Essays on the transmission of shocks between financial, energy and food markets : transmission channels, measurement, effets and management

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Essays on the transmission of shocks between financial, energy and food markets: Transmission channels, measurement, effects and management

Essais sur la transmission de chocs entre les marchés financier, énergétique et alimentaire : Canaux de transmission, mesure, effets et gestion

Thèse Nouveau Régime

Présentée et soutenue publiquement le 22 Septembre 2017

Pour l'obtention du grade de Docteur en Sciences de Gestion

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- CRCGM (EA 3849) -

Acknowledgments

First of all, I would like to express my sincere gratitude to my supervisor Professor Mohamed AROURI for his confidence, patience, support, continuous guidance and helpful advice during the different steps of this thesis preparation.

I would like also to thank the Head of the Research Center in Business and Management of Clermont-Ferrand (CRCGM) for having accepting me to be member of this center.

My special thanks go to all the members of the jury, Professors Christophe RAULT and Julien FOUQUAU for having accepting to report this thesis, Professors Benjamin WILLIAMS and Ouidad YOUSFI for agreeing to participate to the jury of this thesis defense.

I am grateful for the endless support and encouragement which my family has given to me in every situation making my years of study enjoyable.

My deepest thanks go out to my husband Abdelwahed BARKAOUI for his enthusiasm and his continuous encouragement without them this thesis would never have existed.

Thank you to all the people who contributed in some way to the accomplishment of this work.

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1. Introduction

Au cours de la récente crise financière mondiale de 2007-2008, les prix des marchés alimentaires internationaux (notamment les produits agricoles clés, y compris le maïs, le soja et le blé) ont enregistré une forte augmentation de leur niveau et ont été caractérisés par une volatilité élevée. Ce comportement était comparable à celui des marchés énergétique et financier pendant la majeure partie de l'année 2008, suggérant ainsi une relation étroite entre les trois marchés.

Cette volatilité des prix des commodités alimentaires n'a pas été sans conséquence. En effet, elle a entraîné une augmentation par environ 75 millions du nombre de personnes en situation de malnutrition. Aujourd'hui, le nombre de personnes souffrant de faim dans le monde a atteint environ un milliard (FAO, IFAD, 2015). L'impact de la volatilité des prix alimentaires sur l'indice de la faim est plus tangible pour les pays vulnérables qui sont des pays pauvres où les ménages consacrent une grande partie de leur revenu pour leur alimentation.

Etant donné l'importance des prix de commodités alimentaires dans l'indice de prix du consommateur dont ils constituent une composante principale et aussi dans la prise de décisions afférentes notamment à la conception de politiques monétaires (Anzuini et al., 2013), un long débat a été déclenché sur l'évolution de ces prix et l'origine de leur volatilité. Cependant, les conclusions dans la littérature pour ce sujet restent controversées en raison de l'implication d'une multitude de facteurs ; ce qui rend cette question une priorité élevée pour l'économie mondiale et un sujet d'actualité puisque les fortes volatilités peuvent menacer la stabilité du marché et peuvent avoir des effets néfastes sur la sécurité alimentaire (Alam and Gilbert, 2017).

Afin d'assurer la sécurité alimentaire, différentes mesures visant à réduire la volatilité des prix des commodités alimentaires ont été discutées dans la littérature (Gilbert, 2012) et ont fait l'objet d'études par de nombreuses organisations internationales. Ces mesures sont liées aux accords de prix multilatéraux, aux disciplines plus strictes de contrôle des exportations, aux

dispositions pour accroître la disponibilité des stocks et pour contenir ou limiter la demande à des fins non alimentaires. Elles se rapportent aussi aux moyens de gestion des risques notamment à travers les marchés à terme des commodités. Le sujet a été également largement débattu au niveau du plan d'action du G20 accordant une attention particulière aux questions liées à la régulation des marchés de commodités. Ce plan d'action met en évidence l'importance d'améliorer l'information sur les marchés de commodités et sa transparence (aussi bien pour les marchés physiques que pour les contrats à terme) afin de permettre aux acteurs du marché de former leurs attentes sur la base des fondamentaux du marché (Tadesse et al., 2014). Comme initiative du G20, le système d'information sur les marchés agricoles (AMIS) a été créé en 2011 dans le but de fournir l'information sur les marchés et d'améliorer sa transparence. Initialement, ce système s'intéresse aux quatre grains qui sont particulièrement importants dans les marchés alimentaires internationaux (blé, maïs, riz et soja). La Conférence des Nations Unies sur le commerce et le développement (UNCTAD/TDR, 2011; UNCTAD, 2012a, 2012b) insiste sur l'importance de réponses politiques et réglementaires fortes et rapides sur les marchés financiers, associées à des mesures relatives aux marchés physiques afin de faire face à la volatilité des prix des commodités causée par la financiarisation. Récemment, un ensemble d'objectifs de développement durable a été adopté par la communauté internationale en 2015 dans le cadre du programme de développement durable à l'horizon 2030. L'un de ces objectifs est « *Eliminer la faim, assurer la sécurité alimentaire, améliorer la nutrition et promouvoir l'agriculture durable* » notamment à travers l'adoption de mesures appropriées pour assurer le bon fonctionnement des marchés de produits alimentaires et leurs produits dérivés et pour faciliter l'accès rapide à l'information sur le marché, y compris sur les réserves alimentaires, afin de limiter la volatilité extrême de ses prix.

La volatilité des prix des commodités alimentaires conduit à réfléchir à ce que la trajectoire du système global alimentaire n'est plus simplement guidée par le règlement des facteurs fondamentaux liés à l'offre et la demande (Kagraoka, 2016; Kristoufek et al., 2012; Prakash and Gilbert, 2011; Serra and Zilberman, 2013; Tadesse et al., 2014; Zhang et al., 2010). Des chocs exceptionnels provenant d'une multitude de sources externes ont un effet sur les prix alimentaires. Les travaux dans la littérature ont relativement admis que plusieurs facteurs ont joué un rôle dans cette volatilité à savoir les chocs climatiques, les fluctuations du taux de change, la volatilité des prix du pétrole, la dépréciation du dollar américain, les politiques monétaires, la croissance économique soutenue dans plusieurs grands pays en développement, l'augmentation des coûts de production et des coûts de transport, la poussée de la demande sur

les marchés à terme des commodités, résultant à la fois de la spéculation et de la diversification des portefeuilles, les niveaux de stocks ainsi que les politiques commerciales. La littérature récente accorde de plus en plus d'attention aux facteurs liés aux effets de contagion entre les marchés à travers les transmissions de rendements ou de volatilités (Gutierrez, 2013; Liu et al., 2017) et souligne que la volatilité des commodités alimentaires pourrait être encore amplifiée dans le futur par le resserrement davantage des liens entre les marchés alimentaire, énergétique et financier.

Néanmoins, les conclusions de cette littérature récente restent controversées. Cette thèse s'inscrit dans cette perspective et a pour objectif d'étudier les liens entre les marchés internationaux alimentaire, énergétique et financier en termes de transmission de rendements et de volatilités et en termes de dépendance notamment durant les événements extrêmes. Elle vise également à comprendre comment en déduire de l'information pour une meilleure gestion du portefeuille.

Cette thèse contribue à la littérature sur le sujet en particulier à travers la prise en compte des liens complexes entre les trois marchés; alors que la plupart des travaux antérieurs ont examiné les liens entre le marché alimentaire d'une part, et les marchés énergétique ou financier d'autre part. En comparaison avec la littérature ayant accordé une importance à la transmission de rendements entre ces marchés, notre travail se distingue par l'attribution d'un intérêt particulier à la transmission de volatilités. En outre, nous nous intéressons à différents types de commodités alimentaires contrairement aux travaux précédents qui se sont focalisés principalement sur les céréales. Notre étude se base sur les prix spot des commodités en plus du lien entre les prix spot et les prix à terme, alors que la plupart des études antérieures ont utilisé les prix à terme en raison de l'indisponibilité des données. Nous considérons la variation des résultats au cours du temps permettant ainsi de vérifier l'impact des éventuelles ruptures structurelles. Les méthodes communément utilisées dans la littérature pour l'analyse de la volatilité des prix correspondent aux modèles d'hétéroscédasticité autorégressive conditionnelle généralisée (GARCH) présentant certaines limites que nous proposons de les dépasser en recourant à de nouvelles méthodes.

C'est une thèse par essais constituée de quatre chapitres visant à:

- Fournir un aperçu de la littérature existante se rapportant à ce sujet (Chapitre 1);
- Examiner l'efficience du marché alimentaire en comparaison avec le marché énergétique et les implications sur la couverture du risque (Chapitre 2);

- Étudier les effets des chocs des marchés financier et énergétique sur les prix des commodités alimentaires en termes de transmission de rendements et de volatilités et explorer les implications sur la diversification du portefeuille (Chapitre 3);
- Analyser l'impact des événements extrêmes sur la dépendance entre les marchés alimentaire, énergétique et financier et vérifier les implications sur la gestion du risque du portefeuille (Chapitre 4).

2. Chapitre 1 - Revue de la littérature

Le premier chapitre fournit une revue sommaire de la littérature sur les potentiels facteurs impactant la volatilité des prix des commodités alimentaires avec un focus sur les travaux récents accordant une importance particulière aux liens entre les prix des marchés énergétique, financier et alimentaire en termes de transmission de chocs de rendements ou de volatilités ainsi qu'en termes de dépendance. En lien avec notre problématique, nous nous sommes intéressés aux travaux conduits exclusivement sur les marchés internationaux. Cette revue de la littérature nous a permis de détecter une divergence entre les résultats obtenus expliquée par la différence entre les techniques de modélisation utilisées, les commodités considérées, la période objet de l'étude ainsi que la fréquence des données utilisées.

En effet, pour les liens entre les marchés alimentaire et énergétique, les travaux dans la littérature peuvent être classés en trois groupes.

Le premier groupe souligne les liens significatifs entre les prix des commodités alimentaires et énergétiques (e.g. Akram, 2009; Baffes, 2007; Balcombe, 2011; Busse et al., 2011; Chang and Su, 2010; Chiu et al., 2016; Ciaian and Kancs, 2011a; Gardebroek and Hernandez, 2013; Ji and Fan, 2012; Koirala et al., 2015; Mensi et al., 2014b; Serra et al., 2011).

Le deuxième groupe indique que les liens entre les deux marchés ne sont pas tout le temps significatifs et souligne leur intensification après certaines ruptures structurelles correspondant à différentes crises (e.g. Du et al., 2011; Han et al., 2015; Kristoufek et al., 2014, 2012; Nazlioglu, 2011; Nazlioglu et al., 2013; Reboredo, 2012; Wang et al., 2014).

Toutefois, le troisième groupe de travaux témoigne de l'absence de lien direct entre ces deux marchés (e.g. Gilbert, 2010; Kaltalioglu and Soytas, 2011; Zhang et al., 2010).

La plupart des études soulignant les liens significatifs entre les marchés alimentaire et énergétique indiquent que ces liens sont principalement expliqués à travers trois canaux clés de transmission. Le premier canal correspond à l'utilisation du pétrole pour la production agricole.

Le deuxième canal est lié à l'utilisation des commodités agricoles comme matière première pour la production des biocarburants à la suite de la croissance des prix du pétrole ; étendant ainsi la relation bivariée entre les marchés alimentaire et énergétique à une relation trivariée. Quant au troisième canal, il se rapporte aux facteurs macroéconomiques liant indirectement les marchés énergétique et alimentaire tels que l'appréciation et la dépréciation des taux de change, les conditions et politiques monétaires, et la financiarisation des marchés de commodités. Une attention particulière a été accordée durant les dernières années à la financiarisation des marchés de commodités et ce à l'issu de l'intégration rapide des marchés boursiers et obligataires avec les marchés de commodités (Adams and Glück, 2015; Creti et al., 2013; de Nicola et al., 2016; Han et al., 2015; Pal and Mitra, 2017).

En ce qui concerne les liens entre les marchés alimentaire et financier, deux points de vue opposés ont été distingués dans la littérature (Cheng and Xiong, 2014a). Le premier point de vue explique les liens entre ces marchés par la financiarisation des commodités (Baldi et al., 2016; Reboredo, 2012); tandis que le deuxième appuie l'impact de l'évolution des fondamentaux du marché sur les prix. Au regard de l'accroissement de l'investissement notamment dans les commodités agricoles à terme à l'issu de la financiarisation des marchés de commodités, la littérature empirique s'est focalisée sur la couverture du risque des commodités et les opportunités de diversification du portefeuille. Une grande partie des travaux suggère que les prix spot et à terme des marchés de commodités constituent des instruments alternatifs d'investissement pour la couverture contre les risques des marchés d'actions et d'obligations (Nicolau and Palomba, 2015; Sensoy et al., 2015).

3. Chapitre 2 - Efficience des marchés alimentaire et énergétique : Evidence et implications

Face à la situation de la volatilité des prix des commodités alimentaires, les moyens de couverture et de négociation de risque deviennent importants. Les contrats à terme sont parmi les instruments les plus importants pour la découverte de prix et fournissent des informations utiles pour la couverture et l'allocation optimale du portefeuille (Nicolau and Palomba, 2015). Ceci souligne l'importance d'étudier la relation entre les prix spot et les prix à terme des commodités et les implications sur les décisions des investisseurs relatives à leurs positions dans les marchés spot et à terme (Fan et al., 2016).

Ainsi, ce premier essai est consacré à l'étude de l'efficience du marché alimentaire. Au vu de la divergence enregistrée entre les prix spot et les prix à terme des marchés de céréales durant

la période 2005-2011, nous nous intéressons à l'efficience de ce type de marché alimentaire en considérant deux produits céréales (maïs et soja). Nous comparons également l'efficience des commodités céréales avec celle du marché de l'énergie (pétrole brut) afin de vérifier si chaque marché de commodités a ses propres particularités en termes de liens dynamiques entre ses prix spot et ses prix à terme. Nous utilisons des données journalières couvrant la période 2000-2015. Afin de tenir compte de l'éventuelle présence de ruptures structurelles et des changements de l'efficience au cours du temps, nous recourons à l'exposant de Hurst variant dans le temps au moyen de la fenêtre glissante et au modèle vectoriel à correction d'erreurs à seuils (TVECM).

Nos résultats indiquent que les commodités alimentaires, similairement au marché du pétrole, présentent une efficience à long terme, mais une inefficience à court terme. Ils permettent également de souligner la variation dans le temps de l'efficience des différentes commodités et la présence de points de rupture structurelle au niveau des séries de l'exposant de Hurst expliqués par les conditions économiques globales principalement la crise financière mondiale de 2008, la financiarisation des marchés de commodités et les fluctuations de prix de pétrole. La cointégration à seuil est révélée entre les prix spot et les prix à terme de chaque commodité avec la présence de trois régimes en fonction de l'écart entre les deux prix.

Nos résultats mettent en exergue l'importance d'établir des stratégies de couverture adéquates pour dépasser les inefficiences du marché que nous estimons à travers le modèle GARCH multivarié à corrélation conditionnelle dynamique (DCC-GARCH). Les résultats de ces estimations indiquent que les poids optimums minimisant le risque du portefeuille sont variables dans le temps, alternent entre les prix spot et les prix à terme et mettent en relief des tendances différentes entre les céréales et le pétrole brut. Contrairement au pétrole brut, plus de céréales à terme que de céréales spot doivent être détenus durant la crise financière de 2008 et durant la période d'éruption de la crise des prix alimentaires (Janvier 2007) ; alors que moins de céréales à terme doivent être détenus en 2004, période au cours de laquelle l'investissement dans les indices a commencé à se répandre au niveau des marchés de commodités. Nos résultats montrent également que les prix à terme des céréales permettent une efficacité de la couverture contre le risque meilleure que celle du pétrole brut et que les périodes d'inefficience des marchés sont caractérisées par la réduction de l'efficacité de la couverture à terme contre le risque.

4. Chapitre 3 - Effets des chocs du prix du pétrole et du marché boursier mondial sur les prix alimentaires : Etude empirique basée sur les modèles TVP-VAR à volatilité stochastique

Le deuxième essai est consacré à l'étude de la transmission de chocs entre les marchés alimentaire, énergétique et financier et du comportement de la volatilité des prix de ces marchés au cours des dernières années. Il permet également de fournir une discussion des implications des résultats obtenus sur la gestion du portefeuille. Pour ce faire, nous utilisons le nouveau modèle vectoriel autorégressif multivarié à paramètres variables dans le temps (TVP-VAR) introduit par Primiceri (2005) offrant une flexibilité extrême avec une spécification parcimonieuse que nous améliorons par l'incorporation de la volatilité stochastique. Nous nous intéressons également à l'évaluation des transmissions totales et directionnelles des volatilités entre les trois marchés en recourant, sur la base de l'approche prometteuse de Diebold and Yilmaz (2012), à un cadre généralisé de vecteurs autorégressifs dans lequel les décompositions de la variance de l'erreur de prévision sont invariantes à l'ordre des variables. Nous considérons des données mensuelles couvrant la période 1980-2012 se rapportant aux prix spot de différents types de commodités alimentaires (récolte, élevage, plantation et foresterie) afin de vérifier s'il y a des particularités pour chaque type de commodité. Les marchés énergétique et financier sont considérés à travers les prix spot du pétrole brut et de l'indice boursier mondial (MSCI).

Nos résultats liés à la transmission de volatilité suggèrent que les volatilités stochastiques des rendements des différents types de commodités pour les trois marchés sont variables dans le temps et présentent des similarités dans l'évolution même si les amplitudes sont différentes. Nous observons que les transmissions de volatilité augmentent considérablement en période de crise, principalement après mi-2008, appuyant ainsi le rôle clé de la crise financière de 2007-2008 dans l'intensification des transmissions de la volatilité entre les marchés alimentaire, énergétique et financier. Nos résultats indiquent aussi que, notamment après la mi-2008, le marché boursier est un émetteur net de chocs de volatilité, alors que les commodités énergétiques et alimentaires sont des récepteurs nets de chocs de volatilité. Ces transmissions nettes de volatilité provenant du marché boursier sont expliquées par le comportement des investisseurs financiers face au risque qui consiste à quitter leurs positions sur les marchés de commodités et aussi par le transfert d'information par le biais des commodités futurs.

En termes de transmission de chocs provenant du marché énergétique ou du marché boursier vers le marché alimentaire, les réponses impulsionnelles montrent que l'impact de ces chocs est

immédiat et à court terme puisqu'il est absorbé au cours d'une période de six mois. Ces chocs sont plus importants notamment durant la période de la « grande modération » (début des années 1980) et la crise financière de 2007-2008. Les chocs du marché boursier sont positivement transmis aux commodités alimentaires, soulignant l'évolution des rendements des marchés alimentaire et boursier dans la même direction. Toutefois, l'amplitude de ces transmissions de chocs est faible.

En se basant sur les résultats de transmission de rendement et de volatilité entre ces trois marchés, nous étudions l'opportunité de diversification du portefeuille. Nos résultats indiquent des ratios de couverture du risque non stables ayant des fluctuations larges nécessitant de la part des investisseurs un ajustement fréquent de leurs positions à terme. Les valeurs moyennes indiquent typiquement des ratios de couverture du risque faibles suggérant l'efficacité de la couverture du risque par la construction d'un portefeuille diversifié. Ces ratios sont plus élevés durant la période de la crise financière. Parmi les commodités de récolte que nous avons considérées, le maïs permet la meilleure couverture du risque et diversification du portefeuille.

5. Chapitre 4 - Dépendance extrême multivariée entre les marchés alimentaire, énergétique et financier : Analyse à travers les méthodes de copule en vigne (Vine copula)

Compte tenu de la présence de différentes crises caractérisant les marchés alimentaire, énergétique et financier, telles que la crise alimentaire, la bulle des prix du pétrole brut, l'implémentation de la politique du programme standard de carburant renouvelable et la crise financière de 2008, une attention particulière est accordée au niveau de ce troisième essai à la dépendance extrême entre ces marchés. Nous recourons à la méthode récemment développée par Aas et al. (2009) de copule en vigne (Vine Copula) qui permet d'étudier les dépendances multivariées de manière flexible. Les prix journaliers des commodités alimentaires (maïs, blé, bovins), énergétiques (pétrole brut, gaz naturel), et financières (indice boursier mondial MSCI) durant la période 2005-2015 sont considérés. Nous prenons également en compte la variable macroéconomique correspondant au taux de change dollar américain.

Nos principaux résultats indiquent que les dépendances entre ces marchés sont faibles et que les dépendances entre les marchés alimentaire et financier passent par le pétrole brut. Ils nous permettent également de souligner l'impact de la crise financière de 2008 dans l'intensification des dépendances entre ces marchés. Nos résultats révèlent qu'il n'y a pas d'évidence de

dépendance de queue symétrique entre les trois marchés. La dépendance entre le maïs et le pétrole brut est caractérisée par la présence de dépendance de queue symétrique, alors qu'aucune dépendance de queue n'est constatée ni au niveau de la dépendance entre le maïs et l'indice boursier ni au niveau de la dépendance entre le blé et l'indice boursier, conditionnellement à une information sur le pétrole brut.

Les dépendances conditionnelles au taux de change dollar américain indiquent l'absence de dépendance de queue entre l'indice boursier et le maïs, la présence d'une dépendance de queue symétrique entre l'indice boursier et le pétrole brut d'une part et entre l'indice boursier et le blé d'autre part durant la période après la crise financière de 2008 et indiquent aussi une dépendance asymétrique entre l'indice boursier et les bovins caractérisée par une dépendance de queue supérieure durant la période précédant la crise financière de 2008 et par une dépendance de queue inférieure au cours de la période qui la suit.

Conditionnellement à une information sur le taux de change et l'indice boursier mondial, nous concluons l'absence de dépendance extrême entre le pétrole brut et le maïs et entre le pétrole brut et les bovins pour les périodes avant et après la crise financière de 2008. Néanmoins, une dépendance de queue symétrique est révélée durant la période post-crise entre le pétrole brut et le blé indiquant que les queues supérieur et inférieur ont la même probabilité de survenance durant les situations de boom ou de crash du marché.

Sur la base des résultats de la copule en vigne, nous estimons les valeurs en risque (VaR). Différents critères de backtesting nous permettent de souligner la précision de cette approche dans la prévision de la valeur en risque.

6. Conclusion

Au vu de la volatilité enregistrée pour les prix des commodités alimentaires au cours de la période de 2008 qui a été accompagnée par un comportement similaire pour les marchés énergétique et financier, cette thèse a contribué à la compréhension les liens entre ces trois marchés. Les résultats issus de ses travaux ont permis de souligner une nouvelle évidence sur l'impact de la crise financière de 2008 dans l'intensification des liens entre ces marchés en termes de transmission de rendements et de volatilités et aussi en termes de dépendance expliqué par la financiarisation des marchés de commodités à travers leur utilisation en tant qu'actifs financiers.

Nos résultats permettent de conclure que la volatilité du marché alimentaire n'est pas causée seulement par ses propres fluctuations mais qu'elle est aussi impactée par les volatilités des prix des marchés énergétique et financier. Les taux faibles observés de transmission de volatilités ainsi que l'effet à court terme des transmissions de chocs entre ces marchés sont en ligne avec nos résultats qui indiquent l'efficacité de couverture du risque pour un investisseur qui détient un portefeuille diversifié ; soulignant ainsi les opportunités que les marchés de commodités pourraient offrir en termes de diversification du portefeuille. Nous soulignons également la spécificité de chaque type de commodité alimentaire impliquant que les politiques de réduction de la volatilité doivent être désignées pour chaque marché à part.

