



Essays on commodity prices and energy markets

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**Essais sur les prix des matières premières et les
marchés de l'énergie**

Essays on commodity prices and energy markets

Soutenue par

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Essays on commodity prices and energy markets

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To my parents

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Résumé en français

Introduction

L'objectif de cette thèse est d'expliquer les dynamiques, les déterminants et les influenceurs potentiels des prix des matières premières. Basée sur la théorie de la finance traditionnelle, l'hypothèse de l'efficience du marché et la théorie de la finance comportementale, cette thèse étudie les corrélations entre les prix en utilisant de nouvelles méthodologies empiriques afin d'obtenir des résultats pertinents, capter les spécificités des marchés et induire des explications économiques intéressantes.

Les marchés des matières premières ont progressé suivant des trajectoires, les rendant structurellement indépendants. Au cours des vingt dernières années, ces marchés ont subi des déréglementations et des changements majeurs, les transformant en actifs négociables. Cela a été appliqué à plusieurs secteurs tels que l'énergie (comme le pétrole, le gaz naturel et, plus récemment, l'électricité), les métaux précieux (tels que l'or, l'argent et le platine), les produits agricoles (tels que le blé et le soja), les produits de base (comme coton et sucre). En conséquence, les produits dérivés des matières premières sont devenus de plus en plus populaires. Le nombre de produits échangés, des investisseurs et le degré d'interconnexion avec le marché financier ont considérablement augmenté. Ainsi, les prix des matières premières ont connu une évolution exceptionnelle, synchronisés avec des hausses majeures et des changements dans la nature des investisseurs avec une augmentation continue de la demande. Ces faits ont suscité des questions cruciales qui méritent une attention particulière de la part de la littérature financière. Il est important d'étudier et d'identifier les opportunités potentielles reportées par les investisseurs en ce secteur bien spécifique.

Ces marchés subissaient des mouvements impressionnants qui, parfois, entraînent des hausses et des baisses. Ces événements sont souvent la conséquence de conflits politiques, de turbulences financières, d'événements économiques et de changements climatiques brusques.

Ainsi, il est essentiel d'analyser la spécification de l'efficience des marchés des matières premières et l'impact du comportement des investisseurs sur leurs prix pour optimiser les stratégies de négociation et de gestion des risques. De plus, étant donné le nombre élevé de changements extrêmes sur les marchés, il est nécessaire de se focaliser sur les prix dans une perspective temps-fréquentielle et de prendre en compte toutes les conditions du marché.

L'importance d'étudier les prix des matières premières, y compris la relation entre les prix au comptant et les prix à terme (par conséquent l'efficacité de l'information et des prix), et les aspects comportementaux sur les marchés des matières premières repose sur plusieurs théories majeures tel que la théorie de l'efficience du marché (Malkiel and Fama (1970), Fama (1991)), La théorie de l'évaluation des actifs (Fama and French, 1987), la théorie de stockage (Kaldor (1939), Working (1960) et Brennan (1958)), et la théorie de la finance comportementale.

Ces théories demeurent incertaines en ce qui concerne l'efficience du marché (en termes d'information et de prix) et l'impartialité (provenant des sentiments d'investisseurs et du marché) dans différentes conditions et fréquences de marché. Cette thèse porte sur les interactions des prix de matières premières dans le contexte de tarification et de l'efficience informationnelle, ainsi que sur les forces motrices comportementales des nouveaux négociateurs et les sentiments du marché.

Les changements massifs des prix et des participants des marchés des matières premières soulèvent deux questions cruciales. La première question s'intéresse à l'interaction entre les prix au comptant et les prix à terme durant les différentes conditions de marché, et la deuxième question porte sur l'impact de l'augmentation et de la diversification des participants du marché sur ces prix. Même si des recherches antérieures ont permis d'étudier ces deux questions, le débat est toujours d'actualité, étant donné les nouvelles caractéristiques des marchés des matières premières.

Dans un premier lieu, le chapitre 1 étudie la relation entre les prix au comptant des matières premières et les prix à terme dans différentes périodes de volatilités extrêmes du marché. La présente étude porte sur huit marchés de matières premières de quatre catégories différentes (énergie, métaux précieux, agricole et denrées alimentaires) pour une période allant de 2002 à 2019. Compte tenu du cadre théorique et de la pénurie empirique concernant l'importance des conditions extrêmes du marché pour la gestion des risques, la diversification des portefeuilles, les politiques d'investissement et les stratégies de négociation, nous avons examiné la dépendance entre les prix au comptant et à terme pour quatre types de copule. Cette approche est conduite en intégrant des modèles GARCH pour spécifier les distributions marginales des prix correspondants.

Les résultats des dépendances entre les prix au comptant et les prix à terme sont différents selon les types de produits, les conditions du marché, les propriétés et le processus de stockage. La dépendance entre le prix au comptant et le prix à terme du pétrole brut est asymétrique et est adaptée à la copule de Clayton. Par conséquent, l'efficience du marché est forte dans des conditions de marché normales à baissières et diminue donc lorsque les prix entrent dans des conditions extrêmement négatives. Les métaux précieux (or et platine) et le coton sont adaptés à la copule Normal, ce qui confirme la forte dépendance entre les prix au comptant et à terme dans toutes les conditions de marché. C'est une confirmation de l'aspect 'refuge' des métaux précieux. Ces produits présentent un haut degré d'efficacité et sont utilisés à des fins de couverture en cas d'incertitude. Les produits agricoles (soja et blé) montrent

un comportement compatible avec la copule de Gumbel. Cela signifie que la dépendance entre les prix au comptant et les prix à terme est forte dans des conditions de marché normales à haussières. Il y a un manque de lien entre les deux marchés dans des conditions baissières.

Dans un second lieu, le chapitre 2 utilise une décomposition temps-fréquentielle et une approche de causalité non paramétrique pour tester la causalité entre les prix des énergies et les indices de sentiment. Les résultats montrent qu'il existe un lien de causalité significatif entre les prix à terme et les indicateurs de sentiment. Cependant, les résultats varient en termes de fréquences temporelles. En utilisant des données quotidiennes de 2002 à 2018 des prix de gaz naturel et de pétrole, nous constatons qu'à court terme, les rendements du prix de pétrole entraînent une incertitude économique importante, tandis qu'à moyen terme, la puissance de cette causalité diminue et demeure bidirectionnelle. À long terme, cette causalité change de direction pour plusieurs raisons économiques. En ce qui concerne les prix du gaz naturel, il existe d'importants flux de causalité à court terme. Alors qu'à moyen et long terme, le gaz naturel cause significativement l'indice d'incertitude économique.

De plus, le sentiment pessimiste des investisseurs permet de mieux prédire les rendements énergétiques que l'indice du sentiment optimiste; Par ailleurs, les investisseurs pessimistes montrent des causalités significatives sur l'ensemble de la période de l'échantillon et pour toutes les fréquences temporelles, le comportement optimiste ne se manifestent qu'à long terme pour expliquer les volatilités des prix du pétrole et du gaz naturel. Enfin, l'indice de volatilité économique semble avoir un meilleur pouvoir estimatif pour les mouvements du prix de pétrole comparé au prix du gaz et un moindre pouvoir de causalité par rapport aux indices de sentiment des investisseurs. Ainsi, les spéculateurs et les investisseurs de ces matières premières auront intérêt d'inclure ces indicateurs dans leur ensemble d'information lorsqu'ils prennent des décisions de placement et lorsqu'ils gèrent des risques.

Finalement, le chapitre 3 analyse l'efficience informationnelle et l'efficience des prix du gaz naturel aux marchés des États-Unis et en Europe. Cette analyse examine empiriquement la direction de causalité entre les prix à terme et les prix au comptant des marchés du gaz naturel américain et européen en utilisant une approche temps-fréquentielle. Les données des prix sont quotidiennes, couvrant la période entre 2013 et 2019. Il s'agit, à notre connaissance, de la première tentative de fournir un compte rendu exhaustif du lien entre les prix au comptant et les prix à terme sur les marchés européens et américains du gaz naturel, basé sur une approche de multi-résolution mobilisant une décomposition en ondelettes des données.

Cette analyse a donné des résultats intéressants. Premièrement, les prix à terme et les prix au comptant du Henry Hub, du NBP et du TTF sont intégrés, ce qui implique que les participants au marché peuvent mieux anticiper la convergence des prix en observant les écarts par rapport aux relations à long terme. L'existence d'une relation de co-intégration renforce la capacité des investisseurs à couvrir leur exposition aux prix du marché par des prix à terme. Ces résultats ont des implications potentielles

pour les entreprises qui couvrent les risques liés à la production au moyen de contrats à terme et pour traders du gaz naturel. Deuxièmement, les tests de causalité non linéaires montrent qu'aucun des deux marchés au comptant ou à terme du Henry Hub ne semble mener l'autre (à quelques exceptions près où les prix des contrats à terme à deux et trois mois de maturité semblent mener les prix au comptant). En d'autres termes, les deux marchés sont efficaces en termes de prix, et l'activité sur le marché au comptant est susceptible d'affecter les prix en tant que marchés à terme. Ce résultat reflète le processus d'ajustement vers une relation à long terme (Brenner and Kroner, 1995). En ce qui concerne les marchés du NBP et du TTF, les résultats ne sont pas unanimes sur les différentes échelles de temps et sur les trois échéances car ils varient entre la causalité unidirectionnelle et la causalité bidirectionnelle.

Chapitre I : Dépendance entre les marchés au comptant et les marchés à terme des matières premières en période de volatilité extrême : Une approche de Copule

Ce chapitre est co-écrit avec mes deux encadrants Pr. Anna Creti et Pr Zied Ftiti.

J'avais l'opportunité de présenter et de discuter cet article à la conférence IRMBAM: "6th International Research Meeting in Business and Management" (01-02 Juillet, 2015 à Nice-France), à la conférence ICEDP: "International conference on Economic and Development Policy" (23-24 Octobre 2016 à Hammamet, Tunisie) à la conférence ISEFI: "The 5th International Symposium on Environment and Energy Finance Issues" (22- 23 Mai 2017 à Paris, France) et à la conférence 35th USAEE/IAEE Conference: "Riding the energy cycles" (12-15 Novembre 2017 à Houston-Texas, USA),.

Le rôle crucial des contrats à terme à réduire les risques et à estimer les prix a motivé plusieurs recherches. Jusqu'à présent, la littérature s'est concentré sur la relation entre les prix au comptant et les prix à terme afin d'étudier la dynamique de gestion des risques entre les deux marchés. En outre, l'intérêt accru des investisseurs financiers et la volatilité exceptionnelle des marchés des matières premières ont accru la capacité des contrats à terme à transmettre des informations à tous les agents économiques.

De plus, les marchés des matières premières sont caractérisés par des niveaux élevés de volatilité, en particulier depuis le début des années 2000. Les stocks et les prix fluctuaient considérablement, en partie de façon prévisible (en raison des arbitrages entre l'offre et la demande, de la saisonnalité et des facteurs fondamentaux) et en partie de façon imprévisibles (en raison de changements climatiques inattendus, de crises financières et de conflits politiques).

Le présent chapitre vise à analyser l'efficacité des marchés des matières premières pendant les périodes d'instabilité. Plus précisément, il étudie la relation entre les prix au comptant et les prix à

terme pendant les périodes d'expansion et de ralentissement.

Contrairement aux études précédentes, nous proposons une base d'analyse plus substantielle, incluant différents types de matières premières. Cette contribution est importante, car elle explique les différences entre tous les types de matières premières et fournit aux investisseurs des informations significatives en termes de diversification de portefeuille en se focalisant sur les périodes de turbulences.

On visait à compléter les études antérieures principalement par deux points. Tout d'abord, nous examinons la relation entre les prix au comptant et les prix à terme en période d'instabilité pour différents marchés. Cette question est cruciale et intéressante pour plusieurs raisons. En effet, la dynamique des prix des matières premières est un débat important qui a des répercussions importantes sur les investisseurs, les décideurs, les traders, les producteurs et les hedgers. Les investisseurs utilisent ces connaissances pour élaborer des stratégies rentables, gérer leurs risques et diversifier leur portefeuille. Deuxièmement, contrairement aux études précédentes, nous étudions différents types de produits afin de fournir des renseignements supplémentaires aux investisseurs.

Bien que les précédentes études se soient concentrées sur la relation entre les prix au comptant et les prix à terme, elles tiennent rarement compte des dépendances asymétriques de la distribution de queue et des co-variations asymétriques possibles entre les deux marchés pendant les mouvements instables. En d'autres termes, le lien significatif entre les prix au comptant des matières premières et les prix à terme ne signifie jamais que les deux marchés ont le même comportement et les mêmes réactions en période d'expansion et d'effondrement. Contrairement à la littérature précédente, nous nous concentrons sur la distribution de queue et sur l'existence d'une dépendance symétrique et asymétrique entre les deux marchés. De plus, nous faisons la différence entre les périodes de marché haussières et baissières. Nous trouvons que cette information est fascinante pour les investisseurs, et les décideurs, car il est crucial de comprendre le comportement du marché en période de mouvements extrêmes positifs et négatifs, où on doit impérativement prendre une décision de placement immédiate pour se protéger des risques potentiels.

Le contexte théorique

Il existe trois théories financières fondamentales qui portent sur la relation entre les prix au comptant et les prix à terme.

Premièrement, la théorie de l'évaluation des actifs, proposée par [Fama and French \(1987\)](#), cette théorie repose sur une hypothèse d'anticipation ; elle affirme que les prix à terme sont des estimateurs efficaces et non biaisés des futurs prix au comptant attendus. Deuxièmement, La théorie du non-arbitrage : Proposée par [Cornell and French \(1983\)](#), cette théorie est basée sur le modèle du coût de portage (the cost of carry model). Troisièmement, la théorie de stockage, cette théorie est basée sur le modèle de non-arbitrage, et affirme que les prix au comptant et les prix à terme sont fortement liés.

Revue de littérature

Un vaste corpus de littérature a exploré le lien entre les prix à terme et les prix au comptant sur les marchés des matières premières, à l'aide de différentes approches empiriques. La littérature existante est classée en fonction des sujets entamés. En effet, les études précédentes ont fourni des indications sur trois objectifs essentiels qui sous-tendent l'analyse de la relation entre les prix au comptant et les prix à terme des produits de base ; la première vise à analyser la causalité entre les deux marchés (p. ex., [Silvapulle and Moosa \(1999\)](#), [Lee and Zeng \(2011\)](#), et [Chang and Lee \(2015\)](#)). La deuxième étudie le processus de découverte de prix ([Wang and Ke \(2005\)](#), [Moosa \(2002\)](#), [Kumar \(2004\)](#), [Yousefi et al. \(2005\)](#), et [Joseph et al. \(2014\)](#)) et la troisième analyse l'efficience et la convergence des marchés en expliquant l'écart entre les prix à terme et au comptant (par exemple [Sahi and Raizada \(2006\)](#), [Bekiros and Diks \(2008\)](#), et [Lee and Zeng \(2011\)](#)).

Données

Ce chapitre utilise des séries temporelles à fréquence journalière de prix au comptant et à terme de huit matières premières différentes provenant de quatre catégories différentes. On a sélectionné l'échéance la plus proche des contrats à terme parce qu'il s'agit des contrats les plus liquides et les plus actifs. Les catégories de produits sélectionnées dans le cadre de cette recherche sont l'énergie (pétrole brut et gaz naturel), l'agriculture (blé et soja), les métaux précieux (or et platine) et les matières premières agricoles (coton et sucre). Pour chaque type, nous avons sélectionné les deux matières premières les plus activement négociées. Les séries des prix sont collectées à partir de DataStream et de Bloomberg pour la période allant de 2002 à 2018.

Méthode empirique

Ce chapitre mobilise le GARCH, le AR-GARCH et le E-GARCH pour spécifier les distributions marginales des prix et applique une approche de copule pour mesurer le lien entre les marchés au comptant et à terme en période de volatilité extrême. Plusieurs raisons ont motivé ces choix. Premièrement, les séries temporelles financières sont connues par leur volatilité, leur non-normalité, l'épaisseur de queue de distribution, leur symétrie et leur asymétrie. Dans ce contexte, les originalités de cette approche adoptée sont son insensibilité aux observations aberrantes et aussi sa capacité à identifier la dépendance dans l'ensemble de la distribution, en faisant la différence entre les périodes de changements extrêmes négatifs et positifs. Ainsi, cette approche tient compte des changements structurels qui se produisent dans le marché au comptant et à terme.

De plus, les modèles GARCH offrent un moyen souple et efficace pour étudier les distributions marginales et la variabilité dans le temps des prix des matières premières. Les Copules sont utiles pour étudier la structure de dépendance entre les marchés étudiés pendant les périodes non stables (périodes

d'expansion et d'effondrement), car les matières premières ont connu des hauts et des bas inhabituels importants avec un changement considérable dans la nature des fluctuations. Les paramètres des copules identifient la nature de la dépendance (symétrique, asymétrique, forte ou faible). Tandis que les queues inférieure et supérieure saisissent la dépendance pendant les marchés baissiers et haussiers, respectivement.

Résultats et interprétation

Les résultats des dépendances sont différents selon les types de marchandises, les conditions du marché, les propriétés du marché et le processus de stockage. La dépendance du prix du pétrole brut par rapport au prix au comptant à terme est asymétrique et est adaptée d'une copule de Clayton. Cela signifie que l'efficience du marché est élevée dans des conditions de marché normales à baissières et qu'elle diminue lorsque les prix au comptant et à terme entrent dans des conditions extrêmement défavorables. Les métaux précieux (or et platine) et le coton sont dotés d'une copule normale, ce qui confirme la forte dépendance entre les prix au comptant et à terme dans toutes les conditions de marché. C'est une confirmation du caractère de refuge des métaux précieux. Ces derniers sont utilisés à des fins de couverture en période d'incertitude. Les produits agricoles (soja et blé) suivent une copule de Gumbel, ce qui signifie que la dépendance entre les prix au comptant et les prix à terme est forte dans des conditions de marché normales à haussières. Il y a un manque de lien entre les deux marchés dans des conditions baissières. Le gaz naturel enregistre des résultats particuliers, où la dépendance est potentiellement faible durant les périodes de changement extrêmes positif et négatifs.

Chapitre II : L'incertitude économique et le sentiment des investisseurs exercent ils un effet significatif sur les prix à terme de l'énergie? Une étude multi-fréquentielle

J'avais l'opportunité de présenter et de discuter cet article à la conférence ISEFI: "The 6th International Symposium on Environment and Energy Finance Issues" (24-25 Mai 2017 à Paris, France), à la conférence IRMBAM: "the 9th International Research Meeting in Business and Management" (5-7 Juillet 2018 à Nice, France), et à the 36th USAEE/IAEE North American Conference: "Envolving Energy realities" (23-26 Septembre 2018 à Washington DC, USA).

Le trading sur le marché à terme des matières premières énergétiques est relativement élevée par rapport à la taille du négoce des produits physique et de la production. Cette augmentation d'investissement de dérivés énergétiques s'explique par la participation croissante d'investisseurs financiers à la recherche de nombreux avantages à court et à long terme. Ce phénomène a été observé à partir de 2002 dans le contexte de la "financiarisation des marchés des matières premières" ([Tang and Xiong \(2012\)](#), et [Hamilton and Wu \(2015\)](#)), suivie de fortes variations des prix de l'énergie ([Basak and Pavlova, 2016](#)). Le comportement de ces investisseurs peut avoir une incidence sur les prix, les

stratégies de placement et la volatilité des marchés. En outre, la croissance massive de placements sur le marché de l'énergie a exacerbé la contagion entre les facteurs économiques et les prix de l'énergie, ce qui a accentué la volatilité de leurs prix. ([Hamilton, 2009](#)).

Certes, tous ces acteurs du marché ont des comportements irrationnels et biaisés ([Baker et al., 2016](#)), ainsi lorsque les participants au marché ont tendance à être pessimiste ou optimiste en raison de biais cognitifs, les investisseurs irrationnels génèrent un risque systématique ce qui engendre un déséquilibre entre l'offre et la demande. Par conséquent, les investisseurs en matières premières, les traders, les spéculateurs et les hedgers ont un intérêt considérable pour la finance comportementale, non seulement pour comprendre les aspects comportementaux mais aussi pour être conscients de l'influence potentielle sur les prix des matières premières dans différents horizons.

Ce chapitre tente de réexaminer les flux de causalité entre le sentiment des investisseurs/du marché et les prix de l'énergie afin d'expliquer les anomalies du marché et d'apporter un éclairage sur l'effet des sentiments sur les prix.

Le contexte théorique

La finance comportementale, la théorie moderne du portefeuille et les hypothèses d'efficience de marché sont considérées comme les théories financières les plus discutées dans la littérature. Ces dernières théories ont eu un impact considérable sur la finance et l'économie à l'ère moderne. Les interactions dynamiques entre ces théories financières ont suscité un considérable intérêt de la part des experts en investissement, et des chercheurs universitaires, étant donné qu'elles expliquent la façon dont les investisseurs prennent leurs décisions ainsi que les volatilités des prix des actifs. En effet, ils donnent un aperçu complet des tendances du marché et expliquent les fondamentaux et les anomalies des prix. Cependant, elles font l'objet d'un large débat car elles présentent plusieurs contradictions.

Alors que l'hypothèse d'un marché efficient suppose que les prix reflètent pleinement l'information accessible au public et que la théorie moderne du portefeuille suppose que les investisseurs prennent leurs décisions en fonction des niveaux de risque et qu'ils sont caractérisés par un comportement rationnel, la théorie de la finance comportementale indique que les émotions, la psychologie et les facteurs cognitifs et sociaux jouent un rôle essentiel dans l'évolution des prix des actifs. Elle permet d'expliquer les anomalies des évolutions des prix, la faible corrélation entre leurs valeurs réelles et leurs fondamentaux. En un mot, elle explique les mouvements brusques à la hausse et à la baisse des prix à l'aide de théories fondées sur la psychologie.

Revue de littérature

La littérature analysant les prix de l'énergie indique généralement que les facteurs macroéconomiques fondamentaux sont des déterminants des prix tels que les conditions macroéconomiques mondiales, les chocs économiques, les chocs monétaires, les arbitrages de la demande et de l'offre, les investissements

spéculatifs, la volatilité des marchés boursiers, les fluctuations des taux de change, les capacités de production, les changements climatiques, et le coût de stockage.

Cependant, la théorie de la finance comportementale a remis en question la théorie financière traditionnelle, en confirmant l'existence de biais psychologiques dans le comportement des investisseurs. Ce fait conduit la littérature des théories classiques de tarification basées sur les fondamentaux à une finance comportementale prenant en compte les humeurs et les croyances des investisseurs lors de la prévision des prix (par exemple, [De Long et al. \(1990\)](#), [Baker and Wurgler \(2006, 2007\)](#), [Baker et al. \(2012\)](#), [Schmeling \(2009\)](#), [Kurov \(2010\)](#), [Garcia \(2013\)](#), et [Lin et al. \(2018\)](#)). Par ailleurs, le caractère incomplet du marché et les anomalies causées par les acteurs du marché ont le pouvoir d'influencer leur capacité à couvrir les risques ([Staum \(2007\)](#), et [Crès et al. \(2016\)](#)). En conséquence, les décisions d'investissement (vente ou achat) concernant les actifs risqués changent, ce qui entraîne des volatilités des prix, et ainsi peut conduire à une mauvaise évaluation ou à une surévaluation des prix.

Données

Pour analyser la relation entre les prix de l'énergie et les indices de sentiment des investisseurs et du marché, nous utilisons des données journalières des prix à terme du pétrole et du gaz naturel et plusieurs indicateurs de sentiment pour la période allant de 2002 à 2018. Les indicateurs de sentiment utilisés dans le cadre de cette recherche ont fait l'objet d'études antérieures et ont été largement utilisés dans la littérature financière pour refléter les sentiments du marché et des investisseurs individuels. Pour le sentiment des investisseurs individuels, nous adoptons l'indice de l'American Association of Individual Investors (AAII) Survey. Cet indice de sentiment reflète le comportement optimiste et pessimiste des investisseurs concernant les estimations du marché ([Brown \(1999\)](#), and [Brown and Cliff \(2004\)](#)). Pour refléter le sentiment du marché, nous appliquons d'abord l'Economic Policy Uncertainty (EPU) créé par [Baker et al. \(2016\)](#). Deuxièmement, on utilise l'indice de volatilité (VIX) pour refléter les attentes du marché quant à la volatilité suggérée par les prix des options et des indices boursiers. Sur le plan conceptuel, le VIX et l'EPU reflètent le sentiment du marché, mais diffèrent à bien des égards. Tant dis que l'EPU reflète l'incertitude des politiques économiques majeures, le VIX reflète l'incertitude des rendements boursiers.

Méthode empirique

Néanmoins, l'incidence de la fréquence temporelle des placements ait une importance économique cruciale pour la relation entre les prix de l'énergie et le sentiment des investisseurs/du marché. En outre, les différents types d'opérateurs sont soumis à des anticipations hétérogènes basées sur les fondamentaux du marché, des caractéristiques idiosyncrasiques (telles que l'aversion au risque et les informations disponibles) et des biais psychologiques. Par conséquent, les décisions d'investissement en fonction de la fréquence temporelle et les changements d'horizons d'un type d'opérateurs à l'autre pourraient rendre le marché très hétérogène. On s'attend à ce que cette hétérogénéité crée des réactions contradictoires

et perturbent les nouvelles informations produites sur les marchés de l'énergie. Nécessairement, une validation plus poussée de la causalité temps-fréquentielle entre les prix de l'énergie et les indices de sentiment est cruciale. Pour ces raisons, cette étude utilise une interaction multi-fréquentielle utilisant la décomposition en variation, proposée par [Dragomiretskiy and Zosso \(2015\)](#), afin de fournir plus d'informations sur plusieurs horizons.

C'est une approche moderne de décomposition qui a démontré sa supériorité dans un large éventail d'applications en raison de ses avantages par rapport à d'autres méthodologies. Elle se caractérise par sa capacité optimale à traiter le bruit qui peut survenir dans les signaux de sentiment ([Dragomiretskiy and Zosso, 2015](#)). Elle est considérée comme une approche unique avec une théorie distinguée qui surmonte les limites d'autres méthodes de décomposition telles que la décomposition en mode empirique et la décomposition en mode empirique d'ensemble. Plus précisément, elle résout plusieurs problèmes économétriques. Dans ce contexte, elle est considérée comme une méthode nouvelle, pleinement intrinsèque et adaptative, qui extrait les modes de manière non récursive, compte tenu de son caractère quasi-orthogonal. Ainsi on pense que c'est la meilleure approche de décomposition pour faire face aux fortes volatilités des prix de l'énergie et aux bruits des indicateurs de sentiment.

Résultats et interprétations

Les résultats montrent que le sentiment pessimiste des investisseurs prédit mieux les rendements énergétiques que l'indice du sentiment optimiste. Alors que les investisseurs pessimistes montrent une causalité significative envers les prix sur l'ensemble de la période de l'échantillon et pour toutes les fréquences temporelles, le comportement optimiste ne se manifestent qu'à long terme pour causer la volatilité des prix du pétrole et du gaz naturel. En outre, les résultats montrent que les mouvements des prix de pétrole sont une source importante d'incertitude économique, alors qu'à moyen terme, cette puissance dominante diminue et la causalité devient bidirectionnelle. À long terme, l'incertitude en matière de politique économique entraîne des fluctuations des prix du pétrole.

En ce qui concerne les prix du gaz naturel, il existe d'importants flux de causalité entre les prix du gaz naturel et l'indice d'incertitude de politique économique à court terme. Alors qu'à moyen et long terme, c'est le gaz naturel qui provoque l'incertitude économique.

L'indice de volatilité a un meilleur pouvoir estimatif pour les prix du pétrole comparé aux prix du gaz naturel et un pouvoir de causalité moindre comparé aux indices de sentiment des investisseurs.

Chapitre III : Quelle est l'efficacité des marchés du gaz naturel dans la pratique ? Une approche basée sur les ondelettes

Cet article est co-écrit avec ma collègue Amina Baba, doctorante à l'Université Paris Dauphine, et rattachée au laboratoire LEDa CGEMP, et notre encadrante Pr. Anna Creti.

Ayant commencé cet article au cours du dernier semestre de mon doctorat, je n'ai pas eu le temps de le présenter aux conférences.

L'environnement institutionnel des marchés européens du gaz naturel a connu un changement significatif au cours de la dernière décennie. Les transactions National Balancing Point (NBP) Britannique et aux plateformes gazières de la Title Transfer Facility (TTF) néerlandais ont considérablement gagné en traction

Parallèlement, la pratique ancrée de l'indexation du pétrole dans les contrats à long terme de gaz naturel a été progressivement remplacée par l'indexation sur les plateformes pour mieux refléter la dynamique des fondamentaux.

Néanmoins, l'Europe n'a pas encore entièrement créé un marché du gaz véritablement concurrentiel qui exige des informations non discriminatoires, fiables et actuelles sur le marché boursier ([Garaffa et al., 2019](#)). Dans un contexte de réserves dispersées et de nombre limité de fournisseurs, le potentiel d'arbitrage élevé, surtout à court terme, reste inexploité par les acteurs du marché en raison de l'accès limité aux infrastructures, le manque d'informations fiables et des coûts élevés des transactions ([Stronzik et al., 2009](#)).

La question de l'efficacité des marchés du gaz naturel européens est donc critique et soulève des inquiétudes quant à leur capacité à constituer un soutien important pour la gestion des risques financiers des portefeuilles gaziers. Tels qu'ils émanent les théories de [Cootner \(1964\)](#) et de Fama dans les années 1960, les prix observés dans un marché efficient devraient refléter instantanément toutes les informations disponibles. En tout temps, 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 gratuitement à un grand nombre d'opérateurs qui ne peuvent à eux seuls exercer une influence significative sur les prix ou contrôler systématiquement le marché.

Cet article contribue à la littérature de plusieurs façons. Il s'agit, à notre connaissance, du premier article qui examine la question de la tarification du gaz naturel et de l'efficacité informationnelle dans les plateformes gazières européennes (NBP et TTF) et américaines (Henry Hub) utilisant l'approche par domaine de fréquences. En fait, la plupart des études antérieures ont ignoré la possibilité que l'orientation, l'étendue et la force de la causalité de Granger puissent varier à différentes échelles de temps. De plus, la littérature sur les prix à terme du gaz naturel en Europe est peu abondante, car le marché est plutôt récent comparativement à l'expérience nord-américaine. En outre, les études antérieures ont négligé les non-linéarités qui régissent la dynamique des matières premières énergétiques et ont surtout examiné les effets causaux linéaires entre les prix au comptant et les prix à terme. Des études empiriques plus

récentes montrent l'importance de tenir compte des non-linéarités de la dynamique des prix dans l'étude des effets de causalité en raison, entre autres, des récessions, des événements extrêmes imprévus, des coûts de transaction, du pouvoir de marché, des tensions géopolitiques, des informations asymétriques ou de la rigidité des prix.

De plus, la littérature ne fournit pas de consensus clair quant à l'orientation de la causalité entre les prix au comptant et les prix à terme du gaz naturel. Ces divergences résultent de spécifications différentes de la volatilité des marchés au comptant et à terme, des périodes considérées et des méthodologies employées. Enfin, nos résultats permettent d'établir une évaluation de la capacité des hubs à fournir des prix de référence fiables pour les quantités de gaz sous contrat. Nous considérons le sujet comme très opportun, car les contrats à long terme sont de plus en plus fondés sur l'indexation et les participants au marché cherchent également à couvrir efficacement les risques associés à leurs portefeuilles physiques de gaz.

Revue de littérature

Différentes contributions potentielle se soulèvent en étudiant le marché du gaz . Premièrement, la plupart des études antérieures ont ignoré la possibilité que l'orientation, l'étendue et la force de la causalité de Granger puissent varier à différentes échelles de temps. Deuxièmement, parmi les études qui ont analysé l'industrie du gaz naturel au moyen de la théorie du stockage, la majorité se sont concentrées sur le marché nord-américain (voir, par exemple, [Dincerler et al. \(2005\)](#) et [Serletis and Shahmoradi \(2006\)](#)). Troisièmement, les études empiriques sur les processus de tarification sont également assez limitées pour les marchés européens et ont négligé les non-linéarités qui régissent la dynamique des matières premières énergétiques et ont surtout examiné les effets de causalité linéaires entre les prix au comptant et à terme. Quatrièmement, la littérature ne fournit pas de consensus clair sur l'orientation de la causalité : ces faits proviennent de l'utilisation de méthodologies différentes et de périodes étudiées qui doivent être fortifiées.

Données

L'échantillon couvre la période allant de 2013 à 2019. Les contrats à terme standardisés ayant trois échéances d'un, deux et trois mois sont pris en compte. Les prix journaliers du gaz naturel au comptant et des contrats à terme de un, deux et trois mois aux États-Unis sont téléchargés à partir du site Web de l'Energy Information Administration (EIA), tant dis que les prix du gaz naturel au comptant et à terme au Royaume-Uni et aux Pays-Bas sont fournis par Argus. Le Henry Hub américain présente une volatilité beaucoup plus élevée que les hubs européens (UK NBP et NL TTF). Nous limitons la date d'entrée en vigueur à 2013 pour tenir compte des changements importants survenus jusqu'à présent sur les marchés européens du gaz naturel en termes d'efficacité du marché.

Méthode empirique

Notre analyse tient compte des principaux problèmes méthodologiques susceptibles d’avoir une incidence importante sur la nature des résultats. Tout d’abord, nous obtenons un aperçu de la décomposition temporelle de nos données en appliquant une décomposition d’ondelettes discrètes (MODWT) aux rendements des prix au comptant et à terme à un mois de maturité de la NBP, du TTF et du Henry Hub. Nos séries temporelles sont transformées en domaine de fréquence sans perte d’information dans le domaine temporel, et la méthodologie des ondelettes évite perdre certaines caractéristiques paramétriques de la série et tient compte de la covariance, de la volatilité en fonction du temps, et des ruptures structurelles. De plus, elle nous permet de ne pas négliger un aspect important des marchés du gaz naturel caractérisé par une dynamique fortement saisonnière. Ensuite, on a utilisé des tests de causalité linéaire et non linéaire pour étudier la direction de la causalité et en s’appuyant sur le test de [Diks and Panchenko \(2006\)](#).

Nous effectuons également plusieurs vérifications de robustesse pour nous assurer que nos résultats se maintiennent dans différentes configurations en réalisant une comparaison inter-commodités avec le marché pétrolier, en répétant l’analyse pour les contrats à terme de deux et trois mois et en utilisant des filtres différents selon la méthode d’ondelettes.

Résultats et interprétation

Ce chapitre constitue la première tentative d’établir un compte rendu exhaustif sur l’efficience des prix et l’efficience informationnelle des marchés du gaz naturel des États-Unis et de l’Union Européenne. Nous nous basons sur la décomposition maximale par ondelettes discrètes (MODWT) des données journalières des prix au comptant et des prix à terme à différentes échéances du Henry Hub américain, de la NBP britannique et du TTF néerlandais entre 2013 et 2019. Des tests de causalité de Granger linéaires et non linéaires et des tests de marche aléatoires multi-échelles sont étudiés. Nous constatons que les prix à terme et les prix au comptant du Henry Hub (N.-B.) et du TTF sont intégrés. De plus, des tests de causalité multi-échelles montrent que les marchés du Henry Hub présentent une forte causalité bidirectionnelle entre les marchés au comptant et à terme. Les marchés de l’UE sont globalement efficaces en termes de prix, en dépit de certaines incohérences dans le sens de la causalité entre les échelles de temps et les échéances des contrats à terme. Enfin, pour les trois marchés à terme sélectionnés, l’efficience informationnelle n’est atteinte qu’à long terme. Les résultats permettent d’établir une évaluation de la capacité des hubs à fournir des prix de référence fiables pour les quantités de gaz sous contrat à travers une discussion sur le rôle crucial de la liquidité et des capacités de stockage.

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Introduction

The essays on commodity markets developed in this thesis aim to explain commodity prices dynamics, drivers, and mechanisms. Based on Traditional finance theory, the Efficient market hypothesis and Behavioral Finance theory, this thesis investigates spreads between commodity prices using novel empirical methodologies to provide effective results and interesting economic implications. This dissertation begins with an introduction to commodity markets.

The objective of investors and speculators who trade in the financial markets is to adopt successful strategies that maximize their profit concerning their risk profile. An investor can operate in specific assets, whether in physical or derivatives markets. Financial investors and speculators trade derivatives to seek hedging advantages, optimal risk management, and diversification benefits. In this context, an increasing interest in commodity markets is undeniable; they are in the process of becoming mainstream. Starting from the 2000s, many major financial institutions and investment banks start trading commodities, especially energy commodities. In fact, during this period, commodities were considered as a buffer against risk and a compelling portfolio diversifier, given their intrinsic risk-return characteristics.

Consequently, commodity trading has become the origin of profits for prominent and prestigious financial companies such as Goldman Sachs, Morgan Stanley, and Citibank, as they offer fruitful arbitrage opportunities. Simultaneously, and accordingly, many and various investors have penetrated commodity markets such as speculators, pension fund, hedge fund, and portfolio managers. These financial investors have classified commodities as a separate asset class that could be included in financial portfolios with traditional stocks and bonds to improve risk-return performance. Additionally, advanced technologies and financial innovations offered easy access into commodity markets with much lower costs compared to traditional trading operations. Thus, this encouraged previously atypical investors to increase their participation and trading activities. In this manner, all of these confluences of forces have widely raised the interest in, and the importance of investigating commodity prices.

Furthermore, the massive increase of financial investors and of financial intermediaries in commodity markets combined with exceptional and unprecedented price movements in the beginning of the 2000's, give rise to commodity prices and make it a significant economic issue. Most notably, investors traded commodity derivatives more than ever. Hence, prices registered extraordinary spikes, especially during

the financial turmoil of 2008. The price movements of 2008 originate a political firestorm starting from the United States and spread out elsewhere. The coincidence of the increasing financial investors and rocketing prices caused several changes in commodity market behaviors, investment strategies, and regulations. To sum up, the 2000s have seen commodities exhibiting economic and political implications that they had lacked during the previous era.

These trends are of interest to financiers (speculators, traders, money managers, swap dealers, and hedge fund), investors, politicians, and risk managers. This chapter is presented as follow: First, a general description of commodity markets is developed in section 1, in addition to its essential properties. Second, this introduction presents the most important stylized facts that occurred in commodity markets such as financialization in section 2 and remarkable events in section 3. Third, I review the theoretical background of this thesis in section 4. Finally, I introduce the thesis road map in section 5.

1. Commodity markets

What is a commodity?

In economics, a commodity refers to any marketable product (a good or a service) to satisfy any needs or wants. The commodity is inspired by the French word "commodité," which refers to any product that offers benefits or useful services. A commodity is considered as a common good with a standard quality, which can be traded in international competitive and liquid global markets. Accordingly, the commodity can be interchanged with a substitutable good affording similar qualitative features across a market. In this manner, commodities produced by different producers are considered as equivalent without a significant qualitative distinction. By this definition, a commodity price is determined by equality between supply and demand in a competitive and liquid market. The commodity is produced by many producers in similar quality and is demanded by many consumers. The availability and the demand for commodities have significantly increased over the centuries. Even though commodities are equivalent, their prices may differ with respect to many factors such as transportation costs, exchange rates, delivery places and periods, and qualitative differences. To overcome these differences, commodities are classified into different grades. Moreover, to be tradable and deliverable, commodities must respect minimum standards called "a basic grade" or "contract trade" (Chatnani, 2010). To recapitulate, a commodity is a product that respects the following properties: 1) The commodity quality is uniform regarding producers, 2) They are produced and sold by many producers, and demanded by many different consumers, 3) The price is based on the arbitrage between supply and demand.

There are several categories of commodities: agriculture commodities (raw grains such as corn, soybean, wheat), metals (industrial metals such as copper and aluminum and precious metals such as gold,

silver and platinum), ferrous (such as iron), soft commodities (such as coffee, cotton, and sugar) and energy commodities (such as crude oil, heating oil and natural gas). It exists other complex markets which are “commoditized” such as electricity and currency given its compatibility with the definition and the general properties of commodity markets.

The markets

Commodities are sustained by the market structure that involves physical (spot) and derivative (futures and forward) markets. In terms of microstructure, commodity markets include four separate groups of participants:

- **Consumers:** they buy and use processed commodities to satisfy their preferences; they do not specifically trade in derivatives markets.
- **Speculators (or financial investors):** they trade in the futures market and generally do not hold physical commodities.
- **Producers:** they are mainly the farmers of the commodities.
- **Processors:** they are the intermediaries who transform raw commodities into final products, for example, oil refineries, grain mills, and food processors.

To understand the exchange activities between these four groups and the associated prices to every market, figure 1 characterizes the supply and demand in a simplified way.

Commodity market witness several properties different from equity markets. These properties even vary across commodities. Let us review the essential properties;

- **Fundamental price drivers:** Diverse and complicated fundamental price drivers appear in commodity markets.

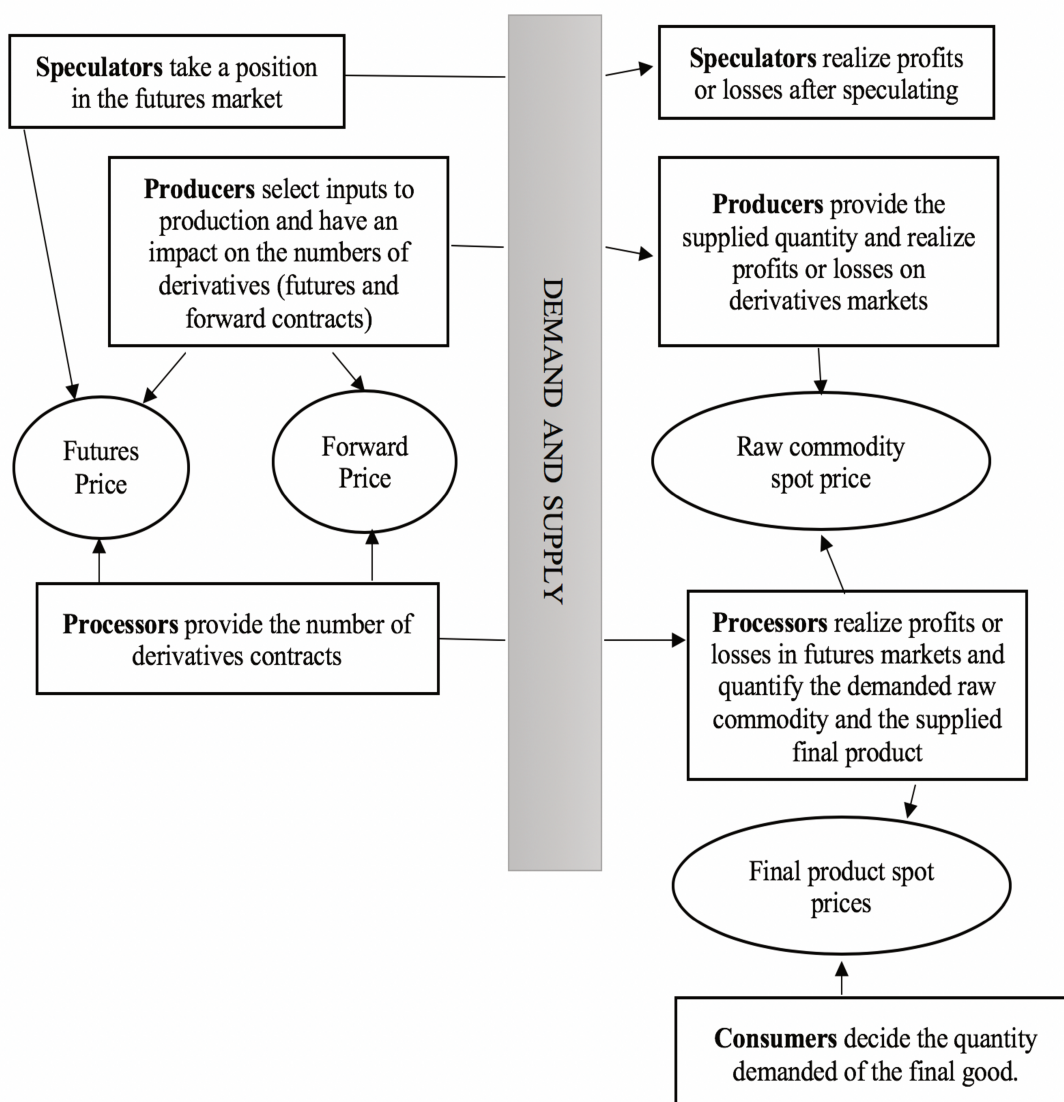
To some extent, these drivers are complex to integrate into pricing models. Indeed, market participants have to manage various abrupt changes of weather, storage and transportation process and cost, and technological progress. Even storage costs and transportation processes vary among commodities. Consequently, derivatives prices must respond, respectively, to market fundamentals. Besides, commodity market participants such as consumers and suppliers have their own set of drivers, based on the commodity type, that should be included in the model. Abrupt changes of some fundamentals such as hurricanes or wars are not easy to estimate and consequently, hard to capture in pricing models.

