de flexibilité sous la perspective des développements récents du marché gazier. Elle s'articule autour de trois axes d'étude cherchant à rendre compte du poids contractuel de cette industrie, de son degré de financiarisation ainsi que l'inter-flexibilité croissante qui se dessine avec le marché électrique.

MOTS CLÉS

Gaz naturel; flexibilité de destination; efficacité; complémentarité; énergies renouvelables

ABSTRACT

The question of flexibility in the natural gas industry reflects the very nature of the commodity: demand is not particularly flexible (especially residential) and supply does not always react to price signals in view of the heavy required investments in production, transportation and storage infrastructures. The new situation posed by the electric demand for natural gas serving as a back-up to the intermittency of renewable energies poses enormous technical, physical, organizational and regulatory challenges. In this context, the supply and demand for flexibility is the result of a complex interaction between several factors: among them the development of natural gas trading hubs, renewable electricity production levels, the availability of cargoes of liquefied natural gas (LNG) or the development of floating storage. This thesis focuses on the challenges that call for flexibility mechanisms from the perspective of recent developments in the gas market. Three lines of research are investigated to account for the contractual weight of this industry, the degree of financialization of the gas market and finally the increased inter-flexibility that is emerging with the electricity market.

KEYWORDS

Natural gas; destination flexibility; efficiency; complementarity; renewable energy