Nos résultats permettent également de souligner l'impact des prix à terme sur la performance des investissements et la couverture du risque. Ils mettent en exergue la réduction de l'efficacité de la couverture du risque à terme durant les périodes d'inefficience du marché, indiquant ainsi que les prix à terme ne sont pas toujours un outil efficace de gestion du risque face à la volatilité des prix alimentaires et que les investisseurs doivent ajuster les poids des actifs dans le portefeuille en fonction des conditions du marché.

Cependant, cette thèse présente certaines limites qui résident principalement dans le manque de prise en considération d'autres chocs exogènes, tels que les facteurs macro-économiques, les niveaux de stocks, les facteurs de changement climatique, qui pourraient impacter les liens entre les marchés alimentaire, énergétique et financier. L'intégration de ces variables nous permettra, certes, d'obtenir une analyse plus approfondie de nos résultats.

En perspective, ce travail pourra être enrichi par l'incorporation de ces chocs exogènes. Il pourra également être complété par l'étude des liens entre les prix alimentaires internationaux et régionaux. L'évaluation de l'impact socio-économique de ces résultats sur le bien-être des individus pourrait également constituer une perspective potentielle pour de nouvelles recherches.

Summary of the thesis

This thesis aims to contribute on surrounding the complex links between international financial, energy and food markets and understanding their interactions having causing the sudden changes in food prices during the 2008 financial crisis.

After a brief introduction of the context and the literature review related to it, we investigate in the second chapter of this thesis the efficiency of grain markets versus energy markets, as well as their common behavior. To unveil structural breaks and efficiency changes over time, we employ the time-varying rolling Hurst exponent and threshold vector error correction models. We find that all studied commodities exhibit long-run efficiency, but inefficiency in the short run. Three regimes-two structural breaks-are detected for each commodity underlying the time-varying efficiency of the different commodities. The most important break corresponds to the 2008 global financial crisis highlighting thus the key role played by the financial crisis in accentuating the divergence between commodities spot and futures prices. Threshold cointegration is revealed between spot and futures prices of each commodity with the presence of three regimes depending on the gap between these prices. Our findings emphasize the importance of establishing adequate hedging strategies to roll out market inefficiencies, which we estimate based on a multivariate DCC-GARCH model. Optimal weights minimizing the portfolio risk are time-varying, alternate between spot and futures, and show different patterns between grains and crude oil. In terms of hedging effectiveness, grain futures are better than are crude oil futures. Market inefficiency periods are marked by reduction in futures hedge effectiveness.

The third chapter is devoted to the investigation of shocks transmission between international food, energy and financial markets and to provide some insights into the volatility behavior during the past years and discuss its implications for portfolio management. To do this, we present a new time varying parameter VAR (TVP-VAR) model with stochastic volatility approach which provides extreme flexibility with a parsimonious specification. We resort also to a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering for the assessment of total and directional

volatility spillovers. Our main findings suggest that volatility spillovers increase considerably during crisis and, namely after mid-2008, when stock markets become net transmitter of volatility shocks while crude oil becomes a net receiver. Shocks to crude oil or MSCI markets have immediate and short-term impacts on food markets which are emphasized during the financial crisis period. Moreover, we show that augmenting a diversified portfolio of food commodities with crude oil or stocks significantly increases its risk-adjusted performance.

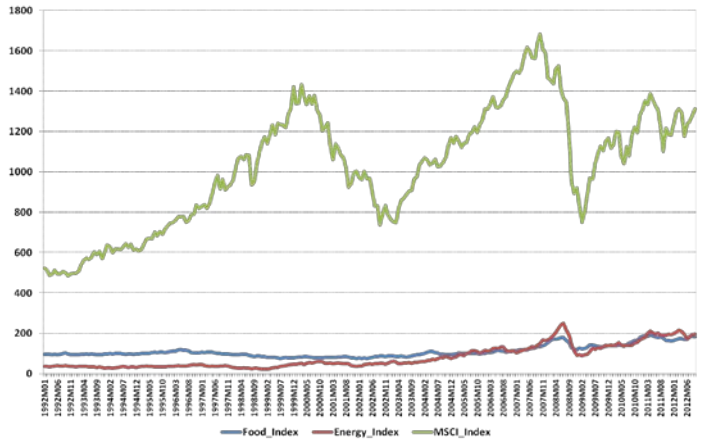
In view of the impact namely of the 2008 financial crisis detected in the previous chapters, a particular attention is given in chapter four to extreme dependence between food, energy and financial markets. We propose to use a recently developed method (Vine Copulas) which allows studying multivariate dependencies in a flexible manner. We take also into account a leading macroeconomic variable corresponding to U.S exchange rate. Our main results underline that dependencies between these markets are low and more important after the 2008 financial crisis. They also reveal that there is no evidence of symmetric tail dependence between these markets. We find that dependencies between food and financial markets pass through crude oil. The accuracy of the Vine copula ARMA-GARCH approach in the prevision of the risk is underlined.

Key words: Food; energy; financial; time-varying efficiency; hedging, rolling Hurst exponent; threshold vector error correction model; DCC-GARCH; TVP-VAR, stochastic volatility; volatility spillovers; portfolio diversification; hedge effectiveness; extreme dependence; Vine copulas; portfolio risk.

General introduction

During the recent world crisis of 2007-2008, energy and food markets prices (namely for the key agricultural commodities including corn, soybean and wheat) have recorded a sharp increase in their levels and have been characterized by high and similar volatility throughout most of 2008 (Du et al., 2011; Reboredo, 2012; Shalini and Prasanna, 2016). The behavior of these commodities was similar to that of financial markets suggesting a close relation between these commodity markets and financial markets.

This phenomenon is illustrated through figure 1 below which presents the evolution of monthly price indices of food, energy and MSCI world stock markets during the period 1992-2012 showing that these prices have a similar pattern and experienced a synchronized boom in mid-2008 and a synchronized bust after September 2008.



Food price index, 2005 = 100, includes cereal, vegetable oils, meat, seafood, sugar, bananas, and oranges price indices.
Energy index, 2005 = 100, includes crude oil, natural gas, and coal price indices.
The MSCI world index is a broad global equity benchmark that represents large and mid-cap equity performance across 23 developed markets countries.

Figure 0.1: Evolution of price indices during the period 1992-2012

(Source: IMF[1] and MSCI/)

[1] International Monetary Fund

Looking in further detail to the different categories of commodities (meat, dairy, cereals, vegetable oil and sugar) composing the Food and Agricultural Organization (FAO) food price index as illustrated in figure 2 below, we notice that this behavior is comparable for all food categories. Meat price index includes four types of meat products corresponding to poultry, bovine meat, pig meat and ovine meat. Dairy price index consists of butter, SMP, WMP and cheese price quotations. Wheat, maize and rice are considered in the cereals price index. Vegetable oil price index consists of an average of 10 different oils. Sugar price index corresponds to the index form of the international sugar agreement prices with 2002-2004 as base.

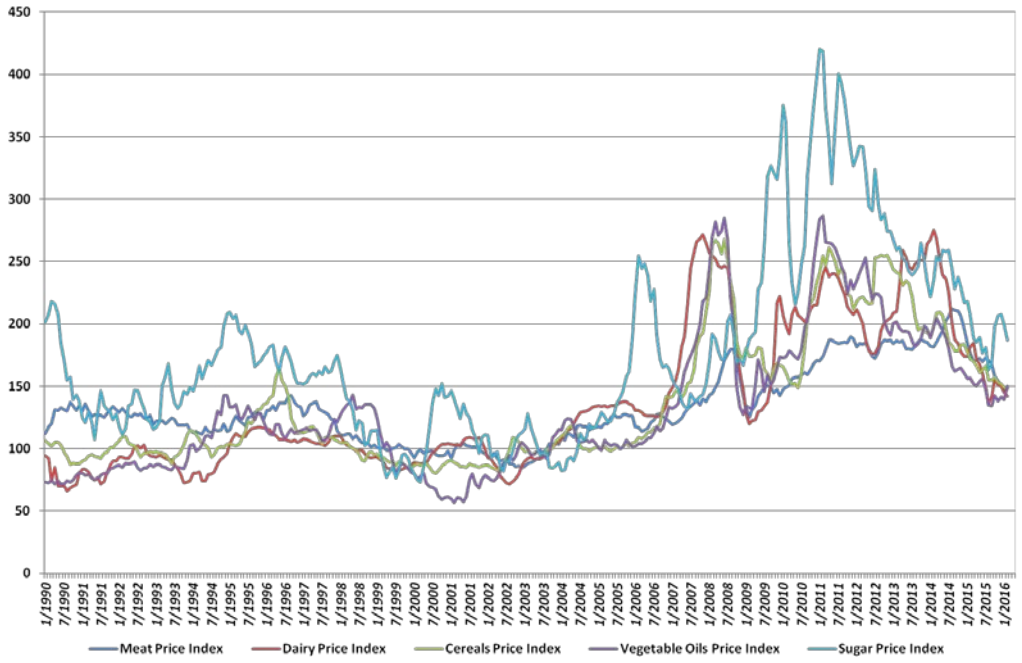


Figure 0.2: Evolution of FAO food price index during the period 1990-2016

(Source: FAO)

Food prices volatility recorded during the 2007-2008 crisis has resulted in an additional number around 75 million of people suffering malnutrition (Headey, 2011). Today, around one billion people are hungry worldwide (FAO, IFAD, 2015) and there still remain countries for which the hunger index is alarming as illustrated in figure 3 below.

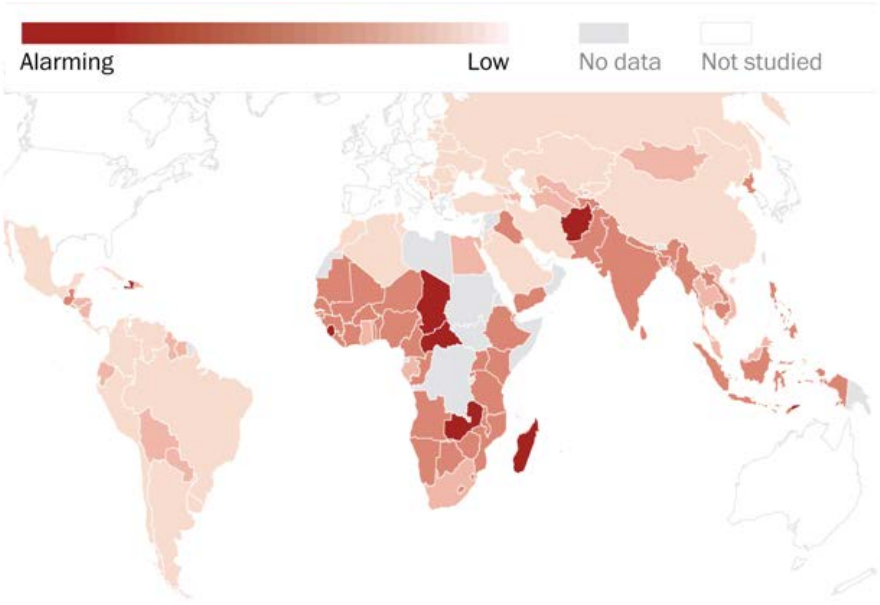


Figure 0.3: Hunger index in the world in 2015 year
(Source: International Food Policy Research Institute)

The impact of prices volatility on hunger index is more tangible for vulnerable countries which are poor countries and where households spend a high proportion of their income on food (Grebmer et al., 2011; Nazlioglu, 2011; Tadesse et al., 2014; Zhang et al., 2010). By reference to FAO (2008) report, the average share of food expenditure in the total consumption price index is around 45% for the 20 countries having the lowest per capita income, while in the 20 richest countries it achieves only 16%.

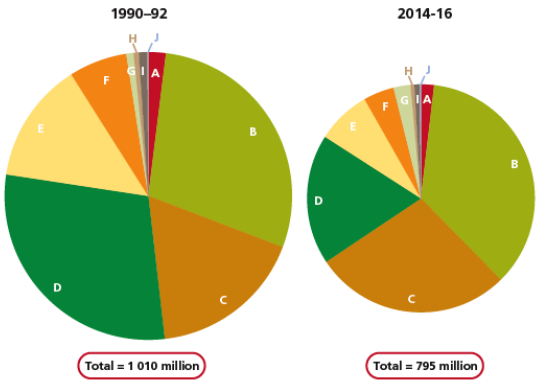
Considering that food commodity prices constitute an important component of consumer price index and are crucial in particular for the conduction of monetary policies (Anzuini et al., 2013), the investigation of their evolution and the driving forces behind them becomes an issue of particular importance. Even if a long debate has been triggered in the literature about this topic, conclusions remain controversial due to the involvement of a multitude of factors which makes this issue a high priority for the world and a topic of current discussions.

This subject has raised the attention of the international community since high volatilities can threaten market stability and may have adverse effects on food security (FAO, IFAD, 2015). Regardless of whether countries are importer or exporter of commodities, economies are affected by the external shocks due to the spectacular volatility of commodity prices that can result in economic instability and increased poverty (Alam and Gilbert, 2017).

In order to ensure food security, different measures to reduce price volatility and insure food security have been discussed in the literature (Gilbert, 2012) and have been subject of investigation from many international organizations (such as Food and Agriculture Organization, International Fund for Agricultural Development, International Monetary Fund, Organization for Economic Cooperation and Development, United Nations Conference on Trade and Development, World Food Program, World Bank, World Trade Organization, International Food Policy Research Institute and United Nations High Level Task Force). These measures include ones related to multilateral price agreements, tighter export control disciplines, arrangements to increase stock availability and measures to contain or limit demand for non-food purposes. They cover also risk management means namely through commodity futures markets. The subject has been also largely debated in the G20 action plan granting a particular attention to the issues related to commodities markets regulation. This action plan highlights the importance of improving market information and its transparency (either for physical markets or commodity futures exchanges) so that to allow market actors to form expectations based on fundamentals and to detect shortages early (Tadesse et al., 2014). As an initiative of the G20, the Agricultural Market Information System (AMIS) was established in 2011 so that to facilitate market information and enhance transparency. The initial focus of AMIS is on four grains (wheat, maize, rice and soybeans) which are particularly important in international food markets. United Nations Conference on Trade And Development (UNCTAD/TDR, 2011; UNCTAD, 2012a, 2012b) insists on the importance of strong and prompt policy and regulatory responses concerning financial markets, coupled with measures relating to physical markets in order to face commodities prices volatility caused by financialization. Recently, a set of sustainable development goals has been adopted by the international community in 2015 as part of the 2030 agenda for sustainable development. One of these goals corresponds to "*End hunger, achieve food security and improved nutrition and promote sustainable agriculture*". Among the targets of this goal lays the adoption of appropriate measures to ensure the proper functioning of food commodity markets and their derivatives and to facilitate timely access to market information, including on food reserves, in order to help limit extreme food price volatility[2].

[2]More details about the remaining targets of this goal can be found on the following link https://sustainabledevelopment.un.org/?menu=1300.

Although the worldwide efforts towards the improvement of food security, wide differences still persist among regions (figure 4).



	Number (millions)		Regional share (%)	
	1990–92	2014–16	1990–92	2014–16
A Developed regions	20	15	2.0	1.8
B Southern Asia	291	281	28.8	35.4
C Sub-Saharan Africa	176	220	17.4	27.7
D Eastern Asia	295	145	29.2	18.3
E South-Eastern Asia	138	61	13.6	7.6
F Latin America and the Caribbean	66	34	6.5	4.3
G Western Asia	8	19	0.8	2.4
H Northern Africa	6	4	0.6	0.5
I Caucasus and Central Asia	10	6	0.9	0.7
J Oceania	1	1	0.1	0.2
Total	1 011	795	100	100

Figure 0.4: Distribution of hunger in the world

Source : (FAO, IFAD, 2015)

As for the factors explaining food prices volatility, the recent literature is giving more and more attention to the factors related to spillovers cross markets besides the traditional markets factors related to offer and supply and those afferent to macroeconomic factors and underlines that this volatility could be more amplified in the future through the further tightening of the links between food, energy and financial markets (Gutierrez, 2013; Liu et al., 2017).

Nevertheless, the conclusions of this literature remain controversial which prompted us to focus on this thesis on the links between international food, energy and financial markets. This thesis aims to investigate these links in terms of returns spillovers, volatilities spillovers, and dependence namely during extreme market conditions, and is also intended to understand how to deduce information from these links for a better portfolio management.

This thesis contributes to the literature on the subject particularly through considering the links between the three markets taken together; while most of the previous works have dealt with the links between either energy and food markets or financial and food markets. In comparison with previous literature having attributed a particular interest to the transmission of returns between these markets, our work is distinguished by a special focus on volatilities spillovers between these markets. In addition, we look for different types of food commodities, although most of previous works were mainly dedicated to grains. We also differ from most of

the previous works through considering spot prices of the different commodities in addition to the link between spot and futures prices, while most of the previous studies resorted to futures prices due to the lack of data. We consider the variation of our findings over time which is prominent since it allows checking the eventual impact of possible structural breaks. The commonly used methods in the literature for the investigation of prices volatility correspond to the generalized autoregressive conditional heteroskedasticity (GARCH) models which encounter certain limits that we propose to overcome by resorting to new methods.

This three essays dissertation is composed of four chapters aiming to:

- Provide an overview of the existing literature related to this subject (Chapter 1);
- Examine the efficiency of food market compared to energy market and its implications on hedging (Chapter 2);
- Investigate the effects of financial and energy markets shocks on food commodities prices in terms of transmission of returns and volatilities and explore the implications on portfolio diversification (Chapter 3);
- Analyze the impact of extreme events on dependence between food, energy and financial markets and check the implications on portfolio risk management (Chapter 4).

The first chapter provides a summary review of some relevant studies done in the literature as regards to the investigation of the links between energy, financial and food markets prices in terms of transmission of either returns or volatilities shocks, dependence and usefulness in risk hedging and portfolio diversification. This literature review tries to give some explanations to the divergence on the results in the previous studies and highlights their limits.

Facing the situation of food prices volatility, the ways of hedging and trading risk become important. Futures contracts are considered in the literature among the most important instruments for price discovery and for providing useful information for hedging and optimal portfolio allocation (Nicolau and Palomba, 2015). This underlines the importance of studying the relationship between spot and futures prices. Thus, chapter two is devoted to the investigation of food market efficiency. In order to take into account the eventual presence of structural breaks, we apply time-varying Hurst exponent and threshold vector error correction models to spot prices and 1-month futures contracts of grain commodities (corn and soybean) daily observed during the period 2000-2015. We also compare the efficiency of grains to oil efficiency in order to check if each commodity market has its own peculiarities regarding the

dynamic link between its spot and futures prices. Our results indicate that grains, similarly to oil market, exhibit long-run efficiency and inefficiency in the short-run namely during the 2008 global financial crisis characterized by a divergence between spot and futures prices. Comparison between grains and crude oil markets efficiency reveals different patterns for these markets. In fact, contrary to crude oil, more grains futures than spot have to be held during the periods of the 2008 financial crisis and the eruption of the food price crisis (January 2007) while less grains futures than spot have to be held in the 2004 year when index investment started to flow into commodity markets. We also find that grain futures provide better hedge effectiveness than crude oil futures and that periods of inefficiency are accompanied by a reduction in the hedge effectiveness of futures.

Since market inefficiency is confirmed during certain periods, market participants will not base their trading decisions only on the fundamentals of supply and demand. They will also take into account other markets and portfolio diversification opportunities. This finding leads us to study in the next chapter how shocks on levels and volatilities are transmitted between food, energy and financial markets and their impact on portfolio diversification. For our empirical study, we consider monthly data observed for a long span period from 1980 to 2012. Different types of food commodities are considered (crops, livestock, plantation and forestry) allowing thus to check if they constitute a homogeneous asset class in the matter of their links with energy and stock markets. As for the energy market, we consider crude oil. Financial market is considered through its key component which is represented by MSCI world stock market index. In order to take into account the variation over time of impulse response functions of food commodities to a shock on energy or stock market, we resort to the multivariate time-varying parameter vector autoregressive (TVP-VAR) model introduced by Primiceri (2005) offering an extreme flexibility with a parsimonious specification that we extend through the incorporation of stochastic volatility. In addition, this chapter attempts to investigate the relation between food commodities, crude oil and stock market in terms of risk spillovers and how this volatility spills over the markets during the time. For the investigation of these volatility spillovers, we proceed with a promising methodology referring to Diebold and Yilmaz (2012) approach based on a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering. We determine total volatility spillovers as well as directional and net volatility spillovers. Time varying volatility spillovers from energy and stock markets to food markets are investigated through the application of a rolling windows approach. The main findings of this chapter indicate the presence of low

volatility spillovers from crude oil or world stock market MSCI to most food commodities. We also find that volatility spillovers from world stock market MSCI to food commodities reach their peak during the 2008 financial crisis, in particular for corn commodities that are largely traded on stock markets as alternative asset classes and are, thus, more financialized and which have the highest investment inflows underlying that volatility spillover channel from stock to food commodities is explained through commodity index traders. We also underline the change in patterns for net volatility spillovers after mid-2008. Findings in this chapter emphasize also the opportunities of portfolio diversification offered by food commodities.

Having confirmed the impact of the 2007-2008 financial crisis on increasing spillovers between food, energy and stock markets, we devote the fourth chapter for the investigation of extreme dependence in order to identify how food, energy and stock markets are linked during extreme events. We resort to vine copulas method recently developed by Aas et al. (2009) offering greater flexibility and permitting the modeling of complex dependency patterns using the rich variety of bivariate copulas which can be arranged and analyzed in a tree structure to facilitate the analysis of multiple dependencies. We apply them to daily data of agricultural (wheat and corn), livestock (live cattle), and energy commodities (crude oil and natural gas) in addition to MSCI stock market covering the period 2005-2015. We also consider a macroscopic factor corresponding to U.S. exchange rate. To check the eventual change in dependence structure surrounding the 2008 financial crisis, we divide our sample into two periods (pre-crisis and post-crisis). Findings of this chapter indicate that dependencies between these markets are low and more important during the post-crisis period than the pre-crisis period. They mention that there is no evidence of symmetric tail dependence between the three markets. We also find that dependencies between these markets are different conditional to the information on other markets. As regard to the prevision of the risk of a portfolio composed of different types of commodities, we underline the accuracy of the Vine copula ARMA-GARCH approach in the prevision of the VaR according to different backtesting criteria.

Chapter 1

Literature Review

1. Introduction

This chapter provides a literature review of some of relevant studies which tried to investigate the potential factors affecting food commodities prices by discussing the modeling techniques, commodities, data frequency and time span considered in these studies besides their main empirical findings.

In addition to the traditional markets factors related to offer and supply and those afferent to macroeconomic factors, the recent literature related to commodities prices fluctuations is giving more and more attention to spillovers cross markets (Gutierrez, 2013). Most conclusions agree that volatility in one market is not only caused by its own previous fluctuations, but is also influenced by the fluctuations from other markets (Liu et al., 2017).

Since our scope concerns world prices, our review is limited to studies dealing with international markets and not domestic ones. In order to cover the boom and bust cycles in prices, we review previous studies considering a large set of data. We provide a review of papers focusing on different types of food commodities so that to check if previous works find particularities for each type of food.

We start by providing a review of studies focusing on the potential factors impacting food commodities prices. Later, a special attention is given to the previous studies dealing with the relation between food and energy markets. Afterward, we provide a literature review related to the spillovers among food and financial markets. Our review of the literature on the links

between these markets is devoted to studies focusing on the investigation of either returns or volatilities transmission to check how they spill over from one market to another one. We also look over studies dealing with the analysis of the dependence between these markets with a particular attention to those approaching tail dependence.

2. Potential factors impacting food commodities prices

A review of works in the literature focusing on food commodities prices dynamics reveals that these prices are impacted by a large set of potential factors which can be summarized mainly into market fundamentals and macroeconomic factors in addition to spillovers among markets.