- **Seasonality:** Doubtlessly, commodities exhibit high seasonality compared to other markets. The supply and demand show dramatic changes in particular types of commodities such as agricultural commodities and heating oil. For instance, the supply of agricultural commodities is based on harvest cycles where the weather patterns mainly drive heating oil.

- **Demand and supply:** spot price relies on demand and supply, as shown in figure 1. When the demand is higher than the supply, the price increase, and vice-versa, they constitute the main fundamental price drivers.
- **Convenience yield:** According to the theory of storage, holding a storable physical commodity generate benefits (Geman, 2009). The ownership of the commodity (inventories) enables investors to avoid risks of unexpected changes and to anticipate manufacturing interruptions. The benefit of holding a commodity is known as the convenience yield. This convenience yield is calculated as the sum of the received benefits by the commodity holder minus significant costs such as storage cost. Thus, when the spot price surprisingly increases, the inventory holder tends to sell the physical inventories and replace it with derivatives. However, when the spot price sharply decreases, the inventory holder tends to increase their inventories.
- **Liquidity:** The commodity market faces illiquidity, which is a major problem for traders. This issue decreases trading volume and boosts the spreads (bid and ask). However, the financialization and the electronification of commodity markets improved the market quality, via eliminating costs of entry, drastically. The electronification of commodity markets enables market participants to benefit from price deviations regarding fundamental values. Thereby, these facts boost market liquidity: the Electronic market is increasingly competitive, open, and transparent. All exchange members acquire equal opportunities to bountifully supply and demand liquidity, which attracts new investors, especially financial traders.
- **Storage:** the storage process and costs depend on commodity nature. Although it plays a crucial role in determined commodity prices, indeed, when the commodity exhibits excessive supply with fixed commercial consumer demand, commodity futures are in Contango, and the volatility between spot and futures prices significantly decreases. Consequently, futures premium increase to cover the totality of the cost of storage. However, when commodity supplies tend to be low, purchasing managers raise their inventory level to assure the availability of the commodity in question. Hence, futures prices reach out Backwardation, and the volatility of the corresponding spot and futures prices increases.

The theory of storage in commodity markets was initially proposed by Working (1949). Later, the theory was further developed by Kaldor (1939), who originated the idea of the convenience yield. After that, Brennan (1958) introduced the curves for supply-demand storage. Weymar et al. (1968) contributed to the theory by investigating a link between the probability of stockout and the convenience yield. Finally, Schwartz (1997) extended the theory by considering the yield as a mean-reverting stochastic process.

Figure 1: Commodity supply and demand process



Source: Author

- **Diversification:** in the early 2000's the correlation between commodity market and equity market is low, and even positive in some cases. That is why most investors and financial institutions considered commodities as a buffer against risks and a major portfolio diversifier. Crucially, these diversification benefits have been widely proven during financialization until the global financial crises of 2008. Notably, during this period, commodities exhibit volatile and even negative correlation with stock markets, which significantly decreased from 2008 (Creti et al., 2013).
- **Regulation and intervention:** Governments and international institutions intervene in commodity markets to stabilize the prices. The primary mission of market regulators is controlling and overlooking the market users, the exchanges, and the trading activities in commodity markets. For example, the Commodity Futures Trading Commission (CFTC) is an independent agency founded to regulate commodity futures and options in the United States. CFTC proved that

commodity futures markets exhibited massive volatilities over time, and nowadays, they include a colossal disposition to severe complexes in futures contracts. In this context, CFTC intervenes to protect the market members from fraud, systemic risk, and abusive practices.

- **Volatility:** Commodity prices are highly volatile, and exhibit broadly based massive ups and downs. These volatilities often cause political unrest and have the most considerable economic and social impact on nations. They may emanate from climatic conditions, labor strikes, geopolitical events, and financial turmoil. Besides, the increased number of financial investors, particularly speculators, and the increased commodity derivatives also have raised price volatilities. These facts increased market exposure to events and news. For instance, commodity prices abruptly respond to economic and financial volatilities.

Today, CFTC highlights the economic advantages of the commodity futures markets by boosting their competitiveness, liquidity, and efficiency, and by guaranteeing the financial integrity of the clearing process. The CFTC helps to improve the price discovery mechanism and the offsetting price risk in commodity futures markets.

Given that commodity markets exhibit high volatilities, producers, consumers, and investors often seek efficient strategies for hedging and managing risks. In response to this need, markets for commodity trading significantly increased (as detailed in the following section) and became progressively widespread. Commodity derivatives, which are a modern version of commodity goods, are traded in these markets. Futures contract and options are traded in organized markets, and forward contracts and swaps are traded in Over-The-Counter (OTC). Undeniably, futures contracts are among the most traded instruments of these derivatives, given their essential role in transferring information to all economic agents and cash and storage markets. In fact, the price discovery role of commodity futures prices and the capacity they provide to reduce trading risks increases the importance of understanding commodity prices volatilities. In the other hand, price volatilities have a significant impact on demand for hedging in both futures markets (via futures contracts) and cash market (via physical instruments such as inventories). Producers use futures prices as a reference to make their supply strategies and physical traders base their spot prices on futures prices.

Furthermore, the spread between commodity spot and futures prices provides a measure of the marginal value of storage. Thus, investigating the relationship between the spot and futures market is vital in its own, given the unprecedented events that occurred in commodity markets. This information offers important directions to investors.

These two prices are determined in two interrelated markets: The cash market known as the spot market for immediate delivery and futures and forward markets for speculation and future delivery.

Spot market and prices

Commodity physical markets have existed over the entire history around the world. A commodity spot market is a physical market place in which consumers and producers meet in order to exchange standardized or graded products for immediate delivery at a price referred to as the "spot price." Because commodity markets are exposed to volatilities in production and consumption, market agents (producers, consumers, and investors) hold inventories. Indeed, holding inventories have several advantages; producers and consumers hold inventories to reduce risks of stockouts, to adjust production over time, to reduce costs, and to avoid prices increase. In this context, inventories make scheduling more comfortable and decrease marketing costs in periods of fluctuating demand.

Consequently, the spot price depends on inventories, demand, supply, futures prices, and shocks. The demand may also be a function of predictable variables (such as weather, capital stocks, and aggregate income) and random variables (such as random shocks, investors behaviors or taste changes and technologies). The supply is also a function of predictable variables (such as cost of production and capital stocks) and unexpected events (such as strikes, economic shocks, hurricanes...).

Futures markets and prices Vs. Forward markets and prices

According to traditional hedging theory, derivatives are mainly used to hedge physical positions. To do so, hedgers take the futures opposite positions with the same magnitude regarding the physical market position ([Ederington \(1979\)](#); [Johnson \(1960\)](#)). So, they either buy futures positions (taking long positions) if prices intend to increase in the future or sell futures positions (taking short positions) if prices intend to decrease in the future.

A **forward contract** is an agreement between two agents exchanging commodities at a settled time in the future for a price fixed at the time of the agreement. Even though a futures contract is a particular type of a forward contract, there are some differences between both contracts. Forward contracts are private agreements between separated individual parties, traded in cash values at maturity. They are flexible in their unique terms and conditions because one of their counterparties can default.

Futures contracts are standardized contracts under the control of clearinghouses, which manage the creditworthiness of transactions and limit the risk of default. Besides, they are bought and sold on futures exchanges, created in the Midwestern United States during the 19th century. Whereas, in Europe and Japan, this kind of futures contract already existed centuries earlier ([Geman, 2009](#)).

Futures contracts are "market to market," which denotes that the settlement and the transfer of funds are made at the end of the corresponding trading day. For example, consider a futures contract for 1000 barrels of crude oil, for a six months delivery from now: if the futures price drop by 50 cents per barrel, the holder of the short position will receive 500\$ from the holder of the long position before the end of the trading day. However, if the futures price increase by 30 cents per barrel, 300\$ will circulate

on the contrary direction. These daily operations decrease the risk of being on default on the contract. The considered settlement price will be fixed as the last trade price at the close. Futures contracts are extremely used compared to the other derivatives given the flexibility of the market. The physical delivery is not a must in the futures market; Only 2% of futures positions are physically delivered. The others are closed out, i.e., rolled over before maturity, given that they are mostly used for hedging and speculation objectives so that delivery is not necessary.

2. Financialization and electronification of commodity markets

Commodity futures offer significant benefits to financial investors due to their low and even negative correlations with stocks and equities ([Gorton and Rouwenhorst, 2006](#)).

Since the turn of the millennium, commodity derivatives markets registered significant changes and growth in trading volume and market participants. Many investors start pouring billions of dollars into commodity derivatives markets, especially futures markets, seeking particular investment benefits of this distinct asset class. In fact, after 2000, the growth of the commodity derivatives market was noticeably faster than any other asset class. Accordingly, the number of commodity exchanges have raised with the diversity of the existing contracts. They are mainly localized in the world's leading economies, as shown in Table 1 .

Table 1 represents open interests for thirteen commodity futures contracts traded in different markets, using data from Commodity Futures Trading Committee (CFTC) for energy (crude oil and natural gas), agriculture (wheat, corn and cocoa), soft (cotton, and sugar), metals (gold, silver, platinum, palladium and nickel). The open interest positions include reportable and non-reportable positions. The reportable positions encompass commercial and non-commercial traders. That is why open interest is considered as a generalized presentation of the total trading volume of futures contracts. Table 1 shows that the growth rate in open interest futures positions between 2000 and 2019 is 6 times higher for crude oil, soybean, and cotton, 11 times for gold, 8 times for corn, and 2 times for cocoa than the growth between 1990 and 2002.

This growth in the open interest of futures is synchronized with a dramatic change of market participants in the commodity futures markets ([Cheng and Xiong, 2014](#)), while traditionally, privy investors were the marketplace dominators. They used to earn risk-premiums by taking opposite positions of producers and processors. Historically, financial investors had never been engaged in the market place on such a grand scale. They dedicate enormous amounts of capital to the commodity markets, spurring fast growth. According to CFTC estimations, the exchange-traded futures and futures options trading volume boomed from 630 million contracts in 1998 to 3.8 billion contracts in 2009, i.e., about sixfold increase.

Table 1: Commodity exchanges

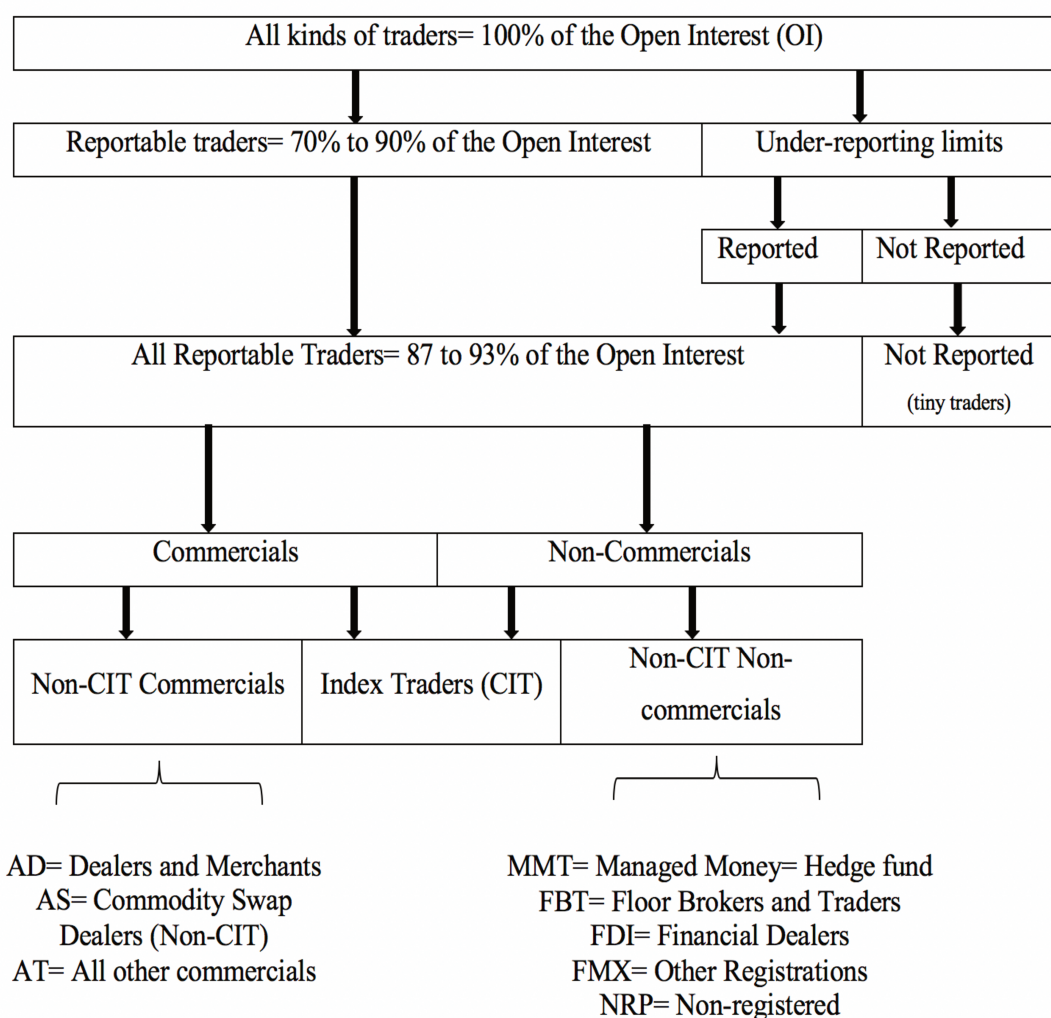
Commodity	Exchange	Localization	2[4]*Contract Units	Open Interests			Growth rate		
				1990	2002	2019	1990-2002	2002-2019	1990-2019
Crude oil	NYMEX	New York	Contracts of 1,000 Barrels	286406	437133	2120930	53%	385%	641%
Natural gas	NYMEX	New York	10,000 MMBTU'S mmbt's	1258	434291	1286501	34422%	196%	102166%
Wheat	CBOT	Chicago	1000 Bushels until 1998, then 5000	272485	25438	442962	-91%	1641%	63%
Corn	CBOT	Chicago	1000 Bushels until 1998, then 5000	898680	445525	1621715	-50%	264%	80%
Soybean	CBOT	Chicago	1000 Bushels until 1998, then 5000	481625	153854	673773	-68%	338%	40%
Cotton	ICE	Atlanta	Contracts of 50,000 Pounds	39592	62930	224007	59%	256%	466%
Cocoa	ICE	Atlanta	Contracts of 10 Metric Tons	53748	96773	251408	80%	160%	368%
Sugar	ICE	Atlanta	Contracts of 112,000 Pounds	162340	176587	901214	9%	410%	455%
Palladium	NYMEX	New York	Contracts of 100 Troy Ounces	6314	1122	28529	-82%	2443%	352%
Platinum	NYMEX	New York	Contracts of 50 Troy Ounces	19442	6348	86645	-67%	1265%	346%
Gold	COMEX	Chicago	Contracts of 100 Troy Ounces	149393	113020	455232	-24%	303%	205%
Silver	COMEX	Chicago	Contracts of 1,000 Troy Ounces	95260	67412	186506	-29%	177%	96%

Note: This table represents the commodity exchanges and the growth of the trading volume of commodity futures between 1990 and 2019 due to collected data from CFTC. NYMEX is the New York exchange, CBOT is the Chicago Board Of Trade, COMEX is commodity Exchange, and CME is the Chicago Mercantile Exchange

Furthermore, the net investment flows to different commodity futures indexes were nearly 200 billion dollars during the 2008 Q2. In this context, the global commodity index investment grew from 50 billion dollars in 2004 to 300 billion dollars in 2010 ([Irwin and Sanders \(2011\)](#); [Sanders and Irwin \(2011\)](#)). These evolutions have been dubbed the "financialization" of commodities ([Cheng and Xiong, 2014](#)).

Composition of futures market participants

Figure 2: Commodity futures markets participants



Source: This figure is inspired from the research paper of [Robe and Roberts \(2019\)](#)

After 2000, the participation of financial investors in commodity markets has widely increased.

These investors are colloquially recognized as speculators because their main purpose is to realize profits, and they are typically not engaged in holding physical commodities, production, and consumption. The CFTC, as a futures market regulator, classified investors into commercial and non-commercial traders and register their positions in the Commitment of Traders (COT) report. Investors are commercial participants if they trade futures contracts for hedging objectives with a commercial link with the physical commodity market, and they are non-commercial participants otherwise. Lately, [Robe and Roberts \(2019\)](#) provided more details about market participants and devised the COT's four categories into nine sub-categories, as presented in figure 2.

The appearance of new market participants, as presented in figure 2, has spawned a considerable amount of academic research. Its focus to date has been on their effect on trading volume and market structure ([Tang and Xiong, 2012](#)), commodity prices volatilities ([Irwin and Sanders \(2012\)](#); [Socin and Xiong \(2015\)](#)), risk premia ([Hamilton and Wu, 2014](#)), realized volatility ([Brunetti et al. \(2016\)](#)), and markets cross-correlations ([Basak and Pavlova \(2016\)](#); [Bruno et al. \(2016\)](#); [Büyüksahin and Robe \(2014\)](#); [Kilian and Murphy \(2014\)](#); [Knittel and Pindyck \(2016\)](#)).

Figure 3 shape this massive growth of financial investors in commodity futures, identified by the non-commercial positions and spreads positions. Admittedly, a clear structural break is observed during 2002-2003, followed by a continuous increase that remains until today. In this context, [Isleimeyyeh \(2017\)](#) measured the speculative activities using the working “T” index by [Working \(1960\)](#). This index characterizes the relationship between hedgers and speculators. In other words, this index estimates the speculation activities that exceed the hedgers’ positions ([Büyüksahin and Robe, 2014](#)). The results show a significant surplus of speculation for ten different commodities starting from 2002. After the 2000s, as open interest growth started to boom, so did the non-commercial positions in the commodity futures market for all commodity sectors. Mainly, this growth is more evident for non-commercial long positions who represents CITs and hedge funds.

Consequently, this financialization of commodity markets has sparked pressing concerns among the

international economy and the world's policymakers, surrounding its implications on dominant market performances and operations. Indeed, this financialization has questioned the fundamentals and the return properties of commodity futures. A large stand of literature favored the idea that the massive growth of investor flows generated an increase in commodity futures prices, volatility, and market cross-correlations (Bhardwaj et al. (2015); Büyüksahin and Harris (2011); Irwin et al. (2009); Irwin and Sanders (2012)). The important volatilities, price bubbles, and doubts around the accuracy of prices led many experts pundit to condemn the occurrence of new investors for such results.

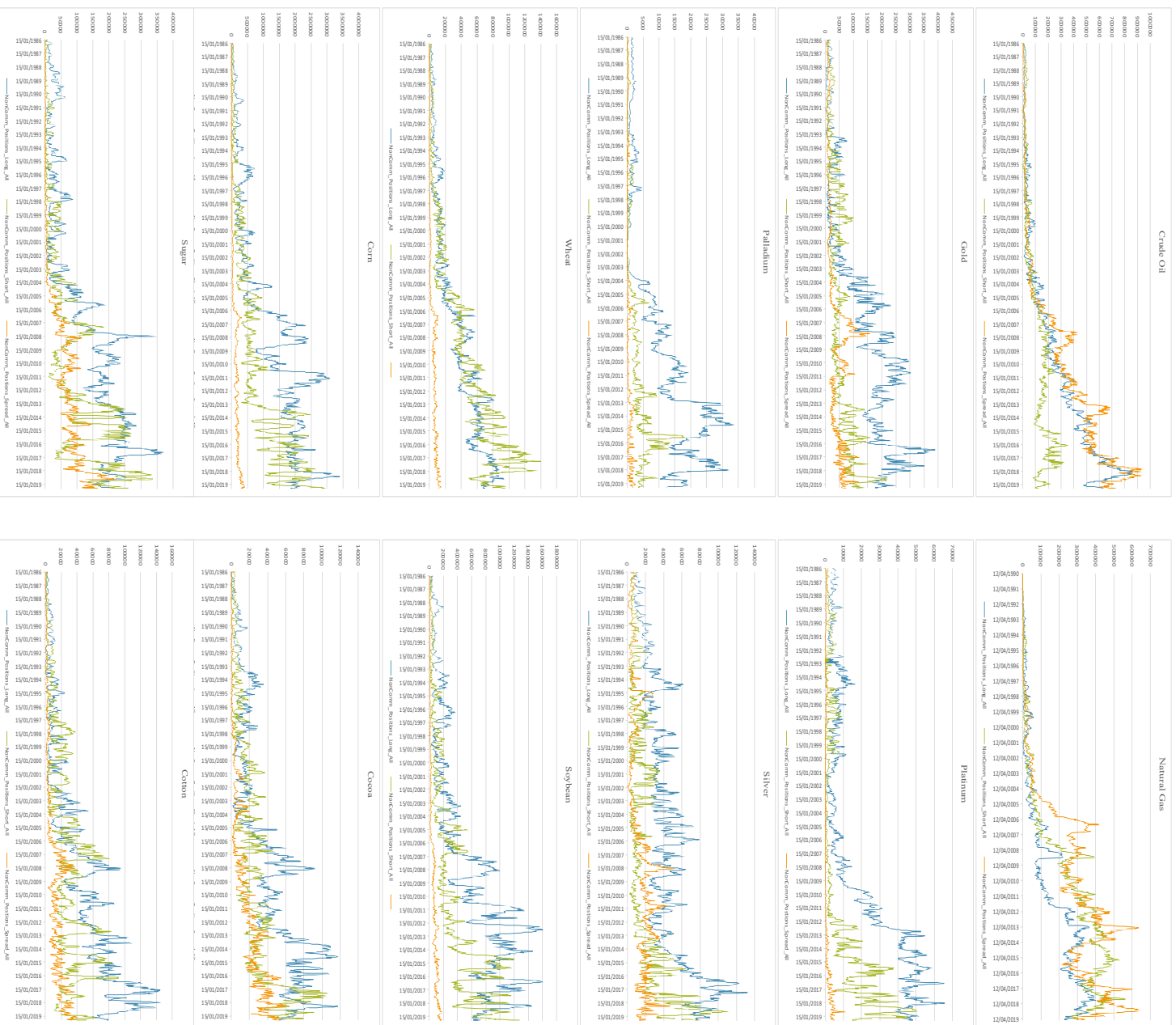
A major cause behind the financialization is the increased development of electronic trading platforms. These platforms have lowered transaction costs and facilitated trading activities. Moreover, the birth of commodity index traders (CITs) institutions, such as pension funds, insurance companies, and endowments, spurred investments in commodity markets. The number of CITs quintupled, and commodity trading hedge funds roughly tripled between 2000 and 2009.

3. Events and stylized facts

Occasionally, commodity markets exhibit impressive movements that, sometimes, lead to booms and busts. These events are often the consequence of political conflicts, financial turmoil, economic event, and weather abrupt changes. These events are often the reason for political unrest. Figure 4 represents global commodity price indexes, which measure changes in the levels of commodity prices. These indexes are considered as an investment tool that tracks a group of commodities to estimate their price and investment returns performances. Also, they are widely traded on exchanges because they enable investors to achieve more straightforward investments without entering the futures market.

These indexes change based on unanticipated volatilities that may result from short- and long-term events. As shown in figure 4, investing in commodity indexes gained popularity in the early 2000s as these index prices start to fluctuate. Prices continue to grow due to commodity financialization and register a massive drop around 2006 caused by Lehman Brothers bankruptcy. Later, commodities indexes restart to raise and register a pick during the global financial crises in 2008, particularly in energy markets. Whereas, agriculture commodities exhibit a worldwide good harvest, which explains

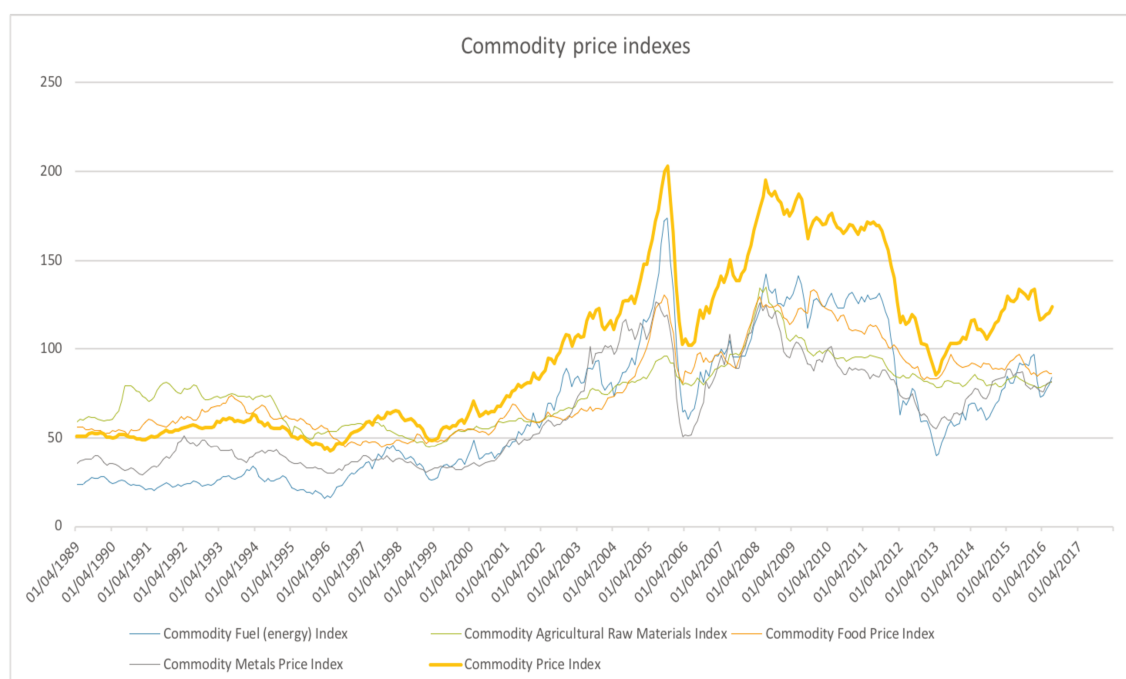
Figure 3: Commodities non-commercials futures positions



Source: CFTC (from 1986 to 2019). **Blue** line represents the Non-commercial Long positions, **Green** line represents the Non-commercial Short positions, and the **Orange** line refers to the Non-commercial Spreads.

the lower picks compared to the other markets. In 2011, a significant downturn in the global commodity index was observed. This decrease is strongly linked to the decrease of the commodity fuel index caused by the Libyan civil war of 2011 in addition to a drop in all commodities indexes caused by the North African turmoil. Over three consecutive months, the Libyan oil production fell by 1.6 million bbl/day from February to April and reached zero by the end of May. In December 2011-January 2012, the geological conflicts about the nuclear issue and the saber-rattling from Iran and the west caused a supply disruption leading to decrease global commodity and fuel indexes. A higher decrease showed up in 2013, caused by the Syrian crises, and spilled over to Iraq. Iraq was and is an essential oil producer and exporter. In 2014, several political and economic events occurred, such as the emergence of ISIS, the OPEC decisions after the meeting of November, the Ukrainian Crises. In 2016, the sanction relief of Iran increased price movements. Later commodity indexes continued to rise, providing efficient hedging strategies. They have the most significant impact on global economies.

Figure 4: Commodities price indexes



Source: Data of commodity price indexes of the corresponding figure from 1989 to 2018 is extracted from Data Stream software

4. Theoretical background: What has been learned so far?

The importance of studying commodity prices, including the relationship between the spot and futures prices (consequently the informational and pricing efficiency), and the behavioral aspects in commodity markets relies on several major theories.

The efficient market hypothesis (EMH) is the dominant paradigm in finance for the past decades. This hypothesis states that the futures prices are an efficient estimator of the spot prices conditional on an information set, including the risk premium. EMH assumes that investors cannot generate unexpected returns. [Malkiel and Fama \(1970\)](#) classified EMH into three versions depending on the available information. First, the weak form efficiency assumes that current prices reflect their historical information. Second, the semi-strong form of efficiency asserts that prices reflect all public information in addition to historical price data. Third, the strong form of efficiency, which assumes that prices reflect all the previous information, including private information. Literature exhibit two different conclusions. A vast literature supported the hypothesis of [Fama \(1991\)](#). However, other researches recognized numerous anomalies inconsistent with the hypothesis, and evidence against the EMH continued to amount in several markets.

The asset pricing theory is proposed by [Fama and French \(1987\)](#) and originated from the efficient market hypothesis (EMH). This theory assumes that the futures prices are an efficient predictor of the expected spot prices, taking into account the risk-adjusted discount, the risk-free rate, and the risk premium. If futures prices are found to be a significant and unbiased predictor of spot prices, the market is considered informationally efficient, and price discovery mechanism function of the futures markets is confirmed.

The theory of storage proposed by [Working \(1949\)](#) and [Brennan \(1958\)](#) states that spot and futures market are strongly related. Consequently, they exhibit two situations; Backwardation when spot prices exceed futures prices and Contango otherwise. However, the relationship and the volatilities of futures and spot prices can strongly deviate from fundamentals when unpredictable events occur, depending on the nature of the commodity and the specification of its storage process and costs. The non-arbitrage theory known as the cost-of-carry model states that the futures prices are also an unbiased predictor of the expected spot prices, taking into consideration the convenience yield and the cost of physical storage. .

These previous theories, under the context of traditional financial theories, have dominated commodity pricing theories, roughly, for 30 years. They believe that investors are rational when making decisions. More precisely, they assume that investors use all available information to conduct rational estimations about future prices and investment strategies. In this manner, investors pursue self-interest under the model of the maximization of expected utility under risk, proposed by [Morgenstern and Von Neumann \(1953\)](#) and [De Bondt \(1998\)](#) . Subsequently, commodity prices reflect fundamental determinants and would only fluctuate when a fundamental positive or negative news occurs. Consequently, traditional economists assume that markets exhibit informational and pricing efficiencies. .

However, the reality is way different; Markets display abnormal variabilities for many reasons, and investors do not have rational behaviors and thoughts ([Shiller \(2003\)](#), [Shiller \(1999\)](#)). On the contrary,

investors behaviors are driven by greed and fear. Thus, they speculate commodities between extraordinary highs and lows. Accordingly, in stock markets, the literature proved that investors decisions are significantly driven by extreme emotions and subjective judgments, consistently from irrational expectations for future economic performance such as financial turmoil, political changes, and stock price fluctuations. These investors behaviors constitute a part of academic discipline referred to as "**Behavioral Finance**".

Behavioral Finance shed light on the psychological aspects of investors decisions and highlight their importance in driving prices.

As I mentioned before, the trading activity in the commodity futures market widely exceeds the physical production volume. The rise in commodity trading volume originates from the increasing participation of investors, hedgers, traders, and speculators. In fact, from 2002 to 2008, investors trade commodities futures seeking diversification benefits, because commodities displayed very low and even negative correlation with equity markets. Starting from 2008, the contagion effect between stock and commodity markets heightened, and diversification benefits start disappearing ([Büyüksahin and Robe \(2014\)](#); [Creti et al. \(2013\)](#)). Even though investors continued to place significant capitals in commodity markets, trading volume registered unprecedented levels. The behavior of these market participants has the potential to influence prices, trading strategies, and investment performance.

In the other hand, the diversity of market participants (as shown in figure 2), characterized by several psychological biases, can impact commodity markets and prices. Indeed, [Coakley et al. \(2011\)](#) concluded that traders' behaviors significantly impact the prices of 17 different commodity futures contracts in the US market. [Cummins et al. \(2015\)](#) funded evidence of behavioral influence in metal markets.

5. Thesis road map

Commodity market efficiencies (informational and pricing) and unbiasedness (originating from investors and market sentiments) under different market conditions and time-frequencies remain unsettled in the cost-of-carry model, the asset pricing theory and the efficient market hypothesis. This thesis focuses on commodity prices interactions under the context of pricing and informational efficiencies, and the behavioral driving forces of new traders and market sentiments.

As has been explained previously, the massive changes occurring in commodity markets, prices, and participants raise two critical questions to investigate. The first question is interested in the interaction between the spot and futures prices under different market conditions, and the second question focus on the impact of the increasing and diversified market participants on commodity prices. Even though prior researches have investigated these two questions, the debate is still on, giving the new features occurring in commodity markets.

To answer these questions, this thesis conducts three essays on commodity markets using new

empirical methodologies that bring more insights on commodity markets dynamics and innovations. Doubtlessly, the entry of new types of institutional investors is an essential channel through which this investigation boost market understanding. Therefore, it is necessary to shed more light on the time-frequency dynamics of commodity prices given the speed of the market's changes, events, and volatilities, in the first place. Second, this research analyzes the impact of behavioral aspects from traders and markets on prices. This thesis is undertaken to explore the market efficiencies, the dynamic price discovery, the risk management, and the potential of behavioral aspects in influencing commodity prices. These investigations help investors to conduct optimized strategies and manage their risks. This thesis is divided into three main chapters.

First, chapter 1 investigates the relationship between commodity spot and futures prices under different market extreme conditions. This study investigates eight commodity markets from four different categories (energy, precious metals, agriculture, and soft commodities) using data from 2002 to 2019. Taking into account the theoretical framework and the empirical shortage concerning the importance of market extreme conditions for risk management, portfolio diversification, investment policies, and trading strategies, we investigated the dependency between spot and futures prices for four types of commodities. We used the copula approach mixed with GARCH family models to specify commodity returns marginal distributions.

The results of spot-futures dependencies are different depending on commodity types, market conditions, market properties, and storage process. Crude oil spot-futures price dependency is asymmetric and fitted with Clayton copula. Consequently, market efficiency is strong in normal and bearish market conditions and declines when spot and futures prices enter into extreme positive conditions. Precious metals (Gold and platinum) and cotton are fitted with Normal copula, which confirms the strong dependence between spot and futures prices under all market conditions. It is a confirmation of the safe heaven characteristic of precious metals. These commodities exhibit high efficiency, risk transfer, and are used for hedging during uncertainties. Agriculture commodities (Soybean and Wheat) are fitted with the Gumbel copula. That means that the dependency between the agriculture spot and futures prices is strong in normal to bull market conditions. There is a lack of connection between both markets in bear conditions.

This study has several policy implications; not all the commodities are alike. In fact, the commodity pricing could lose its' standard formation features under market uncertainties in some cases depending on different factors, as indicated earlier. Besides, the risk transfer mechanism through hedging using futures could be affected in different market conditions. Consequently, to avoid huge risks during market uncertainty, policymakers and investors may limit or increase their positions and limit the prices to restore risk management and the price discovery mechanism when the market exhibit asymmetry during different market conditions. These measurements should take into account whether the market is bearish or bullish. More particular, these controls should be further made during the absence of dependency during extreme market conditions.

Second, chapter 2 is motivated by the challenging results of behavioral finance theory to traditional finance and classical pricing models such as the Efficient Market Hypothesis and the asset pricing theory. This paper uses a variational mode decomposition and a non-parametric causality approach. The results provide evidence that a significant causal-flows does exist between energy futures returns and sentiment proxies. However, results vary with respect to time frequencies. Using daily data from 2002 to 2018, we find that in the short run, WTI returns significantly cause economic uncertainty, while in the medium run WTI leading power decreases and causality remains to be bidirectional. In the long run, EPU causes WTI returns. Whereas for natural gas prices, there are significant causal flows from EPU to natural gas prices in the short-term. While in the medium and long run, natural gas causes EPU. In addition, bear investor sentiment better predicts energy returns compared to the bull sentiment index. While bearish investors show significance over the entire sample period and for all the time-frequencies, bullish investors manifest only in the long run for both crude oil and natural gas returns. Regarding VIX, it has better estimative power for WTI returns compared to HH returns and less causality power compared to investor sentiment indexes. Commodity speculators should include market and sentiment proxies in their information set while making investment decisions and managing risks.

Third, Chapter 3 analyzed pricing and informational efficiencies of the natural gas market in the United States and Europe. Our analysis empirically examines the direction of causality between the return series of futures and spot prices of US and European natural gas markets using a 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 can 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, and 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 (Brenner and Kroner, 1995). Concerning NBP and TTF markets, results are not unanimous across the different time scales, and the three maturities as it varies between unidirectional causality from futures prices to spot market prices and bidirectional causality.

In summary, it is possible to conclude that Henry Hub, NBP, and TTF markets show statistically significant bidirectional causality or unidirectional causality. It means that these markets are interconnected.

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. However, informational efficiency is reached in the long-run.

Overall, it can be argued that the findings of this work shed some appealing new light on the true nature of causality between the NG spot and futures prices at NYMEX. Thus, this additional knowledge of the nature of causality may contribute 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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Chapter 1

Dependence between commodity spot-futures markets in extreme value periods: A Copula Approach

1

Abstract

The dependence across commodities spot and futures prices is a critical claim for asset allocation and portfolio management. However, commodity futures market efficiency under different market extreme conditions is an unresolved issue by the traditional financial theories (The Efficient market hypothesis, the asset pricing theory, and the non-arbitrage theory). This paper design four mixtures of copula-based and GARCH models to investigate the symmetric and asymmetric dependencies between spot and futures returns within four types of commodities (energy, precious metal, agricultural and soft commodities) from 2002 to 2018. Our empirical findings reveal interesting results. We show that dependencies differ during extreme movements based on the nature of the commodity, their storage process, and their seasonality process. The dependence is strong in normal conditions and declines when the market enters into bearish (for Wheat and soybean markets), or bullish conditions (for crude oil market). Whereas precious metals remain efficient under all market conditions. Natural gas and sugar markets were an exception, where the dependence between spot and futures returns is very sensitive to market changes. These results are useful for market participants and policymakers. Indeed, our findings suggest some promising diversification advantages within commodity categories; however, during normal conditions, the spot-futures relationship remain insensitive to global financial conditions.

Keywords: Copula approach, Tail dependency, Commodity spot and futures markets, Efficiency, Extreme value periods.

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1.1 Introduction

High levels of volatilities characterize commodity markets, particularly, from the beginning of the 2000s (Brunetti et al., 2016). Inventories and prices go up and down considerably, in part expectedly (due to demand and supply arbitrages, seasonality, and fundamentals) and in part unexpectedly (due to unpredictable weather changes, financial turmoil, and political conflicts).

Furthermore, the price discovery role of futures contracts and their exceptional capacity in reducing risks has spawned much academic research. Its focus to date has been on the relationship between spot and futures prices to investigate risk management dynamics between the two markets. Moreover, the increased interest of financial investors and the exceptional volatilities in commodity markets heightened the capacity of futures contracts in transmitting information to all economic agents.

Mostly, previous studies investigated cointegration, linear and non-linear causality², and time-frequency dependency using different methodologies. The results delivered from previous literature are classified into three categories. The first category is based on investigations of the Efficient Market Hypothesis³. Results show that a strong dependency between spot and futures prices across all market frequencies. The second category is interested in the price discovery mechanism. Findings show evidence of cointegration between commodities spot and futures prices⁴. The asset pricing theory motivates the third category. Results show a significant time-varying causality flows between spot and futures across different frequencies⁵. Even though the literature confirms a significant relationship between commodity spot and futures prices, the results will be erroneous during periods of abrupt changes that highly occurred during the last decade.

In fact, as a period defined by financial turmoil, few other markets have been subject to profound transformation over the last decade as commodity markets. Admittedly, the most remarkable part of the change is registered in price levels. Both spot and futures prices have spiked records not seen since the 1970s. For major commodity producers (whether they are individuals, nations, or companies), such a heady witnessed significant strategic change. An era of unprecedented benefices appears, even though the counterpart consumers have generally suffered from rising costs of commodities, including raw materials, energy, and food essentials. Price movements are a consequence of a range of macroeconomic factors spanning trends. Facts and fantasies in commodity markets originate from the financialization of commodities in 2002, the global financial crises in 2008, the economic growth of Asian countries, the demographic expansion in the middle east, the technological innovation (i.e. electronification of the market), the economics volatilities of the real interest rate across the West, and political conflicts (Wars

²see Alzahrani et al. (2014) and Huang et al. (2009).

³see Serletis and Andreadis (2004), Lim et al. (2008), Charles and Darné (2009), Khediri and Charfeddine (2015) and Gu and Zhang (2016).

⁴see Wang and Wu (2013) and Mehrara and Hamldar (2014).

⁵see Chang and Lee (2015) and Polanco-Martínez and Abadie (2016).

in Iraq, terroristic attacks and the rising role of OPEC decisions). Beyond these facts, the structure, trading volume, market agents, and price dynamics that build up the prospect of modern commodity markets have also witnessed massive changes with a rapid price movement. Perhaps, the most noticeable feature of commodity markets booms and busts was unpredictability, at least for financial investors and experts.

Most notably, oil prices witnessed massive volatilities that spilled over other commodity markets such as agricultural, and minerals, creating a commodity market boom. Also, the 2008 financial collapse caused a commodity crash. Metals futures contracts fell nearly by 60% between March and December 2008. While agriculture and energy prices spiked to high levels in July 2008 (crude oil was for 143\$ per barrel). Later the recession of commodity futures prices in 2010-2011 caused by the growing emerging Asian countries and OPEC politics, have influenced commodity prices, in particular, oil prices ([Allsopp and Fattouh, 2013](#)).

The second structural change is due to the increasing trading volume in commodity markets. Investors preferred the tech-driven new economy, investment facilities, and low costs in the futures market, stretched from 2002. Indeed, commodities are considered as a buffer against logistical disruption and acute crises. Consequently, the increasing activity of financial investors as participants in the commodity futures markets seeking hedging and diversification benefits had a significant effect on commodity prices ([Basak and Pavlova, 2016](#)). The prices of commodities have exhibited high volatilities synchronized with the financialization leading to various booms and busts([Tang and Xiong \(2012\)](#), [Büyüksahin and Robe \(2014\)](#), [Hamilton and Wu \(2014\)](#), and [Boons et al. \(2014\)](#)).

This paper aims to analyze the commodity market efficiencies during unstable periods. More precisely, we investigate the relationship between commodity spot and futures returns during booms and busts. Contrary to previous studies, we propose a more substantial basis of analysis, including different types of commodities. This contribution is significant, as it explains the differences between all commodity types and gives the investors global information about commodity markets. It is helpful for institutional investors, interested in commodity markets, who are still seeking diversification benefits and risk management during turbulent market conditions.

From an empirical point of view, this paper engages the GARCH, the AR-GARCH, and the E-GARCH to specify price behaviors and we apply a copula approach to measure the connection between spot and futures markets in extreme volatility periods. Several reasons motivated these choices. First, financial time series are known by their volatilities, non-normality, fat-tails, symmetry, and asymmetry. In this context, the originalities of this adopted approach are its insensitivity to outliers' observations and also its capacity to identify dependence in the entire distribution, during extreme positive and negative changes. Thus, this approach takes into account the occurring jumps and regime shifts in the commodity spot and futures. Commodity time series are characterized by structural breaks and fat

tails, given the presence of potential co-jumps⁶ (Fong and See (2002), Lee et al. (2010), Arouri et al. (2012), Wang and Wu (2012), Mensi et al. (2014), Charfeddine (2016), and Wang et al. (2016)).

Consequently, the spot-futures relationship could be significantly impacted by structural breaks due to jumps (Chen et al., 2014). Moreover, GARCH models provide a flexible and efficient way to investigate the marginal distributions and the time-variability of commodity prices. Second, Copula is useful to investigate the dependence structure between the studied markets during non-stable periods (boom and bust) since commodities experienced significant un-usual ups and downs with a considerable change in the nature of the fluctuations. The copulas parameters identify the nature of spot-futures dependency (whether it is symmetric, asymmetric, strong or weak). While lower and upper tails capture the dependence during bearish and bullish markets, respectively.

In this paper, we aim to complete previous studies mainly through two points. First, we investigate the relationship between spot and futures prices in the case of commodity markets during unstable periods. This issue is interesting at several levels. Indeed, the price dynamics of commodities are a meaningful debate with powerful implications on investors, policymakers, hedgers, producers, and regulation issuers. The investors use this knowledge to make profitable strategies, manage their risks, and diversify their portfolio. Second, contrary to previous studies, we investigate different types of commodities to provide further information for investors. This issue completes previous studies, as it focuses only on one or two types of commodities.