Previous works have mainly focused on co-movement and transmission of shocks in levels and few among them have given particular attention to volatilities transmission. In their review of the existing empirical studies focusing on food markets volatility, Brümmer et al. (2013b) classify these previous studies according to the considered eventual drivers of food volatility. The frequency of theoretical and empirical studies focusing on each category of these drivers is provided by Brümmer et al. (2013a) as illustrated in figure 1.1 below.

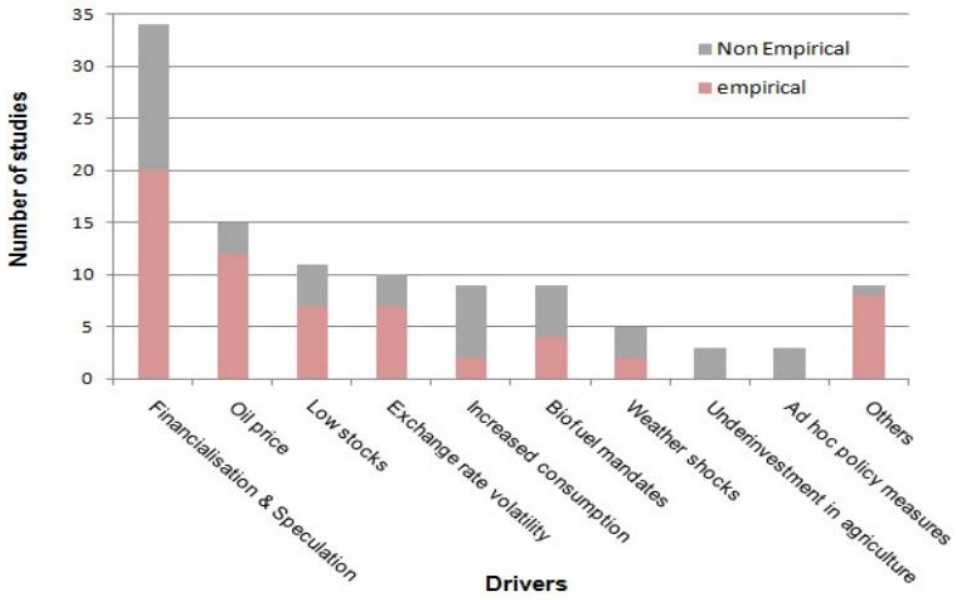


Figure 1. 1: Drivers of food price volatility

(Source: Brümmer et al., 2013a)

2.1. Macroeconomic factors and market fundamentals:

One strand of the literature underlines the impact of macroeconomic factors and market fundamentals on food commodities prices.

The effect of macroeconomic shocks (such as inflation and industrial production) in affecting monthly prices of a set of apparently unrelated commodities (wheat, cotton, copper, gold, crude oil, lumber and cocoa) from April 1960 to November 1985 is underlined by Pindyck and Rotemberg (1990). Their findings indicate that this effect can be either directly through affecting commodity demands and supplies or indirectly via affecting expectations about future supplies and demands.

By applying bootstrap methodology to daily agricultural commodity futures prices observed during the period 1985-2010, Gutierrez (2013) finds that price changes during the 2008 financial crisis are explained by market fundamentals.

Several studies have underlined the contribution of U.S. dollar exchange rates on commodity prices fluctuations since international trades of agricultural commodities are denominated in U.S. dollar (Akram, 2009; Alam and Gilbert, 2017; Balcombe, 2011; Brümmer et al., 2016; S. L. Chen et al., 2014). Through the analysis of the behavior of real prices of crude oil, food, metals and industrial raw materials quarterly observed during the period 1990-2007 on the basis of structural VAR models, Akram (2009) finds that decreases in real interest rates or US dollar lead to increases in food commodity prices. Balcombe (2011) underlines the role of exchange rate in predicting the volatility of monthly and annual prices of different types of food commodities during the period 1957-2009 by means of random parameters models with time varying volatility and a panel regression approach. S. L. Chen et al. (2014) identify U.S. nominal exchange rate and excess demand for certain commodities as two common factors responsible for changes in international commodity prices. Their study is based on a factor analysis procedure applied to a panel of 51 international commodity prices, including non-fuel commodity indices, food index, beverage index, and agricultural raw material index spanning the period January 1980-December 2009. Based namely on structural VAR analysis of individual commodities, Alam and Gilbert (2017) findings underline the impact of U.S. dollar exchange rates appreciation on the reduction of monthly spot prices of agricultural commodities during the period ranging from 1991-m1 to 2014-m5 through lowering the demand for these commodities. In a recent study, Brümmer et al. (2016) identify volatility drivers and spillovers effects for the monthly spot prices of two agricultural commodity groups (oilseeds and

vegetable oils markets) by means of a standardized GARCH framework and a VAR model with consideration of exogenous variables related to financialization, oil prices, stocks data, exchange rates, consumption, and weather shocks. Their findings underline the most important identified impact of exchange rate volatility on increasing agricultural commodities prices volatility, contrary to financialization and speculation.

The increase in commodity prices concomitant to the 2007-2008 global financial crisis has raised the debate on whether this increase may have been caused by the growth in global liquidity resulting mainly from the exceptional monetary policies in major economies introduced to stabilize their domestic economies and financial sectors in response to the crisis. This issue has been largely discussed by another broad of studies focusing on the impact of monetary policies on commodity prices.

Most of these studies have considered U.S. interest rate as an indicator of monetary policy position (Frankel, 2008) and debate on the role of interest rates on commodity prices through influencing storage arbitrage and consequently the demand for commodities. However, previous findings recognize that interest rates may not fully represent the impact of a monetary policy shock and, more importantly, their movements can reflect the endogenous response of monetary policy to general developments in the economy. The dilemma on the short and long-term policy effects of monetary policies on commodity prices is still debated (Belke et al., 2013; Algieri, 2014).

To investigate the relationship between U.S. monetary policy and commodity prices, Anzuini et al. (2013) consider monthly US variables from 1970 to December 2008 corresponding to federal funds rate, money stock, CPI, industrial production index, commodity price index, and specific commodity index (crude oil, metals and food). Their investigation is based on a commonly used system in analyzing the effects of monetary policy shocks (standard VAR). Transmission channels through which monetary policy shocks may directly affect commodity prices in accordance with direct transmission channels suggested by Frankel (2008) are also analyzed in this study. Anzuini et al. (2013) results indicate a significant impact of U.S. monetary policy shocks on commodity prices while this impact is not overwhelmingly large. However, Anzuini et al. (2013) argue that a stronger effect of monetary policy on commodity prices may pass through the indirect channels of expected economic growth and inflation (Barsky and Kilian, 2004).

Belke et al. (2013) study is among the ones which accentuate the impact of liquidity increase in rising commodity and food prices. By resorting to a global cointegrated vector-autoregressive

(CVAR) model applied to quarterly prices of various commodity and food indices during the period 1980-2011 and through the consideration of different global liquidity measures, Belke et al. (2013) find a positive long-run relation between global liquidity and the development of food and commodity prices, and that food and commodity prices adjust significantly to this cointegrating relation.

Byrne et al. (2013) provide a substantial survey on the link between real interest rates and real commodity prices. Their study allows to detect the presence of a common factor explaining the co-movement of real commodity prices related to real interest rates as suggested by Frankel (2008) and to risk as suggested by Beck (2001, 1993). Based on Factor Augmented VAR approach applied to yearly data of different types of commodities (including food, beverages, metals) observed from 1900 to 2008, Byrne et al. (2013) findings indicate that both real interest rates and risk are negatively related to real commodity prices where shocks to the real interest rates are absorbed within a five year period while the risk impact has a shorter term. The risk impact (economic policy uncertainty) is also underlined in a recent study of Alam and Gilbert (2017) whose findings indicate that uncertainty may increase commodity prices through reducing supply and production.

Algieri (2014) focuses on the effects of economic and financial factors corresponding to S&P 500, crude oil, U.S. dollar/euro exchange rate and monetary variables on commodities (corn, rapeseed, soybeans, soybean oil, sugar and wheat) daily futures prices over the period May 2005-June 2013. Monetary variables considered in his study are related to the open market operations and the federal funds interest rate. His findings regarding the effect of monetary liquidity on commodity prices, issued from the application of univariate and multivariate GARCH family models, underline the non-significance of this effect, implying that monetary liquidity does not influence commodity returns on a daily basis. Algieri (2014) argues that the absence of an immediate impact from monetary policy does not imply the absence of a positive long-run relationship between global liquidity and the development of food commodity price returns, and that the effects of monetary policy on prices occur with significant lags and not immediately.

The significant effect of global liquidity on commodities prices (considered through the Commodity Research Bureau price index) is also underlined by Beckmann et al. (2014) study based on a Markov-switching vector error correction model and which emphasizes also the time-varying characteristics of this effect.

Belke et al. (2014) address the interactions between monetary aggregates, interest rates, inflation and commodity prices on a global level through the long-run equilibrium relations. A detailed summary of literature focusing on the relationship between global liquidity and asset prices is provided in their study with a discussion of theoretical issues regarding the linkages between interest rates, money growth and asset prices. Belke et al. (2014) findings emphasize the role of monetary factors in explaining commodity prices movements. Their findings allow also to identify the presence of a negative relation between the interest rate and commodity prices and to conclude, thus, that global liquidity and interest rates are valuable indicators of commodity prices inflation and of a more generally defined inflationary pressure at a global level.

Using a broad commodity index and sub-indices of fuel, metal, and food commodities and applying Structural VAR (SVAR) model, Hammoudeh et al. (2015) find that a U.S. monetary contraction leads to an immediate rise in the broad commodity price index, which possibly reflects an aggregation bias, greater expected inflation and speculation, high production costs or some overshooting due to overreactions.

In a more current study, Kang et al. (2016) focus on the impact of global liquidity on agricultural, metal and energy commodities prices over the period from January 2004 to April 2014 and consider the eventual presence of a short-run effect contrary to previous works focusing mainly on the long-run relationship between global liquidity and commodity prices. Their investigation is based on a structural vector auto-regression (SVAR) model allowing to deal with the short-run relationship between global liquidity and commodity prices. Data studied correspond to global liquidity indicators in addition to supply, demand and prices of commodities; while the previous literature on the long-run relationship often ignores supply factors. Two kinds of liquidity measures are used in their study where the first one is a quantity-based measure and the second one is a price-based measure including interest rate spreads, asset prices and the risk attitude of investors. Price-based measure of global liquidity is estimated based on dynamic factor analysis following Chen et al. (2012) and Matheson (2012). Kang et al. (2016) findings indicate that the impact of global liquidity on commodities prices has strengthened since the global financial crisis. They also emphasize the superiority of the price-based liquidity indicator, which incorporates the future expectations of market participants on an immediate basis; contrary to quantity indicators, in explaining commodity price dynamics since the global financial crisis.

de Nicola et al. (2016) indicate that commodities prices volatilities decrease with a fall in the interest rate explained by smoothing transitory shocks through lower inventory costs, while correlations of prices returns increase.

Recently, Alam and Gilbert (2017) indicate that monetary policy, global economic conditions, and the U.S. dollar exchange rates play an important role in the dynamics of agricultural commodities prices during the period ranging from 1991-m1 to 2014-m5. Their study is based on monthly spot prices of agricultural commodities (corn, wheat, oat, and soybean) and measures of global economic conditions and macroeconomic uncertainty in addition to monetary policy through the real interest rate of the U.S., which is constructed using the Federal Fund Rate (FFR) and CPI inflation rate. Financial market condition is accounted for through the use of S&P 500 index. They also use the West Texas Intermediate (WTI) oil price, and the price of potassium chloride as fertilizer price. Alam and Gilbert (2017) study is distinguished by the consideration of inventory levels[3] playing an important role in commodity prices determination (Frankel, 2014). By applying structural VAR analysis of individual commodities and FAVAR analysis of the common factor, Alam and Gilbert (2017) find that, in addition to global demand and U.S. dollar exchange rates, monetary policy plays an important role in the dynamics of agricultural commodities prices. Moreover, like in Anzuini et al. (2013), the responses in Alam and Gilbert (2017) analysis are, while significant and sizeable, not overwhelmingly large. However, unlike Hammoudeh et al. (2015) and Anzuini et al. (2013), Alam and Gilbert (2017) do not find in the impulse response functions any initial increase in commodity prices due to a contractionary monetary policy shock.

Regarding the channels through which monetary policy shocks may exert their impact on commodity prices, some studies admit the presence of indirect channels related to expectations of inflation and economic growth (e.g. Barsky and Kilian, 2004), while others agree on the presence of direct channels in addition to the indirect channels (e.g. Frankel, 2008). Direct channels through which monetary policy shocks may affect commodity prices have been summarized by Frankel (2008) into three channels corresponding to the inventory, the supply, and the financial channels. According to the inventory channel, low interest rates tend to reduce the opportunity cost of carrying inventories, increasing thus the demand for commodities. The supply channel refers to the creation of an incentive, on the supply side, not to extract exhaustible commodities today due to the lower interest rates. The financial channel, finding

[3] Inventory in a period is defined as carried over stock from the previous period plus production in that period minus disappearance (use) in that period.

its theoretical foundation in the overshooting models, is explained by the decline in the carrying cost of speculative positions in the futures market due to a decrease in interest rates, putting thus upward pressure on futures prices and, by arbitrage, also on spot prices.

2.2. Spillovers among markets:

Recent studies indicate that different sources can explain the volatility of food commodities not only fundamental rules and macroeconomic factors (e.g. Grebmer et al., 2011; Hajkowicz et al., 2012; Kagraoka, 2016; Kristoufek et al., 2012; Prakash and Gilbert, 2011; Serra and Zilberman, 2013; Tadesse et al., 2014; Wise and Murphy, 2012; Zhang et al., 2010). These studies have focused on the links between different types of commodities in terms of transmission of price levels and risks. However, there is still less agreement about these links (Serra and Zilberman, 2013) since there is a large set of potential factors impacting them.

Zhang et al. (2010) mention that the crisis in price spikes was due to a number of mutually reinforcing factors in global agricultural markets corresponding to a sharp increase in biofuel demand, high oil prices, in addition to rapid economic growth, droughts in key grain-producing regions, a weak US dollar, speculation, and export restrictions.

With reference to Grebmer et al. (2011), three key factors explaining international food prices volatility have been identified (Figure 1.2). These factors are related to the increase in biofuel production, the increase in financial activity through commodity futures markets and the effects of climate change.

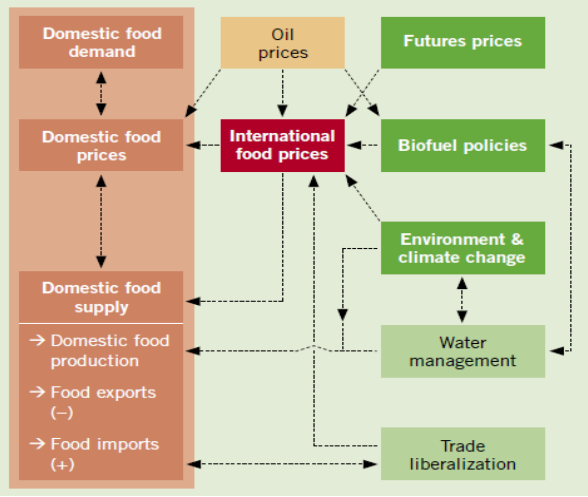


Figure 1. 2: Key factors explaining food prices volatility

(Source: International Food Policy Research Institute, 2011)

Prakash and Gilbert (2011) mention that sources of agricultural commodities volatility may be summed up in natural shocks related to climatic changes, stock levels, agricultural product demand and supply, growing links with energy and financial markets, and macroeconomic factors (exchange rates and interest rates) as illustrated in figure 1.3 below.

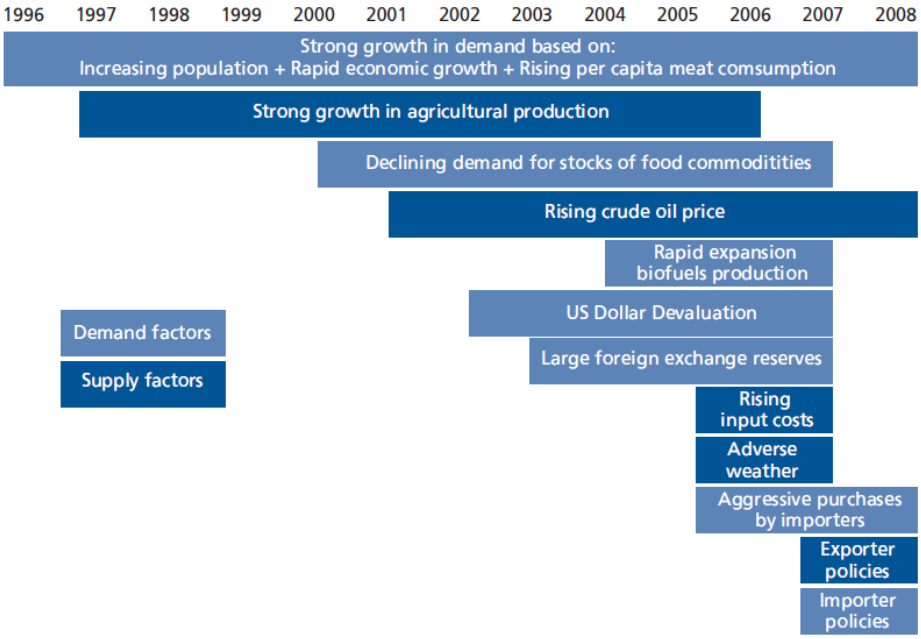


Figure 1. 3: Possible factors explaining the volatility of agricultural commodities

(Source: Prakash and Gilbert, 2011)

A detailed systems model (Figure 1.4) identifying possible factors that influence food price movements and hunger has been drawn by Hajkowicz et al. (2012).

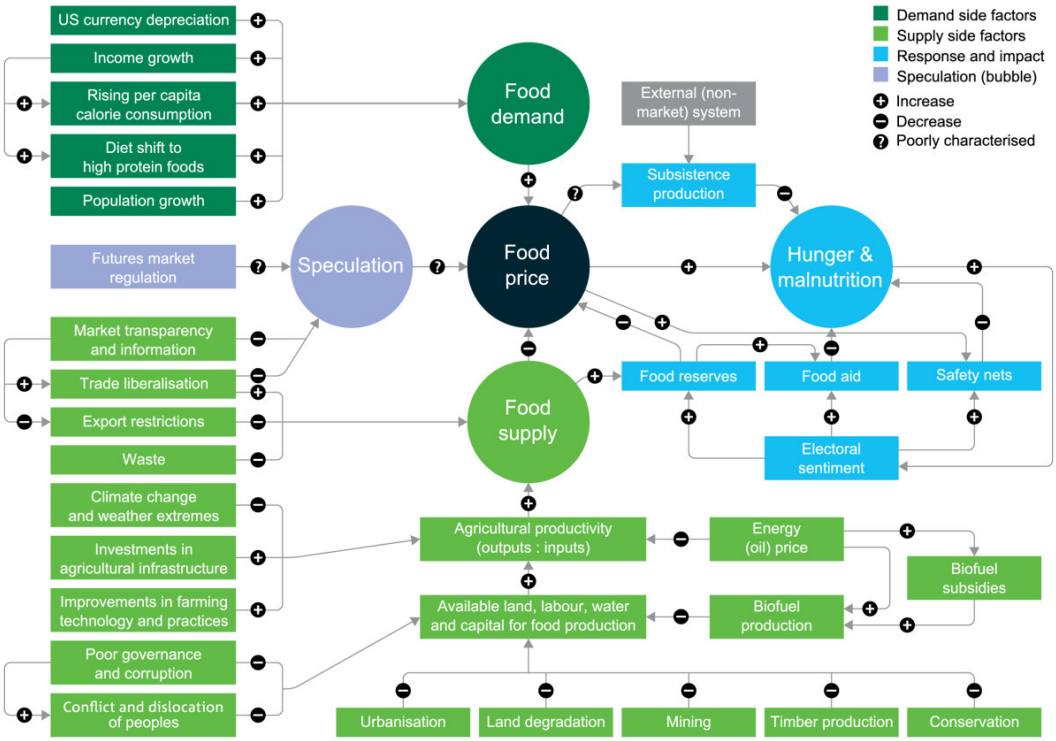


Figure 1. 4: A systems model of possible factors influencing food price movements and hunger

(Source : Hajkowicz et al., 2012)

Kristoufek et al. (2012) mention that both macro factors (economic growth, weak dollar, fiscal expansion, low cost of capital and financialization of commodities) and agricultural sector-specific factors (energy prices, weather, food demand, biofuels, agricultural policies, agricultural underinvestment, and low stocks of agricultural commodities) contribute to the increase in commodities prices.

Wise and Murphy (2012) mention that a paradigm shift influencing the new architecture of food security governance is caused by the deepening integration of agriculture, energy and financial markets in a resource-constrained world made more vulnerable by climate change.

Serra and Zilberman (2013) indicate that a multitude of factors (speculation in futures markets, stocks, changes in food and fuel demand, weather conditions, changes in world population, policy regulations, macroeconomic conditions) can alter both food and energy prices and their links.

Tadesse et al. (2014) propose a framework of the causes of global food price volatility and spikes during the 2007-2008 period (figure 1.5). This framework distinguishes between root, conditional and internal drivers of food prices. Root causes correspond to exogenous shocks including extreme weather events, oil price shocks, economic growth, demand growth and economic shocks (such as the depreciation of the US dollar). Conditional causes are related to market conditions and political environment (concentration of production and export and lack of information and transparency). Endogenous shock amplifiers correspond to the internal causes such as speculation, discretionary trade policies and food stocks-to-use. Tadesse et al. (2014) investigate the main drivers of food price spikes and volatility for wheat, maize, and soybeans. Their results underline the increasing linkages among food, energy, and financial markets and their significant role in explaining food price volatility and spikes in addition to exogenous shocks.

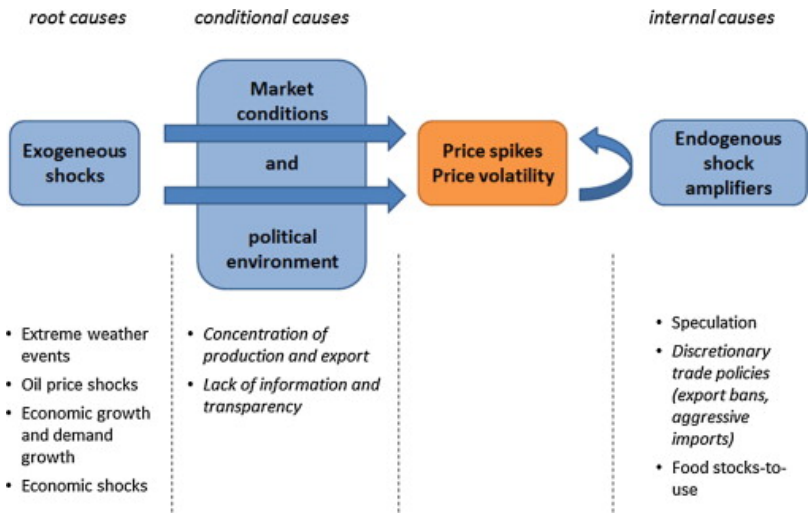


Figure 1. 5: Stylized framework of the causes of global food price volatility and spikes

(Source: Tadesse et al., 2014)

Considering broad categories of commodities including agricultural and energy commodities which prices are monthly observed during the period 1995-2015, and resorting to a generalized dynamic factor model, Kagraoka (2016) finds that four common dynamic factors corresponding to the U.S. inflation rate, the world industrial production, the world stock index and the price of crude oil account for much of the variation in the commodity returns.

Based on the previous exhibited findings, we present in more detail, in the following, some of the most important studies in the literature dealing with transmission of shocks from energy and financial markets to food markets.

3. On the relation between food and energy markets

The impact of oil prices on food prices was investigated in the literature through different methodologies. Equilibrium frameworks were used in order to simulate the links between energy and food prices on a macroeconomic level (Ciaian and Kancs, 2011b; de Gorter and Just, 2009a, 2009b; De Gorter and Just, 2008). However, these models have been criticized for their poorly performance and lack of validation against historical data (Beckman et al., 2011), in addition to their inability to reveal the short term impacts. More recently, and with the availability of high frequencies time-series data, the econometric models are used for the assessment of this impact.

A review of the literature focusing on the linkages between energy and food prices reveals that most of works have namely focused on price levels transmission between food and energy markets with few works dealing with transmission of volatilities between these markets (López Cabrera and Schulz, 2016).

3.1. Divergence on the results:

By reviewing the literature related to the linkages between energy and food markets, we note that there is no consensus on the conclusions on this subject. In fact, results were divergent depending on commodities considered, data frequency, time span, and the methods used for the analysis (Zilberman et al., 2013). Gardebroek et al. (2016) indicate that different data frequencies can lead to different conclusions on volatility spillovers between markets. Few previous works provide a detailed review of the literature focusing on the link between energy and food markets (e.g. Janda et al., 2012; Natanelov et al., 2013; Nazlioglu et al., 2013; Serra and Zilberman, 2013; Zilberman et al., 2013). Studies focusing on this topic can be classified into three groups depending on their findings.

The first group of studies underlines the significant linkages between energy and food prices which can be explained through a multitude of factors (e.g. Akram, 2009; Baffes, 2007; Balcombe, 2011; Busse et al., 2011; Chang and Su, 2010; Chiu et al., 2016; Ciaian and Kancs,

2011a; Gardebroek and Hernandez, 2013; Ji and Fan, 2012; Koirala et al., 2015; Mensi et al., 2014b; Serra et al., 2011).

Another group indicates that linkages between energy and food prices are not always significant and become stronger after certain structural breaks (e.g. Du et al., 2011; Han et al., 2015; Kristoufek et al., 2014, 2012; Nazlioglu, 2011; Nazlioglu et al., 2013; Reboredo, 2012; Wang et al., 2014). These studies consider crises as break points that have to be well considered in order to investigate the relation between energy and agricultural commodity prices (Han et al., 2015).

Nevertheless, the third group of studies reveals no direct link between these two markets prices. (e.g. Gilbert, 2010; Kaltalioglu and Soytas, 2011; Zhang et al., 2010).

3.1.1. Some studies belonging to group 1:

Baffes (2007) examines price transmission between crude oil prices and 35 internationally traded commodities corresponding to food (beverages, cereals, fats and oils, meat, fruits and sugar), raw materials and metals for the 1960-2005 period. He uses an ordinary least squares regression of the individual commodity price on crude oil price by explicitly taking into account inflation and technological change. In addition to price indices, he employs annual prices of individual commodities. His main findings indicate a significant effect of crude oil prices on food commodities prices.

Akram (2009) focuses namely on the spillover effects from crude oil prices to other commodities prices (food, metals and industrial raw materials). Structural VAR models are applied to a larger sample of commodities quarterly observed during the period 1990–2007. He mainly finds positive spillover effects between food and crude oil prices explained by the use of crude oil for foods production and also by an eventual substitution effect.

Chang and Su (2010) apply the bivariate EGARCH model to futures prices of crude oil and grains (corn and soybean) covering the period January 2000-July 2008 and find the presence of significant positive volatility spillovers from crude oil to corn during the period of higher crude oil price (after May 2004) while spillover effects are insignificant during the lower crude oil price period.

Balcombe (2011) results indicate that oil prices volatility is a significant determinant of volatility in most food commodities and that the link between oil and agricultural price volatility will continue or strengthen as the biofuels sector grows. His work is applied to monthly and

annual prices for different food commodities (wheat, maize, rice, soybean, rapeseed, palm, poultry, beef, pig meat, butter, cheese, cocoa, coffee, tea, sugar and cotton) observed during the period 1957–2009. Two econometric methods are used in their analysis corresponding to random parameters models with time varying volatility which they run on the monthly series, and a panel regression approach applied to annual data.

Busse et al. (2011) analyze the behavior of rapeseed futures prices by applying the dynamic conditional correlation (DCC) method. They base their study on daily futures prices of rapeseed, crude oil and related agricultural commodities observed during the period 1999-2009. Their findings suggest an increasing correlation between the returns of rapeseed and crude oil prices. In addition, rapeseed prices present a high sensitivity to shocks and low persistence of low volatility. Busse et al. (2011) mention that crude oil prices determine the profitability of biofuels and any increase (or decrease) in crude oil prices improves (worsens) the competitiveness of biofuels and leads to increasing (decreasing) demand for rapeseed as the main biofuel feedstock.

Ciaian and Kancs (2011b) study price transmission between energy, bioenergy and food prices during the period 1993–2010 taking into account the presence of structural breaks. They divide the sample composed of weekly data corresponding to a variety of foods (corn, wheat, rice, sugar, soybeans, cotton, banana, sorghum and tea) into three periods (1993–1998, 1999–2004 and 2005–2010). The first one is characterized by the reduction in the OPEC spare capacity. The second period is related to the increase in bioenergy policy support in developed economies. The third one corresponds to the significant expansion of biofuel production. They find that the links between energy and food markets are increasing over time and are mainly explained through biofuel channel, whereas the indirect input channel of price transmission is small and statistically insignificant.

Serra et al. (2011) resort to smooth transition vector error correction model to assess price relationships within the U.S. ethanol industry by considering monthly prices of ethanol, corn, oil, and gasoline prices during the period 1990-2008. Their findings underline the presence of long-run relationships among the prices analyzed and strong links between energy and food prices through ethanol market.

Ji and Fan (2012) focus on the influence of oil price volatility on daily prices of non-energy CRB index commodities (crops and metals) observed during the period July 2006-June 2010 by introducing the US dollar index as exogenous shocks. Based on a bivariate EGARCH model with time-varying correlations, their findings indicate that volatility spillovers effects from

crude oil market to non-energy commodities are significant and that volatility spillovers from the US Dollar index to the CRB crop index were weaker after the subprime crisis than before.

Gardebroek and Hernandez (2013) use weekly spot prices to test the level of interdependence and volatility spillovers dynamics among crude oil, ethanol, and corn prices in the United States during the period 1997-2011 through a multivariate GARCH approach. Their results indicate a higher interaction between ethanol and corn markets in recent years, particularly after 2006 when ethanol became the sole alternative oxygenate for gasoline while the volatility spillovers are significant from corn to ethanol prices, but not the reverse, indicating that there is no transmission of volatility from energy to U.S. corn markets.

By resorting to multivariate GARCH models (BEKK-GARCH and DCC-GARCH) for the daily spot prices of major commodities related to oil markets (WTI, Brent, gasoline, and heating oil) and to cereal markets (barley, corn, sorghum, and wheat) observed during the period 2000-2013, Mensi et al. (2014b) investigate the return and volatility spillovers across international energy and cereal commodity markets by taking into account the impacts of OPEC news announcements on these spillovers. Their results provide mainly evidence of significant linkages (in terms of volatility transmission) between energy and cereal markets and underline the influence of OPEC news announcements on the oil markets as well as on the oil–cereal relationships.

Koirala et al. (2015) investigate dependence between agricultural (corn, soybean, cattle) and energy commodities futures prices (crude oil, natural gas, gasoline, diesel, biodiesel). They use both the Clayton and the Clayton-Gumbel mixture copulas applied to daily data covering the period from March 2011 to September 2012. Their main findings indicate that agricultural commodities and energy futures prices are highly correlated and exhibit positive and significant relationship.

Chiu et al. (2016) investigate the trivariate relationship between monthly prices of crude oil, corn and ethanol during the period January 1986-August 2015 through exploring the Granger-causality relationships and impulse response functions between these commodities by means of the vector autoregressive (VAR) model and the vector error correction model (VECM). They consider three sub-periods in their study (1986m1-2004m6, 2004m7-2006m12, and 2007m1-2015m8) based on the structural break points in the crude oil series. Their findings underline the presence of co-integration relationship between the ethanol and the other two series only during the second period (2004m7–2006m12) while the other two periods do not reveal the presence of long-run relationships between these commodities.

de Nicola et al. (2016) study the degree of co-movement and the time-varying properties of pairwise unconditional and conditional correlations among monthly price returns of 11 major energy, agricultural, and food commodities during the period 1970-2013 based on multivariate dynamic conditional correlation models. To check whether the correlations of price returns across markets are driven by economic and financial variables, they also consider nominal interest rate, stock market returns, and exchange rate returns. Their results reveal the high positive correlation between energy and agricultural commodities prices and the increase in their co-movement during the recent years in particular for maize and soybean oil, which are important inputs in the production of biofuels. They also find that many of these correlations are, in general, positively associated with the behavior of financial markets (measured by the volatility of stock market returns), particularly after 2007 but not with the interest rate and exchange rate returns.

A review among the previous works reveals that asymmetric impacts of energy on food commodities prices fluctuations were almost ignored and few recent works have focused on whether the dependence structure is different among boom and bust market cycles.

Most of previous works agree on the symmetry of tail dependence between crude oil and agricultural commodity prices, indicating that food and energy markets are linked to the same degree regardless of whether markets are booming or crashing (Boonyanuphong et al., 2013; Boonyanuphong and Sriboonchitta, 2014). Boonyanuphong et al. (2013) results are based on copula-based GARCH models applied to daily data covering the period from February 28, 2008 to December 15, 2011. Boonyanuphong and Sriboonchitta (2014) apply the C-vine copula based ARMA-GARCH model to daily futures returns spanning the period from March 23, 2005 to January 1, 2013.

Few available recent works recognize that tail dependence between crude oil and agricultural commodity prices is asymmetric (Apergis et al., 2017; Han et al., 2015). Han et al. (2015) investigate price dependencies between energy and agricultural commodity markets (corn, soybean and wheat) using daily futures prices covering the period 2000-2014. Different structural break points in energy and agricultural markets are considered in their study[4]. Their results underline the increase in tail dependence between energy and agricultural commodity

[4] January 5, 2004 when significant index investment started flowing into commodity markets; July 29, 2005 when the Energy Policy Act of 2005 was passed; January 3, 2007 corresponding to the explosion of the food price crisis; September 15, 2008 when Lehman Brothers filed for bankruptcy; October 17, 2012 when new biofuels rules were launched by the EU.

markets during the financial crisis and their asymmetry during the biofuels policy and financial crisis periods where lower tail dependence is much stronger than upper tail dependence. Apergis et al. (2017) use daily data of biofuels and agricultural commodities to capture possible asymmetric causal effects among them during the period 2007-2011. Their empirical results indicate that there are commodity prices that have strong causal (asymmetric) relationships with biofuel energy prices. Their application of threshold analysis indicates the presence of asymmetric movements in the prices between the two markets, supporting the role of a threshold defining two different regimes. The first regime corresponds to the period prior to the 2008 commodity price spikes with faster adjustment toward equilibrium, while the second regime matches the post spikes period.

3.1.2. Some studies as part of group 2:

Du et al. (2011) consider a sample of futures prices for crude oil, corn and wheat markets weekly observed from 1998 to 2009 which they divide into two sub-periods considering the structural break point (October 2006) in agricultural commodity prices. Stochastic volatility models and Bayesian econometric analysis are applied for the analysis of these data. Their results indicate positive volatility spillover among crude oil, corn and wheat markets after the fall of 2006 which they explain by the tightened interdependence between crude oil and these commodity markets induced by the increase in input costs following the increase in ethanol production in addition to the demand boosting. During the first sub-sample period, Du et al. (2011) findings disclose a negative spillover between crude oil prices from one side and corn and wheat prices from the other side indicating that commodity futures could be included in a portfolio in order to reduce price risk in the energy market.

Nazlioglu (2011) focuses on price transmission from world oil prices to three key agricultural commodity prices (corn, soybeans, and wheat) by applying linear and nonlinear Granger causality methods to weekly prices covering the period 1994-2010. His findings underline the oil-agriculture linkages after the food crisis.

Kristoufek et al. (2012) apply minimal spanning trees and hierarchical trees for the analysis of price transmission between agricultural commodities (corn, wheat, soybeans, sugar) from one side and biodiesel, ethanol and related fuels from the other side during the 2003-2011 period. In order to check the impact of the 2007-2008 food crisis, they compare the periods before and after the crisis and find that the connections are much stronger for the post-crisis period. Their finding is also supported further by their recent work (Kristoufek et al., 2014).

The change on dependence behavior between food and energy markets is also confirmed in Reboredo (2012) study. This study resorts to copula models for the investigation of dependence structure between world oil prices and global prices of three key agricultural commodities (corn, soybean and wheat) weekly observed during the period from 9 January 1998 to 15 April 2011. Findings of this study underline the increase in dependence during the last three years of the sample mainly for corn and soybean explained by the increased demand for these commodities for biofuel production purposes subsequent to the increase in oil prices. However, Reboredo (2012) finds that, for the overall sample, food and oil prices tend to move independently, in particular when markets experience extreme upward movements.

The same result has been shared by Nazlioglu et al. (2013) with an extension of the scope of agricultural commodities considered (wheat, corn, soybeans, and sugar) and an increase in their frequency to daily prices observed over a longer sample period from 01 January 1986 to 21 March 2011. Nazlioglu et al. (2013) apply the causality in variance test and impulse response functions. In order to identify the impact of the 2006-2008 food price crisis on volatility transmission mechanism between energy and agricultural markets, Nazlioglu et al. (2013) divide the data sample into two sub-periods where the first one corresponds to the pre-crisis period (January 1986-31 December 2005) and the second one is the post-crisis period (01 January 2006-21 March 2011). Their findings mention that, with the exception of sugar, volatility spillover between oil and agricultural markets is absent in the pre-crisis period and is confirmed during the post-crisis period. They also underline the similar patterns of the behavior of corn and soybeans returns volatility with respect to a shock in oil returns volatility.

Wang et al. (2014) investigate the effects of oil price shocks on spot prices of nine key agricultural commodities (cocoa, soybean, barley, wheat, corn, cotton, rice, coffee and tea) monthly observed during the period 1980-2012. They resort to a structural vector autoregressive (SVAR) model in order to decompose oil price changes into three independent components related to oil supply shock, aggregate demand shock and other oil-specific shocks due to precautionary demand or speculative demand. They find that, during the pre-crisis period (before 2006-2008), oil supply shock or other oil-specific shocks have no significant impact on agricultural commodity prices contradictory to the after crisis period. According to them, the main explanation of the significant impact in the after crisis period is the substitutive effect between biofuels and fossil fuel since bioethanol and biodiesel extracted from corn and soybean, respectively, are considered as the appropriate substitute of crude oil.

3.1.3. Some studies being part of group 3:

Gilbert (2010) stated that there is no direct causal relationship between oil and agricultural prices and the correlation between oil and agricultural prices is due to demand growth in addition to monetary expansion and exchange rate movements.

Kaltalioglu and Soytas (2011) agree on the same finding while investigating volatility spillover between spot prices of agricultural raw material (timber, cotton, wool, and rubber), food (fruits, vegetables, meat, poultry, fish, grocery food and non-alcoholic beverage) and oil monthly observed during the period from January 1980 to April 2008. Their investigation is based on the Granger causality in variance approach developed by Cheung and Ng (1996).

Zhang et al. (2010) apply cointegration estimation and a vector error correction model to monthly price data of fuels (ethanol, gasoline and oil) and agricultural commodities (corn, rice, soybeans, sugar and wheat) covering the period from March 1989 to July 2008. Their findings indicate the absence of long-run price relations between fuels and agricultural commodities prices and the limitation of direct short-run relationships in case of their presence, except for sugar having an influence on increasing agricultural commodity prices through biofuel production affects.

3.2. Transmission channels from energy to food markets prices:

Most of studies revealing significant linkages between energy and agricultural markets state that these linkages are namely explained through three key transmission channels where the first two channels are related to supply (input channel) and demand (biofuel channel) sides and the third one corresponds to macroeconomic factors.

We can cite as an example the study of Baffes (2013) identifying four key channels through which energy and food markets interact as illustrated in the diagram below (figure 1.6) where the first channel (links A and B/C) corresponds to the cost link, the second channel (links D and F) is related to policies favoring the production of biofuels to reduce dependence on imported crude oil. Link E denotes non-biofuel policies affecting food prices that may or may not be affected by energy prices. Links G1 and G2 reflect profitable biofuels and induced innovation respectively.

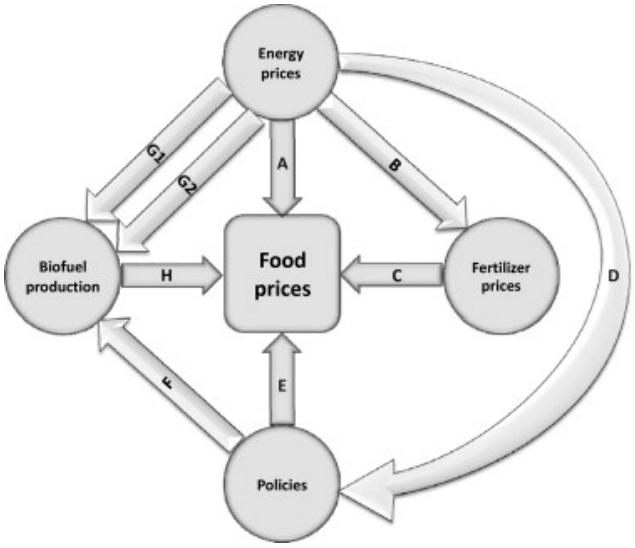


Figure 1. 6: The relationship among energy, biofuels, and food

(Source: Baffes, 2013)

In the following, the main three key channels cited in the literature of prices transmission from energy to food commodities are detailed.

3.2.1. The input channel:

The input channel is explained in the previous studies by the use of oil for agriculture production (e.g. Akram, 2009; Algieri, 2014; Baffes, 2007; Chang and Su, 2010; Du et al., 2011; Gohin and Chantret, 2010; Hanson et al., 1993; Koirala et al., 2015; López Cabrera and Schulz, 2016; Tadesse et al., 2014).

Hence, an increase in oil prices leads to higher production costs such as fertilizers, chemical materials, irrigation, fuel and transportation which, in turn, generate a rise in the agricultural commodities prices (Baffes, 2010; Hanson et al., 1993; Nazlioglu and Soytas, 2011). Ajanovic (2011) states that if two markets are linked by trade flows due to using similar inputs, price changes in one market should lead to changes in the other market.

Agricultural output is used largely as an intermediate input by other sectors, and agriculture buys inputs such as chemicals, which are made using energy-intensive technologies. While agriculture is directly energy intensive, the net impact of a rise in the price of energy depends on the relative energy intensiveness of agriculture compared with other sectors, taking indirect linkages into account as well.

Findings in the previous works indicate that agricultural prices are more likely to be driven by production costs in the medium/long run (Ciaian and Kancs, 2011a; Gohin and Chantret, 2010; Natanelov et al., 2011). In fact, due to the quasi-fixed nature of some farm production factors (e.g. land rental contracts, constrained access to capital and family labor), it is doubtful that agricultural prices perfectly reflect production costs in the very short run.

Theoretical models employed in the literature in order to explain the links between energy and food prices through the input costs channels correspond to equilibrium models. Partial-equilibrium cost studies or input-output framework find that agricultural production techniques are energy-intensive. Marimpi,Maria (2014) indicates that agricultural sector includes many energy-dependent procedures from fertilizers to long distance transportation, through which the price transmission from one sector to others occurs.

This input channel of price transmission between energy and food markets can be explained by means of transaction cost economics theory pioneered by Coase (1937). This theoretical framework shows that the coordination of economic transactions cross markets generates transaction costs. In contrast to neoclassical microeconomic theory, transaction cost economy assumes that markets do not work exclusively through the price mechanism. There are costs involved in using the price mechanism that justify the existence of other modes of organizing economic transactions. The literature that has tried to measure market transaction costs frequently has considered those costs synonymous to transportation costs. Market transaction costs are linked essentially to information and bargaining costs. The combination of market transaction costs and transportation costs forms the exchange costs. In fact, the total economic cost of a commodity includes the direct cost of production, the opportunity cost of producing which depends on price volatility level and the risk-free rate in addition to the cost of marketing and storage costs.

3.2.2. The biofuel channel:

One of the most frequently mentioned channels in the literature through which energy impacts agricultural (and hence food) commodities is related to the use of food crops for the production of biofuels and the expanding use of agricultural commodities such as corn and soybeans as feedstock for biofuels production following the increase in oil prices (e.g. Akram, 2009; Algieri, 2014; Baffes, 2007; Balcombe, 2011; Busse et al., 2011; Chiu et al., 2016; Ciaian and Kancs, 2011a; Du et al., 2011; Gohin and Chantret, 2010; Koirala et al., 2015; López

Cabrera and Schulz, 2016; Nazlioglu et al., 2013; Peri and Baldi, 2013; Reboredo, 2012; Tadesse et al., 2014; Wang et al., 2014; Wei and Chen, 2016).

Previous studies agree on the intensification of the link between biofuels and agricultural commodities with the increase in biofuels production during the recent years (Abbott et al., 2009; Balcombe, 2011; Grebmer et al., 2011; Serra et al., 2011; Koirala et al., 2015; Mitchell, 2008; Serra and Zilberman, 2013; Mensi et al., 2014b; de Nicola et al., 2016), which explains the attention paid to this topic since the passage of the ethanol mandate in the US Energy Policy Act of 2005.

In fact, the increased demand recorded all over the world of petroleum for transportation, industry and electricity use has resulted in a rapid growth in oil prices in the last decade. Biofuels (such as ethanol and biodiesel) has been considered as an alternative to energy market (Chang and Su, 2010; Chiu et al., 2016) and has recorded a rapid growth driven mainly by the political decisions taken by developed countries.

By reference to the World Bank quarterly report related to commodity markets outlook in July 2015 (*Commodity markets Outlook*, 2015), a high increase in biofuels production has been recorded during the 2007-2008 period as it is illustrated in figure 1.7 below.

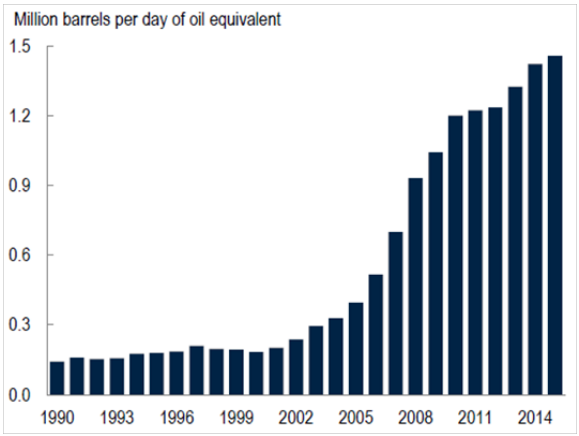


Figure 1. 7: Global biofuels production

(Source: BP Statistical Review of World Energy and World Bank)

Relations between biofuels and agricultural commodities have intensified namely between ethanol and corn markets where an increasing amount of US corn used for ethanol production recorded an increase namely during the 2007-2008 period (figure 1.8 below). Condon et al.

(2015) argue that corn prices increase by three to four percent following an increase in ethanol production by one billion gallons.