While early studies have focused on the relationship between commodity spot and futures prices, they rarely allow for asymmetric tail dependencies and possible asymmetric co-movements between the two markets during unstable movements. In other words, the high significant linkage between commodities spot and futures prices never means that the two markets have the same behavior and the same reactions during periods of boom and bust. Unlike previous literature, we focus on tail dependence and the existence of symmetric and asymmetric dependence between the two markets. Moreover, we make the difference between bullish and bearish market periods. We find that this information is fascinating to investors, hedgers, and policymakers, as it is crucial to understand the market's behavior in periods of positive and negative extreme movements.

The remainder of the paper is organized as follows. Section 1.2 reminds the theoretical background. Section 1.3 reviews the literature. Section 1.4 presents the data. Section 1.5 describes the methodology. Section 1.6 discusses the results, and section 1.7 concludes the paper.

⁶Whether they are simultaneous or individual

1.2 Theoretical framework

There are three fundamental financial theories about the relationship between the spot-futures prices.

The asset pricing theory

Proposed by [Fama and French \(1987\)](#), this theory is based on an expectation hypothesis; it affirms that the futures prices are efficient and unbiased estimators of the expected future spot prices. It is presented as follow;

$$E_t(S_{t+\tau}) = \alpha F_{t,\tau} + \beta (R_t - r_t) S_t + \varepsilon_t$$

Where S_t is the spot price, F_t is the futures price at time t for delivery at time $t + \tau$, R_t is the risk-adjusted discount rate, and r_t is the risk-free rate. Thus $(R_t - r_t)$ represents the risk premium. $\alpha = 1$ and $\beta = 0$ indicate that the futures prices are a significant efficient predictor of the spot price, where α is associated to informational efficiency and price discovery in the futures markets, and β is the risk premium coefficient explaining the risk management in the futures market.

The non-arbitrage theory

Proposed by [Cornell and French \(1983\)](#), this theory is based on the cost-of-carry model as follow;

$$F_{t,\tau} = (1 + r_t)_t - (c_{t,\tau} - p_\tau)$$

Where $c_{t,\tau}$ represents the capitalized flow of the convenience yield, and p_τ is the cost of physical storage per unit. If the prices do not respect the cost-of-carry model, the market is considered inefficient. Consequently, risks increase for hedgers; they need to close their positions before the contracts' expiration. It means that the information flows in the market are not reliable enough.

Furthermore, the asset pricing theory and the non-arbitrage theory are significantly linked. If the futures price is an unbiased and efficient estimator of the expected spot price, the market is regarded as efficient, and the non-arbitrage theory will be verified. However, if the futures price is not an efficient predictor of spot price ($\alpha \neq 1$), it means that a lead-lag relationship exists between spot and futures prices and the non-arbitrage theory do not hold. Thus, the degree of market efficiency, in market booms and busts, could be measured by copula coefficients and tail dependency parameters. Given that process volatilities increase during extreme conditions, hedging and arbitrage activities are more pronounced in these market situations (bullish and bearish markets). Findings could be beneficial to market participants in order to select the best hedging strategies and the appropriate commodity regarding market conditions.

The theory of storage

Proposed by [Kaldor \(1976\)](#) , [Working \(1949\)](#), and [Brennan \(1958\)](#) this theory is based on the non-arbitrage model, as explained previously. This theory states that spot and futures prices are strongly related. The market is either in strong Contango when futures prices exceed spot prices ($c_{t,\tau} < p_\tau$) or in strong backwardation ($c_{t,\tau} > p_\tau$) . The theory of storage states that there is a short-term relationship between spot and futures prices. It is endorsed and evolved due to the occurrence of different types of shocks in the commodity markets. These shocks are the demand shock, the supply shock (significantly related to storage) and the identified booms and busts in several commodity markets ([Jacks and Stuermer \(2018\)](#) , [Kilian and Murphy \(2014\)](#), and [Kilian \(2009\)](#)). Demand shocks have a long-term impact on prices and production of the commodity. Whereas, supply shocks related to storage have a short-term and persistent impact on commodity prices. These facts create temporary turbulence in commodity prices, leading to surprising changes. These short and transitory market movements constitute an opportunity to market agents to benefit during high levels of volatilities. Traders are encouraged to trade, hedgers are intended to manage market risks, and market regulators initiate their policy measures. Although the theory of storage assumes that a significant co-integration does exist between the spot and futures prices in the long-run, it does not take into consideration the short-run dependence. Co-integration is necessary but not enough to validate market efficiency. To verify the Efficient Market Hypothesis, futures and spot prices must reflect all market information, including short-run changes and sudden movement ([Fama and French, 1987](#)). Thus, through this investigation, we explain markets spot-futures dependence during market extreme booms and busts, in order to understand the risk management dynamics, given that traders and speculators intend to make profits during market fluctuation, ([Kaufmann and Ullman, 2009](#)).

1.3 Literature

A vast body of literature explored the link between the commodity markets futures and spot prices, using a different empirical framework. We classified the existing literature according to the investigated topics. Indeed, the previous studies provided insights into three essential objectives behind analyzing commodity spot and futures relationship; The first is understanding the behavior of the causality between the two markets (e.g., [Silvapulle and Moosa \(1999\)](#), [Lee and Zeng \(2011\)](#), and [Chang and Lee \(2015\)](#)). While the second is examining the price discovery mechanism (e.g., [Wang and Ke \(2005\)](#), [Moosa \(2002\)](#), [Kumar \(2004\)](#), [Yousefi et al. \(2005\)](#), and [Joseph et al. \(2014\)](#)) and the third is investigating the markets efficiency and convergence by explaining the spread between futures and spot prices (e.g., [Sahi and Raizada \(2006\)](#), [Bekiros and Diks \(2008\)](#), and [Lee and Zeng \(2011\)](#)).

The causality between commodities spot and futures markets

Quan (1992) started with studying the link between spot and futures prices using a combination between the causality and the co-integration analysis, and found an evident lead-lag relationship between two markets. Later, Silvapulle and Moosa (1999) came out with a non-linear causality approach and re-analyze the causality in the case of the oil market. Results showed a bidirectional causality between oil spot and futures prices. More recently, Bekiros and Diks (2008), and Lee and Zeng (2011) used a non-linear methodology in the case of the oil market. They all agree about a significant bi-directional relationship between oil spot and futures prices. Wang and Wu (2013) studied this issue in a time-varying domain. They found a stronger causality in the long run (using monthly, quarterly, and yearly data) compared to the short run (using daily and weekly data). Kaufmann and Ullman (2009) investigated the causal relationship between oil spot and futures markets using more extensive data from Africa, Europe, the Middle East, and North America. They used a two-step Dynamic Ordinary Least Square error correction model and a full information maximum likelihood estimate for a vector error correction model (VECM)⁷. The authors developed other innovative methodologies to overcome the non-linear problems and information losses. Indeed, Lu et al. (2014) combined correlation and dynamic conditional correlation multivariate GARCH. They found evidence of a time-varying information spillover between crude oil spot and futures markets. The same results were confirmed by Beckmann et al. (2014). However, these authors neglect the real possibility of structural breaks when taking into consideration the different time scales. Information about structural breaks can easily be lost when using traditional time scaling analysis⁸ (Chen et al., 2014). That is why Vacha and Barunik (2012) and Chang and Lee (2015) based their causality investigations on the wavelet coherency. They found interesting dynamic correlations between spot and futures prices in the case of several energy commodities.

Moreover, Nicolau and Palomba (2015) tried to establish the existence of a ‘period-by-period’ prediction of futures prices for estimating spot prices for energy commodities, and vice-versa. They used a bivariate VAR and found that some interactions between spot and futures prices exist and depend on commodity type and futures contract maturity. Zhang and Liu (2018) explored the spot and futures relationship in natural gas markets. They found a significant positive bidirectional non-linear causality between both prices caused by the volatility spillover of the market.

The price discovery mechanism

Garbade and Silber (1983) were the first to explain the spot and futures price movements via an equilibrium model. Taking into consideration seven US commodities, they found that all the markets are correlated, in the middle and short run. Later Koontz et al. (1990) found a strong integration between livestock cash and futures prices; futures have the power to determine spot prices due to Geweke (1982) causality test.

⁷Developed by Johansen (1988) and Johansen and Juselius (1990).

⁸Considering daily, weekly, monthly, and yearly data

This issue is of considerable interest. Indeed, [Moosa \(2002\)](#) extend the framework developed earlier by [Garbade and Silber \(1983\)](#) by allowing the model's coefficients to be time-varying. He found that the futures market represents 60% of the oil price discovery function. [Sahi and Raizada \(2006\)](#) studied the wheat market and found that the wheat spot prices dominate futures prices in the price discovery process.

[Iyer and Pillai \(2010\)](#) also re-examined [Garbade and Silber \(1983\)](#) using a Two-regime Time-Varying Auto-Regressive model. They analyzed the price discovery process for six precious metals commodities in the Indian market. Results showed an essential leading role of futures for five commodities out of six. Additionally, [Chinn and Coibion \(2014\)](#) analyzed energy and precious metals commodities (crude oil, natural gas, and gold). They concluded that metals futures prices are poor predictors of spot prices, while energy futures are significant predictors of spot prices. [Dimpfl et al. \(2017\)](#) studied the price discovery in agriculture markets and found that spot prices have the power to lead futures prices by 90% and there is a strong correlation between spot and futures prices. [Irfan and Hooda \(2017\)](#) investigated the price discovery mechanism in the Indian commodity market; they confirm the evidence of a strong correlation between spot and futures prices.

The market efficiency

The market efficiency is a topical issue since the seminal paper of [Fama \(1991\)](#). More interestingly, studying efficiency in the case of commodity markets is essential for policymakers, investors, and hedgers in term of price predictions, forecasting, diversification, and risk management. Indeed, analyzing spot-future links is one of the issues to investigate the efficiency of commodity and or equity markets.

[Chowdhury \(1991\)](#) investigated the efficient market hypothesis in the case of nonferrous metals traded on the London Metal Exchange. Using a co-integration model, he concluded that futures prices are a biased predictor of the subsequent spot prices. To have better results, [Beck \(1994\)](#) utilized a co-integration and error correction model for 5 US commodities. He found that commodities markets may be momentarily inefficient; None of the commodities remain inefficient for the complete time horizon. [Kellard et al. \(1999\)](#) also considered the time-frequency domain and concluded that markets are only efficient in the long run for the US soybean, live hogs, and live cattle. [McKenzie and Holt \(2002\)](#) investigated the same commodities using the GARCH-M-ECM model and found that the markets are both biased and inefficient in the short run, but efficient and unbiased in the long run. In another hand, [Wang and Ke \(2005\)](#) studied the efficiency of the Chinese agriculture futures markets, they conclude, as the previous studies, a robust long-term efficiency versus a week short term efficiency. Later, [Lean et al. \(2010\)](#) used both mean-variance (MV) and stochastic dominance (SD) to examine the efficiency of the US crude oil market. The authors confirm that there are no arbitrage opportunities between oil spot and futures markets; none of the markets dominate the other. [Ali and Bardhan Gupta \(2011\)](#) studied twelve agriculture commodities; they used Johansen's co-integration with Granger causality test. The

study found that spot and futures prices are significantly co-integrated for ten commodities out of twelve.

Furthermore, results showed market efficiency for all the studied commodities. [Go and Lau \(2017\)](#) studied commodity market efficiency and found a strong correlation between spot and futures prices in backwardation. While during contango, this correlation becomes weaker.

1.4 Data

Our study uses a daily time series of spot and futures of eight different commodity prices from four different categories. We choose the nearest maturity of the futures contracts because they are the most liquid and the most active contracts. We prefer commodity markets as desirable assets for international investors. Indeed, the selected commodity categories under this research are energy (crude oil and Natural gas), agriculture (Wheat and Soybean), precious metals (Gold and Platinum) and soft commodities (Cotton and Sugar). From each type, we selected the two top actively traded commodities. Prices time series are collected from the DataStream and Bloomberg.

Table 1.1: Augmented Dickey and Fuller test

Commodity	Level (0)= I (0)		level (1) = I (1)	
	t-Statistic	P-value	t-Statistic	P-value
Energy				
Crude oil futures	-2.185	0.5000	-15.281***	0.001
Crude oil spot	-2.214	0.4877	-15.853***	0.000
Natural gas futures	-3.662	0.02661	-16.813***	0.001
Natural gas spot	-3.567	0.03579	-16.042***	0.001
Precious metals				
Gold futures	-1.053	0.9302	-16.377***	0.000
Gold spot	-1.087	0.9247	-16.354***	0.000
Platinum futures	-1.938	0.6043	-15.048***	0.000
Platinum spot	-1.119	0.9195	-16.321***	0.000
Agriculture				
Soybean futures	-2.818	0.2324	-14.425***	0.000
Soybean spot	-2.817	0.2322	-14.723***	0.000
Wheat futures	-2.604	0.3222	-16.339***	0.001
Wheat spot	-2.428	0.3971	-15.819***	0.000
Soft commodities				
Cotton futures	-2.773	0.2507	-15.603***	0.000
Cotton spot	-2.704	0.2799	-15.627***	0.000
Sugar futures	-2.137	0.5200	-15.540***	0.000
Sugar spot	-2.073	0.5473	-15.424***	0.000

Note: *** indicates significance level at 1%

The motivations behind selecting these classes of commodities are numerous. The financial literature confirms that commodities play a crucial hedging role against significant risks such as inflation and financial crises ([Nicolau and Palomba, 2015](#)).

The data covers the period between January 2002 and November 2018. The choice of the sample period corresponds roughly to several economic events, in order to have great episodes of extreme movements. These events caused significant movements and extreme changes in all the commodities prices. That is why our contribution consists of understanding the relationship between commodity spot and futures prices during these abrupt changes, which we consider crucial information to all economic agents for several reasons. Indeed, investors and policymakers can have a global idea about the price discovery mechanism during extreme value periods for all types of commodities. Consequently, they can select the best reactive commodity when they face positive or negative abrupt change. These commodities are highly used to avoid risks, to hedge, and to diversify.

We started with specifying the common statistical properties of each commodity time series. For empirical requirements, the data must be stationary. That is why, according to Augmented Dickey and Fuller test presented in table 1.1, we select the commodities spot and futures log returns.

To conduct an adequate analysis, we use commodities spot and futures returns calculated as follow;

$r_f = \frac{(F_{t,T} - F_{t-1,T})}{F_{t-1,T}}$, where r_f is the futures return, $F_{t,T}$ is the futures price at time t and maturity T and $F_{t-1,T}$ is the futures price at time $t-1$ at maturity T .

$r_s = \frac{(P_t - P_{t-1})}{P_{t-1}}$, where r_s is the spot return, P_t is the spot price at time t , and P_{t-1} is the spot price at time $t-1$.

Table 1.2 presents the descriptive statistics and ARCH effect results. Results show that all the commodities spot and futures returns are non-normal given the great significance of the Jarque-Bera normality test. Further, all the returns are fat-tailed, which justify the jumps occurrence in commodity markets. These confirm our interest in studying dependence between spot and futures returns in tails because it will be different from dependence in normal market conditions (Lee and Cheng (2007), and Jena et al. (2019)).

The means of spot and futures returns are close to zero for all commodities. The negative (positive) skewness indicates a higher probability of negative (positive) returns compared to positive (negative) returns. The kurtosis exceeds 3 for all the commodity spot and futures returns; kurtosis is higher than the normal distribution, which indicates that all commodity spot and futures returns are leptokurtosis.

The Ljung-box statistics are significant both for returns and squared returns of all the commodities, which reflect heteroscedasticity for all the commodities spot and futures returns. The choice of lag length (10) is based on Akaike Information Criteria. The Portmanteau-Q test and Lagrange-Multiplier test highlight the ARCH effect; All commodities spot and futures returns display ARCH effect. That is why we select three GARCH models to represent marginal distributions.

1.5 Methodology

1.5.1 Copula Approach

According to financial literature, copula approach succeeded to describe marginal distributions, multi-dimensional dependencies and tail dependencies in financial time series containing extreme movements, high volatilities and risk contagion.

This section introduces the bivariate copula approach to model the average and tail dependencies between commodities spot and futures returns. The cornerstone of copula methods is the [Sklar \(1959\)](#) theorem, which indicates that copula functions have the power to link a joint multivariate distribution $H_{XY}(x, y)$ of two continuous variables X and Y to their univariate marginal functions $H_X(x)$ and $H_Y(y)$ in terms of a copula function $C(u, v)$ as follows;

$$H_{XY}(x, y) = C(u, v)$$

Where H is the joint distribution of a random vectors X and Y , and $u = H_X(x)$ and $v = H_Y(y)$ are the uniform marginals. C is the Copula ($C: [0, 1]^n \rightarrow [0, 1]$), n is the dimension of the copula representing the dependence structures between the uniform marginals. Indeed, following [Joe \(2006\)](#) and [Nelsen et al. \(2008\)](#), copula functions capture the dependence structure by constructing a multivariate distribution function linking two univariate fitted marginals. Following [Patton \(2009\)](#), the joint conditional distribution function can be presented by;

$$H_{X,Y,t}(x_t, y_t | \Omega_{t-1}) = C(u_t, v_t | \Omega_{t-1})$$

Where t represents the time and Ω_{t-1} is the information set at the time $(t-1)$.

The joint probability density of the time series x_t and y_t with marginal densities $h_{X,t}(x_t)$ and $h_{Y,t}(y_t)$, respectively are described as

$$h_{XY,t}(x_t, y_t | \Omega_{t-1}) = c(u_t, v_t | \Omega_{t-1}) \cdot h_{X,t}(x_t) \cdot h_{Y,t}(y_t)$$

Where the copula density is presented by;

$$c(u_t, v_t | \Omega_{t-1}) = \frac{\partial^2 C(u_t, v_t | \Omega_{t-1})}{\partial u_t \partial v_t}$$

Thus, to understand dependencies between two-time series x_t and y_t , we need to specify the two joint densities of X_t and Y_t , then, we characterize marginal density. After that, we fit copula densities based on the log-likelihood function presented by;

$$\ln L = \sum_{t=1}^T (\ln h_X(x_t, y_t | \Omega_{t-1}) + \ln h_Y(y_t | \Omega_{t-1})) + \sum_{t=1}^T \ln c(u_t, v_t | \Omega_{t-1})$$

This equation indicates that two main components constitute the log-likelihood function; the first part represents the marginal density functions of the two time-series, and the second part represents the copula density function.

Besides, the main motivation behind choosing copula is that it offers information about both average dependences and on the probability that two variables jointly exhibit dependencies during extreme upward and downward market volatilities. These extreme dependencies are measured by the upper tail and lower tail dependence, respectively, as follow;

$$\lambda_L = \lim_{u \rightarrow 0^+} Pr \left(X \leq H_X^{-1}(u) | X \leq H_Y^{-1}(u) \right) = \lim_{u \rightarrow 0^+} \frac{C(u, u)}{u}$$

$$\lambda_U = \lim_{u \rightarrow 1} Pr \left(X \geq H_X^{-1}(u) | X \geq H_Y^{-1}(u) \right) = \lim_{u \rightarrow 1} \frac{2 - 2u + C(u, u)}{1 - u}$$

Where λ_L is the lower tail, λ_U is the upper tail and $\lambda_U, \lambda_L \in [0, 1]$. The lower tail dependence indicates that $\lambda_L > 0$. This means that the probability of dependence between two times series X and Y do exist when both variables exhibit minimal values. Then, $\lambda_U > 0$ indicates that there is a non-zero probability of dependence between X and Y when both exhibit extremely high values.

Following the IFM (inference by margins) approach proposed by , the copula approach is mainly decomposed by three key steps. First, we estimate the marginal distribution functions for each commodity return, and then, we select the best-fitted model. Second, we estimate the copula parameters using the results of the first step, and we choose the best-fitted density using maximum loglikelihood estimations. Third, we measure the tail dependencies in line with the results of the second step to identify the dependencies during positive and negative extreme movements.

Table 1.2: Descriptive statistics of the commodities spot and futures returns and ARCH tests

Statistics	Mean	S.D	Skewness	Kurtosis	Jarque-Bera	LB	Portmanteau-Q test			Lagrange-Multiplier test		
Energy							PQ(8)	PQ(16)	PQ(24)	LM(8)	LM(16)	LM(24)
Crude oil futures	0.0003	0.0183	-0.103	6.2195	2002,618***	28.325***	1541***	2584***	3524***	1286***	546***	339***
Crude oil spot	0.0004	0.0246	0.08	7.9288	4679,426***	33.257***	1307***	2383***	3296***	1058***	467***	293***
Natural gas futures	0.0005	0.0357	0.9297	10.617	11829,18***	40.481***	156.1***	201.3***	213.5***	3412***	1646***	925***
Natural gas spot	0.0009	0.0463	2.2207	36.088	214458,5***	219.44***	110.7 ***	180.6***	216.4***	1965***	935***	614***
Precious metals												
Gold futures	0.0003	0.0114	0.0162	9.4437	7989,782***	23.537***	360***	622***	881***	2439***	1105***	692***
Gold spot	0.0003	0.0113	0.0202	9.338	7729,908***	19.834***	335***	598***	840***	2521***	1122***	701***
Platinum futures	0.0003	0.0146	-0.0035	9.7056	8652,107***	30.547***	350***	642***	914***	2890***	1228***	745***
Platinum spot	0.0003	0.0144	-0.2691	6.9354	3035,829***	38.275***	320***	526***	760***	2513***	1140***	703***
Agriculture												
Soybean futures	0.0002	0.0146	0.6183	41.1204	279907,3***	42.632***	685***	688***	691***	2149***	1069***	709***
Soybean spot	0.0002	0.0155	-0.1016	4.964	750,20***	19.367***	467***	487***	491***	1876***	956***	609***
Wheat futures	0.0002	0.0188	0.3595	5.4696	1273,06***	5.4633***	214***	363***	460***	1586***	747***	487***
Wheat spot	0.0002	0.0186	0.3243	6.2483	2111,35***	5.8178***	336***	408***	463***	1700***	829***	543***
Soft commodities												
Cotton futures	6.75E-05	0.0137	-0.4436	11.232	13191,02***	212.11***	441***	821***	1070***	1599***	693***	451***
Cotton spot	0.0001	0.0169	0.0503	4.4051	381,84***	27.399***	543***	545***	546***	3213***	1600***	1063***
Sugar futures	0.0001	0.0144	0.0363	8.2099	5223,91***	179.53***	220***	312***	411***	2006***	976***	622***
Sugar spot	0.0002	0.0205	-0.1117	4.7818	620,51***	19.323***	796***	802***	806***	1572***	778***	514***

Notes: S.D refers to standard deviation, LB refers to the empirical statistics of the Ljung-Box test for autocorrelation of the returns. Portmanteau-Q and Lagrange-Multiplier are the ARCH effect test proposed by Engle (1982). (8), (16), and (24) are the corresponding lag parameters to calculate the test statistics. *** presents the rejection of the null hypothesis of normality (Jarque-Bera test), of no autocorrelation (Ljung-Box test), and of conditional homoscedasticity at a significance level of 1%.

In the following two subsections, we introduce the marginal specification and the copula structures.

1.5.2 Marginal distribution functions

GARCH models have succeeded in describing financial and commodity time series, especially when the objective is to analyze market movements and volatility. Accordingly, the volatility of the commodity time series has some potential features such as dependence, asymmetry, leverage effects, and extreme movements, which make them unpredictable showing clustering in the variability, given recent market volatilities. These facts generally cause a conditional heteroskedasticity, because it is worth noting that commodity returns are stationary. However, the conditional expected variance could be time-dependent.

In order to take into account these potential behaviors, we choose three GARCH family models since commodity spot and futures returns exhibit a significant ARCH effect.

To simulate the commodity spot and futures returns, we choose the standard GARCH, the AR-GARCH (to capture symmetric features) and E-GARCH (to capture asymmetric features) models, which optimally reflect the log information and control potential symmetric and asymmetric behaviors, respectively.

Let $r_{i,t}$ ($t=1, \dots, T$) be the return of given commodity.

Following Grégoire et al. (2008), the standard GARCH (1,1)⁹ The model can be written as follow;

$$r_{i,t} = c + \sigma_t y_t$$

Where r is the return of the commodity I in time t .

$$\sigma_{i,t}^2 = \omega + \alpha_1 \varepsilon_{i,t-1}^2 + \beta_1 \sigma_{i,t-1}^2$$

y_t is an iid random variable with mean=0 and variance=1. Besides $\sigma_{i,t}^2$ is the conditional variance of the commodity return i at time t ; it is a function of the past return innovations $\varepsilon_{i,t-1}^2$ and the past conditional variance $\sigma_{i,t-1}^2$. For the symmetric GARCH, we describe AR(1)-GARCH(1.1) as follow:

$$r_{i,j,t} = a_j + a_1 r_{i,j,t-1} + \varepsilon_{i,j,t}$$

Where $i = \{\text{spot, futures}\}$,

$$\varepsilon_{i,j,t} = v_{i,j,t} \sqrt{h_{i,j,t}}$$

⁹The optimal lag length for the conditional mean and variance processes of the GARCH model and the ARMA-GARCH model was determined using the AIC and BIC. The results can be made entirely available under request addressed to the author.

$$h_{i,j,t} = \alpha_{i,1,0} + \alpha_{i,1,1} \cdot \varepsilon_{i,t-1}^2 + \beta_{i,1,1} \cdot h_{i,1,t-1}$$

Where $r_{i,j,t}$ is the commodity return, t = time scale.

For the asymmetric GARCH, we develop E-GARCH as follow; We consider $r_{i,t}$ is the commodity return, t = time scale and $i = \{\text{spot, futures}\}$,

$$r_{i,j,t} = \mu_{i,t} + \varepsilon_{i,t}$$

$\mu_{i,t}$ is the expected return; $\varepsilon_{i,t} = \sigma_{i,t} z_{i,t}$, is a zero-mean white noise, which is serially uncorrelated where $z_{i,t}$ is a standard Gaussian.

$$\ln(\sigma_{i,t}^2) = \omega + \alpha (|z_{i,t-1}| - E[|z_{i,t-1}|]) + \gamma z_{i,t-1} + \beta \ln(\sigma_{i,t-1}^2)$$

To capture the jump process, we estimate the best fitting model for each commodity's spot and futures return. The fitting performance of each marginal distribution presented in Table 4 is considered based on several tests.

1.5.3 The copula family

This research gives us the possibility to investigate both symmetric and asymmetric structures of extreme dependence between variables in addition to upper and lower tail distributions using a diverse family of copula specifications. First, we investigate symmetric copulas using the bivariate Normal Copula with equal tail dependencies and Frank copula with zero tail dependencies. Second, we analyze asymmetric copulas presented by the Gumbel copula with an upper tail dependence and zero lower tail dependence, and the Clayton copula with upper tail independence and lower tail dependence.

Copula families are described as follow;

1. The bivariate Gaussian (normal) Copula is symmetric and elliptical and has no tail dependence. It is defined by:

$$C(r_{s,t}, r_{f,t}) = \int_{-\infty}^{\varnothing^{-1}(r_{s,t})} \int_{-\infty}^{\varnothing^{-1}(r_{f,t})} \frac{1}{2\pi\sqrt{1-\theta^2}} \exp\left(-\frac{s^2 - 2\theta st + t^2}{2(1-\theta^2)}\right) ds dt$$

Where \varnothing is the univariate standard normal distribution function, θ is the linear correlation coefficient restricted to the interval $(-1,1)$, $r_{f,t}$ and $r_{s,t}$ are the standardized residuals obtained from the GARCH and AR-GARCH models for both futures and spot returns, respectively.

The coefficients of the upper and lower tail are defined as follow:

$$\lambda_L = \lambda_U = 2 \lim_{r_{s,t} \rightarrow -\infty} \Phi \left(r_{s,t} \frac{\sqrt{1-\rho}}{\sqrt{1+\rho}} \right)$$

2. The Gumbel Copula is as an extreme value copula. It is asymmetric and archimedean, more efficient when dealing with dependence in the upper tail and is defined by

$$C(r_{s,t}, r_{f,t}) = \exp \left\{ - \left[(-\ln(r_{s,t}))^\theta + (\ln(r_{f,t}))^\theta \right]^{\frac{1}{\theta}}, \theta \in (1, +\infty) \right\}$$

Its generator is:

$$\phi(t) = (-\ln(t))^\theta, \text{ where } \theta \geq 1.$$

The relationship between Kendall's tau and the Gumbel Copula parameter is as follow:

$$\theta = \frac{1}{1-\tau_C}.$$

The upper tail dependence is given by: $\lambda_{U_G} = 2 - 2^{-\theta}$

The lower tail dependence is given by: $\lambda_{L_G} = 0$

3. The Clayton copula is asymmetric, more powerful in dealing with dependence in the negative or lower tail than in the positive one and is expressed as

$$C(r_{s,t}, r_{f,t}) = \left(r_{s,t}^{-\delta} + r_{f,t}^{-\delta} - 1 \right)^{-\frac{1}{\delta}}, \delta \in (0, \infty)$$

According to Clayton: $\delta \rightarrow 0$ leads to independence and $\delta \rightarrow \infty$ leads to the perfect positive copula.

The relationship between Kendall's tau and the Clayton Copula parameter is as follow:

$$\theta = \frac{2\tau_c}{1-\tau_c}$$

The Clayton Copula is a lower tail dependent since the upper tail dependence $\lambda_{U_C} = 0$, and the lower tail dependence is as follow:

$$\lambda_{L_C} = 2^{\frac{1}{\delta}}$$

4. The Frank copula is symmetric Archimedean Copula and is presented by

$$C(r_{s,t}, r_{f,t}) = -\frac{1}{\theta} \ln \left(1 + \frac{(\exp(-\theta r_{s,t}) - 1)(\exp(-\theta r_{f,t}) - 1)}{\exp(-\theta) - 1} \right), \theta \in (-\infty, +\infty)$$

The generator of Frank Copula is given by:

$$\phi(t) = -\ln \frac{e^{-\theta t} - 1}{e^{-\theta} - 1}, \text{ where } \theta \neq 0$$

Frank Copula is symmetric, the upper tail dependence and the lower tail dependence are the same and are $\lambda_{L_F} = \lambda_{U_F} = 0$

1.5.4 Estimation of copula parameters

To estimate the parameters of the Copula functions, we followed [Cherubini et al. \(2004\)](#) by applying the semiparametric two-step estimation method called Canonical Maximum Likelihood (CML).

Step 1: Non-parametrically estimating the marginal F_{r_f} and G_{r_s} based on their cumulative distribution functions \hat{F}_{r_f} and \hat{G}_{r_s} as follow;

$$\hat{F}_{r_f}(r_f) = \frac{1}{T} \sum_{j=1}^T 1 \{R_{fj} < r_f\}$$

$$\hat{F}_{r_s}(r_s) = \frac{1}{T} \sum_{j=1}^T 1 \{R_{sj} < r_s\}$$

Later, the observations are transformed into uniform variated via the Empirical Cumulative Distribution Function (ECDF) of each marginal distribution.

The unknown copula parameter θ is consequently estimated as follow;

$$\hat{\theta}_{CML} = \underset{\theta}{\operatorname{argmax}} \sum_{j=1}^T \ln c(\hat{F}_{r_f}(r_f), \hat{F}_{r_s}(r_s); \theta)$$

According to [Genest et al. \(1995\)](#), $\hat{\theta}_{CML}$ is consistent, asymptotically normal, and fully efficient at independence under some regularity conditions.

1.6 Empirical results and discussion

In this section, the first step is estimating the marginal distribution parameters as detailed in the methodology section. We estimated GARCH, AR-GARCH, and E-GARCH models for all the commodities spot and futures returns in order to introduce i.i.d observations to estimate copula. The parameters are significant for the commodities returns, which allow us to calculate the parameters of the efficient copula. Results are presented in tables 1.3, 1.4, and 1.5. Second, we select the best-fitted model for commodities marginal distribution. To do that, we estimate the log-likelihood, and we calculate the Akaike Information Criteria (AIC) for each model. Then, we present the statistical properties of the selected model in table 1.6. Fourth, we estimate the copula parameters for each commodity's spot and futures return and we select the best-fitted copula to understand the nature of the relationship between the commodity futures and spot prices in table 1.7. Finally, we estimate the tail dependencies and their limits in (-1) and 1 for the lower and upper tails, respectively, and we present the results in figures 1.1 to 1.8. These figures help understanding more details about commodities spot and futures link during positive and negative market extreme values.

1.6.1 The marginal distribution

Commodity prices time series are known by their volatilities and abrupt changes. In addition, the return series show significant volatility clustering, which can reflect a standard, an asymmetric, or symmetric potential behavior. That is why we should fit marginal distributions to adjust the empirical returns.

In order to take into account these distinctive features of movements, we select three GARCH family models described in section 1.5. The first model is the standard GARCH model. Then, we adopt an AR-GARCH in order to control for potential symmetric dependencies. Finally, we adopt an E-GARCH specification to control for potential asymmetry.

To select the best-fitted model for each commodity return, we choose lags order according to AIC and BIC criterion. Later, we select the adequate model based on loglikelihood and minimum AIC. Tables 1.3, 1.4, and 1.5 report the GARCH model parameter estimations, AIC, and log-likelihood. We found that the AR(1)-GARCH(1.1) model is the best fitted for oil futures, natural gas spot and futures, platinum spot and futures, soybean spot and futures, wheat futures, cotton spot and futures, and sugar spot and futures while gold spot and futures, oil spot and wheat spot are fitted with GARCH model.

Table 1.3: Estimation result for GARCH model

GARCH						
Commodity	u	ω	α_1	β_1	AIC	Log-likelihood
Energy						
Crude oil futures	4.280e-04 (2.267e-04)	2.933e-06 *** (8.103e-07)	5.380e-02*** (6.376e-03)	9.384e-01*** (7.487e-03)	-5.3252	12300
Crude oil spot	6.658e-04* (2.899e-04)	4.537e-06*** (1.246e-06)	5.913e-02*** (6.751e-03)	9.350e-01*** (7.414e-03)	-4.7819	11045.52
Natural gas futures	8.631e-04* (4.386e-04)	2.169e-05*** (4.257e-06)	8.154e-02*** (7.757e-03)	9.055e-01*** (8.581e-03)	-3.9749	9182.238
Natural gas spot	1.956e-04 (4.389e-04)	2.167e-05*** (4.666e-06)	1.574e-01*** (1.137e-02)	8.534e-01 *** (9.373e-03)	-3.7719	8713.378
Precious metals						
Gold futures	2.160e-04 (1.453e-04)	2.007e-06*** (4.505e-07)	4.594e-02*** (5.855e-03)	9.386e-01*** (8.425e-03)	-6.2615	14461.85
Gold spot	2.279e-04 (1.451e-04)	2.033e-06*** (4.649e-07)	4.654e-02*** (6.005e-03)	9.378e-01*** (8.711e-03)	-6.2634	14466.3
Platinum futures	4.122e-04* (1.922e-04)	3.971e-06*** (8.762e-07)	3.103e-02*** (4.281e-03)	9.487e-01*** (8.252e-03)	-5.7511	13283.3
Platinum spot	3.481e-04 (1.779e-04)	2.813e-06*** (6.516e-07)	6.146e-02*** (7.079e-03)	9.250e-01 *** (8.874e-03)	-5.8223	13447.73
Agriculture						
Soybean futures	5.553e-05 (1.772e-04)	3.408e-06*** (7.134e-07)	8.093e-02*** (9.082e-03)	9.075e-01*** (1.013e-02)	-5.8265	13457.47
Soybean spot	2.258e-04 (1.990e-04)	4.272e-06*** (8.500e-07)	6.493e-02*** (6.701e-03)	9.173e-01*** (8.393e-03)	-5.6341	13013.2
Wheat futures	1.820e-04 (2.479e-04)	2.151e-06*** (6.174e-07)	3.043e-02*** (4.196e-03)	9.639e-01*** (5.049e-03)	-5.2083	12029.86
Wheat spot	2.811e-05 (2.372e-04)	1.992e-06*** (6.239e-07)	4.199e-02*** (5.241e-03)	9.531e-01*** (5.865e-03)	-5.2658	12162.89
Soft commodities						
Cotton futures	7.6916e-06 (1.617e-04)	1.291e-06*** (2.905e-07)	5.335e-02*** (5.398e-03)	9.414e-01*** (5.638e-03)	-5.9665	13780.83
Cotton spot	2.154e-05 (2.132e-04)	1.631e-06*** (4.713e-07)	4.325e-02*** (4.731e-03)	9.515e-01*** (5.337e-03)	-5.4635	12619.43
Sugar futures	1.945e-04 (1.713e-04)	2.459e-06*** (6.512e-07)	9.071e-02*** (1.182e-02)	9.037e-01*** (1.254e-02)	-5.8189	13440.02
Sugar spot	9.181e-05 (2.573e-04)	1.261e-06 ** (4.296e-07)	3.636e-02 *** (3.992e-03)	9.615e-01*** (4.117e-03)	-5.0620	11692.33

Note: ***, **, and * rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. The numbers between parentheses are the standard deviations. AIC is the Akaike Information Criterion.

Table 1.4: Estimation result for AR(1)-GARCH(1.1) model

AR(1)-GARCH(1.1)							
Commodity	u	AR(1)	ω	α_1	β_1	AIC	log-likelihood
Energy							
Crude oil futures	4.440e-04 (2.273e-04)	-4.923e-02 *** (1.538e-02)	2.774e-06*** (7.653e-07)	5.210e-02*** (6.094e-03)	9.405e-01*** (7.095e-03)	-5.3272	12305.64
Crude oil spot	6.825e-04* (2.905e-04)	-3.122e-02** (1.537e-02)	4.470e-06*** (1.226e-06)	5.872e-02*** (.678e-03)	9.355e-01*** (7.313e-03)	-4.7824	11047.7
Natural gas futures	8.583e-04 (4.400e-04)	-5.845e-02*** (1.586e-02)	2.182e-05*** (4.307e-06)	8.161e-02*** (7.829e-03)	9.053e-01*** (8.700e-03)	3.9777	9189.698
Natural gas spot	1.956e-04 (4.385e-04)	8.120e-03 (1.635e-02)	2.146e-05*** (4.647e-06)	1.567e-01*** (1.135e-02)	8.541e-01*** (9.375e-03)	-3.7715	8713.503
Precious metals							
Gold futures	2.181e-04 (1.453e-04)	-2.034e-3 (1.574e-02)	2.006e-06*** (4.504e-07)	4.594e-02*** (5.855e-03)	9.386e-01*** (8.424e-03)	-6.2612	14462.24
Gold spot	2.301e-04 (1.452e-04)	-3.605e-3 (1.576e-02)	2.031e-06*** (4.646e-07)	4.652e-02 *** (6.002e-03)	9.378e-01*** (8.705e-03)	-6.2631	14466.63
Platinum futures	4.011e-04 (1.920e-04)	3.285e-02** (1.556e-02)	4.052e-06*** (9.134e-07)	3.142e-02*** (4.436e-03)	9.479e-01*** (8.610e-03)	-5.7517	13285.8
Platinum spot	3.269e-04 (1.772e-04)	5.180e-02 *** (1.539e-02)	2.841e-06*** (6.606e-07)	6.207e-02*** (7.175e-03)	9.242e-01*** (9.025e-03)	-5.8244	13453.67
Agriculture							
Soybean futures	5.117e-05 (1.724e-04)	1.751e-01*** (1.597e-02)	3.490e-06 *** (7.016e-07)	8.285e-02*** (8.754e-03)	9.049e-01*** (9.796e-03)	-5.8518	13516.98
Soybean spot	5.117e-05 (1.724e-04)	1.751e-01 (1.597e-02)	3.490e-06*** (7.016e-07)	8.285e-02*** (8.754e-03)	9.049e-01*** (9.796e-03)	-5.6337	13516.98
Wheat futures	1.807e-04 (2.476e-04)	2.226e-02 (1.525e-02)	2.133e-06*** (6.145e-07)	3.049e-02*** (4.205e-03)	9.639e-01*** (5.048e-03)	-5.2083	12030.99
Wheat spot	2.732e-05 (2.370e-04)	1.713e-02 (1.534e-02)	1.997e-06*** (6.264e-07)	4.224e-02*** (5.278e-03)	9.528e-01*** (5.904e-03)	-5.2657	12163.6
Soft commodities							
Cotton futures	2.384e-05 (1.579e-04)	1.923e-01*** (1.537e-02)	1.268e-06 *** (2.807e-07)	5.257e-02 *** (5.288e-03)	9.420e-01*** (5.507e-03)	-5.9994	13857.72
Cotton spot	2.051e-05 (2.129e-04)	3.647e-02** (1.522e-02)	1.645e-06*** (4.743e-07)	4.322e-02*** (4.730e-03)	9.515e-01 *** (5.350e-03)	-5.4644	12622.36
Sugar futures	1.832e-04 (1.657e-04)	1.952e-01*** (1.567e-02)	2.609e-06*** (7.001e-07)	9.431e-02*** (1.267e-02)	8.994e-01*** (1.363e-02)	-5.8519	13517.05
Sugar spot	9.230e-05 (2.571e-04)	1.936e-02 (1.509e-02)	1.266e-06** (4.317e-07)	3.647e-02*** (4.015e-03)	9.613e-01*** (4.144e-03)	-5.0620	11693.31

Note: ***, **, and * rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. The numbers between parentheses are the standard deviations. AIC is the Akaike Information Criterion.

Table 1.5: Estimation result for E-GARCH model

E-GARCH										
Commodity	u	AR(1)	MA(1)	ω	α_1	β_1	γ	SHAPE	AIC	log-likelihood
Energy										
Crude oil futures	2.2433** (0.0001)	1.1704 (0.0265)	1.1528 (0.0266)	-7.5607*** (0.0983)	-1.7036* (0.0269)	76.5118*** (0.0117)	43.7845*** (0.0392)	44.4388*** (0.0899)	4.9717	11487.77
Crude oil spot	3.7256*** (0.000344)	169.8522*** (0.004399)	-95.645*** (0.008116)	-5.9913*** (0.149851)	5.5875*** (0.020632)	51.1945*** (0.017556)	56.9354*** (0.026559)	33.2526*** (0.120020)	4.4400	10259.9
Natural gas futures	0.84588 (0.000495)	-2.52263** (0.037967)	0.60350 (0.037188)	-3.65380*** (0.124406)	-6.0699*** (0.057390)	35.87245*** (0.025065)	10.12604*** (0.121495)	23.32229*** (0.171187)	3.8408	8876.48
Natural gas spot	5.7072*** (0.000510)	-7.4280*** (0.075420)	11.5537*** (0.058425)	-2.7246*** (0.132468)	1.0575 (0.035797)	25.2568*** (0.035599)	6.1506*** (0.211037)	10.7428*** (0.371781)	3.6885	8524.838
Precious metals										
Gold futures	3.32766*** (0.000130)	0.19560 (0.003282)	0.25611 (0.004200)	-7.31081*** (0.120708)	-2.8293*** (0.025009)	69.56315*** (0.012925)	37.07625*** (0.040183)	41.99438*** (0.095136)	5.9901	13839.19
Gold spot	3.241750*** (0.000111)	0.001357 (0.630513)	0.001924 (0.631674)	-7.471304* (0.117482)	-4.3203*** (0.025156)	71.271429*** (0.012616)	37.457343*** (0.040048)	41.925324*** (0.095296)	5.9916	13842.61
Platinum futures	3.2435* (0.000092)	-15.3687*** (0.012934)	18.2483*** (0.013248)	-16.4702*** (0.055780)	-2.0790*** (0.022804)	142.7609*** (0.006300)	49.4560*** (0.030793)	34.9259*** (0.114461)	5.4215	12526.23
Platinum spot	13.2700*** (0.000049)	-14.8307*** (0.007930)	14.9067*** (0.011765)	-6.3444*** (0.143636)	-2.8929* (0.022448)	57.2186*** (0.015718)	42.9983*** (0.035473)	34.5956*** (0.115556)	5.5270	12769.77
Agriculture										
Soybean futures	0.66085 (0.000266)	-3.44825** (0.017109)	2.44236*** (0.062786)	-7.47183*** (0.108135)	-2.9624*** (0.027548)	73.51477*** (0.012231)	41.20536*** (0.039438)	40.43435*** (0.098836)	5.6383	13026.9
Soybean spot	1.2991 (0.000156)	58.2717*** (0.012132)	-54.449*** (0.012480)	-4.9467*** (0.152223)	-1.9440** (0.030289)	49.4587*** (0.018180)	38.0902*** (0.045099)	42.3008*** (0.094489)	5.2815	12203
Wheat futures	0.52337 (0.000285)	0.20294 (0.029370)	0.23690 (0.026970)	-9.93089*** (0.086869)	-2.9887*** (0.023559)	93.24163*** (0.009645)	47.15726*** (0.033573)	39.16490*** (0.102068)	4.8162	11128.66
Wheat spot	0.78445 (0.000137)	0.27520 (0.011846)	0.19607 (0.013260)	-6.84943*** (0.124106)	0.10937 (0.024508)	62.70762*** (0.014342)	46.53070*** (0.034854)	36.67061*** (0.109025)	4.8792	11274.05
Soft commodities										
Cotton futures	0.35889 (0.000143)	-3.75882*** (0.054612)	8.47674*** (0.049785)	-8.29018*** (0.118931)	5.22195*** (0.023227)	72.52960*** (0.012391)	43.24368*** (0.032145)	33.08075*** (0.120663)	5.7480	13280.15
Cotton spot	0.42260*** (0.000202)	-5.15484*** (0.050470)	6.42910*** (0.048746)	-7.06999*** (0.105844)	-0.6790*** (0.024040)	70.41394*** (0.012770)	40.01637*** (0.043042)	42.58901*** (0.093840)	5.0846	11748.31
Sugar futures	0.42938 (0.000245)	-13.9716*** (0.015869)	10.17033*** (0.042154)	-7.16584*** (0.134088)	3.51699*** (0.022821)	63.06304*** (0.014252)	47.73473*** (0.030158)	32.15387*** (0.124165)	5.6406	13032.2
Sugar spot	0.85713 (0.000123)	1.32238 (0.004666)	1.67052* (0.004127)	-7.45127*** (0.120665)	6.78478*** (0.022258)	64.09864*** (0.014023)	50.78873*** (0.030121)	35.10066*** (0.113717)	4.6834	10821.92

Note: ***, **, and * rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively. The numbers between parentheses are the standard deviations. AIC is the Akaike Information Criterion.