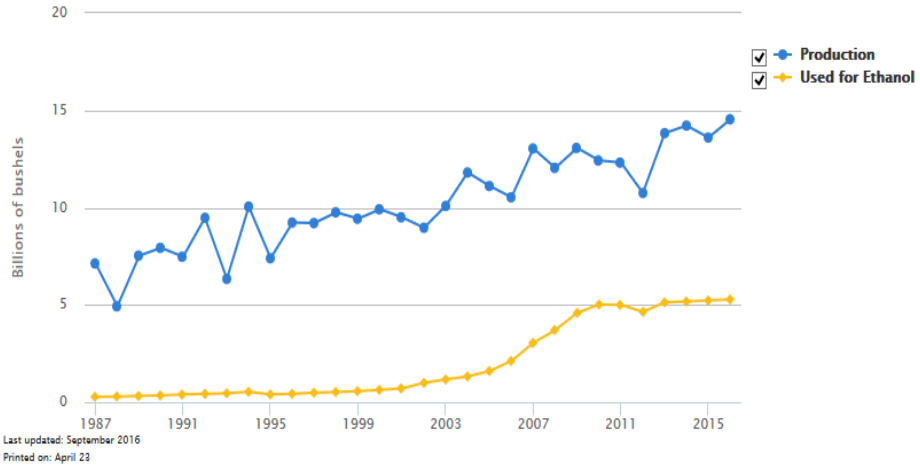


Figure 1. 8 : U.S. corn used for ethanol production

(Source: USDA 2016)

In fact, because of biomass demand in biofuels production, the biomass price increased due to the direct biofuels channel. The price for food commodity increased because the use of biomass in biofuels production increased competition for all inputs, thus pushing input prices up and causing a further upward adjustment of food commodity price.

According to OECD-FAO, 2012, biofuels production requires, on average, 11% of global production of coarse grain, 11% of vegetable oil and 21% of sugarcane over the 2008–2010 period.

This statement has been supported by Natanelov et al. (2013) study on the relationship between crude oil, corn and ethanol during the period 2006-2011 and whose findings indicate that current technologies to produce biofuels are mainly based on commodities such as cereals, sugar, and oilseeds.

A review on the literature dealing with the impact of biofuel policies on grains and oilseed prices is provided by De Gorter et al. (2013). These biofuel policies are varied and include, among others, biofuel consumption mandates, biofuel consumption subsidies, production subsidies for both biofuels and feedstocks, environmental regulations, import tariffs and tariff-rate quotas.

Referring to Lam et al. (2009), biofuel transmission channel also links indirectly prices of food commodities not used to produce biofuel since food products (whether convertible into biofuel or not) are substitutes among each other. Ciaian and Kancs (2011b) agree on the same finding and mention that biofuels agricultural commodities respond to biofuels and are then followed by other commodities after adjustments in the factor markets.

Although some agreement about the factors responsible for increasing agricultural commodities prices in 2008, the literature reveals distinct estimates of the extent of the effect caused by biofuels. According to the National Research Council (2011), the impact of biofuels on the increase in corn prices during the period 2007-2009 ranges from 17% to 70%. Hochman et al. (2010) place these estimates between 3% and 75%. These disparities were explained by the differences in the analytic approaches used for their estimation and the differences in the policy instruments, geographic coverage and timeframe considered in addition to the different assumptions about demand and supply elasticities. A review of studies illustrating the range of disparities is provided by Zhang et al. (2013) and by Condon et al. (2015) in a more recent paper.

Economic modeling techniques of biofuels impact can be classified into structural models based on economic theory and reduced form models dealing with the statistical properties of time series as underlined by Janda et al. (2012). Structural models include partial equilibrium and computable general equilibrium models. Interaction among supply, demand, and prices through the market clearance are explained in these models by equilibrium equations (Kristoufek et al., 2012). Zhang et al. (2013) provide a review of some studies quantifying the impact of biofuels on agricultural commodities based on structural models. Detailed discussions on the results of these models with respect to economics of biofuels are provided by Rajagopal and Zilberman (2007).

The partial equilibrium structural models are based on the assumption of constancy of prices and quantities in other markets. Partial equilibrium models are therefore suitable for providing good indication of short-term response to shocks (Janda et al., 2012). Examples of partial equilibrium models used in the assessment of the impact of biofuel development include AGLINK/COSIMO model developed by OECD and FAO, ESIM model developed by the Economic Research Service of the US Department of Agriculture, FAPRI model of the Food and Agricultural Policy Research Institute, and the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) of the International Food Policy Research Institute.

An example illustrating the application of partial equilibrium models corresponds to Tokgoz et al. (2008) paper measuring the impact of an increase in crude oil price on US farm prices taking into consideration the effects occurring through biofuels, production costs and transportation costs but not the macro-economic effects. Organization for Economic Cooperation and Development and FAO (2008) also examines the long-run impacts of oil prices on world agricultural markets using the AGLINK/COSIMO system of partial equilibrium models.

Computable general equilibrium models have the benefit of allowing the assessment of the impact of biofuels on the whole economy by taking into account simultaneously all the linkages between biofuels and other markets. GTAP model and its variants are the most popular ones being part of this models category. The major disadvantage of computable general equilibrium approach lies in their suitability for the treatment of developed countries better than developing countries.

Gohin and Chantret (2010) investigate the long-run relationship between world prices of some food and energy products using a computable general equilibrium mode allowing to capture interactions among the different economic sectors and considering the impact of macro-economic linkages. They find a positive relationship due to the cost-push effect.

In order to combine the strength and eliminate the weaknesses of partial equilibrium and computable general equilibrium models, an integrated modeling framework has been presented by Birur et al. (2010).

3.2.3. Macroeconomic factors:

The last channel discussed in the literature explaining prices transmission from energy to food markets is related to the co-movement of commodity prices with macroeconomic factors and financial indicators.

A range of studies underlines the role of exchange rates appreciation and depreciation on the direction and the origins of volatility transmission between oil and agricultural prices (e.g. Nazlioglu and Soytas, 2012, 2011; Olson et al., 2014).

Gilbert (2010) indicates that the link between food and oil prices is an indirect causal link explained by a common cause, whether monetary conditions, demand growth or exchange rates. He agrees that the principal channel through which monetary and financial activities have affected food prices over recent years corresponds to index futures investment.

Gohin and Chantret (2010) indicate that energy prices have a significant impact on real income as well as on trade balances and that the subsequent impact of these macro-economic effects on world agricultural markets depends on the macro-economic policies pursued around the world (e.g. free versus fixed exchange rate regime, wage policy with respect to price inflation, etc.).

Another growing body of literature attributes the link between crude oil and agricultural commodities prices to the rapid integration of stock and bond markets with commodity markets, specifically during the financial crisis (Adams and Glück, 2015; Creti et al., 2013; de Nicola et al., 2016; Han et al., 2015; Pal and Mitra, 2017).

Creti et al. (2013) study is based on dynamic conditional correlation GARCH methodology applied to data observed during the period 2001-2011 covering, among other commodities, energy, agricultural, food, oleaginous, exotic and livestock commodities.

Adams and Glück (2015) use the state-dependent sensitivity value-at-risk (SDSVaR) model with daily returns of S&P GSCI commodities indices (corn, wheat, cattle, crude oil, heating oil, copper, aluminum, gold) and S&P 500 index as a proxy of stock market over the period 1994-2013 to check spillovers across these markets.

In a recent work, Han et al. (2015) highlight the key role played by the financial crisis which is characterized by heavy use of agricultural commodities as financial assets (financialization) in emphasizing the links between food and energy markets. Their study relies on multivariate normal mixture models for the identification of price dependencies between energy and agricultural commodities (corn, soybeans, and wheat). Daily futures returns covering the period 2000-2014 are considered and different sub-periods are examined in this study corresponding to structural break points[5].

de Nicola et al. (2016) study the degree of co-movement and the time-varying properties of pairwise unconditional and conditional correlations among monthly price returns of 11 major energy, agricultural, and food commodities during the period 1970-2013 with consideration of economic and financial variables corresponding to interest rate, exchange rate, and stock market. They mainly find a statistically positive association between the co-movement of commodity price returns and stock market uncertainty namely after 2007.

[5] January 5, 2004: significant index investment started to flow into commodity markets; July 29, 2005: the Energy Policy Act of 2005 was passed; January 3, 2007: the food price crisis erupted; September 15, 2008: Lehman Brothers filed for bankruptcy; October 17, 2012: the EU launched new rules for biofuels.

Pal and Mitra (2017) underline the link between commodity markets financialization and the transmission of price and risk from crude oil to world food index and eventually to commodities which are primary feedstock for biofuel such as corn and soybean. This is illustrated through the increasing preferences for commodity derivatives over traditional investment instruments such as equities and bonds after the financial crisis period. Their study is based on wavelet analysis applied to monthly data of crude oil prices and world food price index observed during the period January 1990-February 2016.

4. On the relation between food and financial markets

With the rapid growth in index investment in commodity futures and the financialization of commodities futures, several studies were focusing on the links between commodities futures and other assets through assessing either the spillovers among them or their co-movement with a particular attention to the potential diversification benefits from investing in commodities futures.

In fact, following the financialization of commodities markets, an increase in the investment namely in agricultural commodities futures market has been recorded (Baldi et al., 2016; Reboredo, 2012). According to the quarterly index investment data reports of the Commodity Futures Trading Commission (CFTC)[6], exchange-traded funds have sharply increased from $12 billion in 2002 to $200 billion in 2008 and hedge funds were also particularly active in agricultural commodity derivatives markets.

This inflow of index traders has caused a change in the structure of futures markets and the manner according to which commodities are linked to other assets (Adams and Glück, 2015). In fact, in addition to the traditional type of traders corresponding to speculators and hedgers with commercial interest in commodities futures market, commodity index traders emerged as new financial actors. This new type of actors is distinguished from the traditional speculators in the sense that their discussions are based not only on individual commodities prices but on prices of a broad range of commodities and portfolio considerations since they are active across different markets.

[6] http://www.cftc.gov/marketreports/indexinvestmentdata/index.htm.

Besides the growing rate of the participation of financial investors in these markets, the nature of index investment has recorded a change in its structure. In fact, enhanced index strategies have been adopted in addition to traditional strategies based on the replication of major indices through investing in the front end of the curve and passively rolling into the next contract each month. These enhanced index strategies are based on a mixture of passive and active management elements. They thus attempt to generate modest excess returns compared to index funds and other passive management techniques[7].

Following this increase in index investment in commodity futures, the empirical literature has given particular attention to commodities risk-hedging and portfolio diversification opportunities in addition to the investigation of the links between commodities and stock markets and whether the inclusion of commodities in financial portfolios as part of a diversification strategy may result in higher correlations and volatility spillovers between commodities and financial markets.

A review of the extant literature that debates on diversification benefits issued from investment in commodities reveals that spot and futures commodities markets have been considered as alternative investment instruments for hedging against risk in equity and stock markets, due to the lower diversification benefits from stock and equity investments during financial crises, accompanied by the growing financialization of commodity markets (Nicolau and Palomba, 2015; Sensoy et al., 2015), which makes the focus on the efficiency of commodities markets of particular interest in order to allow investors to decide their appropriate positions in the futures markets so that to compensate for the risk from corresponding holdings in the spot market (Fan et al., 2016).

Previous works underline the importance of improving market information and its transparency, either for spot markets or commodity futures markets, so that to allow market actors to form expectations based on fundamentals and to detect shortages early (Tadesse et al., 2014). In fact, efficient markets where futures prices provide unbiased estimates of the future spot prices are a mean of risk management.

In fact, during recent years, commodity markets have been considered by investors as financial assets (Mensi et al., 2013; Reboredo and Uddin, 2016; Vivian and Wohar, 2012) and as part of a portfolio diversification strategy to diversify investment and hedge against inflation (Arezki et al., 2014; Creti et al., 2013; Tadesse et al., 2014; Tang and Xiong, 2012). Two examples of

[7] A detailed description of enhancement techniques is provided by Riepe and Werner (1998).

studies focusing on diversification benefits through the inclusion of commodities into a portfolio can be cited (Büyükşahin et al., 2010 and Jebabli et al., 2014). Büyükşahin et al. (2010) use DCC GARCH model for daily, weekly, and monthly returns during the period 1991-2008. Their main findings indicate the increase in the co-movement between equity and commodities during periods of financial market stress and allow to identify substantial variations over time in the potential diversification benefits that commodities could bring to equity investors. Jebabli et al. (2014) consider two hedged portfolios each one composed of different types of food commodities (crops, plantation and forestry, and livestock) and either crude oil or MSCI world stock market covering, on a monthly basis, the period 1980-2012. Their results related to hedge effectiveness issued from the variance–covariance matrix obtained from the application of a TVP-VAR model underline the diversifications benefits offered by food commodities and namely maize which prvide the most useful risk management tool for hedging and for portfolio diversification.

Literature review reveals that few attention has been attributed in the previous studies to food markets efficiency despite the fact that these markets, and namely grain markets (wheat, corn, and soybean), have recorded during the 2005-2011 period a divergence between their spot and futures values (Adjemian et al., 2013; Aulerich et al., 2011).

Although the large number of recent studies dealing with the impact of financialization on commodity futures and spot prices and with the effect of commodity futures trading on the spot market (Brooks et al., 2015) following the recent fluctuations of commodities prices which were accompanied by a substantial increase in trading activity in the futures market, the debate on the literature concerning the impact of financial investors on commodity prices and futures speculation was not resolved. Arezki et al. (2014) provide a review of some studies approaching this topic underlining the divergence on their conclusions. In fact, two polarized views can be distinguished (Cheng and Xiong, 2014a) where the first one corresponds to the bubble view and the second one to the business-as-usual view.

4.1. The bubble view:

The bubble view considers that the bubble in energy and agricultural commodities during the period 2007-2008 is caused by commodity index investors. Studies supporting this view underline the rising relationship between commodities and stock markets through the

financialization of commodities and underline the negative impact of futures speculation on commodities prices (Gilbert, 2010; Singleton, 2014; Tang and Xiong, 2012).

Studies supporting this view agree that commodities are increasingly regarded as an investable asset class providing diversification benefits, low correlations with stocks and bonds, and good hedging properties against inflation. As a result, many new commodity index funds were established and their activities increased trading volumes and altered the balance of transactions between hedgers and speculators (Irwin and Sanders, 2012; Masters, 2008).

However, even if the empirical literature on commodities financialization has contributed to the debate on this subject, theoretical literature related to it remains scarce (Basak and Pavlova, 2016). Among these empirical studies, we cite here below few ones as an example and not an exhaustive list.

Liu and Tang (2010) underline the evidence of cointegration between four commodities markets and market fundamentals before 2004, while after this period, they indicate that the mainly reason behind the rise in commodities prices corresponds to the rise in speculative activities caused by large open interests recorded for various commodity futures.

Diebold and Yilmaz (2012) investigate daily volatility spillovers between commodities markets given by Dow-Jones/UBS commodity index from one side and the US stock (S&P500), bond (US Treasury bond yield), and US Dollar from the other side during the period 1999-2010. Their findings underline the increase in linkages between the Dow-Jones/UBS commodity index and the other markets after the beginning of the subprime crisis and the occurrence of volatility spillovers from the S&P 500 to the commodity index throughout the crisis. Their main findings indicate also that commodity market was a net recipient of modest levels of volatility shocks from the stock and bond markets.

Tang and Xiong (2012) focus on the role of speculation in the co-movement of commodity prices and find increased co-movement after 2004 between commodities which is more pronounced for commodities on the S&P GSCI and DJ-UBS commodity indices than for non-indexed commodities, confirming thus the growing relevance of index trading. They attribute these findings to the entry of institutional investors into commodities futures market.

UNCTAD (2012b) indicates that prices of financialized commodity markets should follow the prices on other purely financial markets and that price co-movement between these markets can be explained through the common critical feature shared by both stock and commodities markets corresponding to financial investors position.

Bicchetti and Maystre (2013) investigate rolling window bivariate intraday return correlations among equities (S&P 500) and several commodities futures (corn, wheat, soybeans, sugar, live cattle, and crude oil) during the period 1998-2011. Their findings indicate increased volatility or return linkages between agricultural and energy markets, and between commodity and financial markets around 2006-2008.

Creti et al. (2013) highlight the role played by the 2007–2008 financial crisis in emphasizing the links between commodities and stock market and the financialization of commodity markets.

Delatte and Lopez (2013) emphasize the increase in co-movement between commodities (metal, agriculture and energy) and stock index returns over time which becomes stronger after the 2008 financial crisis. Their study is based on copula approach applied to daily data during the period January 1990-February 2012.

Mensi et al. (2013) apply bivariate VAR-GARCH models to S&P500 and commodity price indices (wheat, beverage, gold, crude oil, and Brent oil) during the period 2000-2011. They find a significant volatility transmission between commodities markets (except wheat) and the S&P 500.

Silvennoinen and Thorp (2013) find that financial shocks appear to be important predictors of correlation dynamics between commodities and stocks. They also mention the increase in correlation between S&P-GSCI commodity index and the stock market index S&P 500 along with the increase in speculators[8] participation in commodity derivatives market underlining thus the impact of financialization.

Silvennoinen and Thorp (2013) estimate sudden and gradual changes in correlation between stocks, bonds and commodity futures returns, using double smooth transition conditional correlation (DSTCC–GARCH) models with weekly data covering the period 1990-2009. Their results show that conditional weekly return correlations of equities and two commodities (corn and soybeans) increased in the period 2002-2003, while correlations of equities and two other commodities (wheat and crude oil) peaked in mid-2008. They also find that commodity-bond relations remain relatively constant. Unlike other investigations of commodity futures returns such as Büyükşahin et al. (2010) and Chong and Miffre (2010), the results of Silvennoinen and Thorp (2013) do not show weakening correlation between commodities and conventional stock

[8] In particular hedge funds that hold positions in both equity and commodity futures markets.

and bond returns, but, on the contrary, they present evidence favoring closer commodity and financial market integration, more consistent with Cheung and Miu (2010) and Daskalaki and Skiadopoulos (2011). Their results reveal also a significant decline in diversification benefits to investors across equity, bond and stock markets.

Algieri (2014) underlines the significant positive effect of S&P500 on daily commodities futures prices (rapeseed, soybeans, soybean oil, sugar and wheat) during the period May 2005-June 2013, revealing that the movements in stock market returns put an upward pressure on agricultural commodity futures returns. His findings indicate that the evolution of commodity and stock returns in the same direction reduces their potential substitutability in portfolios and risk diversification for investors.

Büyükşahin and Robe (2014) underline the key role played by hedge funds in the transmission of shocks from stock markets to commodities.

Aboura and Chevallier (2015) underline the presence of increasing return and volatility spillovers between commodity and financial market which are stronger particularly since 2008 due to the financialization phenomenon. Their modeling of cross-market relations with multivariate volatility processes is based on the asymmetric dynamic conditional correlation model with one exogenous variable applied to daily data of aggregate indices observed during the period 1983-2013.

Adams and Glück (2015) apply the state-dependent sensitivity value-at-risk (SDSVaR) model of Adams et al. (2014) allowing to account for directional spillovers across markets. Their results, in line with Cheng et al. (2014), underline the presence of substantial and unidirectional risk spillovers from stock to commodity markets after the 2008 financial crisis, even if financial investors have been interested by commodities since 2004. Adams and Glück (2015) underline also the persistence of risk spillovers from stocks to commodities which remain high throughout the period 2008-2013 contrary to the implication of the loss spiral argument which states that commodities are expected to revert to their pre-crisis behavior after 2009. They explain this persistence by the investment style effect reflecting the investment behavior of commodity index traders. Adams and Glück (2015) conclude that risk spillover from stock to commodity markets after the 2008 financial crisis are not only a phenomenon of the financial crisis but also of a style effect corresponding to the investment behavior of commodity index traders (financialization) explaining that risk spillovers are not limited to the financial crisis but continue to affect portfolio risk even after the crisis period. In conformity with the economic theory of financialization in commodity markets, Adams and Glück (2015) results show that

risk spillovers from stock market are higher for commodities with higher volatilities explained by liquidity and loss spiral model as it has been stated by Brunnermeier and Pedersen (2009) and Cheng et al. (2014).

By using price series and dynamic conditional correlation approach, Girardi (2015) analyzes the time-varying correlation of 16 agricultural prices with stock market returns. Their results indicate that the recent increase in correlation between agricultural prices and stock market dynamics is explained by a combination of financial turmoil and financialization.

The impact of the financialization of the commodity futures market, measured through Total Open Interest (TOI) and Open Interest in Dollars (OID), on commodity prices co-movement has been also investigated by Pradhananga (2015). Her findings underline the significance of this impact which is explained by the increase in liquidity across different commodity markets due to increasing investment in commodity indices.

In a more recent study, Baldi et al. (2016) agree on the generation of the link between agricultural and financial markets through financialization. Their study is based on the investigation of volatility impulse response functions between commodity and stock markets and the impact of two of the most important bubble bursts (the 2000 dot.com bubble and the 2008 financial crisis). Weekly data from 1970 to 2015 are used corresponding to S&P 500 Index as the proxy for the overall stock market and to three indices for agricultural markets related to S&P Agriculture Index, S&P Grain Index and S&P Corn Index. Their results underline a significant increase in volatility spillovers from stock to agricultural markets after the 2008 financial crisis due to a greater exposure of commodity to uncertainty about the economy, and turmoil in stock markets and bond markets. Baldi et al. (2016) findings indicate that volatility spillovers from stock markets to commodity markets were negative before and after the dot.com bubble, contrary to the period after the 2008 financial crisis during which volatility spillovers increased significantly in particular for more financialized commodities which are largely traded on stock markets as alternative asset classes (such as corn).

Basak and Pavlova (2016) provide a theoretical model for the assessment of the impact of financialization on commodities prices through focusing on the identification of the economic mechanisms through which institutions may influence commodity futures prices and how their presence may affect commodity spot prices and inventories. Their results underline the impact of financialization on the increase of commodities futures prices correlations and volatilities with a more pronounced impact for index futures than non-index futures. They also show the increase in the correlations between equities and commodities futures following the

financialization of commodities. Although this increase was explained in the literature through the transition in commodity futures markets, due to the inflow of institutional investors in the mid-2000s, from large segmented commodities to commodities linked together as well as with the stock market through the cross-holdings in their portfolios, Basak and Pavlova (2016) explain through the emergence of this index as a new (common) factor in commodity futures and stock returns. They also demonstrate how financial markets transmit shocks not only to futures prices but also to commodity spot prices and inventories mentioning that spot prices go up with financialization and shocks to any index commodity spill over to all storable commodity prices. Basak and Pavlova (2016) model allows to conclude that financial market serve as a conduit in transmitting outside shocks to commodity spot prices.

de Nicola et al. (2016) results indicate the presence of an overall positive increasing link between the standard deviation of S&P500 stock price returns and the co-movement of energy, agricultural, and food commodities price returns during the period 1970-2013. They also underline the association between the increase in stock market volatility and the increase in commodities prices co-movement after the 2007, revealing an eventual integration of energy and agricultural markets with financial markets and the financialization of commodities markets.

The study of Ohashi and Okimoto (2016) indicates that financialization of commodities through index investment starting around 2000 is one of the main sources of increases in the commodity excess co-movement and explains it through the theoretical model of Basak and Pavlova (2016). This study is based on Pindyck and Rotemberg (1990) excess co-movement theoretical framework. In their empirical analysis, Ohashi and Okimoto (2016) resort to STDCC model, which allows to capture long-run trends of excess co-movement in addition to short-run fluctuation, and apply it to monthly data of agricultural raw material, beverage, metal indices and average oil prices during the period 1983-2011 after filtering the influence of common macroeconomic shocks in order to rule out the impact of market fundamentals and check co-movement among commodity returns due to commodities financialization.

Öztek and Öcal (2017) investigate the eventual impact of the financial crises on the dynamic nature of daily return correlations between tow commodity sub-indices (agriculture and precious metals) and stock markets during the period 1990-2012. Their investigation is based on smooth transition conditional correlation and double smooth transition conditional correlation multivariate GARCH models (STCC-GARCH and DSTCC-GARCH) for the modeling of time varying conditional correlations between the markets. In regards to

agricultural commodity sub-index, their findings underline the impact of financial crisis in increasing the correlation between this index and stock market (S&P 500) and, hence, indicate that agricultural commodity market provides better portfolio diversification opportunities during calm periods though opportunities partially eliminated during financial crises. Their empirical application suggests that portfolio diversification across commodity and stock markets offers higher gains compared to investing only in stock market during post sample. Besides, portfolio provides better improvements during calm periods compared to high volatile times as implied by the estimated models. Öztek and Öcal (2017) underline the upward trend in correlation and which shifts up in August 2008 indicating that correlations between commodity and stock markets started to increase during the recent financial crisis in the US.

4.2. The business-as-usual view:

The second view (business-as-usual view) agrees that there was no bubble and that relations between commodities and stock markets are governed by market fundamentals. We review hereafter some of the main studies that agree on this view.

Sanders and Irwin (2010) conclude that there is no evidence of the impact of non-commercial investors on agricultural futures prices through testing the relationship between index fund positions and returns across 12 commodity futures markets issued from the CFTC's commodity index traders report during the period 2006-2008.

Stoll and Whaley (2010) conduct six analyses to investigate the impact of investment in commodity futures on their prices and find that changes in futures prices are caused by fundamental market factors related to supply and demand for the commodities and not inflows and outflows from commodity index investment.

In a following work, Sanders and Irwin (2011) extend the data span by taking into account the 2004-2005 period not examined in their previous study (Sanders and Irwin, 2010) and considered in some works as the period of most rapid buildup in index positions (Tang and Xiong, 2012). Their analysis is done using long-horizon regressions applied to U.S commodity futures markets corresponding to corn, soybeans and wheat observed from 2004 to 2009. Their findings show a little evidence of the impact of index fund investments on futures commodities price bubble.

Irwin and Sanders (2012) find no evidence of the impact of index investment on the spike recorded in particular in commodities futures prices and energy futures prices during the 2007-

2008 period. They agree on the fact that markets were sufficiently liquid to absorb the large order flow of index funds in recent years. Their analysis is based on actual commodity index investment data issued from CFTC's quarterly index investment data report.

Bruno et al. (2013) study two price indices, composed respectively by grains and livestocks, through a structural VAR model. They argue that increasing correlation of these indices with the S&P 500 stock market index is mainly due to the evolution of market fundamentals and that the role played by financialization is limited or even inexistent.

Gao and Liu (2014) investigate the regime dependence structure between the S&P 500 index and futures prices of diverse commodities (animals, grains, softs, energy, industrials, metals and precious metals) with weekly data from 1979 to 2010 by resorting to bivariate regime switching GARCH models. Their main findings specify that the mutual volatile regimes of commodity futures and stocks tend to be infrequent and short-lived indicating that none of the commodity groups share a common volatility regime with stocks, and that the regime-switching patterns of grains, industrials, metals, or softs are independent on that of stocks.

Etienne et al. (2015) study, which is based on futures prices of corn, soybeans, and wheat daily observed during the period 2004–2013, reveals that bubbles occurrences are generally short-lived, small in magnitude, and likely to be influenced by extreme movements in the fundamental factors affecting market behavior and not by speculation.

Through the application of structural VAR analysis on monthly spot prices of agricultural commodities, a recent study of Alam and Gilbert (2017) reveals insignificant effect of financial market conditions (proxied by S&P 500 index) on the dynamics of agricultural commodities prices over the period from 1991-m1 to 2014-m5.

This view agrees that speculation on futures markets has no impact on commodities prices and that measures aiming to stabilize the commodities market through additional regulation of investors activities to regulate speculative trading in the futures market is probably unnecessary and could have adverse consequences for liquidity and market depth, and worse, may force speculators into the cash markets (Brooks et al., 2015; Kim, 2015).

Brooks et al. (2015) findings show that the presence of speculators in the futures market lowers price volatility and prevents extreme price movement in the spot market. Their study is based on monthly futures prices of agricultural and energy commodities (crude oil, heating oil, gasoline, natural gas, wheat, corn, soybeans, Kansas wheat, cocoa, coffee, cotton, sugar, lean hogs, and live cattle) widely traded in the U.S. futures market spanning the period February

1967-December 2011. Their findings underline the dominance of this stabilizing effect during the post-2003 period, during which increased speculators participation in the commodities futures market is considered responsible for the substantial spot market prices fluctuation.

Based on cross-sectional analysis, Kim (2015) finds that speculators either have no effect on spot prices fluctuations or stabilize spot markets during periods of large price movement namely the recent period of financialization by contributing to lower spot prices volatility, to enhance price efficiency, and to better liquidity in the commodities markets. Kim (2015) results indicate that financialization does not relate to increased commodity price volatility. By assessing also the effect of futures speculation on market quality using liquidity and price efficiency measures, Kim (2015) finds that when liquidity increases, information is better incorporated into prices, thus enhancing information efficiency. A variance ratio test that he applies to assess how the futures trading activity of speculators relates to short-term efficiency in the spot market shows that futures speculation either has no effect or improves liquidity and short-term efficiency in the commodity market.

4.3. Economic mechanisms linking financial and commodity markets:

Divergence between the conclusions requires the analysis of specific economic mechanisms through which financialization can impact commodity prices. Investigation among previous works in the literature reveals that the link between commodity markets and stock market may be explained mainly through three channels corresponding to the speculative storage, the information discovery role of commodity futures, and the risk sharing function of commodity markets (Cheng and Xiong, 2014a).

4.3.1. Storage channel:

Deaton and Laroque (1996, 1992) state that the relationship between futures prices and spot prices can be explained through the classic theory of storage originally developed by (Working, 1933). The storage model was exhaustively presented by (Williams and Wright, 1991). It studies how speculators will engage in commodity transactions based on their expectations of future price changes. According to this theory, a solid theoretical link between spot prices and futures prices can be observed. The difference can be summarized with cost of carry.

The economic fundamental of commodity markets corresponds to a balance between physical supply and demand. Thus, storage allows to respond to this fundamental through saving excess

supply and acting as buffer stock for future supply-demand imbalances (Cheng and Xiong, 2014a).

According to this theory, futures price could be greater or less than the spot price depending on the net (of storage costs) marginal flow of benefits from holding the physical commodity.

$$F_{t,T} = (1 + r_T)S_t - \left(c_{t,T} - k_T\right)$$

where:

$F_{t,T}$: the futures price of a commodity at time t for delivery at $t + T$

S_t : the spot price at time t

r_T : the risk free T-period interest rate

k_T : the per-unit cost of physical storage

$c_{t,T}$: the capitalized flow of marginal convenience yield over the period t to $t + T$

Fao (2009) report mentions that the high level of speculative activity in agricultural commodities markets in the last few years, characterized namely by the increase in the shares of non-commercial traders in maize, wheat and soybean markets, coincided with the increase in prices of these commodities in the physical markets which pushed researchers on the literature to focus on the impact of speculation in increasing food prices.

Some works agree that large buy orders can increase prices through an effect on the order book if markets are not sufficiently liquid (De Long et al., 1990; Grossman and Miller, 1988; Shleifer and Vishny, 1997).

4.3.2. The information channel:

According to the information channel, prices can be affected by private information held by investors (Goldstein et al., 2014; Goldstein and Yang, 2014; Grossman and Stiglitz, 1980; Hellwig, 1980).

This information can be related to fundamental determinants of the futures prices, different costs of private information production, or a different understanding of macroeconomic trends or political processes (Singleton, 2014). Previous findings underline the role of the information discovery channel in the transmission of speculative demand shocks to prices.

Recently, Sockin and Xiong (2015) propose a model to explain the economic mechanism behind the transmission of commodity price changes from the financial to the physical level. They mention that the link between commodities and stocks is indirectly impacted by informational frictions though their effects on the intensification of block investments and portfolio rebalancing and highlight that increased long positions are the main driver behind risk spillovers between these markets.

4.3.3. Risk sharing channel:

Beck (1993) states that shocks to financial market risk potentially affect the risk premium and therefore can have an impact on commodity futures prices.

Under the asset pricing theory, the futures price is a biased estimate of the future spot price, and it is given by:

$$F_{t,T} = E_t(S_{t+T}) - (R_T - r_T)S_T$$

where:

R_T : the risk-adjusted discount rate

$R_T - r_T$: the risk premium

According to the risk sharing channel, financial investors can drive up futures prices by lowering the risk premium. In fact, in case sudden falls in prices of other markets may lead to risk reduction, financial investors may have to relax their long commodity positions transmitting hence external shocks to commodity markets. Therefore, risk sharing in commodity markets is affected by financialization through the dual roles of financial investors both as providers of liquidity to hedgers when trading to conform hedging needs and as consumers of liquidity from hedgers when trading for their own needs (Acharya et al., 2013; Cheng et al., 2015).

More details about theoretical frameworks for risk premium mechanism can be found in Acharya et al. (2013) and Hamilton and Wu (2015).

5. Conclusion

With the concomitant changes in prices of food, energy and financial markets during the recent years, the latest studies have given a particular attention to the links between these markets mainly in terms of spillovers (in returns or volatilities) and dependence.

Divergences on the conclusions related to the links between energy and food markets are detected in the literature and are mainly explained by the type of commodities considered, the frequency of data, the time period and the methods applied for the analysis of these links. Links between these markets were explained namely by the input and biofuel channels in addition to macro-economic variables. The input channel is related to the use of oil in the production of food commodities. The biofuel channel is associated to the use of agricultural commodities as feedstock for biofuel production. Exchange rates, monetary conditions, and the integration of commodities with stock markets are the main macro-economic variables explaining these links.

In the matter of transmission channels between financial and food markets, two polarized views were distinguished (the bubble and the business-as-usual views). The bubble view explains these channels through commodities financialization while the business-as-usual view considers that these channels are due to the evolution of market fundamentals.

Our review of the literature dealing with food commodities prices development allowed us to detect a number of limitations in the previous studies. In fact, due to the lack of data availability, most of previous works have focused on futures markets (available from exchanges) and few studies have given attention to spot prices or the connections between spot and futures prices. In addition, the existing literature suffers from the consideration of few types of food markets. Besides the nature of commodities, few individual commodity contracts or widely used indices (e.g., S&P Goldman Sachs Commodity Index) have been used in the literature while the usefulness of commodities may vary by the type of index considered. In addition, the literature review has revealed the absence, among previous works, of comprehensive analysis that considers a large number of potential drives and investigates their joint effects in a dynamic model of interlinked markets. In addition, few attention has been attributed in the previous studies to volatility spillovers in the analysis of food prices dynamics.

Chapter 2

Time-varying efficiency in food and energy markets: Evidence and implications

This chapter is a version of paper co-authored with David Roubaud.

1. Introduction

Considering the role of futures contracts in price discovery and risk management (Chang et al., 2011; Chang and Lee, 2015; Figuerola-Ferretti and Gonzalo, 2010; Irwin and Sanders, 2011; Nicolau and Palomba, 2015; Peck, 1980; Ruan et al., 2016), studying futures markets and the relationship between the spot and futures prices of commodity markets has become an imperative subject attracting the attention of producers, policymakers, hedgers, and speculators. In efficient markets, new information is impounded simultaneously into spot and futures markets (Zhong et al., 2004). Investors have to take into account the possible deviation of spot and futures prices from one another in the short term, due to exogenous events (Ruan et al., 2016).

Increasing interest in this issue has been recorded, namely since the occurrence of passively and actively managed exchange traded funds (ETFs).[9] In fact, one of the most important decisions to be made by investors is to decide their management strategies based on past information. A review of the extant literature that debates the superiority of active versus

[9] The Investment Company Institute Fact Book (2014) indicates that the total number of passively and actively managed ETFs had increased to 1,332 and total net assets were 1.675 trillion USD by the end of 2013.

passive management strategies, in terms of increase in market efficiency, reveals that the theories on this subject are conflicting and, thus, conclusions have not been made.

During recent years, spot and futures commodity markets have been considered alternative investment instruments for hedging against risk in equity markets, due to the lower diversification benefits from equity investments during financial crises, accompanied by the growing financialization of commodity markets (Nicolau and Palomba, 2015; Sensoy et al., 2015), which makes the focus on commodities of particular interest.

An investigation into the previous literature reveals that the debate on market efficiency has been mainly devoted to energy and stock markets. Among the studies devoted to the investigation of market efficiency, few have focused on food markets. With the sustained, growing divergence between the futures and spot prices of grain markets (wheat, corn, and soybean) during the period from 2005 to 2011 (Adjemian et al., 2013; Aulerich et al., 2011), the efficiency of food markets has become controversial, which prompted us to pay particular attention to these kinds of commodities.

To restrain or reduce the risk of unfavorable price changes because spot and futures prices for the same commodity tend to move together, hedging through trading futures contracts has been considered a solution (Chang et al., 2011). Information on hedging is required by investors in order to decide their appropriate positions in the futures markets, allowing them to compensate for the risk from corresponding holdings in the spot market (Fan et al., 2016). Even if particular attention has been accorded during recent years to hedging through commodity futures, papers in the empirical literature that focus on commodities risk-hedging in a time-varying framework are scarce (Mellios et al., 2016).

Our paper contributes to the literature by studying the time-varying efficiency of grain markets (corn and soybean) compared to energy markets, and investigating the impact on hedging through futures in an inter-temporal context. We opt for the time-varying rolling Hurst exponent and threshold cointegration methods, which allow us to take account of the structural breaks and capture the nonlinearity in the adjustment of the deviations toward long-run equilibrium. In order to check the usefulness of the futures markets as a tool for risk management, we focus on estimating optimal hedge ratios and evaluating the effectiveness of hedging based on a multivariate dynamic conditional correlation generalized autoregressive heteroskedasticity (DCC-GARCH) model. To the best of our knowledge, this is the first study

that investigates the link between the efficiency of these markets and hedging in a time-varying context.

The remainder of this paper proceeds as follows. Section 2 summarizes a literature review of the main previous studies dealing with market efficiency and hedging. Sections 3 and 4 present our proposed methodology and data with a pertinent preliminary analysis, respectively. Section 5 is devoted to the discussion of our empirical findings. Finally, Section 6 summarizes our conclusions and discusses their policy implications.

2. Literature review

The efficient market hypothesis was introduced by Fama (1970) and can be subdivided into three forms (weak, medium, and strong), according to the different information sets taken into consideration.[10] The attention has been mainly paid to the weak form of the efficient market hypothesis, according to which futures prices cannot be predicted on the basis of past spot prices.

Two main financial theories focusing on the relationship between spot and futures prices can explain the results of the investigation on market efficiency (Fernandez, 2017; Nicolau and Palomba, 2015). The first one corresponds to the non-arbitrage theory, or theory of storage (Adjemian et al., 2013; Kaldor, 1939), according to which the difference between spot and futures prices is explained by the cost of carry (the sum of the cost of storage and interest rate) and convenience yield. The second one is the asset pricing theory, according to which the price of a futures contract is influenced by the expected future spot price, conditional on the information set. Based on these theoretical models explaining the spot-futures relationship, spot and futures prices are expected to be linked to each other.

Furthermore, only a few of the available studies address the time-varying efficiency in order to detect the changing degree of market efficiency over time and the existence of potential structural breaks (Khediri and Charfeddine, 2015). Moreover, recent studies indicate that the market is not perpetually in an equilibrium state (Lo, 2005, 2004). Lo (2004) extends the traditional efficient market hypothesis to an evolutionary framework (the adaptive market hypothesis), in which market efficiency varies continuously over time and across markets, thus

[10] More details about the different forms of market efficiency are provided by Fama (1991).

allowing for the study of market dynamics due to changing business, social, and political conditions.

In the economic literature, particular attention has been paid to the weak-form efficiency in energy markets, since energy price movements substantially affect the performance of most economic sectors at different levels and through various channels (Lescaroux and Mignon, 2008). Most of recent studies focusing on energy market efficiency underline the presence of a time-varying efficiency (see, e.g., Arouri et al., 2013; Chen et al., 2014; Fan and Xu, 2011; Khediri and Charfeddine, 2015; Mensi et al., 2014; Ortiz-Cruz et al., 2012; Sensoy and Hacihasanoglu, 2014; Zhang, 2013; Zhang et al., 2014).

Arouri et al. (2013) test the short- and long-run efficiency of nine energy and precious metal markets, and employ linear cointegration, nonlinear cointegration, and error-correction models (ECMs), which allow the efficiency intensity to change per regime. Their findings reject the short-run-efficiency hypothesis and identify two distinct regimes; in the first regime, the efficiency hypothesis is supported and, in the second, rejected. Considering the West Texas Intermediate (WTI) spot crude oil prices and one-month futures in the period from January 1986 to December 2012, P. F. Chen et al. (2014) underline the effect of structural breaks on the efficiency of oil markets. With weekly data on the last month to maturity crude oil futures during the period from January 7, 2000 to September 11, 2009, Fan and Xu (2011) find that the oil market presents two structural break points (March 12, 2004 and June 6, 2008). The first structural break is explained by strong oil demand and the vast amounts of speculative funds pouring into the oil futures market since 2003. The second is related to the financial crisis. Using a rolling sample approach, Khediri and Charfeddine (2015) investigate the time-varying market efficiency of daily spot and futures energy returns for a series of one-month maturity contracts. Mensi et al. (2014) examine the time-varying levels of weak-form efficiency and the presence of structural breaks for two worldwide crude oil benchmarks-the WTI and European Brent crude oil indices—over the period from January 2, 1990 to September 18, 2012. They adopt two different approaches, the Hurst exponent, provided by the rescaled range R/S analysis, and Shannon entropy. Applying entropy to daily WTI prices, Ortiz-Cruz et al. (2012) find that the market is efficient, with two episodes of inefficiency connected to the US recessions in the early 1990s and late 2000s. Sensoy and Hacihasanoglu (2014) apply a rolling-window approach (covering the period from 1990 to 2013) and estimate the time-varying generalized Hurst exponents of several daily energy futures contracts with different months to

maturity. They find that the results depend on the time to maturity of the contracts and that the efficiency of energy futures markets decreases as the time to maturity increases. Further, they argue that time variation in the efficiency of the energy futures can be severe due to several factors, such as a financial crisis, supply shocks, and regulations. Zhang (2013) applies the rolling-window approach to daily data on four major crude oil markets in the period from December 28, 2001 to April 18, 2013, and finds that crude oil markets are weak-form efficient in the long run, with some inefficiencies in the short run during certain extreme events.[11] Zhang et al. (2014) use the time-varying GAR(1)-TGARCH(1,1) model to test the weak-form efficiency of crude oil spot markets during the period from December 2001 to August 2013. Their findings show that efficiency is time-variant and underline the significant impact of the 2008 financial crisis.

The main findings of recent studies on stock markets highlight the variability in time of their efficiency. For example, Ito and Sugiyama (2009) measure the time-varying structure of market inefficiency for stock returns by using monthly returns for the Standard and Poor's (S&P) 500 stock index from January 1955 to February 2006. They adopt a time-varying autoregressive (AR) model, in which the AR coefficients can vary over time and are estimated via Kalman smoothing. Alvarez-Ramirez et al. (2008) analyze the dynamic behavior of the US stock markets by estimating the Hurst exponent through detrended fluctuation analysis over moving windows for the historical Dow Jones (1928 to 2007) and S&P 500 (1950 to 2007) daily indices. Rodriguez et al. (2014) focus on the efficiency of the US market, reflected by the Dow Jones Index (DJIA) with daily frequency (during the period from January 1929 to March 2014). They apply the fractal scaling exponent from the detrended fluctuation analysis implemented over a rolling window. In order to investigate the evolution of market efficiency and cross-correlation in the pre-crisis and crisis periods of the Shanghai Composite Index and Shenzhen Composite Index, Ma et al. (2016) resort to detrended fluctuation analysis as well as detrended cross correlation analysis with a rolling-window approach. One of their findings indicates that the financial crisis had a negative impact on the efficiency of the Shanghai equity market, while the impact on the Shenzhen equity market efficiency was positive. Moreover, in a recent study, Charfeddine and Khediri (2016) underline the time-varying behavior of Gulf Cooperation Council stock market efficiency, in accordance with the adaptive market hypothesis, and

[11] The effects of extreme events on short-term market efficiency are discussed in detail in Wang and Wu (2012).

emphasize the importance of the investigation of time-varying efficiency in determining periods of inefficiencies and their origins. Regarding the speed of convergence to efficiency for stock markets, some studies show that weak-form efficiency might not be attained immediately (Chordia et al., 2005). Using intraday returns for 150 New York Stock Exchange stocks in the calendar years 1996, 1999, and 2002, Chordia et al. (2005) find that weak-form efficiency seems to prevail for return intervals from five minutes to one day; the evidence suggests that the market is not strong-form efficient over short return intervals of a few minutes.

Yet, little attention has been paid in the literature to food market efficiency. Most previous studies on the subject focus particularly on spatial market efficiency. A few studies address food market efficiency in an inter-temporal context by checking if spot and futures markets react simultaneously to news that affects both markets (Shu and Zhang, 2012). An example of studies on food market efficiency is that of McKenzie and Holt (2002), who examine the efficiency of four agricultural commodities markets (live cattle, hogs, corn, and soybean) during the period from 1959 to 2000. Their main findings underline the efficiency of these commodity markets and their long-run unbiasedness, despite some inefficiencies in the short run. Kumar (2004) focuses on agricultural commodities in India and concludes that the futures markets are not efficient. Further, Wang and Ke (2005) investigate the efficiency of the Chinese wheat and soybean futures markets; they show a long-term equilibrium relationship between futures and spot prices for soybean and weak short-term efficiency for the soybean futures market.

Nevertheless, researchers have seldom compared the efficiency of different commodity markets. In a recent study, Kristoufek and Vosvrda (2014) compare the efficiency of 25 commodity futures markets across various groups-metals, energy, soft commodities, grains, and other agricultural commodities-during the period from January 2000 to July 2013, by means of the efficiency index proposed by them in 2013 (Kristoufek and Vosvrda, 2013). They find that energy commodities are the most efficient, followed by soft commodities, grains, and metals; the other agricultural commodities (mainly livestock) represent the least efficient group. However, Kristoufek and Vosvrda (2014) do not take into account the breaks and changes in efficiency over time. Moreover, Chinn and Coibion (2014) analyze a commodity set composed of agricultural, energy, industrial, and precious metals over the period from 1990 to 2012, and concluded that the futures prices of energy and agricultural products, as opposed to those of precious and industrial metals, are generally unbiased estimators of future spot prices. They

attributed these differences among commodities to the evidence of contract liquidity,[12] which has been recently confirmed by Fernandez (2017), whose results show that there is no statistical association between futures contract liquidity and the probability of rejecting the unbiasedness of futures prices, with respect to future spot prices. A larger set of commodity types (agricultural, animal, wood, energy, and metals products) and longer time period (1991 to 2015) are considered by Fernandez (2017); by resorting to a multi-equation estimation of risk premiums and testing for the theory of storage, her findings reject that the futures price is an unbiased estimate of the spot price for all commodity types. Nicolau and Palomba (2015) focus on the analysis of the dynamic relationship between the spot and futures prices of crude oil, natural gas, and gold commodities by considering daily data covering the period from 1997 to 2014. Their findings indicate that some interactions between spot and futures prices depend mainly on commodity type and maturity of futures contracts. They also find that, among the commodity markets analyzed, crude oil is one of the most used for hedging and speculations during financial turmoil, and the market participants are not anymore indifferent to investing in spot or futures, or in choosing the commodity market for further investments.