Table 1.6 presents the statistical properties of the fitted models for each commodity spot and futures returns. Results show that all the residuals are not auto-correlated; indeed, all the Ljung box statistics are insignificant. Therefore, we accept H_0 and we admit that all the margin distribution of the commodities spot and futures returns are independently distributed. The LM test shows the existing of ARCH effect in all the commodities futures and spot returns regressions. Which justify the choice of AR-GARCH model as the marginal distribution for all the commodities returns and that one period lagged squared shocks have a significant impact on current conditional volatility. Jarque-Bera test and Shapiro and Wilk test statistics are highly significant for all the commodities spot and futures returns, which means that the non-normality is evident for each market.

According to table 1.4, the lagged autoregressive AR(1) coefficients are significant at 1% level for all

the selected commodities. This indicates that the past information included in the price return significantly contributes to explain current returns. Furthermore, the GARCH component β_1 is significant for all series which confirm the persistence of the volatility. The parameter is close to 1 for almost all the markets, which means that persistence is high for all the commodities. Besides, all the markets exhibit long memory given the significance of the fractional differencing parameter. Marginal fitting performance findings show that the estimated residuals of each commodity spot and futures fitted model do not reject the null hypothesis of autocorrelation. We also note that the Engle test does not reject the null hypothesis of the ARCH effect, and parameters of the selected models are significant for all the series, which confirms that fitted models are adequate.

Table 1.6: Marginal fitting performance

Commodity	Jarque-Bera	Shapiro-Wilk	Ljung-Box	LM ARCH
Energy				
Crude oil futures	791.5964***	0.985387***	3.652128	16.17242
Crude oil spot	1135.743***	0.9813418***	3.980053	30.7198
Natural gas futures	5246.21***	0.9670732***	8.578338	9.328194
Natural gas spot	68255.04***	0.9455765***	49.55327	2.825902
Precious metals				
Gold futures	5872.424***	0.9566901***	14.24738	20.04143
Gold spot	5640.536***	0.9584802***	11.40593	20.81473
Platinum futures	51026.57***	0.9507624 ***	13.55081	0.946609
Platinum spot	385.7244***	0.9884797***	14.98856	23.11869
Agriculture				
Soybean futures	11142.63***	0.9559633***	6.511314	49.26363
Soybean spot	172.6762***	0.993271***	16.86273	12.85631
Wheat futures	864.751***	0.9801368***	9.415511	8.46107
Wheat spot	404.7204***	0.9905133***	8.648515	10.33299
Soft commodities				
Cotton futures	3790.123***	0.9686552***	49.02431	6.576022
Cotton spot	129.86 ***	0.9945993***	14.51623	14.53884
Sugar futures	2124.083***	0.9719425***	39.38235	19.14922
Sugar spot	207.9118***	0.9917976***	28.79046	20.84797

Note: J-B refers to Jarque Bera test; it tests whether the kurtosis and skeweness of the data are matching a normal distribution. S-W refers to Shapiro-Wilk test which is a test of normality. L-B refers to Ljung Box test which test the autocorrelations. LM ARCH test which is a Lagrange multiplier test to assess the significance of ARCH effect. ***, **, and * rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

1.6.2 Copula modeling

In this section, we report the estimation results of the copulas specifications, presented in table 1.7. In this study, we adopt four different types of copulas; Normal copula, Frank Copula, Clayton copula, and Gumbel copula, as described in section 1.5.

Based on the log-likelihood, we can choose the best-fitted copula for each commodity. Indeed, the smaller likelihood validates the choice of the selected copula (Bold numbers in table 1.7). For crude oil, soybean, and wheat, the Clayton copula remains the best-fitted approach; This confirms the existence of temporal dependence, concentrated on lower-tail dependence; Which means that there is strong dependence in the lower tail. However, it fails to describe the changes in the upper tail dependence. For gold, platinum, and cotton, the normal copula is the best-fitted model; which confirms strong symmetric dependence during both positive and negative extreme values; In fact, Normal copula is insensitive to correlation changes in both upper and lower tails reflecting only strong symmetric dependencies.

Natural gas and sugar markets have Frank copula as the appropriate method to model the dependence between futures and spot prices; this means that dependence is fragile during market booms and busts; indeed, Frank copula fitting indicates that dependency is symmetric and very sensitive to market movements in upper and lower tails. Copula parameters are estimated using Kendall's tau transform method because it is considered as the most efficient estimating approach.

These results are in line with lower and upper tail findings presented in figures 1.1 to 1.8.

Table 1.7: Estimations of copula parameters

Copula Families		Normal copula				Clayton copula				Gumbel copula				Frank copula			
Commodities	statistic	parameter	p-value	Max-loglikelihood	statistic	parameter	p value	Max-loglikelihood	statistic	parameter	p-value	Max-loglikelihood	statistic	parameter	p-value	Max-loglikelihood	
Energy																	
Crude oil	0.70735	0.79682	0.00495	1535	1.5385	4.4291	0.0004995	1291	0.17838	2.4211	0.0004995	2425	1.0127	7.5916	0.00495	1620	
Natural gas	0.076234	0.21291	0.00495	233.6	0.014211	1.1815	0.08342	300	0.02833	1.1582	0.04346	113.9	0.12244	1.2482	0.00495	89.41	
Precious metals																	
Gold	0.001571	0.99667	0.401	6510	0.0068887	36.477	0.00495	7287	0.0021235	19.238	0.9995	11057	0.0014087	75.272	0.7772	10862	
Platinum	0.0018633	0.99645	0.3218	6468	0.018366	26.287	0.001499	8548	0.010736	18.639	0.1563	10380	0.0022388	72.873	0.7673	9529	
Agriculture																	
Soybean	0.0047365	0.64255	0.5099	3970	0.30048	1.5163	0.0004995	608.4	0.039798	1.7994	0.03247	1112	0.1685	4.805	0.9752	657.9	
Wheat	0.0015699	0.98185	0.5891	8190.6	0.031981	17.927	0.02248	5856	0.028513	8.232	0.03646	6153	0.084514	31.191	0.00495	6627	
Soft commodities																	
Cotton	0.026066	0.6458	0.6485	606.7	0.028911	1.9291	0.02248	962	0.018168	1.8082	0.2642	920	0.053651	4.8467	0.203	837.8	
Sugar	0.0097223	0.64827	0.1634	864	0.091733	1.5075	0.0004995	739.2	0.11124	1.8149	0.001499	1241	0.031194	4.8788	0.9851	698.4	

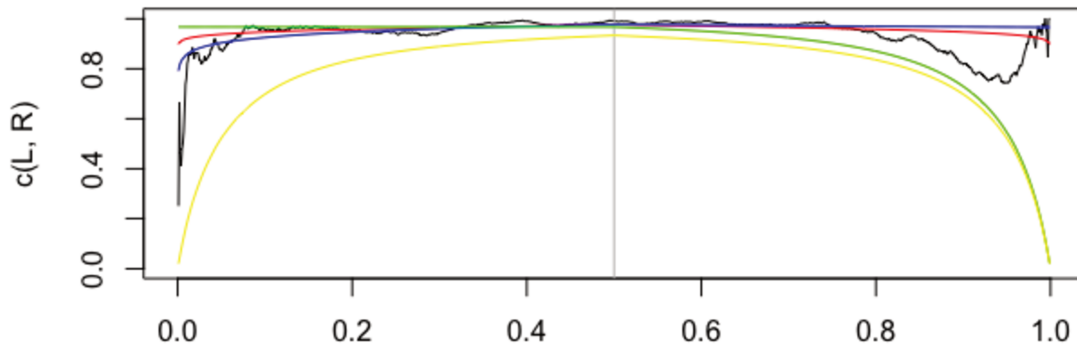
Note: Table 7 represents the parameter of the four adopted copulas. For each parameter, we represent the corresponding statistic, p-value and maximum log-likelihood. The red number indicate the lowest log-likelihood parameter, which refers to the best fitted model for each dependence relationship between the commodities spot and futures prices.

Crude Oil market

The performance of lower tail dependence between crude oil spot and futures returns is relatively higher than upper tail, which justifying the fitting performance of the oil market with the Clayton copula. These findings indicate that the dependence between crude oil spot and futures returns is stronger during bear markets.

In fact, according to Maslyuk-Escobedo et al. (2017) and Aït-Sahalia et al. (2015), crude oil spot and futures exhibit more negative jumps compared to positive jumps. Indeed, the large adverse fluctuations are generally caused by economic, production and supply politics (such as the demanding hike, supply politics, and OPEC decisions), usually planned. Spot and futures markets are prepared for these adverse market movements. Consequently, they simultaneously respond to these movements very quick, which justify the strong dependence of crude oil spot and futures during market busts.

Figure 1.1: Crude oil spot-futures tail dependence



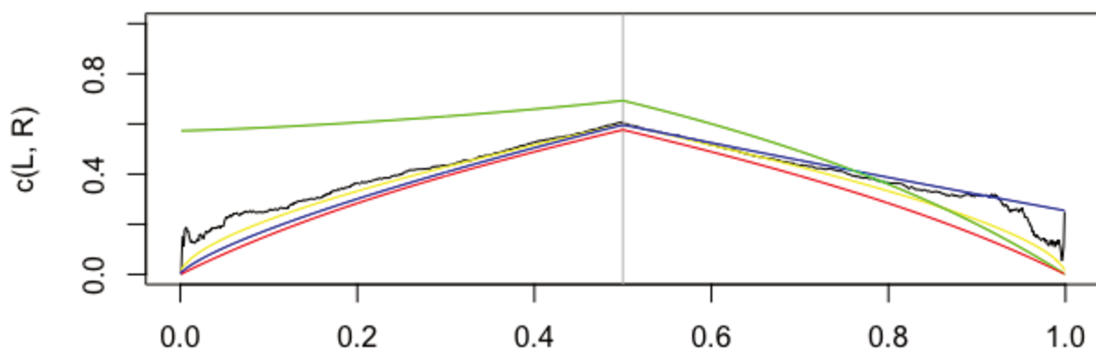
Note: The fig.1.1 represents the the upper tail dependence in the right side (from 0.5 to 1) and the lower tail in left side from (0 to 0.5). The Blue color represents the Gumbel copula tail, the Yellow color represents the Frank Copula tail, the Green color reflects the Clayton Copula tail, and the Red color is the Normal Copula tail.

Whereas, positive picks are caused by several financial, economic and geopolitical surprising events (such as the 9/11 attack, the Iraq war of 2003, financial crises, the Arab spring of 2011 and the Libyan war), which are unpredictable and exhibit active negative picks in spot or futures market. These facts make the market adjustment low and consequently decrease market efficiency during these positive movements.

Natural gas market

Natural gas spot and futures dependency is fitted with frank copula, which explains the weak upper and lower tail. These results indicate that the relationship between spot and futures are close to zero during positive and negative extreme movements.

Figure 1.2: Natural gas spot-futures tail dependence



Note: The fig.1.2 represents the the upper tail dependence in the right side (from 0.5 to 1) and the lower tail in left side from (0 to 0.5). The Blue color represents the Gumbel copula tail, the Yellow color represents the Frank Copula tail, the Green color reflects the Clayton Copula tail, and the Red color is the Normal Copula tail.

Consequently, we can affirm that natural gas futures returns are not an efficient predictor of spot returns during ‘extreme periods.’ According to the US Energy Information Administration (EIA), the natural gas futures market has known extraordinary movements, such as the Amaranth collapse. In 2006, Amaranth Company lost 60% of its regular gain and investments (almost USD 6.5 billion) because of the default estimation of natural gas futures prices. The losses were catastrophic because Amaranth transferred its investments and portfolios to energy trading during 2004–2005, mainly to natural gas, which represented 65% of the total portfolio. The collapse of 2006 was choking for investors and explained the exceptional results of our study. Natural gas futures price failed to behave as expected, and dependence between the physical and futures market was weakly scattered.

Consequently, futures prices failed to predict natural gas spot prices. Indeed, these crises had a significant impact on the futures market while the spot market depended on market fundamentals. In

another hand, natural gas market participants rely heavily on fundamentals when adjusting natural gas prices. First, the extra cold weather causes an immediate increase in natural gas demand spot prices. However, it is a short run impact that causes supply disruption.

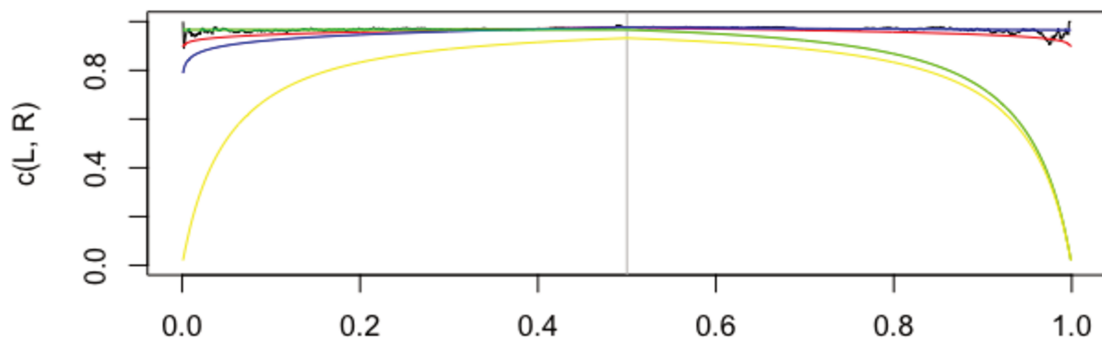
Moreover, natural gas prices movements can be explained by price-inelastic gas demand and the uncertainty of future supply conditions that directly appear in the spot market. Consequently, the weather could have a direct impact on natural gas supply, which affects the storage injection, and consequently increases spot prices. In fact, natural gas spot prices significantly respond to storage changes ([Chiou-Wei et al., 2014](#)). In the same context, exceptional low temperature causes storage withdrawals given the additional demand. Thus, the reaction of storage to natural gas structural break is consistent with the theory of storage; higher natural gas spot prices intuitively stimulate storage to retract natural gas. Aside from weather volatilities, surprising and devastating weather changes such as destructive hurricanes lead to significant storage changes that generate increases in spot prices. However, the natural gas futures market does not directly respond to these market changes, which justifies the low independency between natural gas futures prices and spot prices during market booms. In another hand, oil prices are considered as a major driver of natural gas prices given that they are substitute energy sources ([Villar and Joutz, 2006](#)). Indeed, there is an important physical link between crude oil and natural gas.

As a consequence, shocks in the crude oil market lead to storage shocks in natural gas prices; there is a negative correlation between storage surprises and natural gas spot prices, that responds immediately to market changes. However, it is evident that natural gas spot and futures markets exhibit a positive relationship in the long run, but this relationship weakened during positive and negative extreme values. Futures market exhibit a lagged response to market changes compared to the spot market. These results are in line with [Chiou-Wei et al. \(2014\)](#).

Gold market

Gold is classified as a precious metal and is considered a rare asset. It exhibits a higher economic value compared to other commodities and other metals. In the precious metal market, there are five openly tradable metals on different exchanges; gold is mainly the biggest and the most popular market.

Figure 1.3: Gold spot-futures tail dependence



Note: The fig.1.3 represents the the upper tail dependence in the right side (from 0.5 to 1) and the lower tail in left side from (0 to 0.5). The Blue color represents the Gumbel copula tail, the Yellow color represents the Frank Copula tail, the Green color reflects the Clayton Copula tail, and the Red color is the Normal Copula tail.

In recent years, gold prices regularly registered changes in price and production levels. Even though gold is on the top commodity markets, behind crude oil, its production and price behavior do not respond to classical market fundamentals such as supply and demand. While commodities are traditionally driven by inventories, expected demand, and supply, gold price responds more to interest rates, currency fluctuations, and financial turmoil. Besides, traders consider gold as a currency and a commodity at the same time, given that it has the features of both, and it exhibits an intrinsic value; it is considered as monetary metals. Furthermore, gold is strongly and negatively correlated to the U.S. dollar, financial turmoil, bond yields, and geopolitical conflicts.

Consequently, buying gold is an efficient way to diversify and hedge against risks: investors consider it as a safe haven asset. In this context, investors, seeking safety and diversification benefits, own physical and financial gold contracts.

Moreover, gold prices register its' all-time record pick, when major financial institutions worried about US default on debts. Since then, the gold price decreased regarding the improvement of the US economy and low inflation. However, our data sample includes extreme price movements. During the 2008 financial crises, the US gold market registered a definite high pick, while the equity market dropped by 40%. Price behavior in physical and futures markets determines how market agents should react. All these reasons confirm that the gold market is insensitive to extreme market volatilities, uncertainty, high inflationary periods, and currency debasement periods, which justify our results. Gold spot and futures prices dependency fits with the Normal copula approach; they register symmetric high dependency during good and adverse conditions. That is why we assume that the price discovery mechanism remains efficient in extreme changes. Futures prices have the same power of predicting spot prices. A possible explanation of these results is that gold spot prices volatilities originate from futures prices movements.

Gold spot prices are fixed given the trading activity in Over-The-Counter decentralized markets. Prices are negotiated between market participants (investors, traders, and speculators). Most of the transactions are electronically taken on CME. Indeed, 3-months contract futures are the most traded on CME. Information is updated on daily bases, given that the gold market trades 23 hours a day and six days per week making OTC markets overlapping each other, and information in one market will be very well captured by the other.

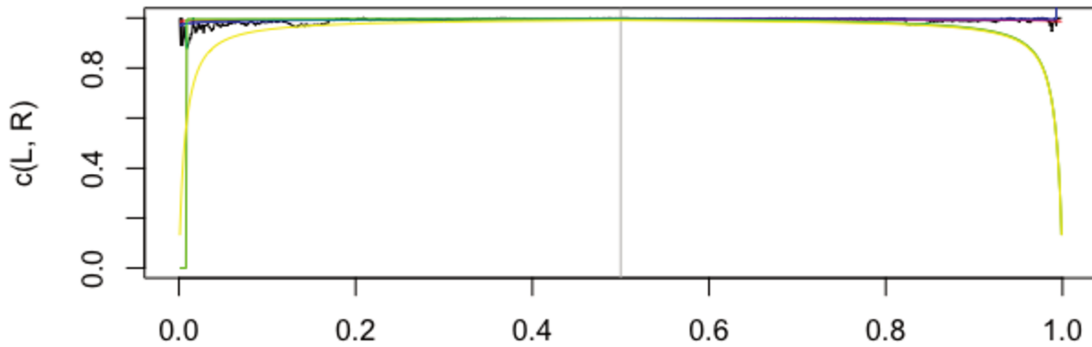
Our results show that the gold market remains very efficient during extreme turbulence and is insensitive to extreme positive and negative picks with symmetric responses to both situations. Investors seeking diversification can use gold as a safe commodity, especially during market volatilities.

Platinum market

Platinum is known as a rare metal and exhibits strong liquidity, short-term volatility, and signifi-

cant long-term security. Platinum has a track record of proven profitable investment. Indeed, when the supply of platinum decreases, the demand increases continually, making platinum even scarcer. Several economic factors influence platinum demand.

Figure 1.4: Platinum spot-futures tail dependence



Note: The fig.1.4 represents the the upper tail dependence in the right side (from 0.5 to 1) and the lower tail in left side from (0 to 0.5). The Blue color represents the Gumbel copula tail, the Yellow color represents the Frank Copula tail, the Green color reflects the Clayton Copula tail, and the Red color is the Normal Copula tail.

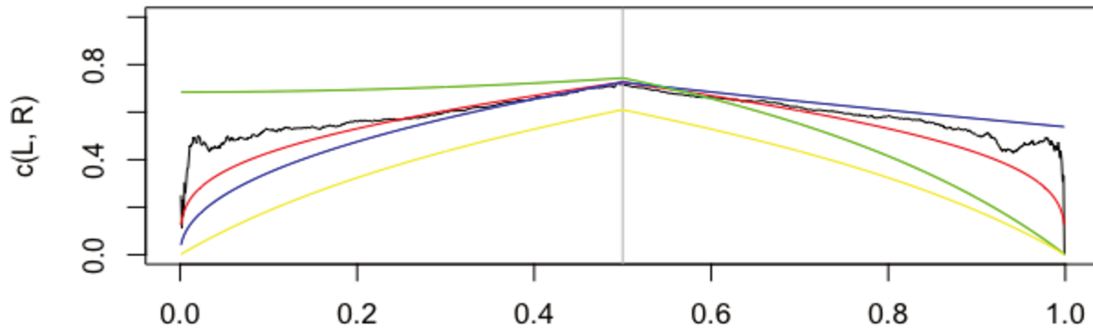
Given that platinum is mined in South Africa, political conflicts and economic instability significantly impact the production and consequently decrease the supply availability. Besides, during the volatilities of market forces (such as interest rate, inflation or deflation, and financial turmoil), investors increase their demand for physical and derivatives platinum contracts.

Our results show similar results compared to gold prices. The platinum spot and futures prices are fitted with normal copula and show symmetric and high upper and lower tails. This means that the dependency between platinum spot and futures is strongly positive, significant, and insensitive to market good and bad news. Doubtlessly, the spot price remains a composite of the futures prices. In another hand, platinum is a tangible storable asset for long periods and is considered as a safe store of value. The all-time price pick was registered in 2008, after the financial crises, in addition to a storage increase by as much as 400%. Futures contract traders increase their speculation on the worldwide futures market with an increase in platinum demand in the spot market to seek security, which leads to symmetric and synchronized fluctuation in both markets. These facts could be explained by the fact

that the platinum is one of the smallest precious metals' markets given its sarcastic feature, which makes it less liquid with higher demand. However, the combination of high demand and limited supply makes it a safe investment, with a negative correlation with extreme economic downs. Moreover, platinum is an extremely storable commodity and is considered as a long-term safe investment; this makes its prices inelastic to changes and market efficiency strong.

Soybean market

Figure 1.5: Soybean spot-futures tail dependence



Note: The fig.1.5 represents the the upper tail dependence in the right side (from 0.5 to 1) and the lower tail in left side from (0 to 0.5). The Blue color represents the Gumbel copula tail, the Yellow color represents the Frank Copula tail, the Green color reflects the Clayton Copula tail, and the Red color is the Normal Copula tail.

Soybean price faces abrupt changes such as, drought, pests, excess supply or demand, and trading activities that significantly affect price volatilities and market efficiencies. Besides, China sharply decreased its' soybean imports from the US because of the great harvest and high exchange costs.

These facts lead to a soybean oversupply in the US. As a consequence, US soybean spot prices dropped, and futures contracts were underestimated, leading to low dependence between spot and futures prices during market busts. Accordingly, our results show that soybean spot-futures dependence are fitted with the Clayton copula, which justifies the low dependency in extreme negative changes. Several factors can explain this specific market behavior. First, the increasing storage costs caused by the supply excess and the lack of warehouse lead to a decrease in cash prices. In a matter of fact, the

soybean oversupply was synchronized with other commodities high production such as wheat and corn. These facts accentuated storage problems, which lead to raise spreads after the drop of soybean bid. In this context, [Irwin et al. \(2011\)](#) demonstrate that high spreads have a significant negative impact on commodity spot-futures coupling. Consequently, the difference between spot and futures prices increase during such periods, given the volatility of the convenience yield.

Second, following [Masters and White \(2008\)](#), commodity investors tend to hedge their positions against risks by buying pressure from index fund. These facts lead to the commodity prices bubble in 2007-2008. As a consequence, the market faces extreme volatilities because prices exceeded fundamental values. Indeed, the index fund investment size was evaluated much bigger than the commodity futures market size. In addition, there is evidence about the significant impact of speculation and trading on driving futures prices and weakened the spot-futures dependency.

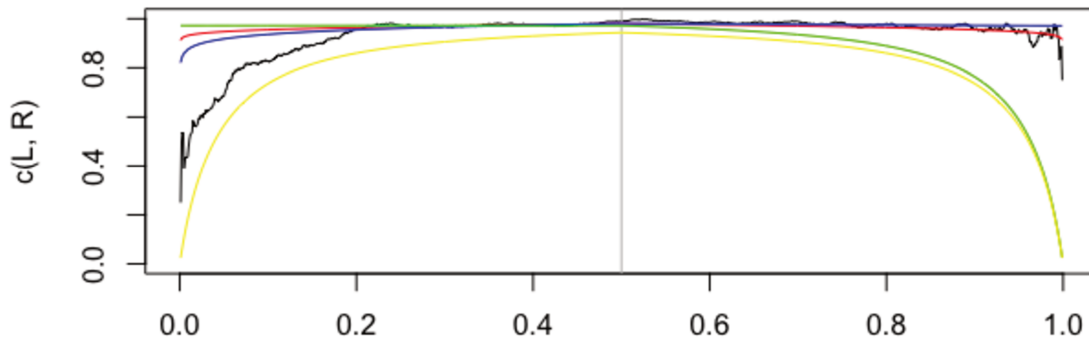
Wheat market

The wheat market is known by its' seasonal features. Indeed, wheat quantities are harvested during June and July, whereas the stocks attain high peaks during the fall and slightly decrease toward the end of the crop year. Our results show that wheat spot and futures prices dependence is fitted with the Clayton copula and register a significant low tail. This means that wheat spot and futures prices are sensitive to negative news; however, they remain immune to positive market changes.

Wheat spot and futures dependency fails to be significant during market busts for several reasons. First, the wheat market structure may be a reasonable explanation for these findings. Indeed, wheat is a local complicated commodity that exhibits around 20 different kinds of global wheat futures contracts. Doubtlessly, the Chicago Board of Trade (CBOT) wheat futures are the most liquid compared to the other contracts. That is why the CBOT futures are considered as a benchmark for the international wheat prices. This cannot be the principal cause of wheat spot futures connections. However, when the global wheat shortages are associated with bountiful US wheat stocks, a low correlation between

wheat spot and futures prices do exist given the lack of liquidity in the wheat spot market (Aulerich et al., 2011). In fact, in July 2009, the US created new territories in areas that produce soft red wheat (SRW) to guarantee the capacity of the delivery system of futures contracts in responding to arbitrages between spot and futures markets.

Figure 1.6: Wheat spot-futures tail dependence



Note: The fig.1.6 represents the the upper tail dependence in the right side (from 0.5 to 1) and the lower tail in left side from (0 to 0.5). The Blue color represents the Gumbel copula tail, the Yellow color represents the Frank Copula tail, the Green color reflects the Clayton Copula tail, and the Red color is the Normal Copula tail.

Consequently, the US wheat market overcomes its shortage and constitutes a favorable stock. These facts lead to over-supply. Accordingly, the spot price decreases compared to the futures price leading to low dependencies between both prices during market busts.

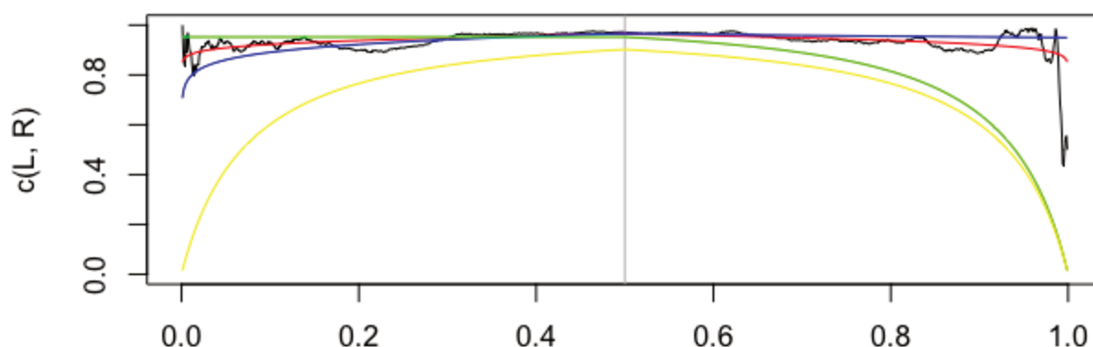
Second, the demand-supply volatilities constitute a major explication of our results. In a matter of fact, in five out of eight crop years of our sample period, wheat consumption was beyond wheat production. As a consequence, the word wheat stock ratio reached its historically lowest level during the beginning of 2008. That is why, before the harvest of 2008, wheat prices sharply increased given that the world is running out of wheat, making production higher and leading to an abundant harvest, (Irwin et al., 2011). This production increased the wheat stocks and decreased wheat prices during the second half of 2008 (Seamon, 2010). In a few months, the US wheat market moved from a shortage to excess storage. In the same time, a bountiful harvest was registered in corn and soybean markets; consequently, grain elevators faced storage difficulties for the expected corn and soybean high harvest,

in addition to the unexpected large production. That is why, in order to avoid over-storage situations, producers were obliged to decrease spot prices. As a result, the spot process fell relatively to futures prices, which justify our results. In fact, according to [Hieronymus et al. \(1971\)](#), the spot price remains below the futures price during the delivery period (for a month) when there is a lack of warehouse space. The difference between futures prices and spot prices is determined by the cost of storage. That is why, during a period of overproduction, a full storage space makes cost higher, spot prices lower and futures prices higher. To summarize, a period of over-supply regarding the storage availability, the difference between wheat spot and futures price is accentuated with lower spot prices.

These results are essential to economic agents and investors. Market efficiencies during extreme movements help spot market investors to decide whether to sell, to store, or to buy. In fact, during extreme negative values, the wheat market registers low dependencies, which means that spot prices are lower than futures prices. Consequently, spot market investors should buy wheat and sell futures contracts in order to hedge their positions.

Cotton market

Figure 1.7: Cotton spot-futures tail dependence



Note: The fig.1.7 represents the the upper tail dependence in the right side (from 0.5 to 1) and the lower tail in left side from (0 to 0.5). The Blue color represents the Gumbel copula tail, the Yellow color represents the Frank Copula tail, the Green color reflects the Clayton Copula tail, and the Red color is the Normal Copula tail.

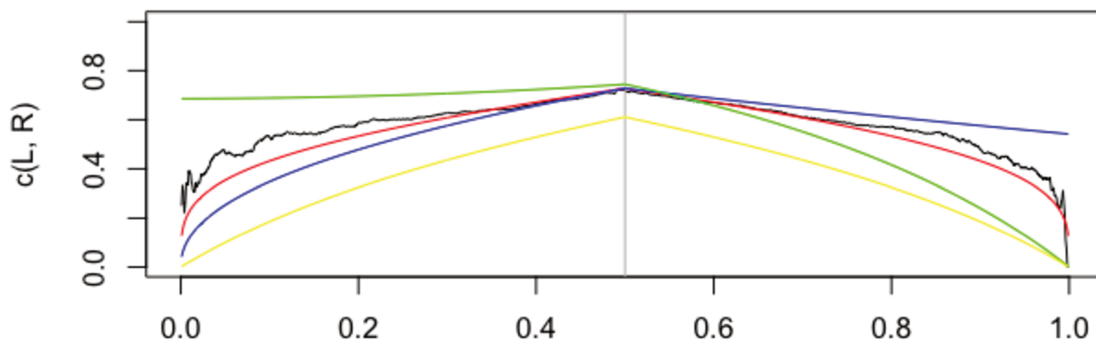
Several factors lead to changes in cotton prices such as; the decline of the production, economic

growth, the Chinese stockpiling, seasonal factors, price volatility, exchange rate, and trading activities. Our findings show that the cotton market is fitted with Normal Copula, which confirms the symmetric high dependence between cotton spot and futures prices when the market is in good and bad conditions. These results can be justified by the stability of the cotton spot market and the continuity of the cotton futures market. Indeed, the cotton futures market is standardized to mirror the spot market, which leads to high dependence in all market practices and conditions. That is why hedging using cotton contracts is encouraged, given that both markets are strongly linked and generally move together.

The cotton market faced extreme price changes, especially during the commodity market bubble in 2008 synchronized with a decline in cotton supply. These facts lead to lower storage costs and the capitalized flow of marginal convenience yields. However, the market risk premium increased. As a consequence, prices in the futures market increased followed by a growing speculative activity and an increase of index fund activity, which leads an increase in the spot prices. That is why futures and cash prices exhibit symmetric and similar responses to extreme movements.

Sugar market

Figure 1.8: Sugar spot-futures tail dependence



Note: The fig.1.8 represents the the upper tail dependence in the right side (from 0.5 to 1) and the lower tail in left side from (0 to 0.5). The Blue color represents the Gumbel copula tail, the Yellow color represents the Frank Copula tail, the Green color reflects the Clayton Copula tail, and the Red color is the Normal Copula tail.

Our results show that sugars spot and futures prices dependency is fitted with the frank copula.

These findings assume that the sugar market is susceptible to market ups and downs and exhibit insignificant dependencies during negative and positive extreme values. Several factors led to abrupt changes in sugar prices. First, global consumption represents a significant price driver.

Since it is a grown commodity rather than mined, crop yield volatilities caused by weather and growing conditions have a significant impact on sugar spot prices. Second, the decision of the US government to regulate sugar content constitutes a primary futures price driver. Third, the growing use of sugar in producing biofuels intensified the connection between sugar, corn, and ethanol, suggesting that sugar is considered as soft biofuel commodity rather than a food commodity. For all these reasons, spot market risks are linked to fundamentals. While that futures market faces "basis risk" caused by speculation and hedging demand. That is why, in the short run, market drivers are different, which leads to different movements of the prices and consequently weaken the spot-futures dependency.

1.7 Conclusion

Commodities are considered as a stimulant of international trade, economic growth, and diversification of financial portfolios. That is why the price dynamics of the commodity spot-futures markets is an interesting topic as it exhibits a significant effect on investors' decisions, regulation issues, and policy-making. Besides, in the context of commodity financialization, various extreme movements occurred in the global economy, leading to price volatilities. In particular, the financial turmoil incited investors to consider alternative assets (such as commodities) to diversify their financial portfolios, usually composed by stocks and bonds, in order to hedge risks, given their high volatile returns and their low correlations with stock markets ([Aroui et al., 2012](#)).

Taking into account the theoretical framework and the empirical shortage concerning the importance of market extreme conditions for risk management, portfolio diversification, investment policies, and trading strategies, we investigate the dependency between spot and futures prices for four types of major commodities (energy, precious metals, agriculture, and soft commodities). We use the copula approach mixed with GARCH family models to specify commodity returns' marginal distributions and

the commodity spot-futures price dependency in different market conditions. We test the market efficiency, the risk transfer, and the price discovery mechanism in regular, bearish, and bullish markets.

The results of spot-futures dependencies are different depending on commodity types, market conditions, market properties, and storage process. Crude oil spot-futures price dependency is asymmetric and fitted with Clayton copula. This means that market efficiency is high in normal and bearish market conditions and declines when spot and futures prices enter into extremely favorable conditions. Precious metals (Gold and platinum) and cotton are fitted with normal copula, which confirms the strong dependence between spot and futures prices under all market conditions. It is a confirmation of the safe haven characteristic of precious metals. These commodities exhibit high efficiency and are used for hedging during uncertainties. Agricultural commodities (Soybean and Wheat) are fitted with the Gumbel copula. That means that the dependency between the agriculture spot and futures prices is strong in normal to bull market conditions. There is a lack of connection between both markets in bear conditions.

Our study has several policy implications; not all the commodities are alike. The commodity pricing could lose its' standard formation features under market uncertainties in some cases depending on different factors, as indicated earlier. Besides, the risk transfer mechanism through hedging using futures could be affected in different market conditions.

Consequently, to avoid huge risks during market uncertainty, policymakers and investors may rise or reduce their positions to restore risk management and to understand the price discovery mechanism, when the market exhibit asymmetry during different market conditions. These measurements should take into account bearish and bullish market conditions. More particular, the controls should be further made when the absence of dependency during extreme market conditions occurs. Further research could investigate the directions of causality between commodity spot and futures prices in order to conduct more precise trading positions in spot or in futures markets and to analyze price discovery across both normal and turbulent periods.

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Chapter 2

Does economic uncertainty and investors sentiment matter for energy futures returns? A multi-scale study

1

Abstract

The literature on energy prices considers fundamentals and macroeconomic factors as the principal drivers of crude oil and natural gas futures prices. However, the Behavioral finance theory challenged this latter assumption. Employing a variational mode decomposition and non-parametric causality approach, this paper provides evidence that a significant causal-flows does exists between energy futures returns and sentiment proxies. However, results vary with respect to time frequencies and to energy market. Using a daily data from 2002 to 2018, of energy futures prices (natural gas and crude oil) and investor/market sentiment proxies (the American Association of Individual Investors, the Volatility Index, and the Economic Policy Uncertainty), we demonstrate that sentiment indices spill over and exhibit significant causalities with energy prices. The interaction between energy prices and economic uncertainty is relatively weak in the short run and strength toward the long run. Besides, bear investor sentiment better predicts energy returns compared to bull sentiment index. While bearish investors show significance over the entire sample period and for all the time-frequencies, bullish investors manifest only in the long run for both crude oil and natural gas returns. Regarding VIX, it has better estimative

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power for WTI returns compared to HH returns and less causality power compared to investor sentiment indexes.

Keywords: Energy futures returns, sentiment proxies, uncertainty, volatility, time-frequency domain, non-parametric causality.

2.1 Introduction

The trading activity in the energy commodity futures market is relatively high compared to the size of physical trading and production. This increase in energy derivatives trading is explained by the increasing participation of financial investors seeking many short and long-run benefits². This phenomenon was noticed starting from 2002 under the context of ‘financialization of commodity markets’ (Tang and Xiong (2012), and Hamilton and Wu (2015)) followed by sharp changes in energy prices (Basak and Pavlova, 2016). The behavior of these market agents exhibits a potential impact on prices, investment strategies, and market volatilities. Besides, the massive growth in energy trading has exacerbated contagion between economic factors and energy prices, which further intensified energy prices volatilities (Hamilton, 2009).

Moreover, the financial turmoil of 2007-2008 spurred the relevance of understanding price volatilities and market agents’ behavior. Many researchers assume that the root cause of this recent crisis is not a fundamental factor but a psychological distortion in traders’ judgment (Tetlock (2007), and Garcia (2013)). In this context, investors and market behaviors registered irrationalities and anomalies leading to several economic booms and busts (Baker and Wurgler (2007), Baker et al. (2016), and Aloui et al. (2013)). Consequently, the role of investor and market sentiment in driving asset prices has been extensively analyzed, yielding challenging results to traditional financial theory and classical asset prices theories³.

Furthermore, the emergence of crude oil and natural gas commodities as asset classes has become widely approved by institutional and retail investors. Academic and practitioners consider commodities as a particular asset class, characterized by its high internal correlation (e.i. internal homogenous risk-return towards other commodities) and low external correlation (e.i. heterogenous risk-return toward other assets). However, commodities have additional particularities; they do not exhibit continuous cash flows. Thus, it is not possible to evaluate the benefits received and the risk assumed from commodity trading activity. That is why commodity prices cannot be fixed using the future cash flow discount, the net present value method, or the equilibrium between demand and supply. It is necessary to consider behavioral aspects aside from market fundamentals and inventories.

Economic agents can invest in commodity markets in different ways⁴. Consequently, one can distinguish different types of investors performing in commodity markets. First, there are commercial investors and physical traders who invest in futures markets in order to hedge their production and consumption. Second, financial traders use traditional arbitrage strategies to benefit from arbitrage

²such as diversification, low-cost transactions, and futures trading facilities compared to physical trading

³Evidence of significant impact of investor sentiment on stock market are also found by Lin et al. (2018), Baker et al. (2016), Yu and Yuan (2011) and Stambaugh et al. (2012).

⁴for example, buying the physical commodity in the spot market, or buying commodity futures, options, and futures index in the derivatives market.

opportunities. These investors use commodity futures, at a relatively low cost, seeking diversification benefits. Third, hedge funds invest in the short-run using energy commodity futures. However, they support mutual risks that can impact their behaviors and consequently, futures prices. Fourth, speculators make their profits from prices' abrupt ups and downs. Though, speculators take offsetting positions to companies that invest in commodity futures or retain physical commodities in order to hedge against prices abrupt changes. That is why speculators behavior also has an essential role in controlling commodity prices movements.

Admittedly, all of these market participants exhibit irrational and biases behaviors (Baker et al., 2016). Therefore, when market participants tend to be bullish or bearish due to cognitive bias, irrational or noise investors generate systematic risk and deviate asset prices from their equilibrium value.

For all these reasons, commodity investors, traders, speculators and hedgers have a considerable interest in Behavioral Finance, not only to understand behavioral aspects but also to be aware of the potential influence on commodity prices in different horizons.

This paper attempts to revisit the causality flows between investor/market sentiment and energy prices to explain market anomalies and to bring insights into sentiments effect on prices. This study is primarily motivated by Shiller (2003) affirmation 'from efficient market theory to behavioral finance' challenging the efficient market hypothesis (EMH) of Malkiel and Fama (1970). It wonders whether EMH holds in the energy market? How psychological and behavioral factors impact energy prices and vice-versa?

To analyze the relationship between energy prices and investor/market sentiment, we use daily data of crude oil and natural gas futures prices and several sentiment indicators for the period between 2002 and 2018. The sentiment proxies used in this research were investigated in previous studies and were widely used by financial literature to mirror market and individual investor sentiment. For individual investor sentiment, we adopt the index of the American Association of Individual Investors (AAII) Survey. This sentiment index reflects the bullish and bearish investors' behavior regarding market estimations (Brown (1999), and Brown and Cliff (2004)). To reflect market sentiment, we first apply the Economic Policy Uncertainty (EPU) created by Baker et al. (2016) based on an automated text-search approach as detailed in section 2.4. Second, we refer to the volatility Index (VIX) to reflect the market expectation of the volatility hinted by stock index option prices. Conceptually, the VIX and EPU reflect market sentiment but differ in many aspects. While EPU mirrors uncertainty about major economic policies, VIX reflects uncertainty about equity returns.

Nevertheless, the impact of investment time frequency (i.e., horizon) is anticipated to have a crucial economic significance for the relationship between energy prices and investor/market sentiment⁵.

⁵Indeed, Chu et al. (2016) and Marczak and Beissinger (2016) highlighted the importance of the time frequency

In addition, as mentioned before, the existing of different types of traders is subject to heterogeneous expectations based on market fundamentals, idiosyncratic features (such as risk appetite and available information) and psychological biases. Hence, time frequency investment decisions and changes horizons from one type of traders to another could significantly make the market very heterogeneous. This heterogeneity is expected to create conflicting responses to news and information disturbance that occurred in energy markets. Necessarily, further validation of time frequency causality between energy prices and sentiment indexes is a crucial enquiry. That is why this study investigates a multi-scale interaction using Variational Mode decomposition (VMD), proposed by [Dragomiretskiy and Zosso \(2015\)](#), in order to provide more information in the time-frequency domain. Several motivations behind the choice of this specific methodology.

VMD is a modern decomposition approach that shown its superiority in a wide range of applications given its advantages compared to other methodologies. VMD is characterized by its optimal capacity to deal with noise that can highly occur in sentiment signals ([Dragomiretskiy and Zosso, 2015](#)). It is considered as a unique approach with a distinguished theory that overcomes other decomposition methods' limitations such as Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD). More precisely, VMD solves several econometrical problems such as lacking mathematical theory and hard-band limits. In this context, it is considered as a novel, fully intrinsic and adaptive method, which non-recursively extracts the modes, given its quasi-orthogonal feature. That is why we believe that it is the best decomposing approach to deal with energy prices' high volatilities and sentiment proxies' noises.

Furthermore, this topic is motivated by the evolution of traditional financial theories and the challenges of Behavioral Finance. The finance theory is developed respecting two key features: Rationality and irrationality, i.e., Standard Finance and Behavioral Finance. Furthermore, the Standard Finance is divided into two aspects; Classical (or Traditional) Finance and Modern Finance. The traditional Finance indicates that investment decision making is mainly based on rationality and expected utility (EU) theory, proposed by [Morgenstern and Von Neumann \(1953\)](#). The modern Finance was based on maximizing utility function using markets informational efficiency. Subsequently, other theories were developed to contribute to EU such as the modern financial theory under the context of portfolio optimization, developed by [Markowitz \(1952\)](#), the life cycle hypothesis by [Modigliani and Ando \(1957\)](#), the permanent income hypothesis by [Friedman \(1957\)](#) and the efficient market hypothesis by [Fama \(1991\)](#). The fundamental assumption of all the modern finance theories is that all investors are rational, risk-averse, and aim to maximize their profit.

In particular, the Modern Portfolio Theory and the Efficient Market Hypothesis are proved to represent financial markets and asset pricing models successfully. A flood of academic researchers tested these theories in the energy market. [Fama \(1998\)](#) assumes that irrational behavior does not have a

investigations when considering the relationship between sentiment and stock returns.

significant impact on market efficiency. He believes that arbitrage by rational traders is responsible for pushing prices to their real value. However, Keynes challenged EMH and stated that irrational behavior could have a more prolonged impact on prices, and irrationality might be insolvent. These theories fail to capture market anomalies and irrational behaviors. Thus, Behavioral Finance is considered an alternative theory to the standard Finance.

Behavioral Finance includes psychology and behavioral aspects when analyzing prices. More specifically, behavioral Finance examines how investors react to market information and economic news, taking into consideration the possible irrational reactions (De Long et al., 1990), cognitive biases (Daniel et al. (1998), and Barberis and Thaler (2003)) and emotional aspects that can drive investors decisions. In other words, this theory emphasized the investor's different behaviors, causing prices volatilities and market uncertainties and inefficiencies.

Based on these theories and stylized facts and given that energy futures are widely used in the financial portfolios, we believe that sentiment proxies could impact energy prices in two different ways. The first is through speculation⁶ behavior and the second through behavioral economic factors⁷.

We extend to the previous literature in two aspects. First, we use investigate both market and investor sentiment impact on energy prices in different time-scales due to the variational mode decomposition. Results are interesting and show differences regarding the time horizons and directions of causality flows between energy prices and sentiment indexes. Our study extends to uncover the non-linear causality aspects using the non-parametric granger causality tests of Diks and Panchenko (2006). Second, our study has broad implications for policymakers, investors, traders and hedgers, based on the shortcomings of the Efficient Market Hypothesis. We persist to sketch sentiment proxies as a competitive explanation for energy futures prices valuations across different market agents.

Findings show that bear investor sentiment predicts energy returns better than the bull sentiment index. While bearish investors show significance over the entire sample period and for all the time-frequencies, bullish investors manifest only in the long run for both crude oil and natural gas returns. Besides, the results show that crude oil returns significantly cause economic uncertainty, while in the medium run, this leading power decreases and causality remain to be bidirectional. In the long-run, the Economic Policy Uncertainty causes crude oil prices fluctuations. Whereas for natural gas prices, there are significant causal flows from EPU to natural gas prices in the short-term. While in the medium and long run, natural gas causes EPU. Regarding VIX, it has better estimative power for crude oil returns compared to natural gas returns and less causality power compared to investor sentiment indexes.

Given the lack of consensus and evidence in the existing literature and paucity of research regard-

⁶Measured by AAIH sentiment index

⁷Measured by EPU and VIX

ing the causal flows between energy futures prices and sentiment individual and economic proxies, our results help to clarify this outstanding issue.

This research proceeds as follows. Section 2.2 presents the theoretical framework. Section 2.3 lists the literature review. Section 2.4 describes the data. Section 2.5 details the methodology. Section 2.6 discusses the results, and section 2.7 concludes the study.

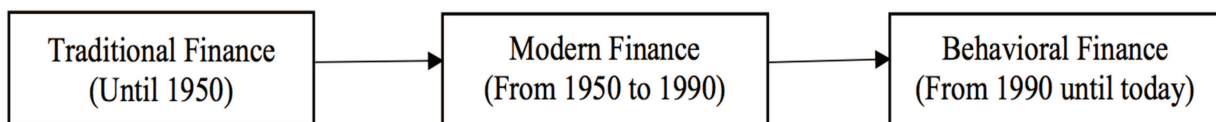
2.2 Theoretical framework

Behavioral Finance, modern portfolio theory, and Efficient market hypotheses are considered as the most discussed financial theories in the literature. These latter theories have had a substantial impact on Finance and Economics in the modern age. The dynamic interactions between these financial theories have attracted increasing interest from investment professionals and academic researchers, given that they shape the way that investors make decisions, and consequently, they influence prices. Indeed, they provide a complete insight into market trends and explain price fundamentals and anomalies. However, they are widely debated since they exhibit several contradictions and consist of overlap.

While the efficient market hypothesis (EMH) assumes that the prices are a full reflect of publicly available information and the modern portfolio theory (MPT) assumes that investors make their decisions based on risk levels, the behavioral finance theory (BFT) indicates that emotions, psychologies, and cognitive and social factors play an essential role in driving asset prices. The behavioral finance help to explain the price anomalies, the low correlation between price values and the "pure" financial fundamentals. In a nutshell, it explains the sharp increasing and decreasing price movements using psychology-based theories.

According to Pimenta and Fama (2014), the evolutionary process of traditional and modern financial theory is illustrated in figure 2.1.

Figure 2.1: Evolutions process of Finance theory



Source: Author

Modern Portfolio theory

The modern portfolio theory was proposed by [Sharpe \(1966\)](#) who further developed the theory with Merton Miller and Markowitz, to win a Nobel Prize in Financial economics in 1990. The classic financial theory assumes that investors are risk averse regarding their wealth. By definition, if investors take risky assets, the risk premium is positive. It indicates that price is determined based on arbitrages between demand and supply until attending equilibrium reflecting the appropriate risk premium. Risks are measured by assets return variabilities. The return variability (known as the standard deviation of returns) is measured by historical data. High standard deviation refers to high risk due to higher dispersion. Literature affirms that riskier assets also provide higher returns in the long-run. Investors are seeking to find an optimal strategy to form optimal portfolios with low risks. In this context, modern Finance significantly contributed to classical theory by providing directions for investment strategies while choosing optimal assets. Indeed, the portfolio risk is measured by the correlation between the assets returns: High correlation announces higher risks. Accordingly, diversification benefits occur when low correlation appears between assets.

For this reason, investors consider their opportunities to add risky performant assets to diversify, with respect to unsystematic risks. The goal is to have a portfolio with maximum returns for a given level of risks. To sum up, investors decisions are made following two main steps. First, the investor selects the optimal risky portfolio based on historical data, returns variabilities and performances. Second, the investor identifies his risk tolerance level, which depends on several factors, such as wealth, individual preferences, tastes, and mood. The individual preferences differ across investors regarding their sentiments, behaviors and risk aversion. That is why, we believe that investors sentiment could play a significant role in driving prices. In addition, optimal risky portfolios constitute the market portfolio that can be affected by market anomalies and behavior measured by market sentiment indexes.

Efficient Market Hypothesis (EMH)

EMH was initially introduced by [Malkiel and Fama \(1970\)](#). It indicated that the market is efficient when prices fully reflect all available information. To clarify the meaning behind "all available information," Fama distinguished three versions of EMH depending on the nature of the information. First, weak form efficiency indicated that current prices are a full reflection of their historical data. Second, semi-strong form efficiency assumes that prices are a reflection of the publicly available information in addition to historical data. Third, the strong form efficiency indicated that prices reflect all kinds of information, including private information. Fama assumes that even though markets exhibit several anomalies for which modern financial theory is not able to consider, EMH is considered as the best theory to analyze and estimate prices and economies. In a matter of fact, Fama is one of the most notable researchers who criticize behavioral finance theory.

Previous literature tested the EMH, finding evidence of market efficiency, and supporting Fama's hypothesis. Whereas, some researches rejected the EMH and recognized the great paradoxes of the joint hypothesis. Furthermore, the evidence against EMH continued to increase, especially after the occurrence of the flood of economic booms and busts. This new trend in academic research was a driving force in the appearance and the growth of the Behavioral Finance Theory.

Before moving to Behavioral Finance, it is essential to highlight some remarkable features of EMH. First, given that current prices reflect all available information in a strong, efficient market, price analysis provides insignificant benefits. This does not mean that investors should not consider assets investments; it means that investors are not able to capture market anomalies and abnormal returns when the market is perfectly efficient. However, the highest returns are registered during a risky investment, and they cannot consistently be generated when the market is efficient. Moreover, even in a very efficient market, financial advisor and investors still can play a very significant role, given that diversification benefits still occur. Even though the role of the investors and financial investors is different depending on investors behavior, risk preferences (bearish, bullish or neutral), future objectives, and market conditions (market sentiment).

Behavioral Finance (BFT)

Although EMH and MPT afford essential and useful insights, something seems to be missed. A flood of academic research in many fields show that investors tolerate particular cognitive and behavioral biases to influence their decision making. Traditional theories do not provide a satisfactory explanation of investors behavior. Besides, the traditional model does not incorporate clarification about the reasons behind market anomalies and do not consider behavioral aspects when studying asset prices.

Behavioral Finance includes innovative insights from other sciences disciplines to describe investors behavior and their decision-making (Shefrin et al., 2010). Thaler (2005) defined behavioral Finance as "simply the open-minded finance." In other words, BFT is a modern finance theory that aims to fill the gap in EMH and MPT by analyzing behavioral biases and psychology, given that normative, traditional financial theories are based on rational investor behavior and show how investors should make decisions. Whereas, BFT provides explanations behind investors decisions; it incorporates evidence on how investors behave into models.

BFT was first surged in the '80s by Kahneman (1979), Shiller (2003), Shefrin et al. (2010), Thaler (2005), Baker and Wurgler (2007) and De Bondt et al. (2008). They indicate that BFT is based on two main hypotheses. First, investors are exposed to sentiment; Investors risk aversion is different. Consequently, they exhibit different opinions and visions about future cash flows that are subject to several psychological and economic factors. Second, arbitrage is limited, and ignoring investor sentiment could be risky and costly.

Moreover, literature shows that BFT has two perspectives: the prospect theory and the irrational use of information, [Prast et al. \(2004\)](#). The prospect theory introduced by [Kahneman \(1979\)](#) assumes that the theory of utility maximization does not hold given that investors are not always rational and exhibit biases behaviors under risks and uncertainty ([Ricciardi and Simon, 2000](#)). Second, [Prast et al. \(2004\)](#) show that investors do not use information rationally and objectively.

Heuristics

A rational investor makes its decision based on available information. However, in practice, financial investors are exposed to cognitive, economic factors, and market anomalies. To solve problems, investors use heuristics, especially in a complex environment. Full evaluations and recognition of available data are perhaps impossible given the information overload.

Consequently, considering all economic news is overly burdensome given the decreasing uncertainty, especially in recent times. Besides, investors have very limited time, mainly when information occurs frequently and surprisingly. For these reasons, investors use heuristics as an appropriate reflection of market news. Consequently, considering heuristics leads to appropriate investment decisions under certain conditions.

Over-confidence

Overconfidence is detected when investors overestimate their ability and exhibit a positive sentiment about market trends. Two crucial aspects mainly cause overconfidence. First, the self-serving bias, which means that investors interpret information to their favor and exhibit overly optimistic expectations. Second, biased self-attribution, which means that investors manifest behavior of superiority. They believe that they have more exceptional skills and knowledge compared to others. Consequently, they attribute success to themselves and blame others about the failures.

Regret theory

Regret theory assumes that emotions are an essential explanation of disposition effect. It includes investors' bad mood, fear, and pessimistic sentiment regarding future market conditions. This emotion received particular importance in Behavioral Finance, given that this negative emotion could evoke substantial impacts and reactions. Empirical investigations provide support for this pillar of Behavioral Finance. They show that negative emotions are important drivers of decisions directions and consequently of prices.

For all these reasons, we believe that BFT had significantly contributed to Finance research by providing a satisfactory clarification of investors individual behavior and market behavior. In this context, modern economists do not consider EMT as wrong, perhaps, incomplete.

For more details, [Baker and Nofsinger \(2010\)](#) provide complete coverage of Behavioral Finance. In addition, [Hirshleifer \(2001\)](#), [Baker and Wurgler \(2006, 2007\)](#), and [Baker et al. \(2012\)](#) among other researchers find evidence of the significant impact of investors behavior and psychology on asset prices.

2.3 literature review

Literature analyzing energy prices generally points to macroeconomic fundamentals as price determinants such as macroeconomic global conditions ([Barsky and Kilian, 2004](#)), economic shocks ([Herrera et al., 2019](#)), monetary shocks ([Leduc and Sill, 2004](#)), demand and supply arbitrages ([Kilian \(2009\)](#), [Dees et al. \(2007\)](#), and [Aguilera et al. \(2009\)](#)), speculative investment ([Kaufmann and Ullman \(2009\)](#), [Möbert \(2009\)](#), and [Kaufman \(2011\)](#)), stock market volatilities ([Arouri et al. \(2011\)](#), [Mensi et al. \(2013\)](#) and [Creti et al. \(2013\)](#)), by exchange rate movements ([Chen and Chen \(2007\)](#), [Wang and Wu \(2012\)](#), [Bal and Rath \(2015\)](#), and [Aloui et al. \(2013\)](#)); by gold prices fluctuations([Sephton and Mann \(2018\)](#), and [Fan and Xu \(2011\)](#)), by other biofuel and agriculture commodities ([Paris, 2018](#)) and by production capacities for crude oil prices. Whereas natural gas prices determinants are mainly based on crude oil prices ([Serletis and Herbert \(1999\)](#), [Hartley et al. \(2008\)](#), [Brown et al. \(2008\)](#), [Geng et al. \(2016\)](#), and [Batten et al. \(2017\)](#)). There is evidence of a significant time-varying effect of crude oil on natural gas prices. In addition to Weather, oil price, coal price, supply shortfall, natural gas imports and exports ([Nick and Thoenes, 2014](#)) and storage, oil prices, crack spread of refined petroleum, two speculative measures and rig count ([Ji et al., 2018](#)). It is worth noting that this literature usually disregards the presence of any sentiment and behavioral factors in explaining energy price volatilities.

However, behavioral finance theory challenged the traditional asset pricing theory, through confirming the existence of psychological biases in investors behavior. This fact drives the literature from the classic pricing theories based on fundamentals to a behavioral finance taking investors moods and beliefs into consideration when forecasting prices (e.g [De Long et al. \(1990\)](#), [Baker and Wurgler \(2006, 2007\)](#), [Baker et al. \(2012\)](#), [Schmeling \(2009\)](#), [Kurov \(2010\)](#), [Garcia \(2013\)](#), and [Lin et al. \(2018\)](#)). Besides, market incompleteness and anomalies caused by market participants have the power to influence their abilities to hedge risks ([Staum \(2007\)](#), and [Crès et al. \(2016\)](#)). As a consequence, investment decision (to sell or to buy) regarding risky assets changes which causes price volatilities, potentially leading to mis-pricing or over-pricing.

Besides, empirical evidence proves that investor sentiment is an essential driver of financial and asset prices. Indeed, previous literature assumes that the volatilities of asset prices are directly linked to the rate of information flow captured by the market ([Maheu and McCurdy, 2004](#)). Besides, the financial literature showed that trading on commodity and financial markets is significantly affected by macroeconomic news, market volatilities and political factors such as weather changes, wars, financial

crises among other news (Lahaye et al. (2011), and Sun et al. (2017)). Accordingly, this news might exhibit investor and market sentiment about potential future market movements. Smales (2014) studied the role of investor sentiment in the gold market and found a negative effect of investors sentiment on market returns. Garcia (2013) proved that investor sentiment has a significant impact on stock price predictability, especially during recession periods. Yu and Yuan (2011) further show that during high sentiment periods, the mean-variance tradeoff decrease because "sentiment traders" are noise traders who lack experience.

Consequently, they may underestimate future price movements. Lin et al. (2018) found that futures markets lose their leading role during high sentiment periods because informed traders are willing to benefit from their information advantages. Qadan and Nama (2018) demonstrate that sentiment volatilities spill over and justify a part of oil prices volatilities.

Indeed, the literature assumes that investor sentiment is strongly related to noise trading, stock over, and mispricing, which consequently can influence future price movements. Building on these findings, the market exhibit anomalies, and uncertainty, which also leads to price volatiles that could predict asset returns. Based on these researches, we believe that investor sentiment may play a significant role in driving energy futures returns. This information could be beneficial to traders, speculators, and risk managers.

The difficulty in exploring the causality between investor/market sentiment and energy futures returns relies on selecting the appropriate sentiment proxies that reflect investors different behaviors and market anomalies in addition to the lack of the theoretical background about the causal relationship between energy returns and sentiments measures.

The challenging affirmation of Shiller (2003): "From efficient theory to behavioral finance" motivates us to explore the impact of different behaviors on energy prices. However, first, what are the sentiment proxies?

The literature provides several definitions of investor sentiment. Starting with De Long et al. (1990), the sentiment was associated with the tendency of investors for noise trading activities in stock markets. Brown and Cliff (2004) refer to investor sentiment as the feeling of optimism and pessimism, which reflect the expected behavior of investors. These sentiments are presented by AAI sentiment indexes which measures both optimistic and pessimistic investors predictions (as detailed in the following section). Baker and Wurgler (2006) provided two of the most used sentiment indexes by the literature; the first index affirms that investors decisions are derived by their proper sentiment, which reflects the demand of speculative investments. This sentiment index, thus, is the reflection of speculations risks. The second index, detailed in Baker and Wurgler (2007), measures the proportions of pessimism and optimism of investors intentions regarding stock markets. These two sentiments proxies were widely used in the financial literature (Yu and Yuan (2011), Cen et al. (2013), and Yang and Zhang (2014)).

Among other sentiment proxies, [Choi \(2010\)](#) and [Kelly and Ahmad \(2012\)](#) analyzed traders' positions and text mining and created a proper sentiment index. Results demonstrate that sentiment indexes influence crude oil prices.

More recently, other researchers create market-specific sentiment indexes such as [Deeney et al. \(2015\)](#) sentiment index for the crude oil market, economic policy uncertainty (EPU), and the volatility index (VIX). According to [Baker et al. \(2016\)](#), EPU plays a significant role in driving economic activity.

Three main components compose the US EPU. The first component is based on uncertainties, collected from major economic US newspapers. Second, it takes into account the consequences of tax provisions and expiring projected revenues. The third component covers the disagreement about the analysts and estimations of inflation and public purchasing policies ([Bernal et al., 2016](#)). Previous literature assumes that EPU is a significant driver of the financial market and plays a significant role in transmitting stress and news to other economic sectors such as commodity markets ([Brogaard and Detzel \(2015\)](#), [Pastor and Veronesi \(2012\)](#), and [Jurado et al. \(2015\)](#)). Several researchers find evidence of a negative relationship between EPU and macroeconomic factors ([Baker et al. \(2016\)](#); [Kang and Ratti \(2013\)](#); [Kim and Kung \(2016\)](#) and [Shahzad et al. \(2017\)](#)).

While VIX also presents a market sentiment measure whether the market is calm or volatile. Researchers interested in VIX concentrate on the US stock market. To the best of our knowledge, very few studies are carried out on the relationship between VIX and energy prices. [Fleming et al. \(1995\)](#) were among the first researchers to explore the impact of VIX on the US stock market and found negative and asymmetric causalities. In the same context, the negative relationship between VIX and US stock returns is confirmed by the literature ([Whaley \(2000\)](#), [Simon \(2003\)](#), [Giot \(2005\)](#), [Hibbert et al. \(2008\)](#), [Frijns et al. \(2010\)](#), [Badshah \(2013\)](#), and [Pati et al. \(2017\)](#)). That is why VIX is referred to as 'investor fear gauge.' Since the interactions and contagions are further increasing between the stock market and energy commodities, we believe that VIX might play a predictive role in energy futures markets. It could be used as a significant influencer of futures energy market volatilities and may explain market anomalies.

While numerous studies focused on the predictability of energy futures returns through macroeconomic fundamentals and economic uncertainties, the explaining role of investor and market sentiment, especially on time-frequency domain, lack empirical investigation in particular for the natural gas market and consequently, our paper is a useful contribution to the existing literature.

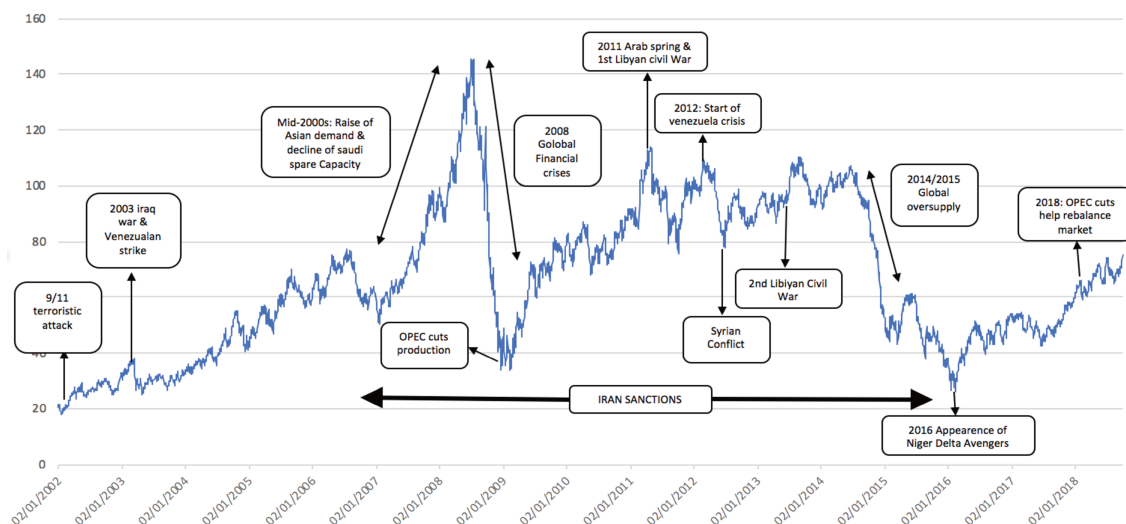
2.4 Data

To explore the causal relationship between energy prices and major investor and market sentiment, we select daily data of West Texas Intermediate (WTI) oil price and Henry Hub (HH) natural gas futures

prices covering the period from January 2002 until December 2018, extracted from DataStream. Energy futures are further converted into log returns in order to have stationary data as required by the methodology as follows;

$$r_t = \ln \left(\frac{p_t}{p_{t-1}} \right), \text{ where } r_t \text{ is the futures log return at time } t \text{ and } p_t \text{ is the original futures price.}$$

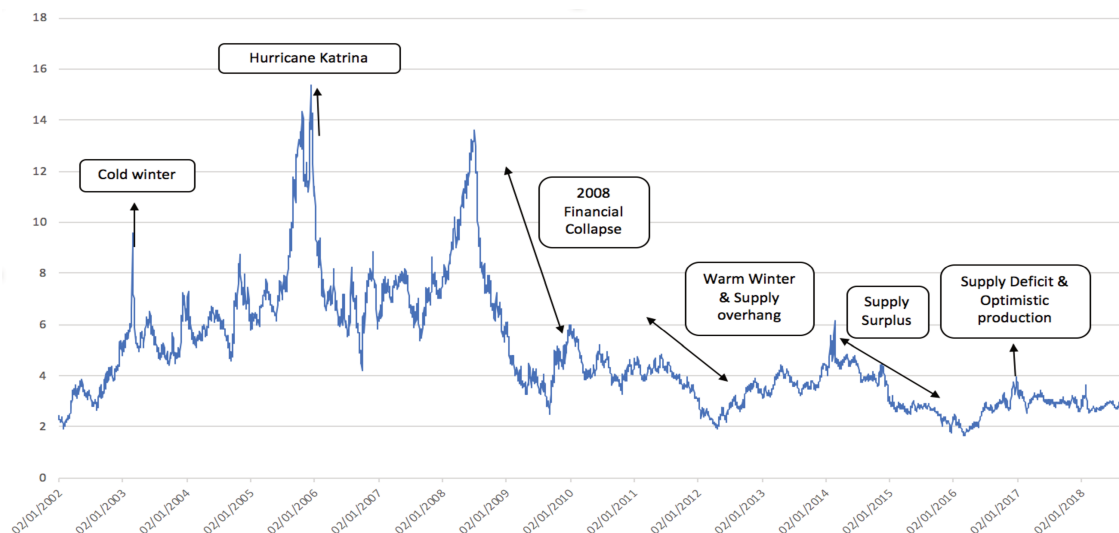
Figure 2.2: Crude oil futures prices (2002-2018)



Note: The WTI futures prices refer to the first maturity daily data extracted from the DataStream platform.

Source: The data is extracted from DataStream and the events-tags are made by the author

Figure 2.3: Natural gas futures prices (2002-2018)



Note: The Henry hub futures prices refer to the first maturity daily data extracted from the DataStream platform.

Source: The data is extracted from DataStream and the events-tags are made by the author

Our sample covers the period from 2002 until the end of 2018. This period includes many extreme movements and structural breaks, as presented in figures 2.2 and 2.3.

We also select several investor and market sentiment proxies. We are acquainted that many investor sentiments are employed in the empirical literature, and till now, there are no reliable or authoritative measures for investors and market behaviors.

Indeed, the difficulty in analyzing the influence of sentiment proxies on energy prices relies on finding the appropriate proxies and on data availability. For these reasons, we apply the most commonly used proxies by the literature in order to efficiently capture all the subjective market behaviors and to provide robust results as follow:

1. Following [Bethke et al. \(2017\)](#) the individual investor sentiment extracted from the American Association of Individual Investors (AAII) survey published on a daily and weekly basis and available since 1987⁸. AAI survey is reported from randomly chosen participants among 1.000.000 members asked about their opinion regarding the future expectation about the stock market for the following six months. Later, AAI classifies them bearish or bullish. Investors are labeled as bullish (bearish) if their sentiment is overly positive (negative) and they are disposed to be too optimistic (pessimistic) which lead them to overreact to positive (negative) news and consequently causes excess (lack) trading volatility and redundant (low) price movements. Numerous researched demonstrated that the bullish and bearish sentiment exhibit a significant effect on price forecasts ([Brown \(1999\)](#), and [Brown and Cliff \(2004\)](#)).
2. According to [Ang et al. \(2005\)](#), the volatility index (VIX) represents the market expectations of the near-term volatility implied by stock index option prices. It mirrors the observable aggregate market volatility and uncertainty about equity returns. A low VIX refers to optimism, while high VIX reflects pessimism accompanied by negative trading days ([Kaplanski and Levy \(2010\)](#), and [Qadan and Yagil \(2012\)](#)). Data is available on the Chicago Board Options Exchange (CBOE)⁹.
3. We also used the Economic Policy Uncertainty (EPU) from the US. This index is a new-based index, developed by [Baker et al. \(2016\)](#)¹⁰. EPU is a compilation of three components. The first is the extracted news from over 1000 newspapers in the US from Access World New's News Bank among them the Miami Herald, The Washington Post, the Chicago Tribune, the New York Time, the Wall Street Journal, the Boston Globe, the Dallas Morning News, the Los Angeles Times and the San Francisco Chronicle. The second component considers the disagreement of the economic expectations as an uncertainty proxy. The third component represents a list of temporary federal tax code provisions extracted from the reports of the Congressional Budget Office (CBO).

⁸<http://www.aaii.com>

⁹<http://www.cboe.com/products>

¹⁰http://www.policyuncertainty.com/us_daily.html

According to [Qadan and Nama \(2018\)](#), EPU and VIX are distinct in several ways and exhibit low correlation. EPU index mirrors uncertainty regarding policies, whereas VIX reflects equity market uncertainty.

2.5 Methodology

The used methodology in this paper relies on (1) Variational Mode Decomposition (VMD); (2) Non-parametric granger causality test. First, we decompose our data set using the VMD approach in order to obtain pairs of sub-energy prices returns and sub-sentiment proxies, presenting short, medium, and long-term time scales. Later, we test the non-parametric Granger causality between energy futures returns and market and investor sentiment proxies following [Diks and Panchenko \(2006\)](#). As presented in the Appendix.

2.5.1 Variational Mode Decomposition (VMD)

This paper adopts the variational mode decomposition approach proposed by , to recompose energy futures returns, economic uncertainty proxies, and Investor sentiments into different sub-periods corresponding to specific times scales. VMD is a novel non-recursive signal processing algorithm that effectively decomposes the original time series f into n discrete subseries x_n ($n = 1, 2, \dots, N$) known as band-limited modes. Each mode is compacting around a certain central pulsation ω_n characterized by its limited bandwidth. This central pulsation is specified in frequency domain, consequently, VMD identify the subseries with specific time scale. Indeed, VMD realize a decomposition in order to have several modes, each mode x_n reflect a different time horizon around a center ω_n (determined during the decomposition process) following the variational algorithm and respecting the VMD constraint

$$\min_{x_n, \omega_n} \sum_n \|\partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) \otimes x_n(t) \right] e^{-j\omega_n t}\|_2^2$$

Subject to:

$$\sum_n \omega_n = f$$

Where n represents the number of modes, δ is the Dirac distribution¹¹, t denotes the time script, \otimes refer to the convolution operator and \cdot_2 is the two-order norm. As a second step, the constrained vari-

¹¹The Dirac delta function $\delta(t)$ is a distribution function introduced by the physician [Dirac \(1958\)](#) and approved by the mathematicians [Bracewell and Bracewell \(1986\)](#) and [Weisstein \(2004\)](#). $\delta(t)$ is considered as a function on the real liner. It takes the value of zero everywhere except at the origin. $\delta(t)$ is defined as follow;

$$\delta(t) = \begin{cases} +\infty & , t = 0 \\ 0 & , t \neq 0 \end{cases}$$

Consequently, it satisfies the following identity function;

$$\int_{-\infty}^{+\infty} \delta(t) dt = 1$$

ational optimization described above can be transformed to a non-variational optimization algorithm using the Lagrange multipliers method and quadratic penalty term as follow;

$$L(x_n, \omega_n, \lambda) = \alpha \min_{x_n, \omega_n} \sum_n \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) \otimes x_n(t) \right] e^{-j\omega_n t} \right\|_2^2 + \|f(t) - \sum_n x_n\|_2^2 + \langle \lambda(t), f(t) - \sum_n x_n \rangle$$

Where λ represents the Lagrange multiplier and α represents the balance parameter of the data fidelity constraint. In addition, $\|f(t) - \sum_n x_n\|_2^2$ is a quadratic penalty term to adjust the acceleration of the rate of convergence. Indeed, the latter equation is the result of the optimization algorithm following the alternate direction method of multipliers (ADMM). It is addressed by detecting the saddle points (x_n^*, ω_n^*) of the augmented Lagrangian L in a sequence of iterative sub-optimizations. Accordingly, the results for x_n , ω_n and λ are displayed as;

$$\hat{x}_n^{m+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i \neq n} x_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_n)^2}$$

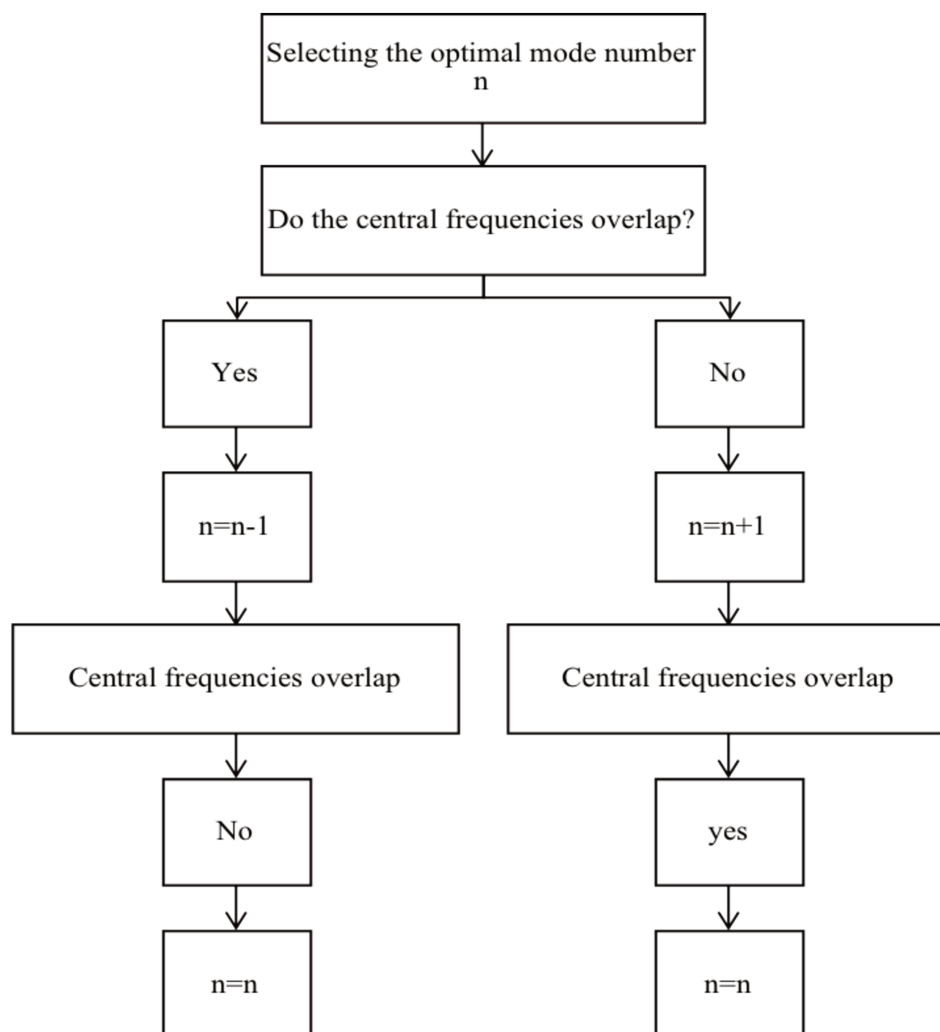
$$\omega_n^{m+1} = \frac{\int_0^\infty \omega |\hat{x}_n(\omega)|^2 d\omega}{\int_0^\infty |\hat{x}_n(\omega)|^2 d\omega}$$

$$\hat{\lambda}^{m+1}(\omega) = \hat{\lambda}^m(\omega) + \tau \left(\hat{f}(\omega) - \sum_n \hat{x}_n^{m+1}(\omega) \right)$$

Where all of the following functions $\hat{f}(\omega)$, $\hat{x}_i(\omega)$, $\hat{\lambda}(\omega)$, $\hat{\lambda}^m(\omega)$ and $\hat{x}_n^{m+1}(\omega)$ are the corresponding Fourier transform of $f(\omega)$, $x_i(\omega)$, $\lambda(\omega)$, $\lambda^m(\omega)$ and $x_n^{m+1}(\omega)$, respectively and m express the number of the realized iterations¹². Before starting the VMD process, the number of modes should be selected, taking into consideration the optimal selection of the parameter n . In fact, to decide the number of modes n , it is better to follow a mode number of fluctuations as explained in Figure 2.4. First, the number of modes is selected randomly, to $n = n_0$. Second, it is necessary to verify the overlapping of central frequencies of mode when the number of modes is n_0 . Two cases are possible; If the central frequencies of modes overlap, then n_0 should be decreased until the central frequencies do not overlap anymore and if the central frequencies of mode do not overlap, increase n_0 until the central frequencies overlap again.

¹²More details are further developed by Dragomiretskiy and Zosso (2015).

Figure 2.4: The process of choosing the number of modes



Source: Author

2.5.2 Non-linear granger causality

The linear Granger causality test is a known statistical method, commonly applied to explore the causal relationships between bivariate time series. Meanwhile, this approach does not capture potential non-linear behaviors among causal relationships and time series characteristics. However, it is agreeably admitted that energy markets, investors sentiment, and economic uncertainty exhibit dynamic features and display nonlinearities such as extreme changes and structural breaks, mainly when the data set contains crisis periods or has a relatively large number of observations. In this purpose, many researchers developed non-linear causality tests to overcome the linear approach weaknesses. Indeed, [Baek and Brock \(1992\)](#) were the first to propose a non-parametric causality test.

Subsequently, [Hiemstra and Jones \(1994\)](#) contributed to [Baek and Brock \(1992\)](#) and improved its performance. This test was frequently used in the economic and financial literature and exhibit high

performance compared to other causality tests proposed by [Bell et al. \(1996\)](#), [Su and White \(2003\)](#) and [Dionisio et al. \(2004\)](#) among others. However, according to [Diks and Panchenko \(2006\)](#), the test is disposed to over-reject the null hypothesis when it shows significance. For this aim, [Diks and Panchenko \(2006\)](#) provided a new non-parametric causality test that overcomes the over-rejection problem. For all this reason, this following causality test is used to investigate the causal relationship between investor sentiment and economic uncertainty, and energy futures returns.

To explore the causal relationship between time series series X_t and Y_t we based our on [Diks and Panchenko \(2006\)](#) test; this non-parametric causality test is described as follow; The null hypothesis H_0 is X_t does not have any additional information about Y_{t+1} .

Considering $X_t^{l_X} = (X_{t-l_X+1}, \dots, X_t)$ and $Y_t^{l_Y} = (Y_{t-l_Y+1}, \dots, Y_t)$ the delay vectors where $l_X, l_Y \geq 1$ are the corresponding delays for X_t and Y_t , respectively. So, the null hypothesis can be displayed as;

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

This null hypothesis can be defined based on joint distributions, joint probability function $f_{X,Y,Z}(x, y, z)$ and their corresponding marginals as;

$$\frac{f_{X,Y,Z}(x, y, z)}{f_Y(y)} = \frac{f_{X,Y}(x, y)}{f_Y(y)} \frac{f_{Y,Z}(y, z)}{f_Y(y)}$$

Where $Z_t = Y_{t+1}$ and the conditional distribution of $Z | (X, Y) = (x, y)$ is equal to the distribution of $Z | Y = y$ under the null hypothesis.

This equality assumes that X and Z are conditionally independent from $Y=y$ for each value of y . Consequently, the null hypothesis could be represented as;

$$q \equiv E[f_{X,Y,Z}(x, y, z) f_Y(Y) - f_{X,Y}(x, y) f_{Y,Z}(y, z)] = 0$$

E is the expectation operator. To estimate q , we followed [Diks and Panchenko \(2006\)](#), and we respected the following equation

$$V_n(\epsilon_n) = \frac{(2\epsilon)^{-d_X-2d_Y-d_Z}}{n(n-1)(n-2)} \sum_i \left[\sum_{k,k \neq i} \sum_{j,j \neq i} (I_{ik}^{XYZ} I_{ij}^Y - I_{ik}^{XY} I_{ij}^{YZ}) \right]$$

Where I denotes the indicator function and verifies $I_{ij}^M = I(\|M_i - M_j\| < \omega)$, M_i and M_j are variables contained in d_M -variate random vector M , ϵ is the bandwidth and n is the number of total observations. The local density estimator of d_M -variate random vector is expressed as;

$$f_M(M_i) = (2\epsilon)^{-d_M} (n-1)^{-1} \sum_{j,j \neq i} I_{ij}^M$$

Consequently, the t-statistics can be described as

$$t_n(\epsilon_n) = \frac{(n-1)}{n(n-2)} \sum_i [\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i) \hat{f}_{Y,Z}(Y_i, Z_i)]$$

The choice of bandwidth is based on simulations where results show that $\epsilon_n = Cn^{-\beta}$, where $\beta \in [\frac{1}{4}, \frac{1}{3}]$, $C > 0$ and $l_X = l_Y = 1$ and the t-statistics satisfies

$$\sqrt{n} \frac{(t_n(\epsilon_n) - q)}{S_n} \longrightarrow N(0, 1)$$

Where S_n is the estimator of the asymptotic variance of the t-statistic and \longrightarrow denotes convergence to normal distribution.

That is why, we assume that the choice of the bandwidth is based on the data length n .

2.6 Empirical results and discussion

2.6.1 Stationarity and Descriptive statistics

The empirical study is based on daily energy futures log returns and market and investor sentiment proxies covering 4185 observations. This data is decomposed by VMD ($k=10$) and apply the Fast Fourier Transform (FFT) on the decomposed modes of all the original dataset in order to have a comparative study on different time scales from high to low frequencies.

We select mode one as the long-term time scale reflecting the lowest frequency, mode 4 represents the medium-term time scale, mirroring a slightly higher frequency and mode 10 reflects the short-term time scales, which represents the highest frequency, following Wang et al. (2018). The corresponding modes are presented in the Appendix.

To initially demonstrate that the used data is non-stationary, we perform two different unit root tests; the augmented Dickey and Fuller (1979) and the Phillips and Perron (1988) test. These tests are commonly used by the literature to test time series stationarity.

Table 7 strongly suggests that all the selected variables are stationary at the current levels, following the ADF test, except for long run AAI bullish. Therefore, we use its first difference for the rest of the study. Later, we present summary statistics in table 2.2. Table 2.2 summarizes the descriptive statistics of investor and market sentiment proxies and energy futures returns in raw data and in the time-frequency domain. The mean and median of energy prices are close to zero. They are asymmetric, and fat-tailed as proved by the skewness and kurtosis results. The Jarque-Bera test is significant for all the selected variables which justifies the non-normality.

However, the mean and median of all the sentiment proxies' raw data exhibit high values, which refers to extreme sentiment volatilities during our sample period either on high or low levels, also justified by the high standard deviations.

Table 2.1: Unit root test

		Augmented Dickey-Fuller Test (ADF)			Philips-Perron Test (PP)		
		Constant & Trend	Constant	None	Constant & Trend	Constant	None
Energy futures returns							
WTI Original signal log difference	Level	-67.969 0	-67.96 0.0001	-67.955 0.0001	-67.987 0	-67.967 0.0001	-67.967 0.0001
WTI M1	Level	-8.432 0	-8.417 0	-8.391 0	-6.965 0	-6.95 0	-6.93 0
WTI M4	Level	-22.114 0	-21.953 0	-21.847 0	-14.823 0	-14.833 0	-14.843 0
WTI M10	Level	-13.055 0	-12.911 0	-12.812 0	-1770.856 1	-1769.857 1	-1769.69 1
HH Original signal log difference	Level	-68.124 0	-68.121 0.0001	-68.1288 0.0001	-68.20528 0	-68.1958 0	-68.203 0
HH M1	Level	-11.574 0	-11.54716 0	-11.54731 0	-6.934817 0	-6.928433 0	-6.928233 0
HH M4	Level	-16.985 0	-16.87708 0	-16.87735 0	-15.73322 0	-15.74467 0	-15.75567 0
HH M10	Level	-8.5935 0	-8.53415 0	-8.53445 0	-5059.355 1	-5042.707 1	-5043.289 1
Sentiment proxies							
AAII BEARISH original signal	Level	-8.168441 0	-8.097 0	-1.924287 0.0519	-11.34841 0	-11.27473 0	-1.84483 0.062
AAII BEARISH M1	Level	-3.839245 0.0147	-3.731973 0.0037	-0.656685 0.433	-2.241651 0.4656	-2.05911 0.2617	-0.080956 0.6557
AAII BEARISH M4	Level	-23.00627 0	-23.00896 0	-23.01164 0	-4.272862 0.0034	-4.274147 0.0005	-4.275411 0
AAII BEARISH M10	Level	-29.964 0	-29.968 0	-29.971 0	-88.213 0.0001	-88.249 0.0001	-88.284 0.0001
AAII BULLISH Ooriginal signal	Level	-8.812 0	-8.21 0	-1.857 0.0604	-11.775 0	-11.02 0	-1.734 0.0787
AAII BULLISH M1	Level	-2.964 0.1424	-2.29 0.1752	-0.526 0.489	-2.189 0.4947	-1.703 0.4294	-0.544 0.4814
AAII BULLISH M4	Level	-22.505 0	-22.508 0	-22.511 0	-4.909 0.0003	-4.91 0	-4.911 0
AAII BULLISH M10	Level	-14.008 0	-14.01 0	-14.011 0	-592.04 0.0001	-592.12 0.0001	-592.22 0.0001
VIX Original signal	Level	-4.672 0.0007	-4.486 0.0002	-1.775 0.0721	-5.519 0	-5.267 0	-1.842 0.0624
VIX M1	Level	-2.963 0.1428	-2.817 0.0558	-1.139 0.2321	-1.121 0.9239	-1.13 0.706	-1.114 0.2412
VIX M4	Level	-18.68 0	-18.683 0	-18.685 0	-4.985 0.0002	-4.985 0	-4.986 0
VIX M10	Level	-16.395 0	-16.397 0	-16.399 0	-718.6 0.0001	-718.731 0.0001	-718.85 0.0001

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.