Regardless of which market is considered, the findings in the literature on market efficiency remain controversial, as they depend on such factors as the sample considered, empirical approach used, and whether the efficiency is assessed in a static or dynamic framework. Moreover, even though the link between spot and futures prices has been explained in the literature through different channels, namely financialization, information asymmetry, and speculative activity, there are still no firm answers as to whether and how financialization may have changed commodity futures markets, and its implications for commodity investors remain unknown to a large extent. In his paper, Zaremba (2015) focuses on the impact of the financialization of commodity futures markets on the potential benefits of passive investment strategies, based on the returns of various asset classes during the period from 1990 to 2012. Conclusions drawn from his paper indicate that market financialization may have resulted in a decline in expected roll returns, and that this decrease in roll yields would destabilize the legitimacy of including commodity futures in traditional stock-and-bond portfolios. In a more recent paper, Bosch and Pradkhan (2016) focus on the impact of the trading activity of different trader types (hedgers, speculators, and commodity index traders) on the rate of convergence between spot and futures markets for different commodity markets (agricultural, energy, and

[12] More illiquid futures contracts are more likely to disprove the unbiasedness of futures prices.

precious metals) over the period from 1999 to 2014. They find that speculators increase the rate of convergence between spot and futures markets, while commodity index traders reduce it. In contrast with these findings, other studies (e.g. Cheng and Xiong, 2014) indicate that hedgers may also provide short-term liquidity to speculators who engage in momentum trading. In addition, some speculators may act as irrational noise traders, who overreact to new information and drive futures prices further apart from fundamental values (Y. L. Chen et al., 2016), thus impacting the rate of convergence between spot and futures markets.

In the literature, two different strategies for the management of a portfolio to gain exposure to commodity futures markets have been identified (active and passive management). While active management consists of beating the market, typically symbolized by a type of index, passive management is based on constructing a portfolio in a way that mimics a market index. Studies dealing with the impact of active and passive management strategies can be categorized into two groups, where the first group argues that active management enhances market efficiency (Chen et al., 2013; T. Chen et al., 2016; Dyck et al., 2013; Grossman and Stiglitz, 1980), while the second one underlines the underperformance of active management, in terms of achieving market efficiency (Busse et al., 2010; Fama and French, 2010; Wermers, 2000). Chen et al. (2013) are the first who study the impact of active management on pricing efficiency; their paper extends the debate over the benefits of active versus passive management by investigating their impact on market efficiency, using data from available ETFs traded on the US market and grouped by management style. Through the application of a variety of empirical methodologies adopted in the literature (random walks, profits of trading strategies, and transaction costs), Chen et al. (2013) find that active management matters to the improvement of market efficiency and helps information be incorporated into prices. In a later paper, T. Chen et al. (2016) find that actively-managed ETFs are associated with higher price efficiency when compared to passively managed ETFs; their empirical tests support the view expressed by Grossman and Stiglitz (1980) that prices of active funds incorporate information in a faster way than do those of passive funds. However, they do not confirm the result of Admati and Pfleiderer (1988) that excessive trading triggered by active managers leads to inefficient price discovery. Further, Andriosopoulos and Nomikos (2014) indicate that there is empirical evidence supporting the idea that passive strategies are better than active ones, especially in the longer term, which has made passive strategies increasingly popular.

The investigations in the extant literature reveal that the debate on hedging through futures contracts is controversial. By comparing the hedging effectiveness between futures markets for non-storable commodities, constituted by livestock (lean hogs, live cattle, and feeder cattle), and storable commodities (corn, soybean, wheat, cotton, and sugar) during the period from 1997 to 2001, using a bivariate GARCH model, Yang and Awokuse (2003) find that hedging effectiveness differs among these two types of commodities, in that it is strong for all storable commodities, but weak for non-storable commodities. They also find that live cattle futures markets cannot provide an effective tool against price risk, and that risk management alternatives, such as forward contracting and long-term marketing agreements, have to be applied. Moreover, Chang et al. (2011) show that futures contracts are favored as a hedging tool because of their liquidity, speed, and lower transaction costs, while Bohl and Stephan (2013) debate the impact of the increasing financialization of commodity trading in futures markets on the relationship between spot and futures markets as well as on the usefulness of futures markets for hedging purposes. In a more recent paper, Zuppiroli and Revoredo-Giha (2016) focus on the hedging effectiveness of European and US wheat futures markets, spanning up to 2014, by resorting to a multivariate GARCH model (the diagonal BEKK). Their findings underline the presence of a slight improvement, after 2007, in the effectiveness of hedging with the European wheat futures markets.

3. Methodology

In this paper, we investigate market efficiency based on the hypothesis of McKenzie and Holt (2002), that efficient markets are characterized by futures and cash prices, which both instantly absorb new information and adjust to their long-run equilibrium relationship. We also consider the market efficiency hypothesis requiring the cointegration of the futures and future spot prices, meaning that futures prices are unbiased predictors of spot prices at maturity (Martens et al., 1998).

Most of the methodologies used in the literature for the assessment of market efficiency focus on the Hurst exponent, Shannon entropy metric, or cointegration models. Mensi et al. (2014) suggest that the Hurst exponent performs better than the Shannon entropy method and is more effective in detecting financial crashes and crises, as well as extreme events. As for cointegration, most of the studies in the related literature employ linear modeling through a

vector error correction model (VECM). However, linear cointegration models fail to account for possible structural breaks in the cointegrating vector (Hanson, 1992; Lardic and Mignon, 2006, 2008).

Based on these previous findings, in this paper, we employ the Hurst exponent and threshold cointegration models (e.g., TVECM) in order to assess the efficiency of the energy and grain markets.

3.1. Hurst exponent

The Hurst exponent, developed by Hurst (1951) is the classical test to detect long memory in time series and has been commonly applied in financial markets (Ma et al., 2016). In this paper, we use the Hurst exponent as a measure of long-term dependence, in order to evaluate market efficiency. An inefficient market demonstrates long-term dependence, which can be proven by a Hurst exponent diverging from 0.5.

The efficiency index can be described by Equation (1), revealing that the larger the efficiency index (EI) value of a market, the more inefficient the market could be. If the Hurst exponent is closer to 0.5, the market will be closer to weak-form efficiency.

$$EI = |H - 0.5| \quad (1)$$

Different methods were used in the literature for the estimation of the Hurst exponent, such as the rescaled range R/S analysis, fluctuation analysis, detrended fluctuation analysis, detrended moving average analysis, generalized Hurst exponent approach, and their variants. The R/S analysis and generalized Hurst exponent approach are robust to heavy tails in the data series (Barunik and Kristoufek, 2010). In contrast, multifractal detrended fluctuation and detrended moving average analysis methods prove to be unsuitable for data with heavier tails and small sample sizes.

Based on these facts, we employ the R/S analysis introduced by Hurst (1951) in order to estimate the Hurst exponent. The R/S is a statistical measure of the variability of a time series, which is given by Equation (2):

$$\left(R/S\right)_T = \frac{1}{\sigma_T}\left[\max_{1\le t\le T}\sum_{t=1}^{T}(r_t - \bar{r}_T) - \min_{1\le t\le T}\sum_{t=1}^{T}(r_t - \bar{r}_T)\right], \quad (2)$$

where T is the time span of the data, r_t is the return of the commodity price at time t, $\bar{r}_T = \frac{1}{T}\sum_{t=1}^{T} r_t$ is the sample mean of the return time series,

and $\sigma_T = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_t - \bar{r}_T)^2}$ is the usual standard deviation estimator.

The traditional R/S analysis is, however, sensible to the presence of short-range dependencies (Lo, 1991). To address this drawback, we use the filtered returns; our goal is to eliminate the short-range behavior of the return series. In line with previous studies (Cajueiro and Tabak, 2004a, 2004b, 2005), we use an AR-GARCH procedure, which allows us to filter the short-range behavior present in the time series and, at the same time, filter the volatility of returns. Next, we apply the R/S analysis to the estimated residuals ε_t of an AR(1)-GARCH(1,1) process, as follows:

$$r_t = c + \delta r_{t-1} + \varepsilon_t, \quad (3)$$

$$h_t = \bar{\omega} + \alpha {\varepsilon_{t-1}}^2 + \beta h_{t-1}, \quad (4)$$

where h_t is the conditional variance of the residuals from the mean equation of the returns, and $\bar{\omega}$, α, and β are the unknown parameters of the variance equation satisfying the conditions: $\bar{\omega} > 0$, $\alpha > 0$, $\beta > 1$, and $\alpha + \beta < 1$.

The R/S statistic and filtered Hurst exponent (H) are computed based on the estimated results of the AR(1)-GARCH(1,1) model and using the standardized residuals $\xi_t = \frac{\varepsilon_t}{\sqrt{h_t}}$.

The R/S is described by the following equation:

$$\left(R/S\right)_T = \left(\frac{T}{2}\right)^H \quad (5)$$

Instead of regular static approaches relying on a single measure of market efficiency for the whole sample period, we opt for time-varying approaches in order to detect the efficiency dynamics due to changing market conditions and institutional factors. The study of time-varying, weak-form market efficiency has received increasingly more attention in recent years. Such studies can be categorized, based on the research framework adopted, into sub-period analyses, time-varying parameter models, and rolling estimation windows. For more details about the different methods used in the literature for the assessment of time-varying market efficiency, see Lim and Brooks (2010). In order to avoid analyzing different sub-periods, we use the rolling-window approach and apply it to the evaluation of the time-varying Hurst exponent. Therefore, we do not have to use a strict cutoff date, a practice usually subject to criticism (Khediri and Charfeddine, 2015). Moreover, arbitrarily chosen sub-periods or non-overlapping intervals could not capture possible structural breaks in time series (Sensoy and Hacihasanoglu, 2014).

3.2. Threshold cointegration

The concept of cointegration, introduced by Engle and Granger (1987), examines whether there is a stationary combination of two (or more) non-stationary variables. Variables are then considered to have a stable relationship (a long-run equilibrium), can be represented in a VECM, and share a common stochastic trend.

Linear cointegration does not account for possible structural breaks in the cointegrating vector, while threshold cointegration extends linear cointegration by allowing the adjustment to occur only after the deviation exceeds some critical threshold, taking thus into account possible transaction costs or price stickiness (Hansen and Seo, 2002). Furthermore, it captures

asymmetries in the adjustment, where positive or negative deviations will not be corrected in the same manner.[13]

It is a regime-dependent model, which is a combination of the threshold autoregressive (TAR) model (Tong, 1978) and VECM (Engle and Granger, 1987).

Futures and spot prices can be represented by a VECM of order p, defined by:

$$\Delta y_t = \mu + \alpha\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + \varepsilon_t,\ t = 1, \dots, T, \quad (6)$$

where $y_t' = [s_t \quad f_t]'$ is a $(K \times 1)$ random vector of spot and futures prices; Δ is the first difference operator; μ is a $(K \times 1)$ constant vector; $\Gamma_i (K \times K)$ is an autoregressive coefficient matrices called the short-run dynamics; ε_t is a K- dimensional white noise process; and $\alpha\beta'$ is a long-run impact matrix where α and β are $(K \times r)$ matrices, in which $\beta' y_{t-1}$ corresponds to the error correction term (ECT), α measures the speed of adjustment toward the long-run equilibrium, and β is the cointegration coefficient.

In a threshold VECM (TVECM), the adjustment process takes place only after the deviation exceeds some critical threshold and is based on the self-exciting TAR model (SETAR). In the SETAR model, the autoregressive coefficients take different values depending on whether the previous value is above or below a certain threshold value, thus exhibiting regime-switching dynamics. Hence, in a SETAR model with three regimes, the linear adjustment process $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$ is extended as:

$$\varepsilon_t = \begin{cases} \rho_L \varepsilon_{t-1} + u_t \text{ if } \varepsilon_{t-1} \leq \theta_L \\ \rho_M \varepsilon_{t-1} + u_t \text{ if } \theta_L \leq \varepsilon_{t-1} \leq \theta_H, \\ \rho_H \varepsilon_{t-1} + u_t \text{ if } \theta_H \leq \varepsilon_{t-1} \end{cases} \quad (7)$$

where L stands for low regime, M for middle regime, and H for high regime. The threshold effect is present when $\rho_H \neq \rho_M$ and $\rho_L \neq \rho_M$, and as long as $0 < P(\varepsilon < \theta_b) < 1$, where $b = L$ or H.

[13] Gonzalo and Pitarakis (2002) study contains a detailed discussion about the advantages and application of threshold models.

The TVECM is estimated for the cointegrated series using the maximum likelihood procedure described by Hansen and Seo (2002). The threshold parameter γ is determined through the following selection criterion:

$$\xi(\hat{\gamma}) = \min \log\left(\left|\frac{1}{n}\sum_{t=1}^{n}\hat{\varepsilon}_t(\gamma)\,\hat{\varepsilon}_t(\gamma)'\right|\right). \quad (8)$$

Next, an additional restriction, in which each regime should contain at least a pre-specified fraction of the total sample (π_0), is imposed on the grid search procedure:

$$\pi_0 \leq P(|z_{t-1}| \leq \gamma) \leq 1 - \pi_0. \quad (9)$$

In order to test the significance of the threshold parameters, we resort to the supLM test and bootstrapping techniques proposed by Hansen and Seo (2002).

4. Data and preliminary analysis

Our dataset contains futures and spot prices for grains (corn and soybean) and energy (crude oil) markets expressed in US dollars. These commodities have been chosen due to the availability of their futures and spot prices. We consider one-month futures contracts since they are, in most cases, heavily traded, in contrast to long-month futures contracts (Chang and Lee, 2015; Sensoy and Hacihasanoglu, 2014).

Futures prices for all commodities are extracted from the Chicago Mercantile Exchange database. Spot prices of grains are collected from the TFGRAIN database and those of crude oil are from the US Department of Energy database. To capture major events in the energy and food markets, we choose a data span from December 1, 2000 to August 17, 2015. Figure 2.1 presents the evolution over time of daily spot versus futures prices for the different commodities included in our study. It shows that, with some divergences, spot and futures prices move closely together.[14]

[14] The superposition of the two curves of spot and futures prices for each commodity is provided in Figure A.2.1 in the appendix.

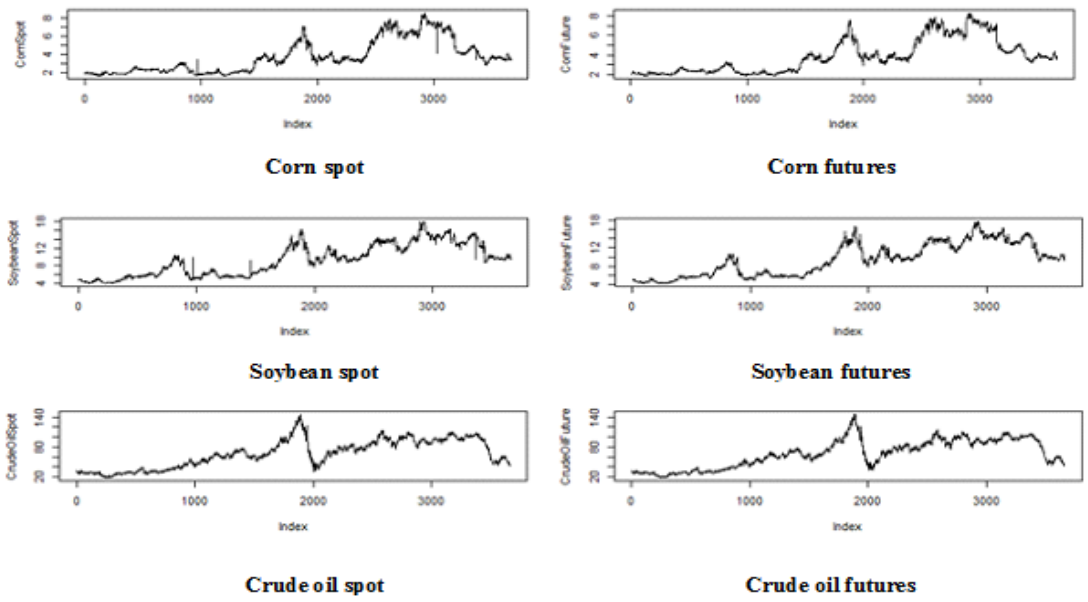


Figure 2. 1 : **Evolution of daily spot and futures prices for corn, soybean, and crude oil**

We start by testing for the presence of unit roots in our time series. To do so, we apply the augmented Dickey-Fuller (ADF) unit root test. The tests we apply indicate that the spot and futures prices of all commodities are non-stationary at levels (Table 2.1). To make our data series stationary, we transform the price data into returns by applying log first difference. These returns are presented in figure 2.2. The results of the ADF test applied to returns, as summarized in table 2.1, show that the first differences of log prices are stationary at the 95% significance level, indicating that our series are integrated of the same order I(1).

		Test in levels		**Test in first differences**	
		Spot prices	**Futures prices**	**Spot prices**	**Futures prices**
Statistic	**Corn**	-1.934	-2.084	-14,518	-14.301
	Soybean	-2.501	-2.346	-14.788	-14.639
	Crude oil	-1.510	-1.480	-14.07	-14.143
p-value	**Corn**	0.606	0.543	0.01	0.01
	Soybean	0.366	0.432	0.01	0.01
	Crude oil	0.786	0.799	0.01	0.01

Table 2. 1: Augmented Dicky-Fuller test results

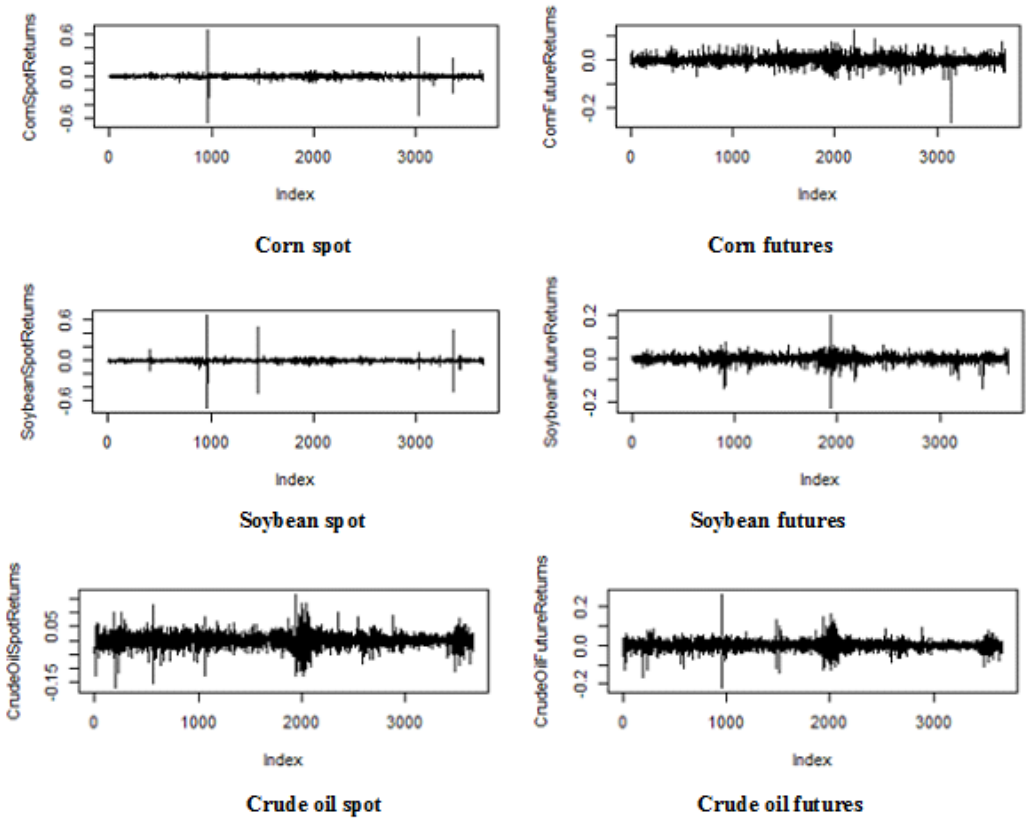


Figure 2. 2: **Evolution of returns (spot and futures) for corn, soybean, and crude oil**

5. Results and discussion

5.1. Analysis of Hurst exponent results

We begin with the estimation of a fixed Hurst exponent over the whole sample period for each commodity, and we compare it to the midpoint $H = 0.5$ corresponding to the efficient market where processes are uncorrelated (short-term memory processes). The results of this estimation are summarized in table 2.2; the estimators are close to 0.5. The Hurst exponents of filtered returns are above 0.5, which indicates the presence of long-range dependence where spot and futures prices are positively correlated and follow local trends, while still remaining stationary.

	Spot prices			Futures prices		
	Corn	**Soybean**	**Crude oil**	**Corn**	**Soybean**	**Crude oil**
R/S Hurst exponent estimator	0.471	0.445	0.537	0.513	0.500	0.535
Filtered R/S Hurst exponent estimator	0.554	0.536	0.554	0.555	0.527	0.555

Notes: R/S = rescaled range.

Table 2. 2: Estimation of the Hurst exponent for corn, soybean, and crude oil over the entire sample

In order to check for the potential changes of market efficiency over time, we apply the rolling sample approach for the estimation of the time-varying Hurst exponent. Our choice of the length of the window was informed by previous research, such as Cajueiro and Tabak (2004b); Sensoy and Hacihasanoglu (2014) and Mensi et al. (2014), which suggests that a good tradeoff between statistical stability and sufficient details in scaling exponent variations corresponds to about four calendar years. In fact, our choice of the rolling window size is important since a relatively low window length yields statistically unstable estimations of the scaling exponent, and a relatively high window length does not provide a clear view of the scaling exponent time variations (Rodriguez et al., 2014). The choice of a four-year window (1,008 observations) is justified by the fact that it corresponds to the duration of political cycles in many countries and is large enough to yield satisfactory statistical significance (Sensoy and Hacihasanoglu, 2014). Next, we compute the Hurst exponent for the first window, followed by estimating it again through rolling the window forward, by removing the first observation of the series and adding a new observation at the end. We continue this process until the last observation is used.

Referring to Ma et al. (2016), who mention that estimation of the Hurst exponent without consideration of confidence intervals does not prove statistical significance, we estimate the confidence intervals of the estimated Hurst exponent. Since commodity return series are characterized by heavy tails, estimation of the confidence intervals based on Gaussian distribution is not appropriate. We, then, resort to the methodology applied by Weron (2002), which consists of using bootstrapping to obtain the approximate functional forms for the confidence intervals of the Hurst exponent estimated through R/S analysis. According to Weron (2002), the upper and lower bounds of the confidence intervals (at 90%, 95%, and 99%

confidence levels) of the Hurst exponent series, estimated through R/S analysis, are given by the following equations, which are presented in table 2.3.[15]

Level	Lower bound	Upper bound
90%	$0.5 - exp(-7.35 * \log(\log M) + 4.06)$	$exp(-7.07 * \log(\log M) + 3.75) + 0.5$
95%	$0.5 - exp(-7.33 * \log(\log M) + 4.21)$	$exp(-7.20 * \log(\log M) + 4.04) + 0.5$
99%	$0.5 - exp(-7.19 * \log(\log M) + 4.34)$	$exp(-7.51 * \log(\log M) + 4.58) + 0.5$

Notes: $M = \log_2 N$ and N is the series length.