Means and medians decrease with frequencies; in the short run, they are close to zero, slightly increase in the medium run and register the highest level on the long run, which indicates that sentiment is more active in the long run. The skewness of the short and medium-run are very low (close to zero). Whereas, in the long-run, the skewness is remarkably positive. The kurtosis is over 3 for almost all the selected sentiment variables (the original time series and the decomposed modes) which justifies the presence of high peaks and fat tails. The Jarque-Bera statistics reject the null hypothesis of normality for all the sentiment modes as well.

Table 2.2: Summary statistics

Variables	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Energy futures prices						
WTI	0.0003	0.001	0.0233	0.0237	6.9136	2670,631***
WTI M1	0.0002	0.0005	0.0043	-0.4231	3.7054	211,6273***
WTI M4	3.15E-06	-1.09E-05	0.0039	-0.0112	5.5959	1174,917***
WTI M10	2.58E-07	2.23E-05	0.0058	-0.0043	6.5868	2242,836***
HH	5.43E-05	-0.0004	0.0324	0.714207	9.3248	7329,78***
HH M1	2.93E-05	-3.97E-05	0.0065	0.1227	4.1459	239,4478***
HH M4	7.59E-07	-6.49E-05	0.0064	0.0069	4.011	178,2248***
HH M10	5.05E-08	-4.98E-05	0.0093	0.0004	6.235	1824,549***
Sentiment proxies						
EPU	99.0813	82.58	65.3207	1.9135	9.2481	9361,485***
EPU M1	99.0699	86.1143	43.202	1.1006	3.5061	889,704***
EPU M4	0.0002	0.0263	10.7684	0.0428	4.6106	453,6644***
EPU M10	1.38E-05	0.103	9.3832	0.0033	4.2668	279,8626***
AAII BEAR	32.5068	31.4	9.49	0.5155	3.1349	188,5508***
AAII BEAR M1	32.5067	31.2371	6.0278	0.4569	2.7785	154,1616***
AAII BEAR M4	6.27E-06	0.0058	2.1477	0.0217	2.8054	6,930758**
AAII BULL	38.7542	38.1009	9.5169	0.4239	2.9861	125,3823***
AAII BULL M1	38.7541	38.335	5.2153	0.8169	4.7796	1017,769***
AAII BULL M4	2.29E-06	0.0246	2.1094	-0.0107	2.6609	20,12021***
AAII BULL M10	-2.00E-08	-0.0008	0.6235	-0.0072	4.6311	463,9755***
VIX	19.1489	16.56	8.8775	2.3134	10.6998	14071,44***
VIX M1	19.1471	16.6405	6.6061	1.1216	3.5479	929,916***
VIX M4	2.50E-05	-0.0237	1.0571	0.0801	6.1991	1789,107***
VIX M10	2.58E-07	-0.0009	0.293	0.1738	14.2244	21990,32***

Note: The following table summarizes the descriptive statistics of the daily investor and market sentiment proxies in addition to the crude oil and natural gas futures prices. We also provide the summary statistics of the sample period is 03/01/2002 to 31/12/2018 for all the data. M1, M4 and M10 refers respectively to mode 1 (long-run), mode 4 (mid-run) and mode 10 (short-run). For WTI and HH, we select the log returns to exhibit stationary data. For the sentiment proxies, data is stationary at the level as proved in table 7.*** reflects the significant level at 1 %.

2.6.2 Non-parametric Granger causality

The selected period of this paper is rich of various extreme movements and structural breaks, as presented in figures 2.2 and 2.3. Based on the financial literature, the non-linearities of commodity prices is a fundamental stylized fact and an endemic characteristic. That is why we assume that energy futures return exhibit non-linearities.

In addition, Behavioral Finance confirms the significant influence of emotions and psychology upon investment decisions resulting in unpredictable and irrational behaviors. Indeed, noise traders play an essential role in driving prices and have a strong interaction with informed traders. These interactions

affect prices, and noise traders will push the prices away from their equilibrium value. Their decisions are made based on their sentiment in addition to market sentiment. In this framework, the market registered some anomalies and informed traders would make profitable strategies and push arbitrage prices toward their equilibrium value again. At some point in this arbitraging process, noise traders will dominate the market before returning into equilibrium. All these reasons assume that investor and market sentiments are a reflection of noise traders' decisions that could not be neglected and generally represented by a non-linear process. This fact explains the suitability of the non-parametric method to measure the causality between energy futures returns and sentiments proxies. The linear method might not be efficient to capture the nature of the causal relationship, and therefore, it is necessary to process a non-parametric causality test.

Non-parametric causality between Sentiment Proxies and crude oil futures returns

Table 2.3 reports the causality results between EPU and crude oil futures returns on the raw level and on the time-frequency domain. Results show evidence of varying causalities between both raw and decomposed data. Moreover, the causalities exhibit different behaviors across different frequencies and over time. Indeed, the original time series indicates no causalities between EPU and WTI. However, significant co-movement is registered mainly in the medium-term and the long-term.

Two characteristics of the US economy can explain these results; First, the US is classified as one of the largest oil importers in the world. Thus, the US economy is susceptible to oil price fluctuations. Second, changes in importing policies appear, and the US starts producing crude oil. This fact gives the US the power to control oil demand and supply. That is why changes in supply policies could influence WTI prices.

Regarding the causality between EPU and WTI, it does not exist in the very short-run and then progressively strengthens towards the medium-term. Interestingly, a bidirectional causality exists in the medium-term except for lag 4 and 5 where WTI plays a leading role. This can be explained by the occurrence of significant political and financial features captured by the medium-run. These historical events (such as commodity market financialization in 2002-2003, the Iraq war of 2003, the global financial collapse in 2008, the European debt crisis in 2011, the uprisings in Egypt and Libya as a consequence of the Arab spring in 2011) significantly affected oil prices.

With regards to the causality direction between EPU and WTI, a logical conclusion can be deducted. In the short-run, the causality is very weak, and the duration of the influence is very low; it is significant for only lag=1. This result probably consistent when market fluctuations are normal. Because, in the short run, the impact of the volatility shocks is insignificant due to the market self-adjustment.

Moreover, the direction of the causality changes across time and frequency. In the medium-run, the

causality is either bidirectional or runs from WTI to EPU. The critical impact of WTI prices shocks on economic uncertainties explains this finding. However, in the long run, the causality direction switches from EPU to WTI; this means the increase of the economic uncertainty leads to the decrease of informed traders and consequently increase noise traders which causes the increase of WTI prices.

To summarize, we conclude that the increase of important economic extreme events, captured by the medium-term, strengthen the link between EPU and WTI. Whereas, in the long-run, the WTI is more potent in leading economic uncertainty. These results are in line with [Antonakakis et al. \(2014\)](#), [Aloui et al. \(2016\)](#), and [Kang and Ratti \(2013\)](#).

Table 2.4 reports the results of the non-parametric causality between the AAIL-Bearish sentiment index. We use the level data (since it is a stationary, according to ADF test) and WTI futures returns on the original level and on time-frequency domain. The findings of the original signals exhibit high causality significance in both directions. Regarding the causality direction, it is worth noticing that it varies across time-frequencies. In the short run, results are bidirectional until log 3. Then, unidirectional; Information flows from investors bearish behavior to crude oil prices. Indeed, the occurrence of detrimental financial and political shocks had a significant fast effect on investors moods, which make them pessimistic.

Consequently, they slow down their activities, which reduces risks in the stock market. Similarly, in the long run, bearish investors have the power to lead WTI prices. Indeed, pessimistic investors are low active traders who reduce market movements and decrease trading volume, which leads to lower risks in stock markets and consequently stabilizes the market in a long-time horizon. Hence, these facts reduce their needs to introduce commodities in their portfolios, which reduce the demand for crude oil futures. We believe that bearish behavior has predictive power for oil futures returns. Since it reflects the future perception of financial investors, we assume that it has to be used as a significant indicator of long-run oil price movements and risk management decisions.

Table 2.3: Nonlinear Granger causality test between EPU and WTI futures returns

$Lx=Ly$	EPU does not Ganger cause futures		WTI futures does not Ganger cause EPU		Conclusion
	T-stat	P-value	T-stat	P-value	
Panel A: Original signal					
1	1.244	0.106	-0.059	0.52362	No causality
2	-0.265	0.60454	-0.334	0.63095	No causality
3	-1.265	0.897	-0.826	0.7956	No causality
4	-1.351	0.91159	-1.02	0.84619	No causality
5	-0.686	0.75373	-0.526	0.70041	No causality
6	0.191	0.42415	-0.04	0.51603	No causality
7	0.324	0.37292	-0.971	0.83417	No causality
8	-0.278	0.60951	-1.006	0.84284	No causality
Panel B: Long					
1	0,710**	0.02387	0.084	0.4665	$EPU \rightarrow WTI$
2	0,740**	0.02295	-0.023	0.50905	$EPU \rightarrow WTI$
3	0.771	0.22027	0.017	0.49314	No causality
4	0.721	0.23553	-0.04	0.51578	No causality
5	0.665	0.25298	-0.149	0.55939	No causality
6	0.549	0.29159	-0.154	0.56123	No causality
7	0,509**	0.030532	-0.122	0.5484	$EPU \rightarrow WTI$
8	0,588**	0.027842	-0.074	0.52958	$EPU \rightarrow WTI$
Panel C: Medium					
1	2,607**	0.00457	3,185***	0.00072	$EPU \leftrightarrow WTI$
2	2,198**	0.01398	2,519**	0.00588	$EPU \leftrightarrow WTI$
3	1,552*	0.06031	1,536*	0.06226	$EPU \leftrightarrow WTI$
4	1.168	0.12137	1,637*	0.05086	$WTI \rightarrow EPU$
5	1.118	0.13174	1,541*	0.06165	$WTI \rightarrow EPU$
6	1,306*	0.09576	1,294*	0.09785	$EPU \leftrightarrow WTI$
7	1,457*	0.07263	1.238	0.10793	$EPU \rightarrow WTI$
8	1,555*	0.05997	1,298*	0.09719	$EPU \leftrightarrow WTI$
Panel D: Short					
1	0.33	0.37083	1,322*	0.09316	$WTI \rightarrow EPU$
2	-1.359	0.91294	1.037	0.01498	No causality
3	-0.6	0.72571	0.959	0.16875	No causality
4	-0.01	0.50408	0.751	0.22623	No causality
5	-0.087	0.53449	1.021	0.15363	No causality
6	-0.033	0.51306	1.001	0.15846	No causality
7	0.053	0.47893	1.077	0.1408	No causality
8	0.003	0.49882	1.175	0.12009	No causality

Notes: The table represents the results of the non-parametric granger causality test between WTI futures returns and EPU index for 8 lags and for bandwidth=0.76 (calculated with respect to data length, and following [Diks and Panchenko \(2006\)](#)). Results for the raw data are displayed in Panel A. Panel B, Panel C and Panel D report the causality results for mode 1 reflecting the long-run causality, for mode 4 reflecting the medium-run and mode 10 reflecting the short run, respectively. *, ** and *** denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

However, in the medium run, the findings suggest a unidirectional causality from WTI futures returns to bearish investor sentiment. Indeed, in this particular frequency and regarding our sample period, the arrows point to up for the US crude oil prices more than down. Besides, the intensity of high picks is stronger than low picks. These price movements slow down the investors trading behavior and negatively influence their moods, which impact their perspective view about the market future.

Table 2.4: Nonlinear Granger causality test between AAIL-BEAR and WTI futures returns

$Lx=Ly$	AAIL-BEAR does not Ganger cause WTI fu- tures		WTI futures does not Ganger cause AAIL- BEAR		Conclusion
	T-stat	P-value	T-stat	P-value	
Panel A: Original signal					
1	5,092***	0.0001	2,655***	0.0039	AAIL-BEAR \rightarrow WTI
2	4,352***	0	2,931***	0.0016	AAIL-BEAR \leftrightarrow WTI
3	3,66***	0.0001	3,295***	0.0004	AAIL-BEAR \leftrightarrow WTI
4	3,323***	0.0004	2,318**	0.0102	AAIL-BEAR \leftrightarrow WTI
5	3,028***	0.0012	2,525***	0.0057	AAIL-BEAR \leftrightarrow WTI
6	2,72***	0.0032	2,934***	0.0016	AAIL-BEAR \leftrightarrow WTI
7	2,271**	0.0115	2,664***	0.0038	AAIL-BEAR \leftrightarrow WTI
8	1,852**	0.032	1,771**	0.0382	AAIL-BEAR \leftrightarrow WTI
Panel B: Long					
1	1.277	0.1008	0.088	0.4647	No causality
2	1,365*	0.0861	-0.094	0.5376	AAIL-BEAR \rightarrow WTI
3	1,436*	0.0754	-0.266	0.6048	AAIL-BEAR \rightarrow WTI
4	1,459*	0.0722	-0.501	0.6918	AAIL-BEAR \rightarrow WTI
5	1,478*	0.0697	-0.583	0.72	AAIL-BEAR \rightarrow WTI
6	1,576*	0.0575	-0.776	0.7811	AAIL-BEAR \rightarrow WTI
7	1,623*	0.0523	-0.978	0.836	AAIL-BEAR \rightarrow WTI
8	1,632*	0.0513	-0.878	0.8101	AAIL-BEAR \rightarrow WTI
Panel C: Medium					
1	1,934**	0.0265	2,11**	0.0174	AAIL-BEAR \leftrightarrow WTI
2	1.221	0.1111	2,021**	0.0216	WTI \rightarrow AAIL-BEAR
3	0.203	0.4194	1,981**	0.0238	WTI \rightarrow AAIL-BEAR
4	0.251	0.4007	1,832**	0.0335	WTI \rightarrow AAIL-BEAR
5	0.883	0.1887	1,813**	0.0349	WTI \rightarrow AAIL-BEAR
6	0.904	0.1829	1,669**	0.0475	WTI \rightarrow AAIL-BEAR
7	1.064	0.1437	1,586*	0.0563	WTI \rightarrow AAIL-BEAR
8	1,313*	0.0946	1,695,**	0.045	AAIL-BEAR \leftrightarrow WTI
Panel D: short					
1	-0.339	0.6326	-0.035	0.514	AAIL-BEAR \leftrightarrow WTI
2	-0.791	0.7854	0.044	0.4824	AAIL-BEAR \leftrightarrow WTI
3	1.016	0.1548	0.094	0.4627	AAIL-BEAR \leftrightarrow WTI
4	1,498*	0.067	-0.058	0.523	AAIL-BEAR \rightarrow WTI
5	1,475*	0.0701	-0.288	0.6135	AAIL-BEAR \rightarrow WTI
6	1,74**	0.0409	-0.394	0.6531	AAIL-BEAR \rightarrow WTI
7	1,737**	0.0411	-0.723	0.765	AAIL-BEAR \rightarrow WTI
8	1,808**	0.0352	-0.389	0.6514	AAIL-BEAR \rightarrow WTI

Notes: The table represents the results of the non-parametric granger causality test between WTI futures returns and AAIL-BEAR index for 8 lags and for bandwidth=0.76 (calculated with respect to data length, and following [Diks and Panchenko \(2006\)](#)). Results for the raw data are displayed in Panel A. Panel B, Panel C and Panel D report the causality results for mode 1 reflecting the long-run causality, for mode 4 reflecting the medium-run and mode 10 reflecting the short run, respectively. , and denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

Table 2.5 shows significant bidirectional causalities between bullish sentiment in raw signal and only in long-run. Indeed, bullish investors may have a significant impact on price movements because active investors are more likely to raise oil market movement. Bullish investors are probably optimistic about future market movements and could over-estimate oil prices, which increase noise trading volume and thus in the long run, leads to upward oil prices. Moreover, from 2002, oil prices register extreme ups

and downs and have moved away from its equilibrium value. Besides, investors consider commodities as a hedge and safe haven against stock market risks. As a consequence, oil prices are considered as one of the most traded commodities; thus, it represents a significant concern for traders. Higher oil prices often weigh on investors behavior, leading to bullish sentiment and raising market risks, especially in the long term.

Table 2.6 highlights the non-parametric causal relationship between crude oil futures returns and VIX, which is considered as a trading indicator of shocks in the US stock market. Regarding the raw data, we observe bidirectional causality between VIX and WTI. However, time-frequency decomposition exhibits different results in terms of causality directions. Indeed, in the short and long term, we notice that VIX has the power to lead WTI futures returns. This result indicates that VIX acts as a significant market sentiment indicator and price influencer in both short and long terms.

Moreover, according to the financial literature, VIX does have an inverse relationship with the market; High VIX leads the market to be fearful and consequently, leads to market falls. It creates a panic environment among traders. Accordingly, contrarians and noise traders find it the best time to buy and to hedge against market risks by using commodities as alternatives. Our short and long run time-frequencies covers major economic events that constitute a source of extreme economic volatility such as commodity financialization, Iraq War and 9/11 terroristic attack, the financial crises, and Arab spring in the long run. These facts explain the increase of the fear index and consequently explain the investors' behavior regarding oil prices, which significantly affect price movements. However, in the medium run, we register bidirectional causality until log 3, then WTI futures returns to play a leading role. In fact, in the medium run, WTI prices vary in different parts of the world, responding to short-run market volatiles and fundamentals such as policy changes, production, supply, and demand. These factors take considerable time to influence oil prices and lead to strong volatilities in the crude oil market, which causes nonlinearities and complex irregularity. In return, such dynamics in the crude oil market cause a significant effect on the worldwide economy captured by VIX. Whereas in the long run, VIX is volatile enough to influence crude oil prices again.

These results reveal that market and investor sentiments are essential indicators of crude oil futures returns. Consequently, commodity traders have an interest in including sentiment proxies in their information set while making investing policies, taking into consideration the time-frequency and the direction of the causalities before deciding to go long or short in the market. We conclude that crude oil market anomalies, which are often hard to predict, could be explained by investors behavior and market sentiment.

Table 2.5: Nonlinear Granger causality test between AAI-BULL and WTI futures returns

$Lx=Ly$	AAII-BULL does not Ganger cause WTI fu- tures		WTI futures does not Ganger cause AAI- BULL		Conclusion
	T-stat	P-value	T-stat	P-value	
Panel A: Original signal					
1	2,426***	0.0076	3,377***	0.0003	AAII-BULL \rightarrow WTI
2	1,761**	0.0391	3,852***	0	AAII-BULL \rightarrow WTI
3	1,568*	0.0584	2,548***	0.0054	AAII-BULL \rightarrow WTI
4	1,703**	0.0442	1,878**	0.0301	AAII-BULL \rightarrow WTI
5	2,364***	0.009	2,197**	0.014	AAII-BULL \rightarrow WTI
6	2,014**	0.022	2,669***	0.0038	AAII-BULL \rightarrow WTI
7	0.785	0.2163	2,645***	0.004	AAII-BULL \leftrightarrow WTI
8	-0.537	0.7044	1,984**	0.0236	WTI \rightarrow AAI-BULL
Panel B: Long					
1	1,436*	0.0754	2,089**	0.0183	AAII-BULL \leftrightarrow WTI
2	1,507*	0.0659	2,088**	0.0184	AAII-BULL \leftrightarrow WTI
3	1,616*	0.0531	2,094**	0.0181	AAII-BULL \leftrightarrow WTI
4	1,705**	0.0441	2,016**	0.0219	AAII-BULL \leftrightarrow WTI
5	1,7**	0.0446	1,948**	0.0257	AAII-BULL \leftrightarrow WTI
6	1,682**	0.0463	2,02**	0.0217	AAII-BULL \leftrightarrow WTI
7	1,616*	0.053	2,218**	0.0132	AAII-BULL \leftrightarrow WTI
8	1,553*	0.0602	2,208**	0.0136	AAII-BULL \leftrightarrow WTI
Panel C: Medium					
1	1.266	0.1027	0.711	0.2385	No causality
2	1.272	0.1017	0.905	0.1828	No causality
3	0.829	0.2034	0.713	0.2379	No causality
4	0.52	0.3015	0.65	0.2578	No causality
5	0.413	0.3399	0.53	0.2979	No causality
6	0.102	0.4595	0.276	0.3911	No causality
7	0.059	0.4766	0.755	0.2251	No causality
8	-0.067	0.5268	0.684	0.247	No causality
Panel D: short					
1	-0.106	0.5421	0.344	0.3655	No causality
2	-0.566	0.7141	0.061	0.4758	No causality
3	-0.065	0.526	0.247	0.4023	No causality
4	-0.234	0.5926	0.157	0.4375	No causality
5	-0.372	0.6449	0.171	0.4321	No causality
6	-0.691	0.7551	-0.016	0.5065	No causality
7	-0.688	0.7541	0.104	0.4584	No causality
8	-0.825	0.7953	-0.314	0.6231	No causality

Notes: The table represents the results of the non-parametric granger causality test between WTI futures returns and AAI-BULL index for 8 lags and for bandwidth=0.76 (calculated with respect to data length, and following [Diks and Panchenko \(2006\)](#)). Results for the raw data are displayed in Panel A. Panel B, Panel C and Panel D report the causality results for mode 1 reflecting the long-run causality, for mode 4 reflecting the medium-run and mode 10 reflecting the short run, respectively. *, **, and *** denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

Table 2.6: Nonlinear Granger causality test between VIX and WTI futures returns

$Lx=Ly$	VIX does not Ganger cause WTI futures		WTI futures does not Ganger cause VIX		Conclusion
	T-stat	P-value	T-stat	P-value	
Panel A: Original signal					
1	6,196***	0	5,061***	0	VIX \leftrightarrow WTI
2	5,117***	0	4,588***	0	VIX \leftrightarrow WTI
3	4,477***	0	4,618***	0	VIX \leftrightarrow WTI
4	3,987***	0	4,354***	0	VIX \leftrightarrow WTI
5	3,737***	0	4,134***	0	VIX \leftrightarrow WTI
6	3,390***	0.0003	3,7***	0.0001	VIX \leftrightarrow WTI
7	2,777***	0.0027	3,226***	0.0006	VIX \leftrightarrow WTI
8	1,906**	0.0283	3,038***	0.0011	VIX \leftrightarrow WTI
Panel B: Long					
1	2,195**	0.014	0.642	0.2605	VIX \rightarrow WTI
2	2,324**	0.01	0.407	0.3421	VIX \rightarrow WTI
3	2,482***	0.0065	0.073	0.4708	VIX \rightarrow WTI
4	2,572***	0.005	-0.247	0.5975	VIX \rightarrow WTI
5	2,528***	0.0057	-0.507	0.6939	VIX \rightarrow WTI
6	2,436***	0.0074	-0.4	0.6556	VIX \rightarrow WTI
7	2,385***	0.0085	-0.326	0.6277	VIX \rightarrow WTI
8	2,223**	0.0131	-0.036	0.5143	VIX \rightarrow WTI
Panel C: Medium					
1	3,912***	0	3,391***	0.0003	VIX \leftrightarrow WTI
2	2,047**	0.0203	3,768***	0	VIX \leftrightarrow WTI
3	1,797**	0.0361	2,973***	0.0014	VIX \leftrightarrow WTI
4	1.281	0.1001	2,483***	0.0065	WTI \rightarrow VIX
5	0.838	0.2011	2,01**	0.0222	WTI \rightarrow VIX
6	0.958	0.169	1,694**	0.0451	WTI \rightarrow VIX
7	1.028	0.152	1,533*	0.0626	WTI \rightarrow VIX
8	1.016	0.1547	1,415*	0.0785	WTI \rightarrow VIX
Panel D: Short					
1	1.273	0.1014	1,673**	0.0472	WTI \rightarrow VIX
2	0.717	0.2367	-0.56	0.7124	No causality
3	2,08**	0.0187	-0.527	0.7008	VIX \rightarrow WTI
4	2,154**	0.0156	-0.783	0.7831	VIX \rightarrow WTI
5	2,013**	0.022	-1.176	0.8802	VIX \rightarrow WTI
6	1,906**	0.0283	-1.495	0.9325	VIX \rightarrow WTI
7	1,641*	0.0504	-1.767	0.9614	VIX \rightarrow WTI
8	1,697**	0.0448	-1.69	0.9545	VIX \rightarrow WTI

Notes: The table represents the results of the non-parametric granger causality test between WTI futures returns and VIX index for 8 lags and for bandwidth=0.76 (calculated with respect to data length, and following [Diks and Panchenko \(2006\)](#)). Results for the raw data are displayed in Panel A. Panel B, Panel C and Panel D report the causality results for mode 1 reflecting the long-run causality, for mode 4 reflecting the medium-run and mode 10 reflecting the short run, respectively. *, **, and *** denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

Non-parametric causality between Sentiment Proxies and natural gas futures returns

The natural gas price is of crucial importance for economic researches and financial traders. Gas plays a significant role as an elementary fuel in both residential and industrial heating markets. It is considered as a primary input for electricity generation. Thus, understanding price drivers and market anomalies is relevant from both a financial and economic perspective.

Natural gas prices discovery process is complicated since it faces numerous fundamentals, which significantly influence the market supply and demand (for example weather changes, excess supply or low demand and storage process among other factors). Furthermore, the natural gas market registers several unforeseen disruptions that could be explained by sentiment proxies or market uncertainties.

Table 2.7 displays the causality results between natural gas futures and EPU, which are different depending on lags and time-frequencies. Raw data exhibits unidirectional causalities. Whereas in the short run, results confirm that EPU granger causes the natural gas process starting from lag 4. However, the causality direction switches in the long run; natural gas prices play a leading role. Several aspects could explain these results. First, natural gas prices (generally caused by either fundamentals or macroeconomic conditions) have a positive impact on production in the short-run. However, it has no effects on supply in the long run.

In contrast, the US demand shock causes a positive impact on natural gas supply in the long-run; Indeed, climate change captured by our data sample causes warm winters. Consequently, it strongly affects natural gas demand negatively. Besides, natural gas supply shocks constitute a reliable driver of natural gas price movements. Indeed, the US market is known for its strong demand, which immediately drives up natural gas prices and increases the supply. This could be a significant explanation of the EPU leading role in the short run. However, the impact of these shocks become weaker in the long term. In part, this can be justified by the increase of HH prices, which causes an increase in the supply in the short run. Thus, natural gas production raises in response to these economic movements and increasing natural gas prices in the short run. EPU is found to be insensitive to natural gas price movements in the short run but significantly affected in the long run. These results are contradictory to Kilian (2009) and Baumeister and Peersman (2013), but they are in line with Nguyen and Okimoto (2019). This is because previous literature does not take into account non-linear and time-frequency dynamics when exploring the link between economic policy uncertainty and natural gas prices, given the occurring of unprecedented economic events.

According to table 2.8, results show a unidirectional causality from AAI-Bearish sentiment to natural gas futures prices for raw data. Results remain robust for all the frequencies. This can be explained by the significant impact of crude oil prices on natural gas prices. Indeed, oil prices are considered as a fundamental determinant of the natural gas price. Besides, bearish investors have a significant impact on oil prices, which explain the corresponding impact of bearish investors behavior on natural gas prices as well. We can admit that the natural gas market is less potent in transmitting information compared to crude oil markets. It is worth noting that natural gas prices are sensitive to economic uncertainty and market policies regarding demand and supply. That is why natural gas traders should consider bearish sentiment when estimating prices, making investment decisions, or managing future risk.

Table 2.7: Nonlinear Granger causality test between EPU and Henry-Hub futures returns

$Lx=Ly$	EPU does not cause HH futures	Ganger futures	HH futures EPU	does not cause	Ganger futures	Conclusion
	T-stat	P-value	T-stat		P-value	
Panel A: Raw data						
1	0.21	0.4168	0.619	0.268		No causality
2	1,425**	0.077	1.111	0.1332		EPU \rightarrow HH
3	2,249**	0.0122	0.849	0.198		EPU \rightarrow HH
4	1,336*	0.0908	1.132	0.1287		EPU \rightarrow HH
5	0.189	0.425	1.123	0.1307		No causality
6	0.093	0.4628	1,302*	0.0965		HH \rightarrow EPU
7	0.55	0.2911	1,532*	0.0628		HH \rightarrow EPU
8	0.208	0.4176	1,865**	0.031		HH \rightarrow EPU
Panel B: Long						
1	-0.071	0.5282	0.568	0.285		No causality
2	-0.118	0.5467	0.872	0.1916		No causality
3	-0.191	0.5757	1.052	0.1463		No causality
4	-0.088	0.5349	1.235	0.1084		No causality
5	0.184	0.427	1,549*	0.0607		HH \rightarrow EPU
6	0.725	0.2342	1,651**	0.0493		HH \rightarrow EPU
7	1.101	0.1354	1,832**	0.0334		HH \rightarrow EPU
8	1.446	0.7414	1,979**	0.0239		HH \rightarrow EPU
Panel C: Medium						
1	2,626***	0.0043	2,905***	0.0018		EPU \leftrightarrow HH
2	2,519***	0.0058	2,914***	0.0017		EPU \leftrightarrow HH
3	1.077	0.1408	1,865**	0.0311		HH \rightarrow EPU
4	0.362	0.3586	1,394**	0.0816		HH \rightarrow EPU
5	0.065	0.4739	1,386*	0.0828		HH \rightarrow EPU
6	-0.276	0.6088	1,324*	0.0927		HH \rightarrow EPU
7	-0.332	0.63	1,426*	0.0769		HH \rightarrow EPU
8	-0.371	0.6445	1,482*	0.0691		HH \rightarrow EPU
Panel D: Short						
1	0.954	0.17	-1.088	0.8616		No causality
2	0.414	0.3395	-0.7	0.7578		No causality
3	0.536	0.2958	-0.588	0.7216		No causality
4	0.975	0.1646	-0.573	0.7166		No causality
5	1,354*	0.0878	-0.313	0.6227		EPU \rightarrow HH
6	1,65**	0.0494	-0.034	0.5135		EPU \rightarrow HH
7	1,662**	0.0482	0.028	0.489		EPU \rightarrow HH
8	1,811**	0.035	0.191	0.4241		EPU \rightarrow HH

Notes: The table represents the results of the non-parametric granger causality test between Henry Hub futures returns and EPU index for 8 lags and for bandwidth=0.76 (calculated with respect to data length, and following [Diks and Panchenko \(2006\)](#)). Results for the raw data are displayed in Panel A. Panel B, Panel C and Panel D report the causality results for mode 1 reflecting the long-run causality, for mode 4 reflecting the medium-run and mode 10 reflecting the short run, respectively. *, ** and *** denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

Table 2.9 displays the causality results between bullish investor sentiment and natural gas futures returns. Interestingly, findings show significant information flow from bullish investor sentiment to natural gas prices. In contrast, time-frequency causality exhibits the opposite direction in the long run. No causalities are captured in the short and medium terms. These results can be explained by the decreasing trend and potential stability of natural gas futures prices in the long run, which creates a positive feeling regarding investors behavior and consequently generate a bullish sentiment.

Table 2.8: Nonlinear Granger causality test between AII-BEAR and Henry-Hub futures returns

$Lx=Ly$	AII-BEAR does not Ganger cause HH fu- tures		HH futures does not Ganger cause AII- BEAR		Conclusion
	T-stat	P-value	T-stat	P-value	
Panel A: Raw data					
1	3,394***	0.0003	-0.366	0.6429	AII-BEAR \rightarrow HH
2	3,226***	0.0006	-1.047	0.8523	AII-BEAR \rightarrow HH
3	3,779***	0.0008	2,075**	0.0189	AII-BEAR \leftrightarrow HH
4	3,136***	0.0008	0.761	0.2234	AII-BEAR \rightarrow HH
5	2,649***	0.004	1,568*	0.0584	AII-BEAR \leftrightarrow HH
6	2,178**	0.0147	0.593	0.2767	AII-BEAR \rightarrow HH
7	1,853**	0.0319	-0.075	0.5298	AII-BEAR \rightarrow HH
8	1,806**	0.0354	-0.073	0.529	AII-BEAR \rightarrow HH
Panel B: Short					
1	0.678	0.2489	-0.305	0.6198	No causality
2	0.709	0.2392	-0.313	0.6228	No causality
3	0.825	0.2048	-0.301	0.6183	No causality
4	1.091	0.1377	-0.139	0.5552	No causality
5	1,556*	0.0598	0.038	0.485	AII-BEAR \rightarrow HH
6	1,876**	0.0303	-0.095	0.5378	AII-BEAR \rightarrow HH
7	1,961**	0.0249	-0.178	0.5707	AII-BEAR \rightarrow HH
8	1,953**	0.0254	-0.428	0.6656	AII-BEAR \rightarrow HH
Panel C: Medium					
1	2,876***	0.002	1,63*	0.0516	AII-BEAR \leftrightarrow HH
2	2,63***	0.0042	1,785**	0.0371	AII-BEAR \leftrightarrow HH
3	2,217**	0.0133	1,888**	0.0295	AII-BEAR \leftrightarrow HH
4	1,918**	0.0275	1,676**	0.0468	AII-BEAR \leftrightarrow HH
5	1,461*	0.072	1,283*	0.0997	AII-BEAR \leftrightarrow HH
6	1,521*	0.0641	1,307*	0.0956	AII-BEAR \leftrightarrow HH
7	1,461*	0.072	1.139	0.1272	AII-BEAR \rightarrow HH
8	1,537*	0.0622	0.953	0.1703	AII-BEAR \rightarrow HH
Panel D: Long					
1	0.383	0.3508	0.215	0.4147	No causality
2	0.506	0.3065	0.969	0.1662	No causality
3	0.209	0.4174	1,351*	0.0883	HH \rightarrow AII-BEAR
4	0.892	0.1861	1,627*	0.0519	HH \rightarrow AII-BEAR
5	1,415*	0.0785	1,919**	0.0275	AII-BEAR \leftrightarrow HH
6	1,5*	0.0668	2,152**	0.0157	AII-BEAR \leftrightarrow HH
7	1,484*	0.0689	2,33***	0.0099	AII-BEAR \leftrightarrow HH
8	1,652**	0.0492	2,395***	0.0083	AII-BEAR \leftrightarrow HH

Notes: The table represents the results of the non-parametric granger causality test between Henry Hub futures returns and AII-BEAR index for 8 lags and for bandwidth=0.76 (calculated with respect to data length, and following [Diks and Panchenko \(2006\)](#)). Results for the raw data are displayed in Panel A. Panel B, Panel C and Panel D report the causality results for mode 1 reflecting the long-run causality, for mode 4 reflecting the medium-run and mode 10 reflecting the short run, respectively. *, ** and *** denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

While in the short and medium term, natural gas prices slowly fluctuate, and the market is considered very smooth compared to the crude oil market. Price fluctuations are very low in the short and medium run, which makes profits minimal and the market less attractive for speculators in the short run.

Table 2.9: Nonlinear Granger causality test between AAI-BULL and Henry-Hub futures returns

$Lx=Ly$	AAII-BULL does not Ganger cause HH fu- tures		HH futures does not Ganger cause AAI- BULL		Conclusion
	T-stat	P-value	T-stat	P-value	
Panel A: Raw data					
1	3,258***	0.0005	-0.058	0.5229	AAII-BULL \rightarrow HH
2	3,252***	0.0005	-0.629	0.7352	AAII-BULL \rightarrow HH
3	3,179***	0.0007	0.677	0.2492	AAII-BULL \rightarrow HH
4	1,746**	0.0403	0.259	0.3978	AAII-BULL \rightarrow HH
5	1,446*	0.074	1.159	0.1232	AAII-BULL \rightarrow HH
6	1.15	0.1251	-0.304	0.6192	No causality
7	0.134	0.4467	-0.232	0.5919	No causality
8	0.209	0.417	0.328	0.3714	No causality
Panel B: Long					
1	1.166	0.1217	2,043**	0.0205	HH \rightarrow AAI-BULL
2	1.257	0.1044	2,133**	0.0164	HH \rightarrow AAI-BULL
3	1.408	0.0795	2,149**	0.0158	HH \rightarrow AAI-BULL
4	1.469	0.0708	2,204**	0.0137	HH \rightarrow AAI-BULL
5	1.24	0.1074	2,089**	0.0183	HH \rightarrow AAI-BULL
6	1.058	0.1451	1,98**	0.0238	HH \rightarrow AAI-BULL
7	0.814	0.2077	1,771**	0.0382	HH \rightarrow AAI-BULL
8	0.656	0.256	1,637*	0.0508	HH \rightarrow AAI-BULL
Panel C: Medium					
1	-0.299	0.6175	1.062	0.144	No causality
2	0.286	0.3872	1.088	0.1383	No causality
3	-0.633	0.7366	0.788	0.2153	No causality
4	-1.377	0.9157	0.486	0.3136	No causality
5	-1.214	0.8877	0.658	0.2553	No causality
6	-1.164	0.8777	0.545	0.2929	No causality
7	-0.98	0.8365	0.71	0.2389	No causality
8	-0.695	0.7564	0.89	0.1867	No causality
Panel D: short					
1	-0.175	0.5696	-0.09	0.536	No causality
2	-0.2	0.5791	-0.282	0.611	No causality
3	0.713	0.238	0.145	0.4422	No causality
4	1.201	0.1148	0.134	0.4468	No causality
5	1.221	0.1109	0.032	0.4871	No causality
6	0.978	0.164	0.333	0.3696	No causality
7	0.792	0.2141	0.351	0.3628	No causality
8	0.445	0.328	0.393	0.347	No causality

Notes: The table represents the results of the non-parametric granger causality test between Henry Hub futures returns and AAI-BULL index for 8 lags and for bandwidth=0.76 (calculated with respect to data length, and following [Diks and Panchenko \(2006\)](#)). Results for the raw data are displayed in Panel A. Panel B, Panel C and Panel D report the causality results for mode 1 reflecting the long-run causality, for mode 4 reflecting the medium-run and mode 10 reflecting the short run, respectively. , and denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

Moreover, upward picks were significantly stronger than downward picks, which do not create any positive feelings regarding investor sentiment, and consequently, causality is found to be insignificant.

Table 2.10: Nonlinear Granger causality test between VIX and Henry-Hub futures returns

$Lx=Ly$	VIX does not Ganger cause HH futures		HH futures does not Ganger cause VIX		Conclusion
	T-stat	P-value	T-stat	P-value	
Panel A: Raw data					
1	3,74***	0.00009	-0.031	0.51243	VIX \rightarrow HH
2	3,379***	0.00036	-0.456	0.67568	VIX \rightarrow HH
3	3,758***	0.00009	-0.239	0.5945	VIX \rightarrow HH
4	2,777***	0.00274	0.183	0.42742	VIX \rightarrow HH
5	2,171**	0.01498	0.694	0.24389	VIX \rightarrow HH
6	1.038	0.14963	0.765	0.222	No causality
7	1.146	0.12593	0.944	0.17256	No causality
8	0.898	0.18462	0.604	0.27291	No causality
Panel B: Long					
1	0.93	0.17624	1.248	0.10597	No causality
2	0.985	0.16238	1.004	0.1577	No causality
3	0.988	0.16159	1.02	0.15383	No causality
4	0.968	0.16651	1.238	0.10785	No causality
5	1.189	0.11713	1.467	0.07113	No causality
6	1.618	0.05279	1,567*	0.05861	HH \rightarrow VIX
7	1.81	0.03518	1,71**	0.04362	HH \rightarrow VIX
8	1.833	0.03341	1,981**	0.0238	HH \rightarrow VIX
Panel C: Medium					
1	-4.131	0.99998	-2.947	0.9984	No causality
2	-3.849	0.99994	-3.904	0.99995	No causality
3	-2.606	0.99543	-4.556	1	No causality
4	-0.999	0.84116	-4.571	1	No causality
5	-0.329	0.6288	-4.436	1	No causality
6	-0.277	0.60924	-3.873	0.99995	No causality
7	-0.496	0.68998	-3.01	0.99869	No causality
8	-0.477	0.68324	-2.016	0.97812	No causality
Panel D: Short					
1	0.5	0.30861	0.366	0.35729	No causality
2	1.139	0.12726	0.47	0.31908	No causality
3	0.462	0.32207	0.363	0.35823	No causality
4	0.29	0.38578	0.434	0.33201	No causality
5	0.128	0.44889	0.517	0.30258	No causality
6	0.039	0.48462	0.642	0.2604	No causality
7	0.145	0.44238	0.58	0.28087	No causality
8	-0.101	0.54023	0.506	0.30635	No causality

Notes: The table represents the results of the non-parametric granger causality test between Henry Hub futures returns and VIX index for 8 lags and for bandwidth=0.76 (calculated with respect to data length, and following [Diks and Panchenko \(2006\)](#)). Results for the raw data are displayed in Panel A. Panel B, Panel C and Panel D report the causality results for mode 1 reflecting the long-run causality, for mode 4 reflecting the medium-run and mode 10 reflecting the short run, respectively. , and denote that the null hypothesis is rejected at the 10%, 5% or 1% significant level, respectively.

Table 2.10 shows that VIX leads natural gas futures returns in raw signal. However, when exploring the time-frequency causality, we found that natural gas futures cause higher VIX. Indeed, HH futures price volatilities boost trading opportunities. Traders usually believe in the long-run bull and generally take long positions on the natural gas market in addition to long-run supply and demand specific policies. These facts encourage investors to make risky decisions and more dynamic movements which impact market volatility. However, in the short and medium term, the insignificance of the causality test is caused by natural gas specific determinants, general trend, seasonality, and low volatiles.

2.7 Conclusion

Classical economic theory leaves no place to behavioral implications in energy commodity pricing discovery. Indeed, classical pricing models and investment decisions believe that investor sentiment does not play any role in price movements and vice versa. This paper questioned this issue and challenged the classical theory by studying the causality between major energy commodities futures prices (Crude oil and Natural gas futures prices) and investor and market sentiment indexes in both directions.

Furthermore, extensive financial literature studied evidence related to investor sentiment. The findings are interesting, and a significant relationship is registered between investor sentiment and the financial market. Based on these facts, investors tend to make profits by exploiting the information provided by investor sentiment proxies; they adjust their decisions based on these findings and consequently maximize their profits by taking into consideration these indexes before making any buying or selling decisions.

Since financial investors hugely grow their interest in commodity assets, we investigate this issue on major energy commodities markets (Natural gas and Crude oil). Furthermore, in order to provide a more effective study, we analyze the time-frequency non-linear causality between commodity futures and investor sentiment using the VMD approach. Consequently, we estimate the significance and the direction of the causality on the long term (low frequency), the medium term (average frequency) and the short term (high frequency), without losing any information when moving from a level to another. In this study, we collected data starting from 2002 until the end of 2018. We choose 2002 as a starting date since it reflects the beginning of commodities markets financialization. Starting from this date, trading volume and non-commercial positions dramatically increased.

Consequently, the role of investors becomes more significant. Whereas previous literature of investor and market sentiment focused mainly on the stock market and in few cases studied energy market cases leaving some unanswered questions; Does investor and market sentiment proxies play a significant role in driving energy prices? Does it vary across the time-frequency domain? If it is the case, what does it mean?

This paper answers these questions to contribute to the existing literature by exploring the causal relationship between energy prices and investor sentiment and economic volatilities on the time-frequency domain.

The adopted methodology is robust to information loss, structural break, and error misspecification, which usually appear in commodity prices time series (Balcilar et al., 2017). Besides, the non-parametric causality approach is efficient in capturing the volatility of energy futures prices.

The main empirical results of the current analysis can be summarized as follow. First, there is a significant causal relationship between crude oil futures returns and EPU in the short, medium, and long run. However, the direction varies across time frequencies. In the short run, WTI returns significantly cause economic uncertainty, while in the medium run WTI leading power decreases and causality remains to be bidirectional. In the long run, after responding to major macroeconomic events and political changes, the economic policy exhibit high uncertainty, which affect crude oil prices. Whereas for natural gas prices, there are significant causal flows from EPU to natural gas prices in the short-term. Uncertainty in supply and demand policies and global political changes captured by EPU have an immediate impact on natural futures returns. While in the medium and long run, natural gas causes EPU.

Second, it is worth noting that bear investor sentiment better predicts energy returns compared to the bull sentiment index. While bearish investors show significance over the entire sample period and for all the time-frequencies, bullish investors manifest only in the long run. This result can be explained by the awareness of financial investors about information flows in both financial and commodity markets.

Third, VIX has better estimative power for crude oil returns compared to natural gas returns. However, it has lower predictive power compared to the other sentiment proxies. A probable explanation of these findings is the former components of these sentiment proxies, where AAIL sentiments are built upon on the future perspective of financial investors, and EPU and VIX are based on past and historical information. These findings infer that sentiment proxies have essential implications on energy returns. However, the time-frequency domain should be taken into consideration in order to conduct efficient investment strategies and favorable risk management decisions.

Investors can use these findings to provide the perfect crude oil and natural gas prices forecasts. Besides, speculators and individual investors can benefit from these results to optimize their hedging activities and make the right decision at the perfect time.

Finally, in sights of high market uncertainties and anomalies, futures researches should add sentiment indexes as a new explanatory variable in the models forecasting time frequency returns and price movements.

Figure 5: AAI-Bullish sentiment decomposition based on VMD

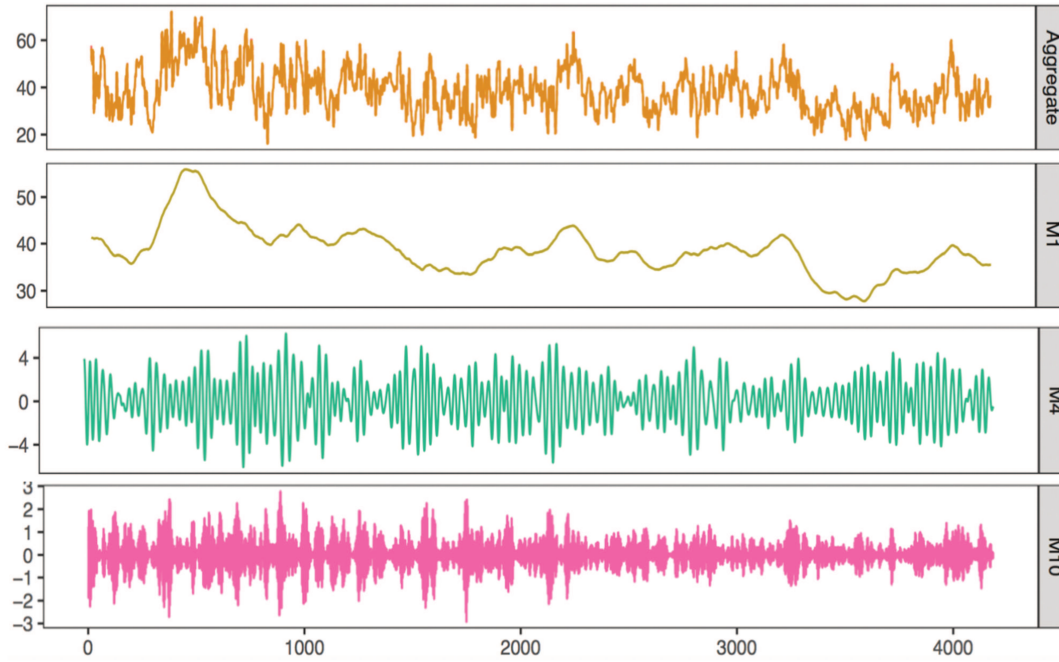


Figure 6: AAAI-Bearish sentiment decomposition based on VMD

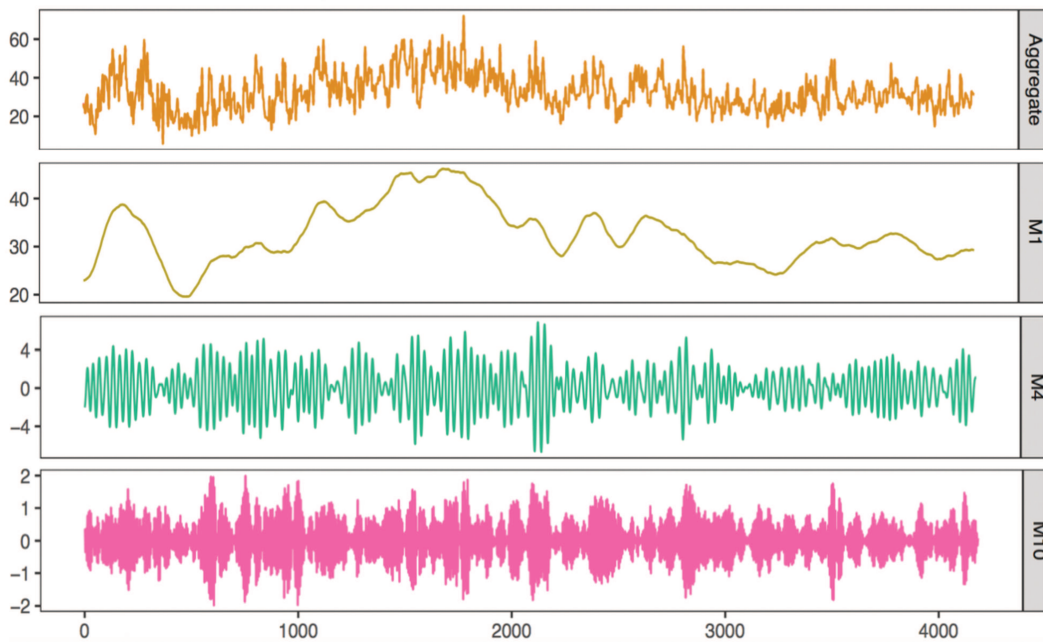


Figure 7: EPU decomposition based on VMD

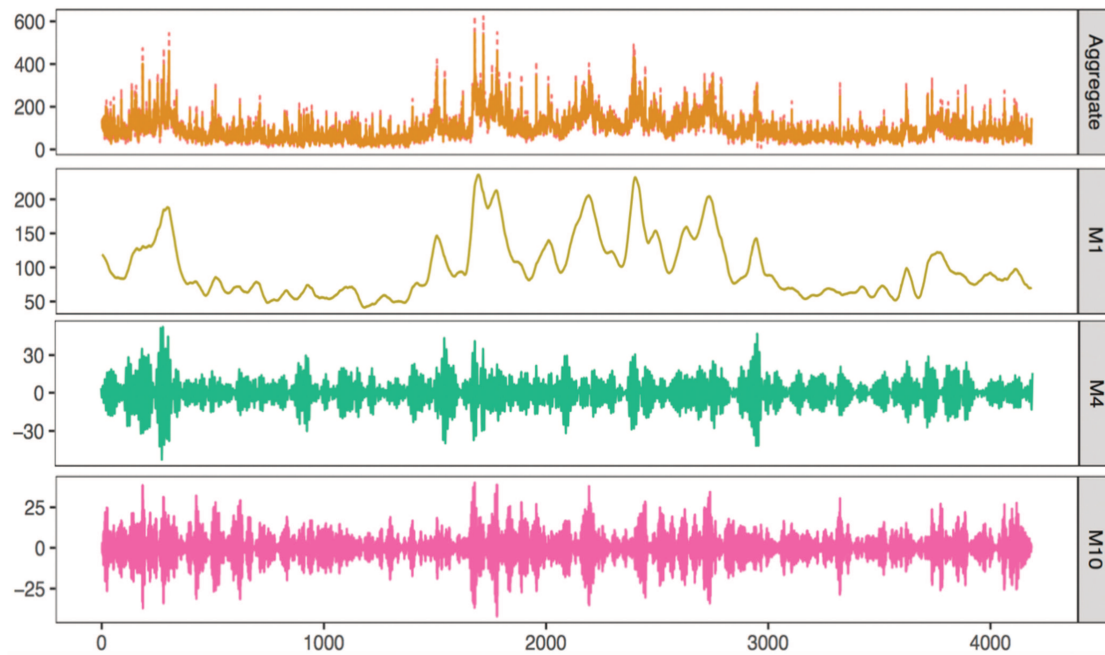


Figure 8: VIX decomposition based on VMD

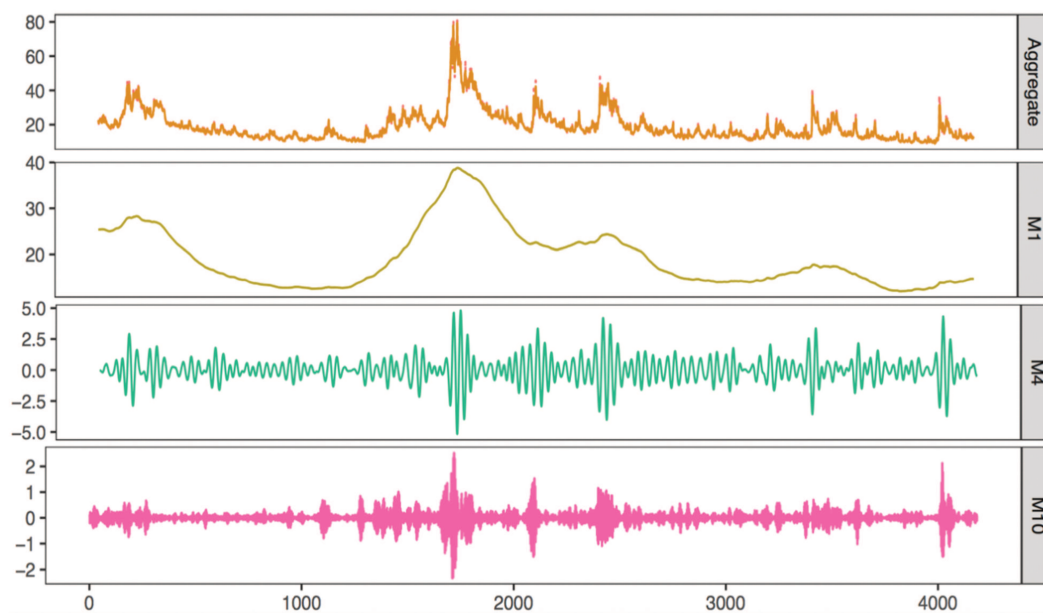


Figure 9: WTI decomposition based on VMD

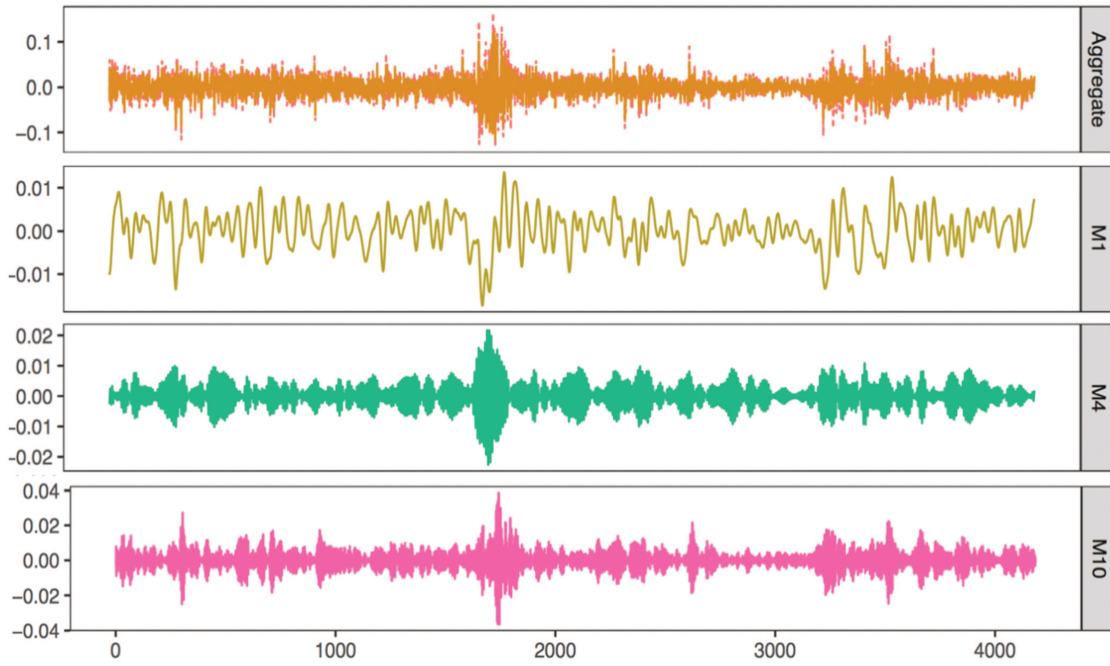
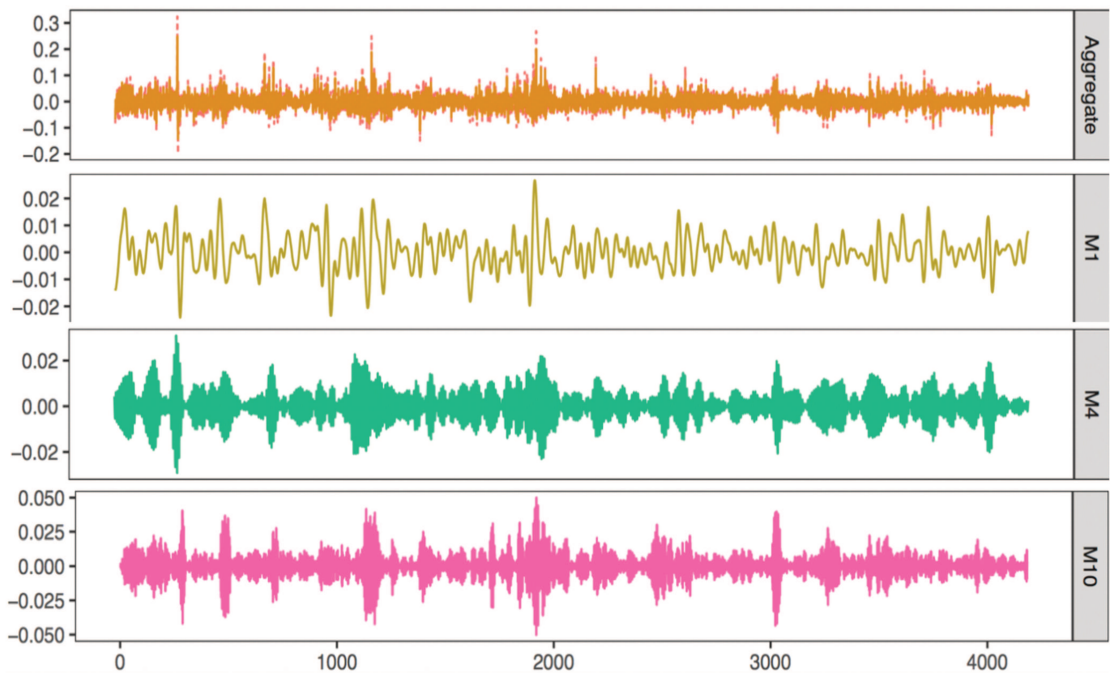


Figure 10: HH decomposition based on VMD



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Chapter 3

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

1

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, NB, 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 contract. 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.

Keywords: MODWT, frequency domain, natural gas, pricing and informational efficiency, multi-scale linear and nonlinear Granger causality, random walk testing.

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3.1 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)². 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 grave disparities between the European Union countries.³

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 et al., 2009).⁴

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 pricing and informational efficiency of the two largest European natural gas markets (UK NBP and Dutch TTF) by drawing a parallel with the US Henry Hub through a wavelet decomposition approach⁵. 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 future prices to new information. First, the pricing efficiency is tested by investigating the existence of a potential cointegrating relationship between spot and fu-

²See also Heather (2016).

³These disparities suggest a path of development towards a more established integration of gas markets at the European scale, though growing (Neumann and Cullmann, 2012)

⁴These 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.

⁵Wavelets 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).

tures prices of the three considered hubs. The step further is to examine the process of price discovery through linear and non-linear causality analyses between spot and futures prices at different time scales. Finally, we measure 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 to 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 MODWT decomposition to NBP, TTF and Henry Hub spot and futures price returns of one-month maturity. Our time series are transformed into frequency domain without loss of time-domain information, and wavelet methodology avoids the need to assume certain parametric models of the series and accounts for time-dependent volatility covariance and structural breaks. More importantly, it allows us not to neglect a major aspect of natural gas markets characterized by highly seasonal dynamics. Moreover, linear and non-linear causality testing have been used to investigate the causality direction by relying on [Diks and Panchenko \(2006\)](#) test. We also conduct several robustness checks to make sure our results hold under different configurations by conducting an inter-commodity comparison with the oil market⁶ repeating the analysis for two- and three-months maturities futures contracts and relying on different filters under the wavelet methodology⁷.

This paper fits into a limited research area that has investigate 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 predictable⁸. [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 et al. \(2005\)](#) 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. They found that the efficient market hypothesis holds only for contracts with only about a month to maturity⁹. The European case is less studied in the literature (see e.g. [Haff et al.](#)

⁶The wavelet methodology has already been applied to the oil market, see [Alzahrani et al. \(2014\)](#) and [Polanco-Martínez and Abadie \(2016\)](#).

⁷results are available under request

⁸Transparency 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.

⁹More 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

(2008) and [Asche et al. \(2006\)](#) that have examined the decoupling of natural gas, oil and electricity prices in the UK market.)

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 (NBP and TTF) and American (Henry Hub) 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. 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 non-linearities 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 prices¹⁰. 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.

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 only 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,

between natural gas spot and futures prices.

¹⁰This has given rise to the use of non-linear causality tests, including that of [Baek and Brock \(1992\)](#) or [Diks and Panchenko \(2006\)](#)

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 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 in section 3.3. The wavelet decomposed data and the resulted empirical evidence of pricing and informational efficiency in Section 3.4 and. Sections 3.5 discuss our results and section 3.6 conclude the paper.

3.2 Related literature

The causality relationship between futures and spot markets is and has been the subject of lively debate. 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 future 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 future 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)¹¹. [Stronzik et al. \(2009\)](#) 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 approximations¹². 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 et al. \(2006\)](#) 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 direction¹³. [Doane and Spulber \(1994\)](#) employed the Granger causality test to 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 prices¹⁴. [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

¹¹See also: [Mohammadi \(2011\)](#)

¹²They 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.

¹³[Garbade and Silber \(1983\)](#) suggests 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 a potent benchmark underlying any future transaction ([Moosa, 1996](#)) or that bidirectional causality between the two markets is more sustainable.

¹⁴Futures markets are also found to cause fluctuations in spot prices ([Brenner and Kroner \(1995\)](#)).

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 et al. \(2005\)](#) and [Serletis and Shahmoradi \(2006\)](#)). Thirdly, the empirical investigations of price discovery process are also rather thin for European markets and have neglected the non-linearities 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 non-linearities 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 informational¹⁵ point of view in European (NBP and TTF) and 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.

3.3 Methodology

In this section, we describe the retained frequency domain approach that is the Maximum Overlapped Discrete Wavelet methodology to decompose the data into different time-frequencies in order to explore market efficiency in different time-scales¹⁶. It allows examining the properties of efficiency on a multiresolution basis. To investigate pricing efficiency, wavelet decomposition is applied to spot and futures price returns to account for the intrinsic seasonality of natural gas markets when investigating 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. Finally, we draw an inter-commodity parallel with the oil case (WTI) for comparison purpose (Results are drawn in the robustness check section).

3.3.1 Maximum overlapped discrete wavelet transformation

A crucial quality of wavelets in exploring time frequency economic data is their capability to decompose the time series into details affiliated to different time scales characterized by increasing frequencies. In

¹⁵Following [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 future prices to new information. The first one is tested by investigating the relationship between spot price and future prices, the second is tested by examining the residuals of future log returns via random walk analysis.

¹⁶Wavelet decomposition is attractive from both the industry and the academic fields as investors, traders and policy-makers seek to understand prices predictability and optimize investment decisions (see [Zavadska et al. \(2018\)](#), [Reboredo et al. \(2017\)](#), and [Nicolau and Palomba \(2015\)](#)).

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 or the signals 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

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

Where j is the maximum integer and respects $2^j \leq$ 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 and crude oil spot and futures prices, the maximum overlapped discrete wavelet transformation 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 a brilliant compactly supported orthonormal wavelets filter which is suitable for discrete wavelet analysis.

Indeed, it conserves the energy of each detail and redistribute it into more bunched form. Besides, the filter width 8 is long enough to ensure the un-correlation between coefficients in the different scales and in the same time it is short enough to reflect fewer boundry condition, Daubechies (1992). In fact, according to previous researches, the length 8 provides robust results. 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 3.1. D₁ is the highest frequency detail which reflects the short-term variations of the energy prices time series due to shocks accruing in a daily basis ($2^1=2$ days). D₂ and D₃ represent the weekly effects and variation on a time scale of $2^2=4$ days and $2^3=8$ days, respectively. D₄ and D₅ measures 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. In addition to S₈ that measures the residue of the original time series after the details from the raw signal; it reflects the smooth movement of the raw data and represent the general trend of the prices.

3.3.2 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 bases, 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 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 follow;

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

Equivalently, we can calculate the wavelet covariance of the scale w_j as follow;

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

Consequently, the wavelet correlation coefficient is obtained by;

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

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

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

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

3.3.3 Price discovery process

A linear and nonlinear granger causality test is employed to detect the pricing efficiencies and understand the price discovery mechanism in Hunry Hub and West Texas Intermediate markets. The corresponding section briefly describes the econometric methodology of the causal relationship between energy spot and futures prices on both raw data and MODWT scales components. The linear causality is a standard granger causality (Granger, 1969) (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 3.3.3 and 3.3.3, respectively.

Linear granger causality test

The granger causality is a bivariate test who provides the predictability of a future estimation of a time series using the historical information of another time series. Empirically, granger causality test requires two stationary time series. That is why, before starting the analysis, we adopt the Augmented Dickey and Fuller (ADF) and Phillips-perron stationarity tests. In case of non-stationarity, we use the log-return data to run the granger causality test two stationary time series x_t and y_t described as follow;

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

This equation is the standard equation of a linear granger causality test based on VAR and having x_t do not cause y_t as a null hypothesis.

Where

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

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 represents the white noise of the model. 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 cointegrated¹⁷, 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.

Non-linear granger causality

The economic literature assume that energy commodity prices exhibit a complex non-linear process with numerous influencing factors. That is why, linear causality may lead to inaccurate results when the tested variables display nonlinear structure. The first non-linear causality test was proposed by [Baek and Brock \(1992\)](#) to investigate the relationship between stationary time series. This test was further developed by [Hiemstra and Jones \(1994\)](#) allowing the non-linear causality testing between independent and identically distributed stationary time series. They justify the existing of short run autocorrelation which correct the original nonlinear test and consequently improve the results. On this basis, [Diks and Panchenko \(2006\)](#) consider to [Hiemstra and Jones \(1994\)](#) test as not persistent with the properties of Granger causality test, and not worthy to drive a causality test. Thereupon, they contributed to previous studies by developing 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 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 describes as follow:

Consider x_t and y_t two stationary time series. According to Granger, 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, suppose that;

¹⁷To test the cointegration, we adopted the [Johansen \(1991\)](#) test

$X_t^{l_X} = (X_{t-l_X+1}, \dots, X_t)$ 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 consider 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 describes 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. Following Bekis and Diks (2008), 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, respecting the null hypothesis, we can assume that the conditional distribution of R under $(X, Y) = (x, y)$ is equal to 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;

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

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 follow;

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

$f_v(V_i) = (2\varepsilon_n)^{-d_v} (n-1)^{-1} \sum_{jj \neq i} I_{ij}^V$ 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 follow;

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

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 follow;

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

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

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 \(2006\)](#) provides the 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. When the data length is more than 4000 the bandwidth is 0,76. For our subperiods, the data length is close to 2000 and consequently the bandwidth is equal to 1.

Informational efficiency and the random walk hypothesis

By informational efficiency, we sought to understand the speed of adjustment of prices to new information in order to classify the market as efficient in the case of fast adjustment and inefficient otherwise. In this context, the market is considered as efficient if it has no memory and future prices could not be predicted by historical information which means that prices follow random walk hypothesis (RWH) in the context of Efficient market theory ([Fama, 1965, 1995](#)).

In this context, [Lo and MacKinlay \(1988, 1989\)](#) and [Cochrane \(1988\)](#) were the first to propose the use of the variance ratio statistics to test the random walk hypothesis on both raw and stationary data ([Urrutia, 1995](#)). Indeed, when the null hypothesis of random walk is rejected, the alternative hypothesis denotes that the time series are serially correlated and consequently, the market is considered inefficient; past movement are of a significant use in predicting future volatilities. The variance ratio method has been widely used and has become the standard approach for testing randomness better than unit root tests ([Lo and MacKinlay, 1988](#)), and ([Ayadi and Pyun, 1994](#)).

Following [Campbell et al. \(1997\)](#) and [Lo and MacKinlay \(1997\)](#), a q-period overlapped returns is used to estimate the variances to procure a better estimator and consequently a more powerful test. In addition, the variance must respect the linear property of the random walk process of a function with a time interval (q). Thus, we consider returns process as a random walk when we found equality between the variance of the (qth) difference and (q) times the variance of the first difference.

Consequently, the variance ratio test based on overlapping observations and under homoscedasticity is expressed as follows:

$$VAR(q) = \frac{\sigma_D^2(q)}{\sigma_d^2(q)}$$

$$VR(q) = \frac{VAR[R_{i,t}(q)]}{q \cdot VAR[R_{i,t}]} = 1 + 2 \sum_{k=1}^{q-1} \left(1 - \frac{k}{q}\right) \rho(k)$$

Where $R_{i,t}(q) = R_{i,t}(q) + R_{i,t-1} + \dots + R_{i,t-k+1}$ and $\rho(k)$ represents the k^{th} order autocorrelation coefficient of $R_{i,t}(q)$.

$$H_0 : R_{i,t} = \mu + \varepsilon_t$$

Where ε_t is the error term and stratifies the following conditions:

$$Cov[\varepsilon_t, \varepsilon_{t-k}] = 0 \text{ for all } k \neq 0$$

$$Cov[\varepsilon_t, \varepsilon_{t-k}] \neq 0 \text{ for all } k = 0$$

Thus following [Lo and MacKinlay \(1997\)](#), the heteroskedastic estimator of the asymptotic variance ratio $VR(q)$ is;

$$\hat{\vartheta}(q) = 4 \sum_{k=1}^{q-1} \left(1 - \frac{k}{q}\right)^2 \hat{\delta}_k$$

Where

$$\hat{\delta}_k = \frac{nq \sum_{j=k+1}^{nq} (p_{i,j} - p_{i,j-1} - 1 - \hat{\mu})^2 (p_{i,j-k} - p_{i,j-k-1} - 1 - \hat{\mu})^2}{\left[\sum_{j=1}^{nq} (p_{i,j} - p_{i,j-1} - 1 - \hat{\mu})^2 \right]^2}$$

To test the null hypothesis, the standardized test statistic $\zeta(q)$ is presented by;

$$\zeta(q) = \frac{\sqrt{jq} (VR(q) - 1)}{\sqrt{\hat{\vartheta}}} \sim N(0, 1)$$

Hence, the null hypothesis of random walk best on variance ratio test denotes that variance ratio is equal to 1 and the test statistic follow a standard normal distribution at the asymptotical level.

For further random walk investigation, we adopt the Automatic variance ratio (AVR) test under conditional heteroskedasticity. The AVR test was proposed by as follow;

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, $m(v) = \frac{25}{12\pi^2 v^2} \left[\sin\left(\frac{6\pi v}{5}\right) - \cos\left(\frac{6\pi v}{5}\right) \right]$ 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;

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

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

Choi (1999) used the data-dependent approach of Andrews 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 following three steps as:

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 $|\{AVR^*(\hat{h}^*; j)\}_{j=1}^K| > |AVR(\hat{h})|$

3.4 Empirical strategy

3.4.1 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 3.1 shows the returns of natural gas spot and futures (one-month maturity) in the US, UK, and the Netherlands. The US Henry Hub exhibits much higher volatility than European hubs (UK NBP and the NL TTF). 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, 2015)).

Figure 3.1: Natural gas spot and futures returns

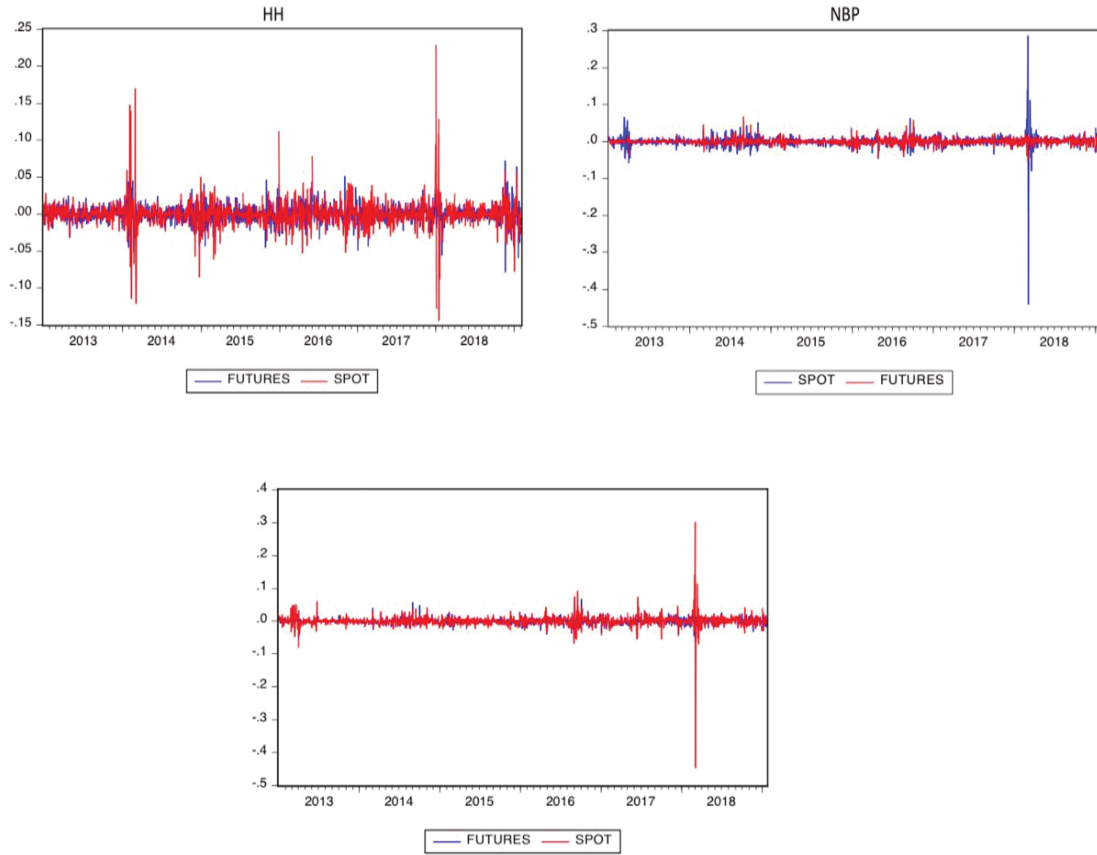


Table 3.2 provides descriptive statistics for the daily returns of natural gas spot and futures prices. The returns of the three natural gas markets have positive skewness, especially the UK NBP spot returns. This means that returns have extreme observations in the right tail of the distribution, suggesting a higher probability to incur extreme gains than extreme losses. Moreover, kurtosis values for the three spot and futures prices are for most cases greater than 3, indicating a larger probability of extreme positive and negative values comparing with a normal distribution. The null hypothesis of linearity of the Jarque-Bera test is strongly rejected for all considered natural gas spot and futures prices.

The Augmented Dicky-Fuller (ADF) and Phillips-Perron (PP) tests are used to check for the stationarity properties of our data (see Table 7 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.

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 to 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 3.1: 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 allow 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 advantages¹⁸. In this paper, the original data have been transformed by the wavelet filter Symmlet [S(8)] up to time scale 8¹⁹.

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 8 to 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 scales. It shows that correlations are all quite high between natural gas spot and futures returns. Moreover, for all considered natural gas markets, correlations are increasing with the time scale and reach almost 1 for the most extended time scales. 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.

¹⁸First, 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 et al., 2002](#)), ([Percival and Mofjeld, 1997](#)). These 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.

¹⁹Table 3.1 displays the frequency interpretation of the multiresolution decomposed scale levels.

3.4.2 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 returns in the three considered hubs. Table 8 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 respectively²⁰. Therefore, results suggest the existence of a long-run relationship between Henry Hub spot and futures prices, NBP spot and futures price, and TTF spot and futures prices. Results are robust to different maturities of futures contracts (one, two, and three months ahead contracts).

3.4.3 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 NB, and TTF gas hubs as it 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, we examine the time-scale components of the level series based on wavelet transformation²¹. Table 3.2 shows that for most of the cases, there is bidirectional Granger causality between Henry Hub spot and futures prices 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 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 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).

²⁰Results 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.

²¹We test Granger causality between the time-scale components of spot and futures prices in the three gas hubs based on an unrestricted VAR.

Furthermore, as in the case where the original 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 future 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 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 market 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 price, 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. Table 3.3 presents 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 3.3, 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. These results reflect the adjustment process towards the long-run relationship (See [Brenner and Kroner \(1995\)](#)).

Concerning the case of the NBP, the results are not unanimous across the different wavelet details

and vary between unidirectional causality from futures prices to spot market prices 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. Inconsistency 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 influence, 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 3.2: Multiscale linear Granger Causality test based on VAR.

<i>Henry Hub</i>													
		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
	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
Long scale	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
<i>TTF</i>													
		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
	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
Long scale	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
<i>NBP</i>													
		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
	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
Long scale	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 future to physical price returns. $S \rightarrow F$ means testing for a Granger cause from the physical prices to the futures prices.

Table 3.3: 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		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 cause from future to physical price returns. $S \rightarrow F$ means testing for a Granger cause from the physical prices to the futures prices.

Table 3.4: 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 cause from future to physical price returns. $S \rightarrow F$ means testing for a Granger cause from the physical prices to the futures prices.

Table 3.5: 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 future to physical price returns. $s \rightarrow F$ means testing for a Granger cause from the physical prices to the futures prices.

3.4.4 Informational efficiency 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 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 \(1999\)](#). According to table 3.6, we argue that results for raw data show deviation from the random walk behaviors, which cause the futures prices to be inefficient for the US and European markets. However, the multi-scaling findings demonstrate evolution of efficiency in time. The results reveal the multiresolution nature of the informational efficiency of the US Henry Hub, the UK NBP and the NL TTF futures prices. The random walk test exhibit significance at short and medium scales, that is from intra-week (D1), weekly (D2) and monthly (D4).

Table 3.6: Multiscale Automatic Bootstrap variance ratio tests- HH futures 1- NBP futures 1- TTF futures 1

	HH FUT 1		NBP FUT 1		TTF FUT 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 Wild Bootstrap p-value for the test. B. CI refers to the Confidence Intervals for Lo-Mackinlay tests from Bootstrap distribution. The corresponding P-value is the Bootstrap p-value for the Chow-Denning test.

Thus, the market is considered inefficient in short and medium run. At longer scales, informational efficiency is significantly reached. Several explanations can justify these findings. In fact, in short run, market participants exhibit low risk aversion levels and consequently, they depend upon low risk premium in the short run ([Gebre-Mariam, 2011](#)). This behavior could be interested by the limited hedging advantages, low opportunities in making storage and transportation arrangements, and insuffi-

cient 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 quantities²².

Furthermore, it is approved that news related to production and marketing of natural gas are not fully available to public (MacKinnon et al., 1999) , (Mu, 2007). In other words, information about natural gas markets are neither meticulous nor transparent. However, to guarantee futures market efficiency, it is indispensable to ensure that information and data on market fundamentals (e.i., demand, supply, production, imports, exports and prices of concurrent gas markets) are publicly available. Besides, factors that exhibit direct impacts on domestic and international natural gas prices, supply and demand (such as weather and storage) should be diagnosed and carried out. For all these reasons, these short run market conditions do not lead to reach market efficiency.

In the long run, investors exhibit higher risk aversion, implement higher storage and transportation costs and consequently call for higher risk premium (Gebre-Mariam, 2011). In fact, several circumstances lead to these behaviors such as, international political disturbances (e.i., oil production disruptions), weather conditions, asymmetry of market information, and irrational behaviors of market participants, (GAS, 2006). In addition, the market is characterized by its self-regulation process, (De Vany and Walls (1995), and Von Hirschhausen (2008)). In fact, long run price volatilities are confusing but are pretended to be self-correcting. This means that increasing prices intimidate future consumption and promote production and supply. Accordingly, the short fall of gas prices is appeased, and price picks are avoided. Though, the market self-correction come after overcoming several hardships.

Furthermore, the US and the European markets generate large storage, which make them prepared to future demand or supply shocks. That is why, in the long term, the market is able to transmit information and estimate future fluctuation. Consequently, natural gas market registers long term efficiency, despite the fundamental differences across countries and continents. Investors and policymakers across countries have to be aware about the dynamics of natural gas futures returns that can differ over time, as this can impact the industry performance and the financial markets. The issue relating natural gas futures emphasize strong effect on the dynamic hedging and risk management strategies.

3.4.5 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 choice off the wavelet transformation method, we repeated our analysis using the discrete wavelet transformation method (DWT)²³. Globally, results applied to HH, NB, and TTF for spot

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. It transforms time series from the time domain to scale domain.

and futures returns of 1, 2- and 3-months maturities are robust to the DWT wavelet decomposition. Moreover, the robustness of our specification to alternative wavelet transformation filter and length has been investigated. More specifically, we relied on the Daubechies Extremal phase filter with different wavelet lengths from 2 to 6. Again, results are still robust and are available upon request.

Comparison with the oil case

Whether based on linear or nonlinear Granger causality testing, the conclusion is quasi-unanimous for WTI with strong bidirectional causality between spot and futures prices of one, two, and three months maturities. These results are in perfect agreement to those of [Silvapulle and Moosa \(1999\)](#), [Bekiros and Diks \(2008\)](#) and [Alzahrani et al. \(2014\)](#) that have suggested non-linear causality between spot and futures prices in both directions. Relying on the time-frequency domain has allowed showing how strong and sustainable is the contemporaneous feedback relationship between spot and futures prices on both natural gas and oil markets. The latter remains very important for all timescales, whether intra-weekly, monthly or approximating the year. This relentless pricing efficiency is also detected when two- and three-months maturity futures are taken into account, which reinforces the robustness of the results. The bidirectional causality that we obtain between the spot and futures markets, invariable according to the time scales considered, implies that neither of the two markets leads the other. Therefore, the activity at the spot market is as likely to affect prices as futures markets. The hypothesis of excessive speculation on these markets is, therefore, rejected because the latter would have suggested that the causality is unidirectional with futures markets as leader. This last point confronts us with the lively debate about the impact of financialization on commodity markets: it appears that fundamentals seem to play a role equivalent to that of financial traders.

3.5 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 flow 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 are informationally efficient only in the long run. This last point shows that the multiresolution approach greatly enriches the analysis by extending the view of our time series from time-based to frequency-based. 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 when long-horizons are investigated, selecting yearly data rather than daily or weekly, the precision of statistical inference is altered because of fewer available data points: a crucial gain yielded by the wavelet analysis.

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 ([OECD et al., 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) follows a long-run equilibrium relationship with wholesale prices ([Mohammadi, 2011](#)). Henry Hub is at a single point of junction of independent pipelines in a continental pipeline transport system that is completely competitive. Trading of Henry Hub futures started in 1990, while trading of TTF futures only took off in 2010. Henry Hub 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 production²⁵. Its role in futures markets could hence only be duplicated in parts of the world where pipeline systems have highly competitive transport ([Makholm,](#)

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.

²⁵50% of US gas production in the past was transferred via it ([ACER, 2017](#)).

2016).

Secondly, a crucial distinction between US and EU gas markets lies on the fact that US Henry Hub 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 hubs²⁶. Physical and virtual gas trading hubs respond to a disparate structure 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 et al., 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 et al. (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 costs²⁷. Last but not least, flexible storage capacity is crucial for efficient intertemporal arbitrage activity²⁸. 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

²⁶ A 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)).

²⁷ They 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.

²⁸ Brennan (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

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 et al. \(2003\)](#)). 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](#)).

3.6 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 specification, controlling unfair speculation, commodity delivery system and coverage, infrastructural support, etc. As natural gas constitutes today a major commodity in the US and Europe 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 scale, and the three maturities as they vary between unidirectional causality from futures prices to spot market prices and bidirectional causality.

In summary, it is possible to conclude that Henry Hub, NB, and TTF markets show statistically significant bidirectional causality or unidirectional causality. It means that these markets are interconnected. 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 appealing new light on the true nature of causality between the NG spot and futures prices at NYMEX. Thus, this additional knowledge of the nature of causality may contribute 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.

APPENDICES**Appendix A:** Unit root tests

Table 7: 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***

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

Figure 2: MODWT Henry Hub spot returns.

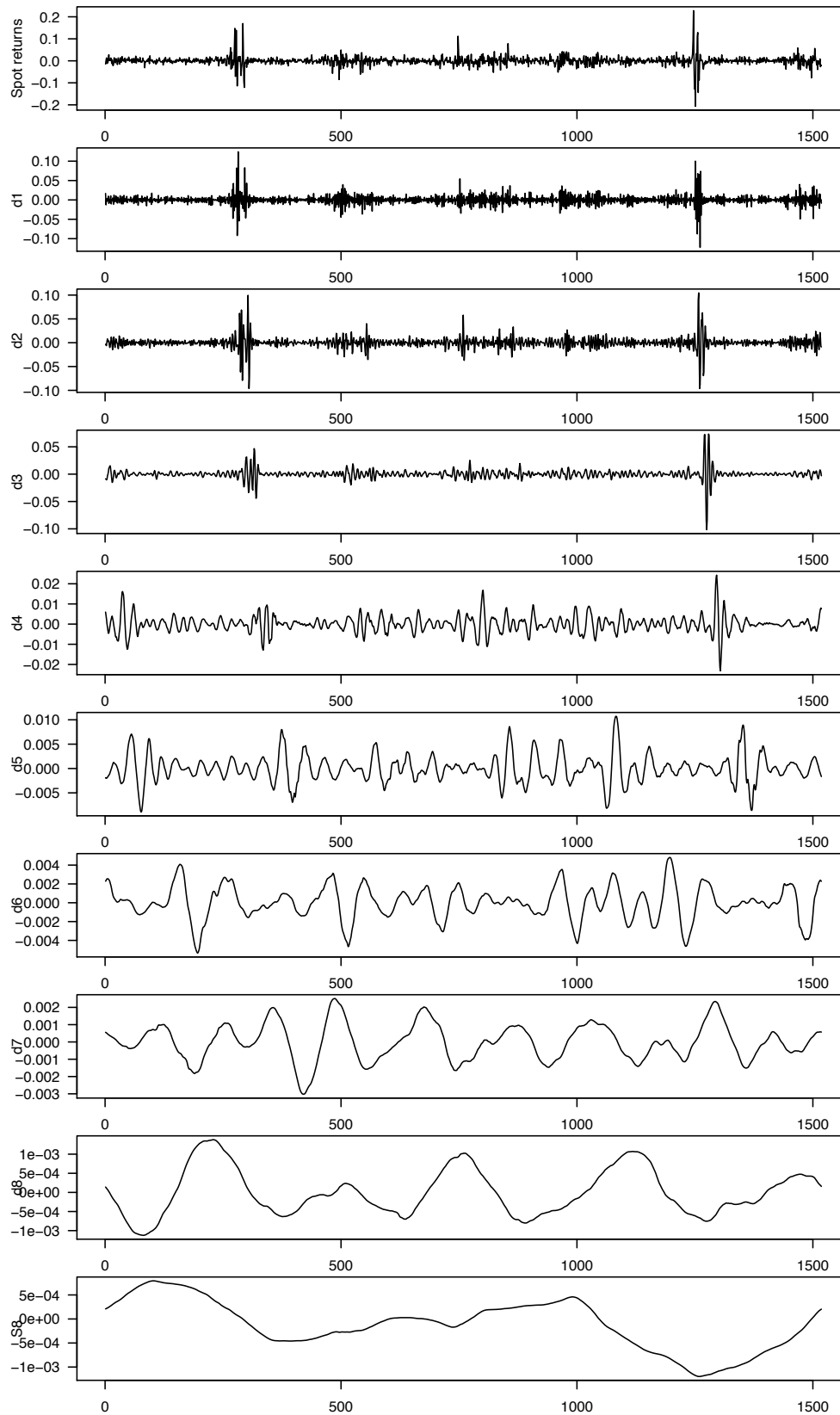


Figure 3: MODWT Henry Hub Futures (one-month ahead maturity) returns.

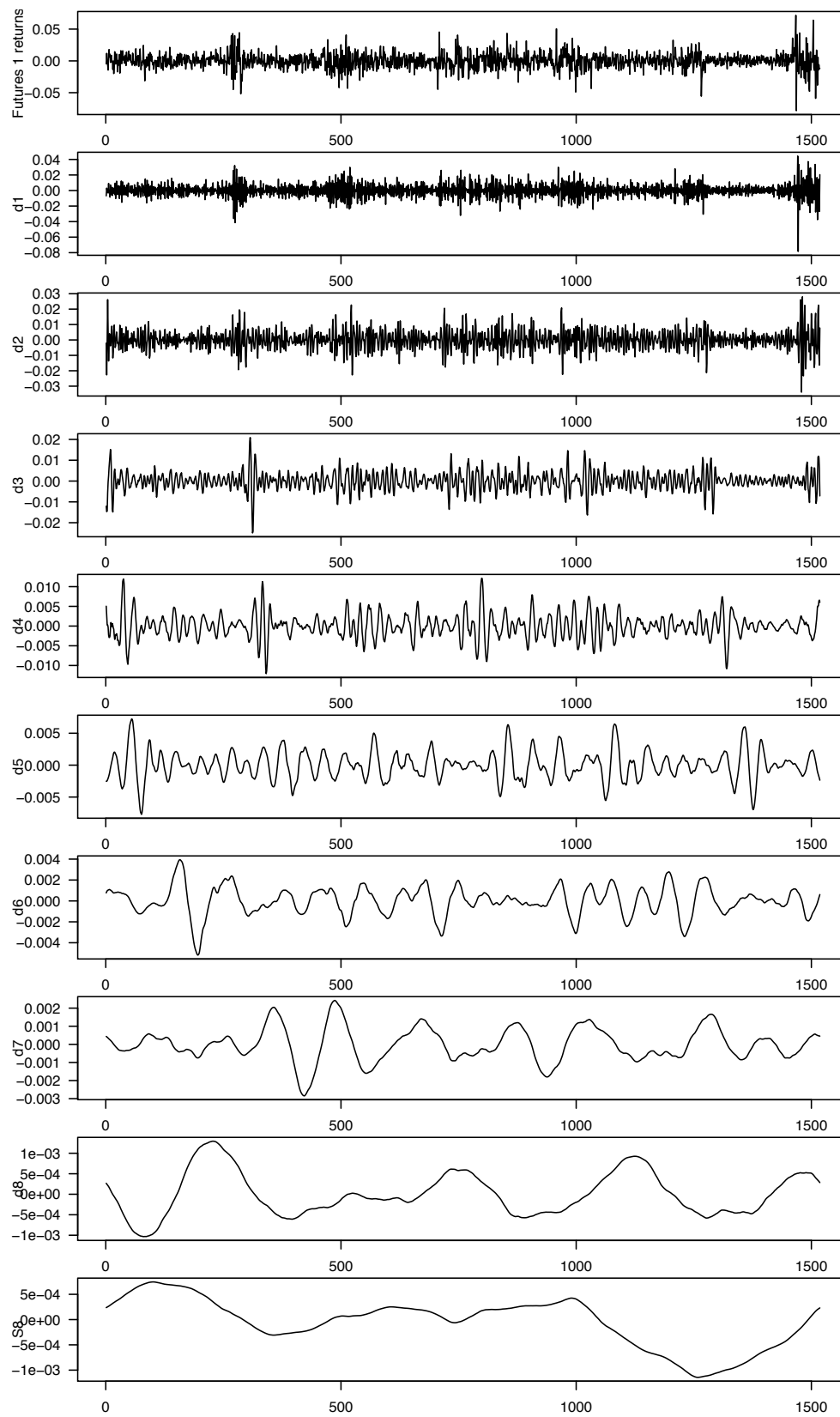


Figure 4: MODWT NBP spot returns(

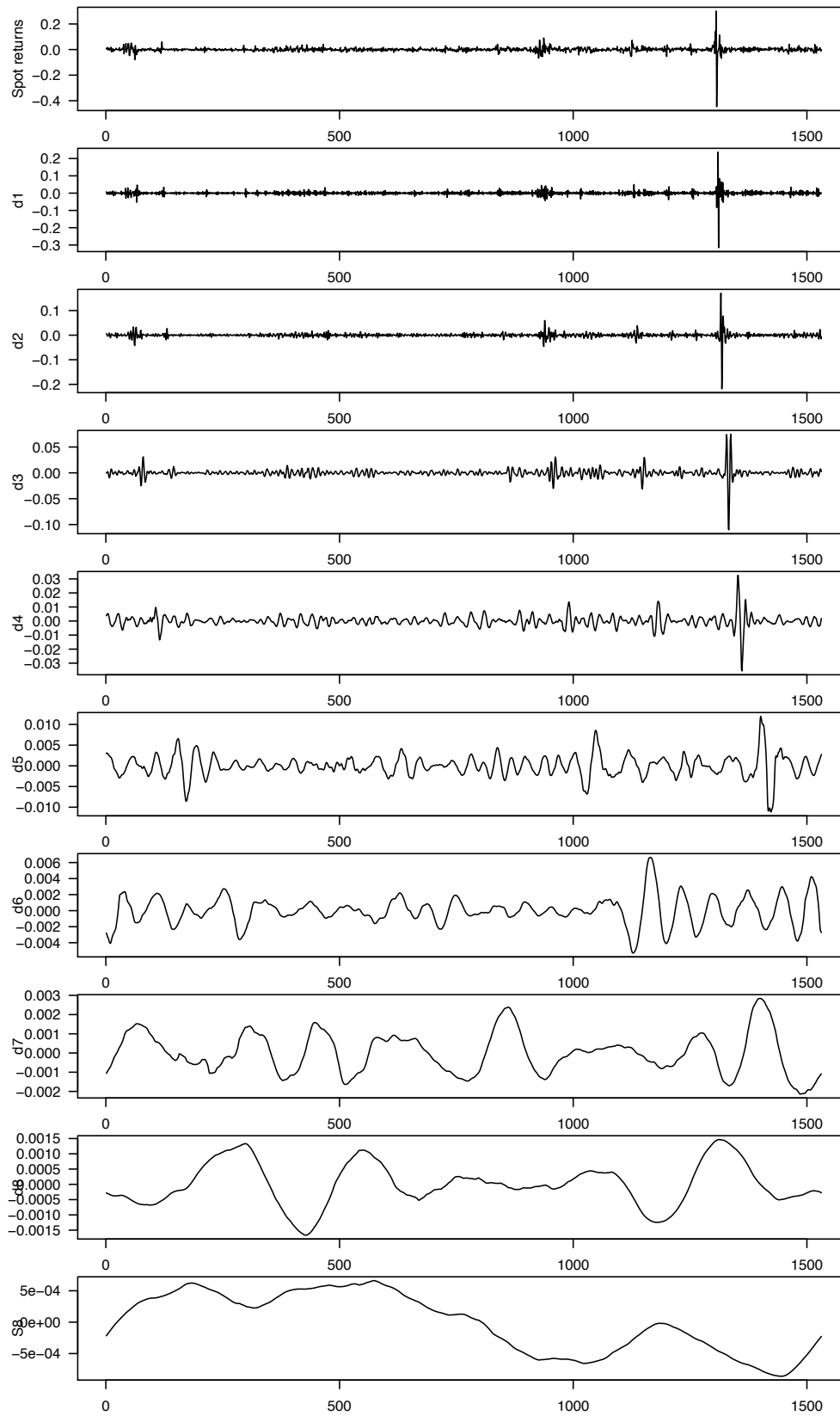


Figure 5: MODWT NBP spot returns(one-month ahead maturity).

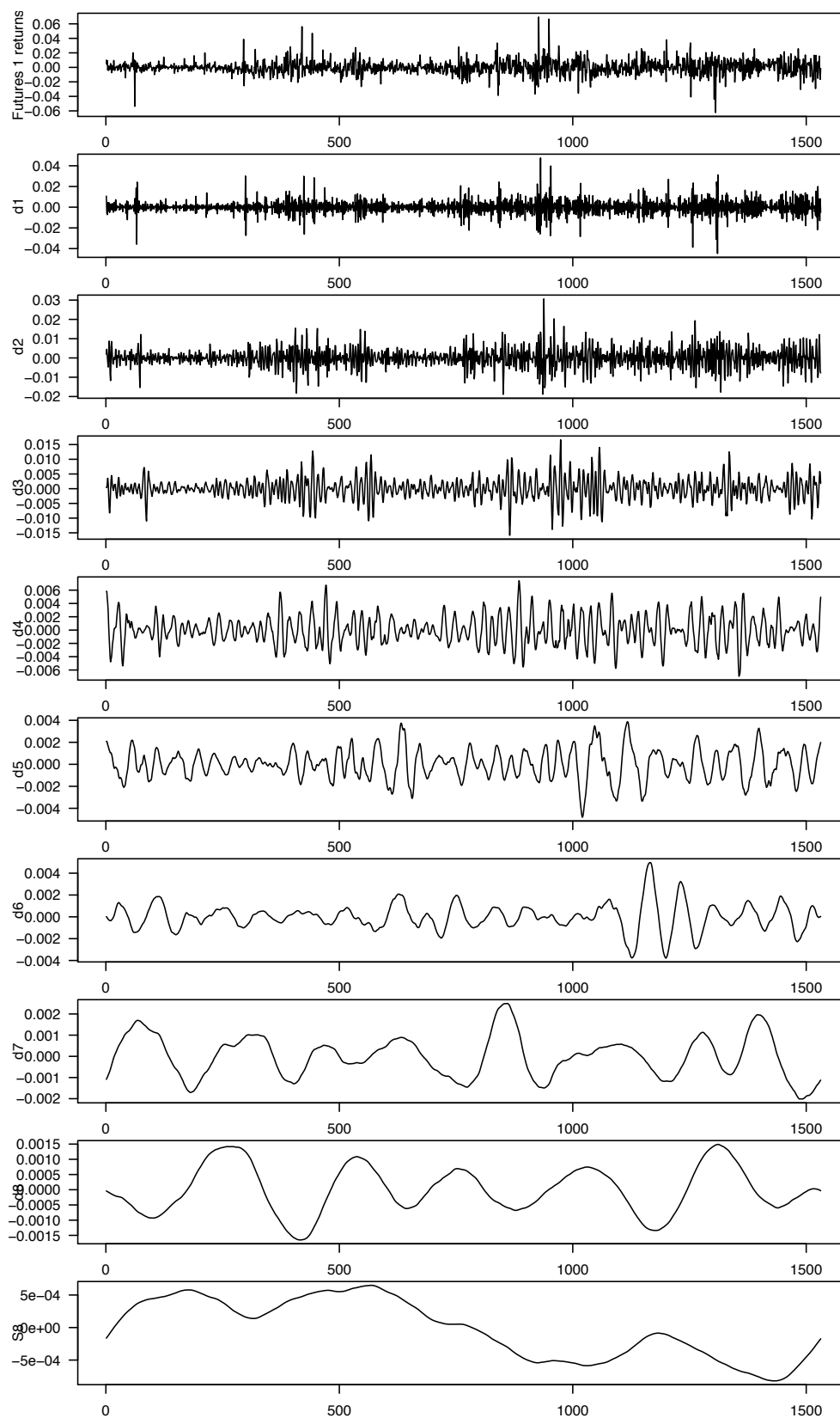


Figure 6: MODWT TTF spot returns

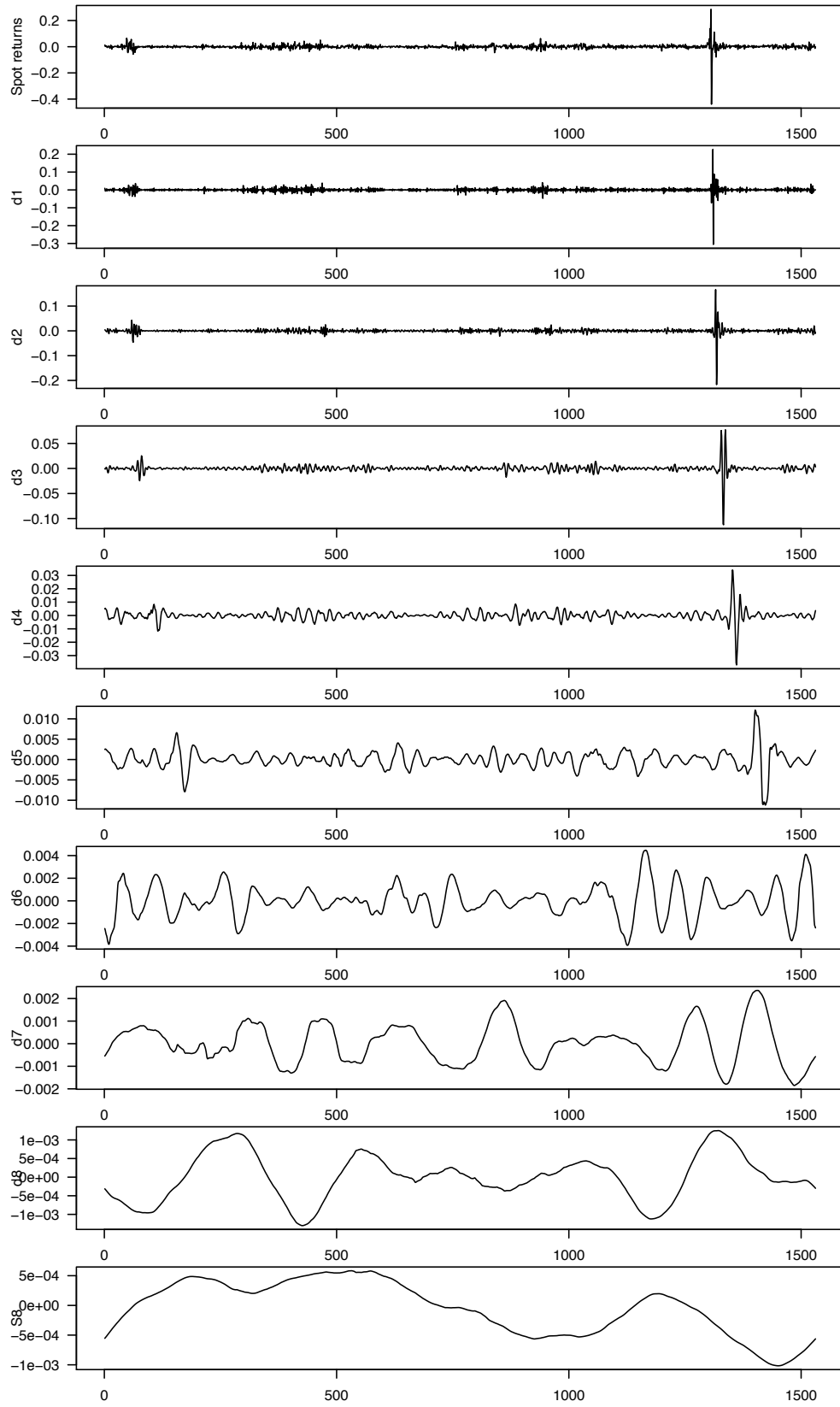


Figure 7: MODWT TTF Futures (one-month ahead maturity) returns.

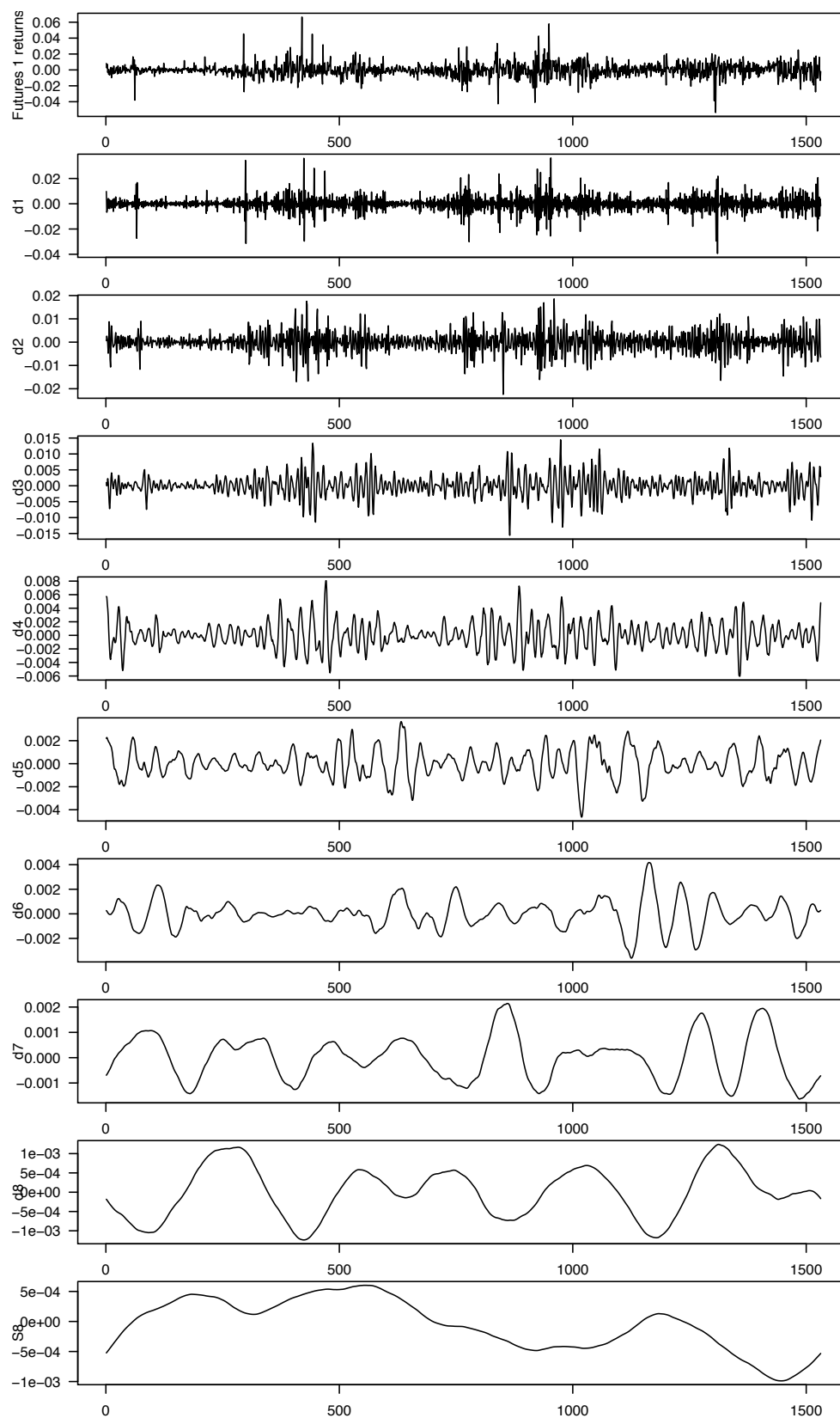


Figure 8: Wavelet cross-correlation between Henry Hub spot and futures1 returns.

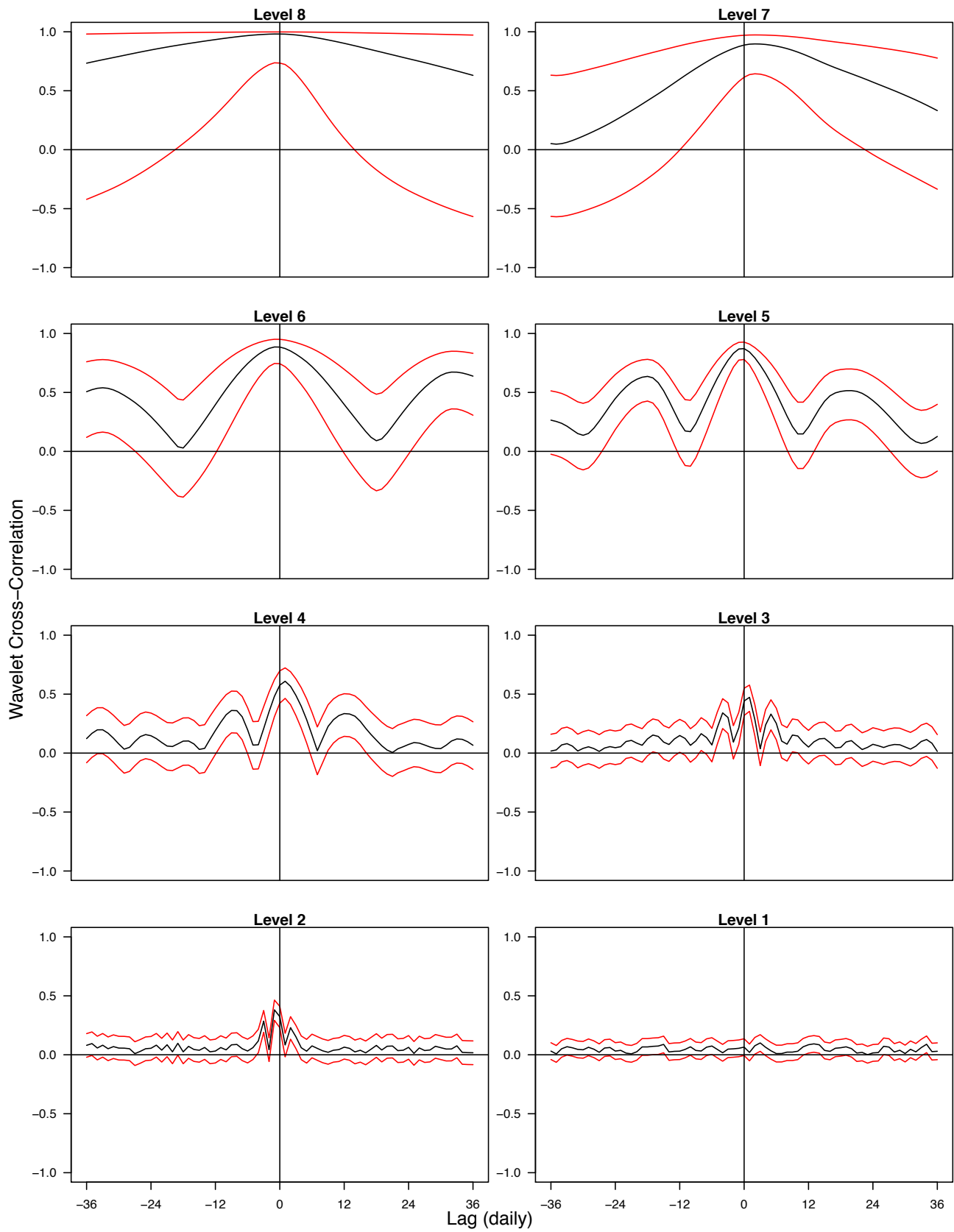


Figure 9: Wavelet cross-correlation between NBP spot and futures1 returns.

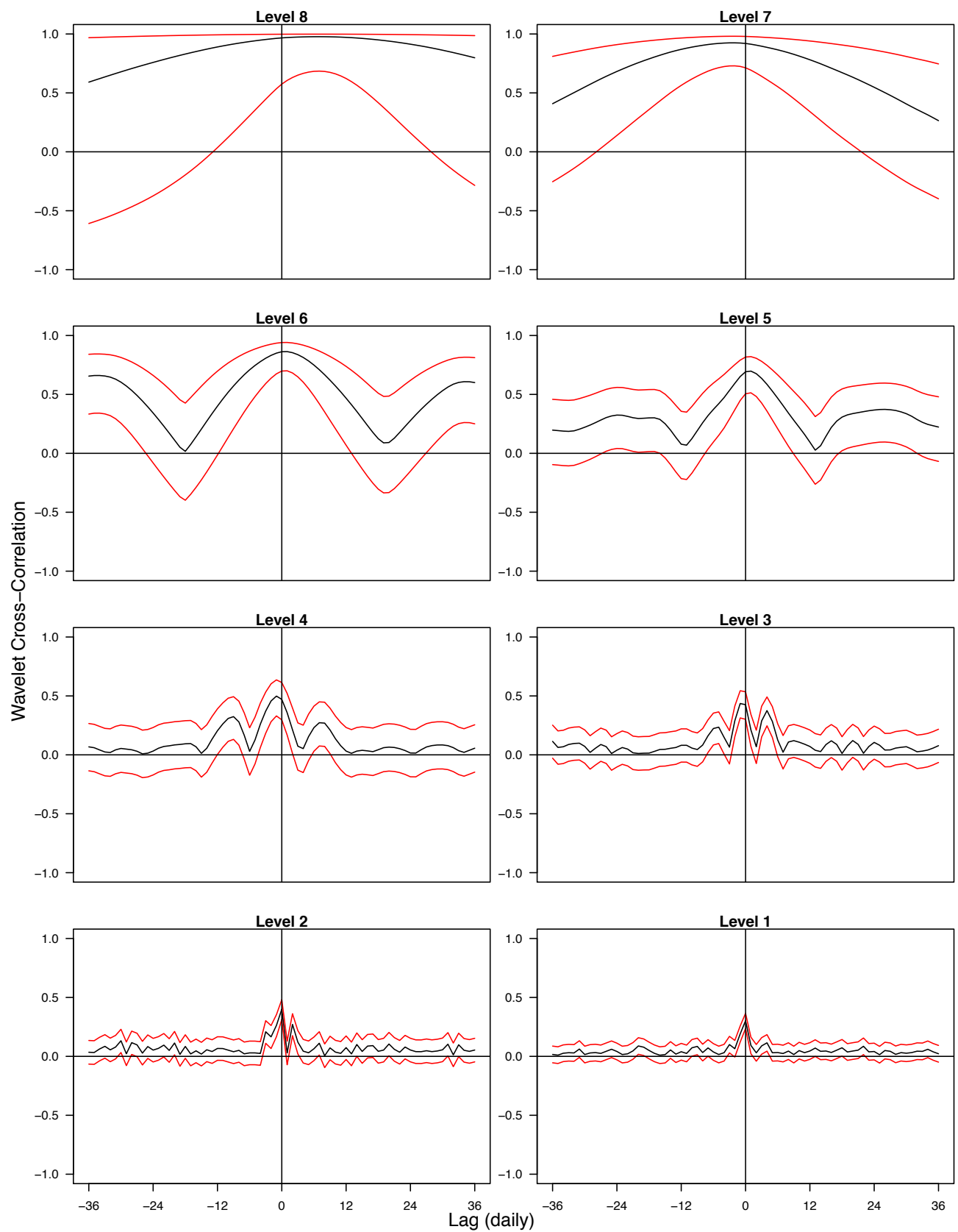
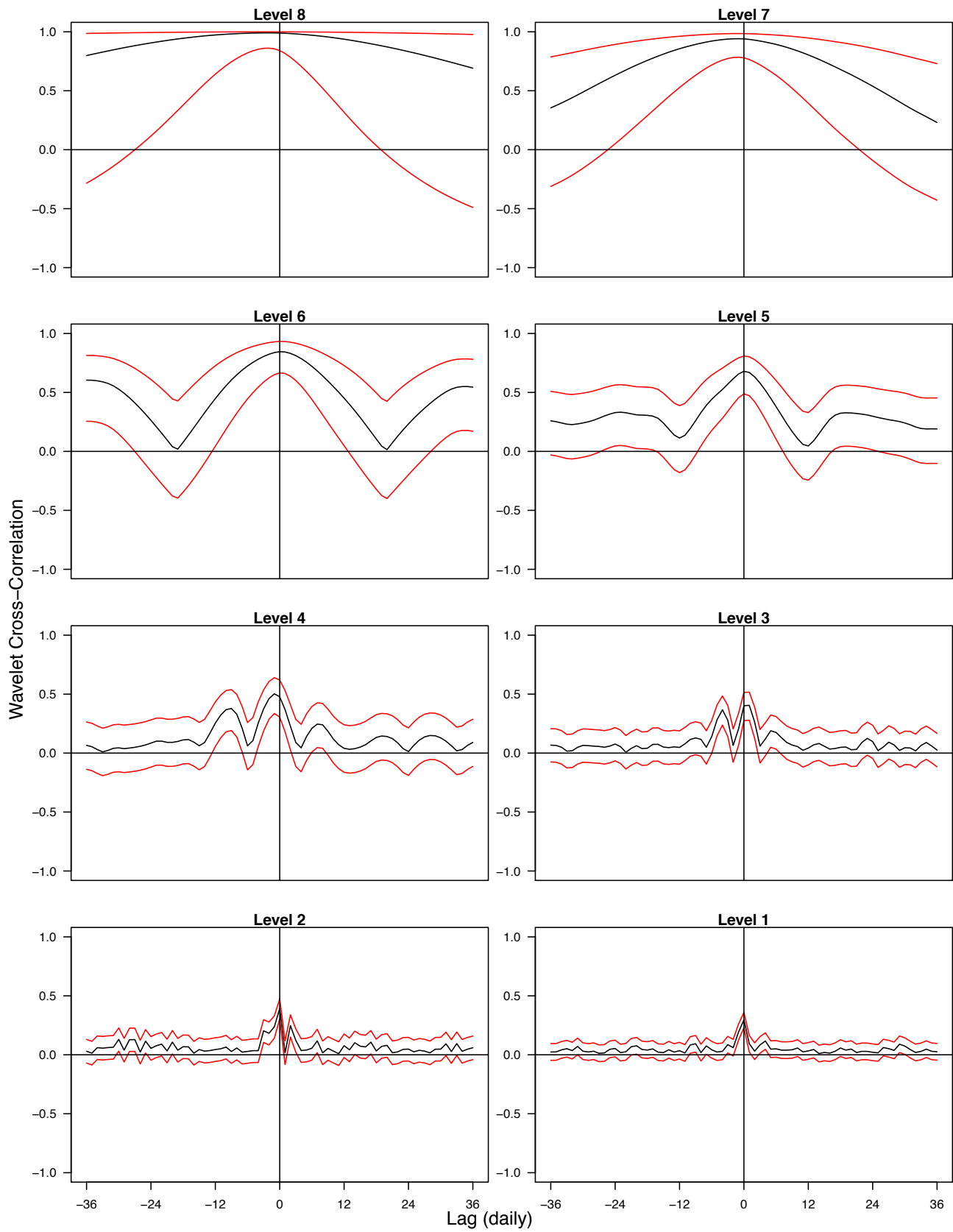


Figure 10: Wavelet cross-correlation between TTF spot and futures1 returns.



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

Table 8: 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>
2[2]*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
2[2]*NBP	None	0.1381	230.9784	0.0000	0.07926	128.9045	0.0000	0.0583	94.3893	20.26184
	At most one	0.0022	3.4421	0.5015	0.0017	2.6397	0.6499	0.0015	2.40365	9.164546
2[2]*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.

Appendix D: Linear Granger causality test based on VECM.

Table 9: Linear Granger causality test based on VECM.

2[3]*Timescale	<i>Maturity 1</i>				<i>Maturity 2</i>				<i>Maturity 3</i>			
	<i>S</i> → <i>F</i>		<i>F</i> → <i>S</i>		<i>S</i> → <i>F</i>		<i>F</i> → <i>S</i>		<i>S</i> → <i>F</i>		<i>F</i> → <i>S</i>	
Original level	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value	Chi-sq	P-value
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

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General Conclusion

Commodities are considered as a catalyst for economic progress and international trade growth. Undeniably, commodities are used as an alternative instrument for portfolio diversification benefits. In the early 2000s, the lower correlation between commodities and equities explained the expanded interest of different market participants (i.e., investors, hedgers, speculators) in considering physical and derivatives commodity assets as significant hedging instruments against equity markets volatilities and risks (Geman, 2005). This commodity financialization continued over the last decade until the financial crises of 2008. The emerging of new types of investors, trading strategies along with the massive inflows of money in commodity markets using new financial tools, endorsed their exposure to financial market news and movements (Stoll and Whaley, 2010). In fact, the investment in commodity index was roughly negligible, increased to 200 billion by 2002 and reached, to 400 billion in 2012 and to 817 billion in November 2018 (BIS).

Furthermore, recent theoretical²⁹ and empirical³⁰ studies found that financialization boosted the commodity-equity correlation. These market changes coincided with exceptional price movements; Indeed, commodity prices reached unexpended and unprecedented heights.

Given the importance of market conditions in managing portfolios and risks, I generate great interest in studying commodity spot-futures price dynamics and determinants. There was a spurt of publications in this area around this period. However, considering the theoretical input and several empirical gaps, this thesis waves strands of three empirical essays about commodity prices dynamics that date back about 20 years.

This dissertation consists of two interesting inter-related subjects. First, market efficiencies, along with market conditions and risks that recently occurred attuned the concern and the informativeness of extreme movements and higher moments in driving the commodity spot-futures relationship. Consequently, we focused our attention on this subject in chapter 1 and 3, by challenging the Efficient market hypothesis of Fama and French (1987). Second, we tried to detect the potential role of investor and market sentiment indexes on commodity prices by including the behavioral finance theory in energy markets. We used novel empirical techniques, usually used in equity and options pricing, and are

²⁹see Basak and Pavlova (2016)

³⁰see Büyüksahin and Robe (2014) and Creti et al. (2013)

familiar in finance but have scarcely been applied in commodity pricing models. Empirical approaches generated in this thesis have specific advantages that enables to answer the chapter objectif. The common character of the used methodology is the precision, the insensibility to extreme changes and the caption of maximum of market news without information loss.

In chapter 1, we investigate the dependence between spot and futures returns for a set of top traded energy, agricultural, precious metals, and soft commodities, during market extreme movements. Empirically, we selected four types of copulas to detect symmetric³¹ and asymmetric³² dependencies, combined with three GARCH models to estimate marginal distributions. Our findings disclose essential features of the futures-spot dependence in all market conditions (i.e., neutral, bullish, and bearish markets). This price discovery process is related to the commodity type, the market properties, and the storage process. Crude oil spot-futures dependency is asymmetric and declines when the market enters into extreme bearish conditions. Precious metals and cotton exhibit high dependencies in all market conditions; they show strong resistance to extreme changes.

Consequently, investors can use these commodities as a safe haven to hedge against risk during high volatilities, given their substantial informational efficiencies. Besides, agricultural commodities (soybean and wheat) show significant dependence in normal to bull market conditions. Exceptions are registered in natural gas and sugar markets, where spot-futures dependencies demonstrate low levels in good and bad market conditions. These kings of disconnections require advances interventions from risk managers and market regulators to stabilize market dynamics and guarantee informational efficiencies.

These results challenge the classical efficiency theory proposed by fama in the 70's and in the 90's, given the emerge of important and significant new features in the market (new classes of traders, financial instruments and trading strategies. That is why, in the following chapter, I take a broader approach and investigated this distinctive feature.

Indeed, the huge emerge of different types of investors in commodity markets along with the raising contagion between equity and commodity markets, make quite plain the value of looking beyond price fundamentals and incorporating sentiment proxies in explaining price volatilities. Besides, some apparent anomalies are detected, challenging the rational pricing literature and theories. That is why, chapter 2, motivated by the behavioral finance theory, investigates the time-frequency non-linear causalities between energy (crude oil and natural gas) futures prices and sentiment indexes. To do so, we employ the variational mode decomposition approach to be able to analyze our issue in different time frequencies

³¹To detect symmetric dependence, we used Normal copula (which considers that dependence is symmetric and steady in upper and lower tails) and Frank copula (which considers that dependence is symmetric and low in upper and lower tails)

³²To detect asymmetric dependence, we refer to Gumbel copula (which considers that dependence is asymmetric and strong in Upper tail only) and Clayton copula (which considers that dependence is asymmetric and strong in lower tail only)

(short, medium, and long run) combined with the non-parametric granger causality test. This methodology is robust to information loss, structural break, and error misspecification, which usually appear in commodity prices time series (Shahzad et al., 2017). The findings are challenging to classical pricing theories. First, there are significant casualties between crude oil futures returns and the Economic Policy Uncertainty (EPU) index in the short, medium, and long run. However, the direction changes in different time frequencies. In the short run, crude oil returns significantly cause economic uncertainty, while in the medium run causality remains to be bidirectional. In the long run, economic policies exhibit high uncertainty due to strong crude oil volatilities, major macroeconomic events, and political changes.

Consequently, they have the power to drive crude oil prices. However, there are significant causal flows from EPU to natural gas prices in the short-term caused by uncertainty in supply and demand policies and global political changes. In the medium and long run, natural gas causes EPU. Regarding individual investor sentiment, we conclude that bear investor sentiment better predicts energy returns compared to the bull sentiment index. However, bearish investors show significance over the entire sample period, and for all the time-frequencies, while bullish investors manifest only in the long run. This can be explained by the awareness of financial investors about information flows in both financial and commodity markets. Third, the Volatility Index (VIX) has better estimative power for crude oil returns compared to natural gas returns. However, it has lower predictive power compared to the other sentiment proxies. These results infer that sentiment proxies have essential implications on energy returns. Moreover, the time-frequency domain should be taken into consideration in order to conduct efficient investment strategies and favorable risk management decisions.

In the previous chapter, I noticed that natural gas market register always exceptional results, as the disconnection between spot and futures prices during market extreme conditions. I believe that these results needed further attention and broader exploration. That is why, the chapter 3 intends to shed more lights on international natural gas market efficiency to explain its corresponding outstanding behavior.

Consequently, chapter 3 analyze time-frequency pricing and informational efficiencies for three natural gas markets to conduct a comparative study between the American and the European markets. A multiscale linear and non-linear Granger causality methods are adopted in addition to random walk testing. The methodology relies 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 for the period between 2013 and 2019. Our results show significant cointegrations in all the natural gas spot and futures prices. Whereas the multiscale causalities show strong bidirectional causalities between Henry hub spot and futures returns in all market frequencies. However, the European markets exhibit lower pricing efficiency across frequencies and maturities. Regarding informational efficiency, the random walk test results are quite similar; markets demonstrate informational efficiency in the long run.

The role of commodity prices is crucial to guide efficient investment strategies, to allocate resources, and to manage risks. In this thesis, I envision different types of market participants by conducting a comprehensive analysis of commodity price dynamics. First, I target practitioners, particularly those specialized in commodity trading and risk management. I believe that the results provide important clarifications and frameworks that can help investors understand new market features that impact prices and how they do so.

Also, I aim policy makers given that commodity prices are always a bone of political disruptions. The intensity of commodity-related controversies has attracted growing interest over time. From the early 2000s until now, commodity prices register severe crashes and spikes. Consequently, they provoke widespread denunciation of the baneful consequences of speculation in commodities. These facts led to several regulatory actions. In this context, the US Congress has imposed limits on commodity speculation to regulate the market in 2010, whereas the European Union endorsed the commodity speculation and consider it as a policy priority. Thereby, I detect distortions in the most traded commodity markets, among others that may require policy intervention.

Together these three chapters of this thesis provide strong challenging results to the efficient market hypothesis. The emerge of so many traders, the new market drivers and the increasing investment explain the abnormal movements of commodity prices registered in recent years. These results do not mean that fundamentals do not play a role in causing commodity prices volatilities. However, new determinants should be taken into account when conduction an investment strategy of forecasting future prices such as behavioral aspects measured by sentiment indices. Indeed, behavioral finance started to significantly manifest in commodity markets.

Future research prospects

In this thesis, I investigated recent evolutions in the commodity markets regarding the financialization, recent financial crises, and market booms and busts. Nevertheless, the nature of commodity investors, financial instrument and trading strategies is changing expeditiously. Indeed, new generations of commodity indices grew in popularity, and are used in different hedging and rolling strategies. These facts grow the market exposure and heightened the cross-market correlation. However, the financial sector also continues to develop new investment tools and strategies.

Besides these facts, finance has crept into commodity markets in severam nes ways that are not involved in this thesis, but are equally interessting and important.

That is why, we need to explore the potential of commodity investments in terms of diversification benefits and in the context of a portfolio management. In future work, we need to focus on commodity

indices movements, the changing causes and roots of the market movements, and the way in which it may impact the market. We can distinguish between the type of traders and analyze their impact on commodity prices. We need to conduct a theoretical research that analyze the impact of different type of investors on markets. Although, [Büyüksahin and Robe \(2014\)](#) concluded a significant different impacts of speculation by type of trader on commodity markets, the present investigation is totally empirical and findings show the importance of hedge fund among others in predictiong the commodity equity cross linquage.

That is why, a theoritical explanation updated to market new features could be a significant contribution to the financial literature .

Moreover, We can investigate the impact of trading volume, open interest and traders' positions on the information flow between spot and futures prices. I believe that this information deserves a higher attention as it can increase the transparency of the market. Sharing such results contribute to ameliorate the market efficiency. Moreover, it would be interesting if we include a larger set of commodities as results could significantly change from a commodity to another.

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RÉSUMÉ

Il est important d'analyser la spécification de l'efficacité des marchés des matières premières et l'impact du comportement des investisseurs sur leurs prix pour optimiser les stratégies de négociation et de gestion des risques. De plus, étant donné le nombre élevé de changements extrêmes sur les marchés, il est important d'analyser les prix dans une perspective temps-fréquentielle et de prendre en compte toutes les conditions du marché. Cette thèse couvre les nouvelles caractéristiques des marchés des matières premières en utilisant des méthodes empiriques récentes et en intégrant les derniers développements en matière d'économie des produits de base et d'économétrie financière. Dans cette thèse, nous prouvons que l'efficacité des marchés des matières premières est sensible aux différentes conditions du marché et aux différentes fréquences temporelles. Les résultats dépendent de la nature du produit, de son processus de stockage, de sa dynamique et de ses volatilités. Le premier chapitre porte sur la dépendance entre le prix au comptant et les prix à terme pendant les périodes de volatilités extrêmes positives et négatives. Le deuxième chapitre sensibilise la théorie de finance comportementale et porte sur l'impact des indices de sentiment des marchés et des investisseurs sur les prix à terme de l'énergie, en prenant en compte le court, le moyen et le long terme. Le troisième chapitre est une étude comparative entre les marchés américains et européens du gaz naturel ; Nous explorons l'efficacité de la tarification et de l'information dans un domaine temps-fréquentiel. Nous confirmons les différentes réactions des produits aux conditions du marché et concluons que les métaux précieux sont les plus efficaces, alors que le marché du gaz naturel est le plus sensible. Nous confirmons également les liens de causalité bidirectionnels et unidirectionnels entre le prix à terme des énergies et plusieurs indicateurs de sentiment, confirmant la présence des aspects comportementaux les marchés boursiers des énergies. Enfin, nous concluons que le marché américain du gaz naturel est plus efficace que le marché européen du gaz naturel.

MOTS CLÉS

[Marchés de matières premières, prix au comptant et prix à terme, efficacité de marché, sentiment d'investisseurs, finance comportementale, économie de l'énergie.]

ABSTRACT

The specification of commodity market efficiency and the impact of investors behavior on commodity prices are important to analyze in terms of profit-making, trading strategies, and risk management. Moreover, given the high occurrence of market extreme changes, it is important to analyze commodity prices in a time-frequency perspective and to consider all market conditions. This thesis attempt to cover recent features in commodity markets efficiency using recent empirical methods and including the latest developments in commodity economics and financial econometrics. In this thesis, we prove that commodity market efficiency is sensitive to different market conditions and to different time-frequencies. The results depend on the nature of the commodity, its storage process, its dynamics, and volatilities. The first chapter the dependence between commodity spot and futures prices during positive and negative extreme periods. The second chapter explicit the behavioral finance theory in commodity markets and focus on the impact of market and investor sentiment on energy futures prices, taking into consideration the short, medium, and long-term. The third chapter is a comparative study between the American and the European natural gas markets; We explore the pricing and informational efficiencies in a time-frequency domain. We confirm the different reactions of commodities to market conditions and we conclude that precious metals are the most efficient, whereas the natural gas market is the most sensitive. We also confirm the bidirectional and unidirectional causalities between the energy futures process and several sentiment proxies. Finally, we conclude that the American natural gas market is more efficient compared to the European natural gas market.

KEYWORDS

[Commodity markets, spot and futures prices, market efficiency, investor sentiment, behavioral finance, energy economics.]