Table 2. 3: Lower and upper bounds of the confidence intervals of the Hurst exponent series estimated through rescaled range analysis, according to Weron (2002)

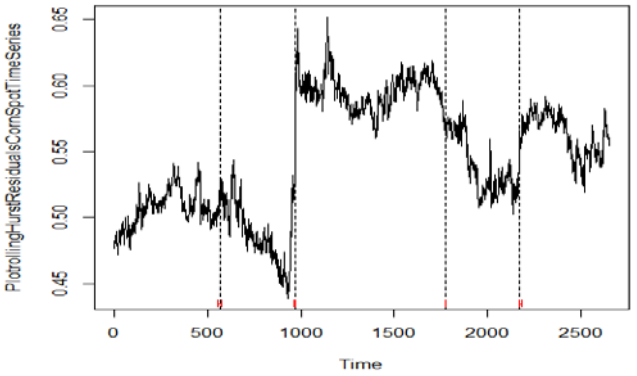
In order to check the optimal number of breaks in the estimated Hurst exponent series of filtered returns, we apply the algorithm described in Bai and Perron (2003) for the simultaneous estimation of multiple breakpoints. The dates of break points minimizing the Bayesian information criterion (BIC)[16] are presented in table 2.4 and figure 2.3. It is clear that the dates of the breaks are namely affected by financial crisis and oil price fluctuations, which underlines the impact of these financial and economic events on market efficiency.

Corn spot	Corn futures	Soybean spot	Soybean futures	Crude oil spot	Crude oil futures
2003-03-26	2002-10-21	2002-09-27	2003-06-16	2002-12-16	2002-12-16
2004-11-02	2004-10-05	2004-11-02	2006-02-02	2004-09-24	2004-09-22
2007-12-24	2006-05-15	2006-12-26	2007-08-31	2007-04-17	2007-04-23
2009-08-21	2007-12-24	2008-07-31	2009-04-30	2008-12-03	2008-11-28
	2009-12-23				

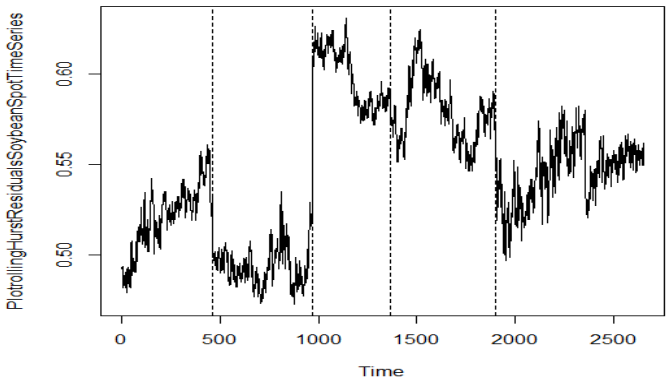
Table 2. 4: Structural break points of the Hurst exponent series of filtered returns

[15] More details about the determination of these bounds can be found in Weron (2002).

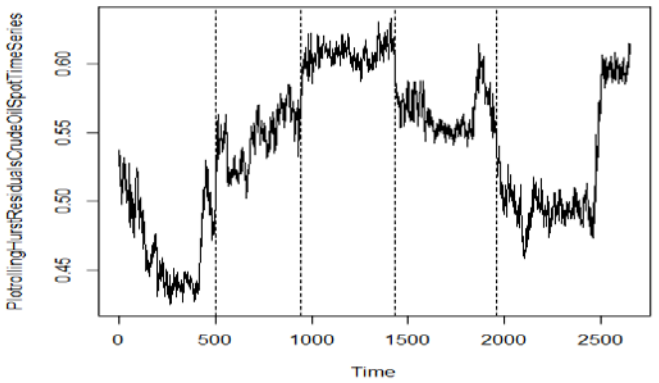
[16] The results on BIC criteria minimization are reported in Figure A2 in the Appendix.



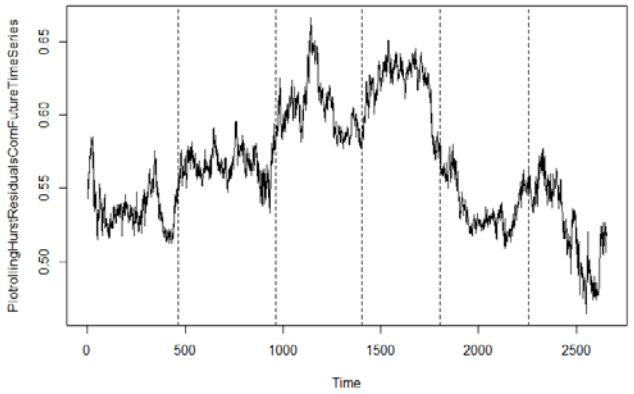
Corn spot



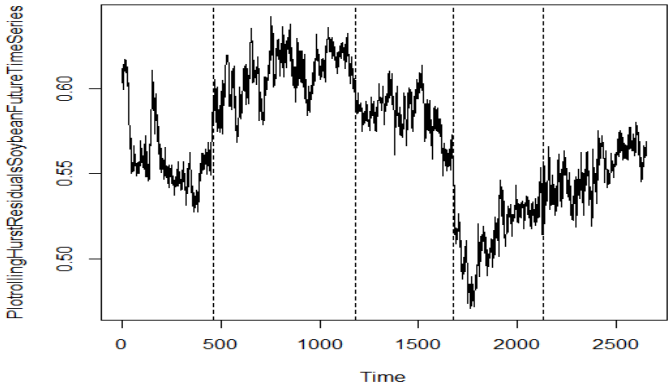
Soybean spot



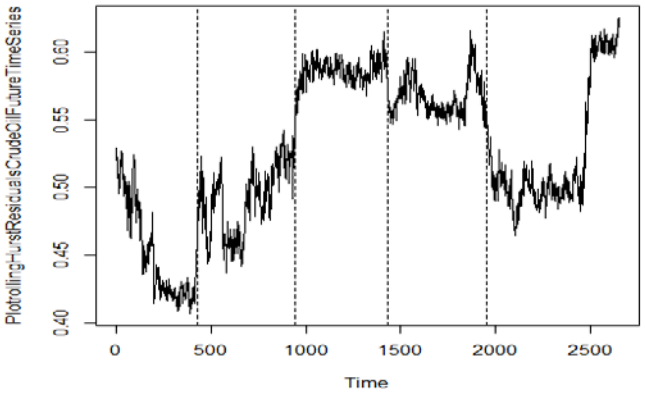
Crude oil spot



Corn futures



Soybean futures



Crude oil futures

Figure 2. 3: Number of structural break points of the filtered rescaled range Hurst exponent series

(Dashed lines correspond to the structural break points, the dates of which are summarized in table 2.4)

Our results show a downward trend of the Hurt exponent for all commodities during the 2008 financial crisis. This declining trend was explained by Kristoufek (2012) through a lack of liquidity due to the fact that investors at shorter investment horizons trade more frequently than do those at longer investment horizons during crisis.

The results of the time-varying Hurst exponent for filtered returns for each commodity are plotted in figure 2.4, showing that the Hurst exponents are time varying while remaining somewhat close to 0.5. In most periods of time and for all of the commodities, the Hurst exponent estimated series falls within the confidence intervals indicating that the null hypothesis of no long-term dependence cannot be rejected. Hence, all of the commodities are long-term efficient. During certain structural breakpoints (namely the 2008 global financial crisis and the period of crude oil price fluctuations), the Hurst exponent estimated series are outside the confidence intervals underlying the presence of short-term inefficiencies explained by global economic conditions. This result is supported by other recent findings concerning the heightened volatility of energy and food markets namely during the 2008 financial crisis period, which was characterized by the most important volatility spillovers between the markets under consideration (Jebabli et al., 2014). Our findings regarding the efficiency of energy markets are in agreement with those of previous studies, highlighting the effect of the great recession (e.g., Ortiz-Cruz et al., 2012; Tokic, 2015, 2010; Zhang et al., 2014) and the crude oil fluctuations period (Chen et al., 2014, Khediri and Charfeddine, 2015) on the efficiency of crude oil market. Compared to previous studies (e.g., Pederzoli and Torricelli, 2013) which indicate that the decline in food market efficiency during the financial crisis is not significant, our results underline the significant impact of the financial crisis on the efficiency of food market hilighting the phenomenon of food commodity financialization.

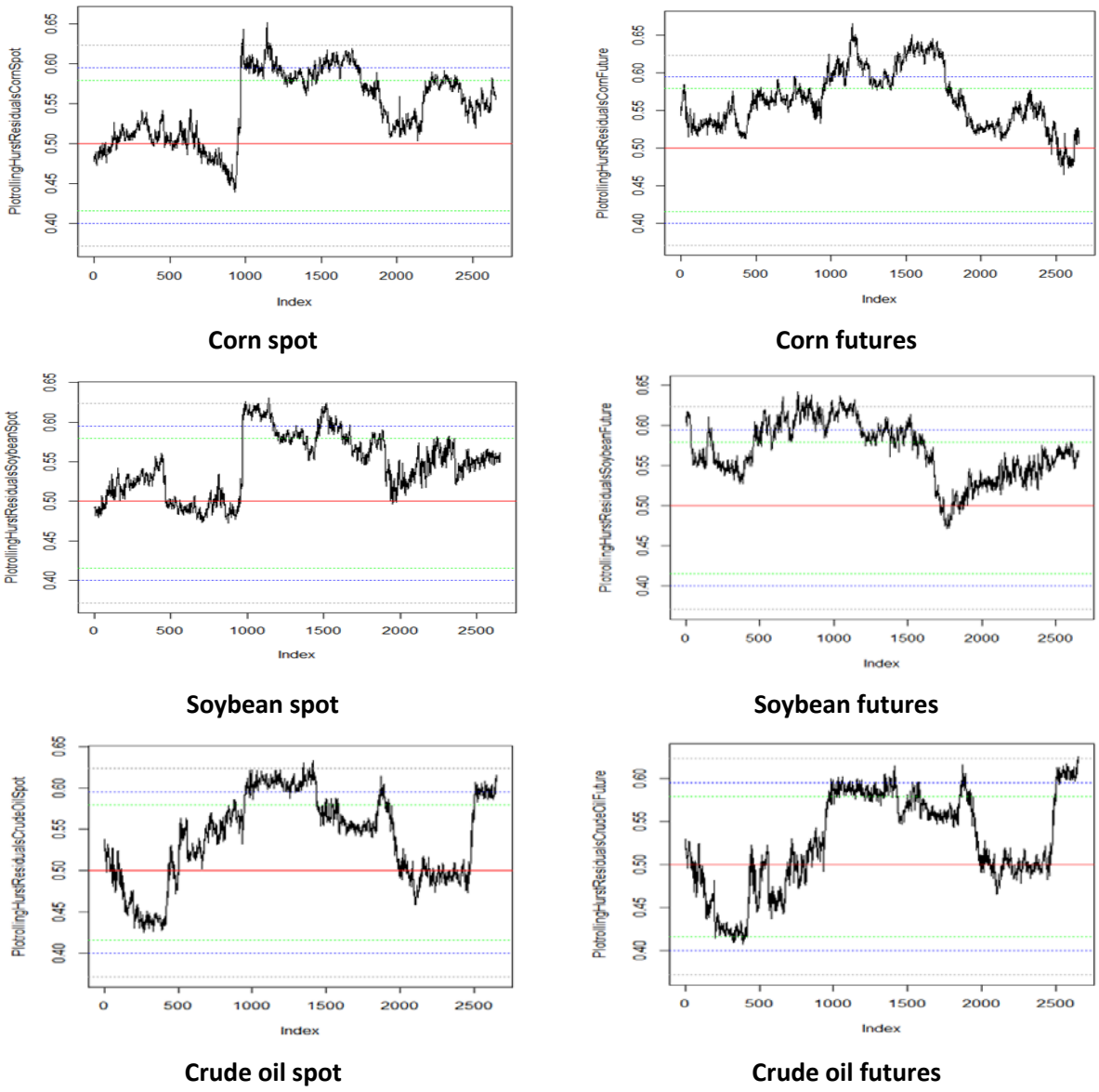


Figure 2. 4: Time-varying rolling Hurst for corn, soybean, and crude oil filtered returns

(confidence intervals at 90%, 95%, and 99% confidence levels are presented in green, blue, and gray, respectively)

5.2. Analysis of results of threshold vector error correction model

For each commodity, the spot and futures prices are integrated of the same order 1, as mentioned above. Next, in order to determine the existence of a stable long-run relationship between spot and futures prices, we employ cointegration techniques. To check the cointegration rank r between spot and futures prices for each commodity, we apply the Johansen cointegration rank test (Johansen, 1995). Statistics from this test and critical values at the 1%,

5%, and 10% levels of significance are reported in table 2.5. They indicate that the null hypothesis $H_0: r = 0$ is rejected, suggesting that there is at least one cointegrating vector, which confirms a long-run equilibrium relationship between spot and futures prices for each commodity.

	Corn				Soybean				Crude oil			
	statistic	**10%**	**5%**	**1%**	**statistic**	**10%**	**5%**	**1%**	**statistic**	**10%**	**5%**	**1%**
$r = 0$	1,478.11	6.50	8.18	11.65	1,543.62	6.50	8.18	11.65	1,554.35	6.50	8.18	11.65
$r \leq 1$	2,825.23	12.91	14.90	19.19	2,884.48	12.91	14.90	19.19	2,519.87	12.91	14.90	19.19

Table 2. 5: Johansen cointegration rank test

Coefficients of the estimated VECM model with $r = 1$ are summarized in table 2.6. Except for the constants and lagged values of futures returns in the equation of spot crude oil prices, all of the coefficients, either for the spot or futures equation, are significant. The significant ECT coefficients reveal that the market reacts to any disequilibrium between spot and futures prices for all commodities.

	Corn	**Soybean**	**Crude oil**
Spot equation			
ECT	-1.644 (0.038)***	-1.689 (0.037) ***	-0.195 (0.065)**
Intercept	1.4e-05 (0.0005)	4.7e-05 (0.0005)	1.8e-05 (0.0005)
Spot returns t-1	0.167 (0.022)***	0.187 (0.021)***	-0.442 (0.043)***
Futures returns t-1	-0.608 (0.027)***	-0.637 (0.026)***	-0.072 (0.044)
Cointegration relation	1	1	1
Futures equation			
ECT	0.146 (0.030)***	0.125 (0.028) ***	1.261 (0.064)***
Intercept	-8.1e-07 (0.0004)	-9.2e-06 (0.0004)	2.3e-05 (0.0005)
Spot returns t-1	-0.070 (0.018) ***	-0.064 (0.016)***	-0.622 (0.042)***
Futures returns t -1	-0.407 (0.022)***	-0.433 (0.020) ***	0.154 (0.043) ***
Cointegration relation	-0.955	-0.919	-1

Notes: standard errors of the coefficients are presented in parentheses: ***, **, and * denote significance at the 0.1%, 1% and 5% levels, respectively; ECT = error correction term.

Table 2. 6: Coefficients of the estimated vector error correction model

Then, to test the null hypothesis of linear cointegration against threshold cointegration, we apply the heteroskedasticity-robust supLM statistic proposed by Hansen and Seo (2002). The results of this test, as shown in table 2.7, lead to the rejection of the null hypothesis of linear cointegration.

		Corn	Soybean	Crude oil
Test statistic		61.093	46.306	58.469
Critical test statistic	**0.90%**	32.915	41.837	52.628
	0.95%	38.600	43.738	54.055
	0.99%	53.532	45.426	58.659
p-value		0.001	0.010	0.020

Table 2. 7: Test of linear cointegration against threshold cointegration

In order to check the number of regimes in the TVECM, we estimate a TAR model for the cointegration relationship based on Seo (2003), in which the long-run relationship, that is, the cointegration relationship in a TVECM, may be specified as a TAR model. We use a multivariate extension proposed by Lo and Zivot (2001) of the linearity versus threshold test from Hansen (1999). The results of this test with 100 bootstrap replications, examining the number of regimes for each commodity, are summarized in table 2.8. From this table, we can conclude that the null hypothesis of one against two regimes is rejected at any significance level for all commodities. The null hypothesis of one against three regimes is rejected for soybeans and crude oil at any significance level, and for corn at 10% significance level. When testing for the presence of two or three regimes, the results indicate that the null hypothesis of two regimes is rejected at the 90% confidence level. From these results, we can conclude that the number of regimes is three (corresponding to two thresholds) for all commodities, which underlines the switching regime behavior of our Hurst exponent series.

		1 VS 2	1 VS 3	2 VS 3
Corn	**Test**	36.075	78.993	42.918
	p-value	0.000	0.010	0.010
Soybean	**Test**	431.283	466.397	35.114
	p-value	0.000	0.000	0.020
Crude Oil	**Test**	27.771	55.121	27.349
	p-value	0.000	0.000	0.020

Table 2. 8: Test of the number of regimes

Based on the results of the tests concerning the number of thresholds, we estimate our TVECM in order to study short- and long-run effects between spot and futures prices for each commodity, through capturing the asymmetries and nonlinearity in the adjustment of the deviations toward the long-run economic equilibrium.

The results of this estimation, as well as the TVECM cointegrating vector and threshold values for each commodity, are reported in tables 2.9 and 2.10.

		Corn	**Soybean**	**Crude oil**
Cointegrating vector		(1, - 0.561)	(1, - 0.510)	(1, - 0.721)
Threshold values	**Threshold 1**	-0.009	-0.006	0.001
	Threshold 2	0.011	0.003	0.005

Table 2. 9: Cointegrating vectors and threshold values of threshold vector error correction model for corn, soybean, and crude oil

Coefficients of the threshold vector error correction model									
	Lower regime			**Middle regime**			**Upper regime**		
	Corn	**Soybean**	**Crude oil**	**Corn**	**Soybean**	**Crude oil**	**Corn**	**Soybean**	**Crude oil**
Spot equation									
ECT	-2.330	-2.043	-1.892	-1.634	-2.240	-3.053	-1.942	-2.177	-1.194
	$(6.2e^{-198})^{***}$	$(7.3e^{-139})^{***}$	$(8.3e^{-97})^{***}$	$(9.9e^{-47})^{***}$	$(7.3e^{-17})^{***}$	$(0.002)^{**}$	$(3.5e^{-253})^{***}$	$(0)^{***}$	$(4.3e^{-31})^{***}$
Const	-0.006	-0.004	0.003	$3e^{-05}$	0.0004	0.0001	0.007	0.004	-0.009
	$(1.8e^{-05})^{***}$	$(0.005)^{**}$	$(0.0001)^{***}$	(0.954)	(0.544)	(0.961)	$(1.4e^{-06})^{***}$	$(1.4e^{-07})^{***}$	$(1.2e^{-11})^{***}$
Spot returns t-1	0.580	0.480	0.513	0.024	0.0002	0.033	0.289	0.371	0.218
	$(4.6e^{-39})^{***}$	$(9.8e^{-28})^{***}$	$(4.0e^{-22})^{***}$	(0.489)	(0.994)	(0.697)	$(1.3e^{-21})^{***}$	$(2.9e^{-29})^{***}$	$(0.0009)^{***}$
Futures returns t-1	-0.526	-0.495	0.735	-0.086	-0.047	-0.020	-0.493	-0.469	-0.501
	$(2.8e^{-40})^{***}$	$(2.5e^{-26})^{***}$	$(9.1e^{-58})^{***}$	$(0.031)^{*}$	(0.271)	(0.785)	$(2.5e^{-38})^{***}$	$(7.2e^{-47})^{***}$	$(6.1e^{-19})^{***}$
Futures equation									
ECT	-0.088	-0.085	-0.766	- 1.166	- 1.523	-3.097	-0.073	-0.166	0.2168
	(0.154)	(0.193)	$(1.3e^{-14})^{***}$	$(7.8e^{-34})^{***}$	$(1.2e^{-11})^{***}$	$(0.006)^{**}$	(0.102)	$(4.5e^{-05})^{***}$	(0.059)**.**
Const	0.007	0.008	0.004	0.0002	0.0002	0.001	-0.005	-0.006	-0.015
	$(1.8e^{-10})^{***}$	$(3.3e^{-12})^{***}$	$(1.7e^{-07})^{***}$	(0.694)	(0.799)	(0.746)	$(0.0002)^{***}$	$(5.7e^{-18})^{***}$	$(2.3e^{-20})^{***}$
Spot returns t-1	0.061	0.056	0.461	0.066	0.036	0.050	0.067	0.134	0.236
	(0.099)**.**	(0.127)	$(1.0e^{-14})^{***}$	$(0.023)^{*}$	(0.129)	(0.603)	$(0.009)^{**}$	$(1.0e^{-06})^{***}$	$(0.0015)^{**}$
Futures returns t-1	-0.553	-0.529	-0.820	-0.219	-0.203	-0.075	-0.679	-0.525	-0.695
	$(3.3e^{-60})^{***}$	$(2.9e^{-41})^{***}$	$(8.2e^{-57})^{***}$	$(1.3e^{-10})^{***}$	$(1.6e^{-08})^{***}$	(0.358)	$(5.9e^{-95})^{***}$	$(2.5e^{-80})^{***}$	$(1.0e^{-27})^{***}$
Percentage of observations in each regime									
	15.8%	19.3%	57.5%	70.8%	43%	19.9%	13.5%	37.8%	22.7%

Table 2. 10: Results of the threshold vector error correction model for corn, soybean, and crude oil

Notes: standard errors of the coefficients are presented in parentheses: **.**, ***, **, *, and denote significance at the 0.1%, 1%, 5%, and 10% levels, respectively; ECT = error correction term.

Thresholds for each commodity mentioned in table 2.9 indicate that, for corn, the lower regime (which represents 15.8%) is when the gap between corn spot and futures prices is below -0.009, upper regime (which represents 13.5%) is when this gap is above 0.011, and middle regime (which represents 70.8%) is when the gap between corn spot and futures prices is comprised between -0.009 and 0.011. Concerning soybean, the lower regime (which represents 19.3%) would occur when the gap between soybean spot and futures prices is below -0.006, whereas the middle regime (which represents 43%) would occur when this gap is comprised between -0.006 and 0.003; when this gap is above 0.003, the upper regime would occur (which represents 37.8%). The crude oil lower regime (which represents 57.5%) is defined by values of the gap between crude oil spot and futures prices below 0.001 and the upper regime (which represents 22.7%) is defined by values of this gap above 0.005; when the gap is between these two thresholds, the middle regime could occur (which represents 19.9%).

Moreover, table 2.10 shows that, except for the futures equation of corn and soybean in the lower regime as well as the futures equation of corn in the upper regime, the ECT coefficients of the TVECM are significant in the three regimes for all commodities, either for spot or futures equations, and the sign of adjustment is negative (except for the crude oil futures equation in the upper regime).

A comparison of the estimated ECT coefficients illustrated in table 2.10 across the three regimes suggests that the adjustment process toward the long-run equilibrium of corn spot prices is faster in the lower regime (-2.330) than in the two other regimes (-1.634 for the middle and -1.942 for the upper), while for soybean spot prices, the speeds of adjustment across the three regimes are very close, and the speed of adjustment toward the long-run equilibrium for crude oil spot prices is faster in the middle regime (-3.053) than in the lower (-1.892) and upper (-1.194) regimes.

If the economy switches to an upper regime characterized by the highest divergence between spot and futures prices, table 2.10 reveals that the influence in the short run, either of spot prices on futures prices or of futures prices on spot prices, is significant for all commodities. This upper regime is explained, in particular, by the financialization of commodities due to the arrival of a new type of market players, active across different markets (commodity index traders), who trade based on portfolio considerations and not on individual commodity prices. This new type of actors has been accompanied by the increase in the investment on these commodities, speculation, and an increase in commodities storage and in the flow of benefits

from holding the physical commodity. Thus, other factors have to be considered in order to have an idea about the futures contracts prices through spot prices.

Lags of futures prices for corn are statistically significant in the three regimes, revealing that futures prices have significant effects on the dynamic of spot prices across the different regimes. However, the size of the effect is bigger in the lower and upper regimes than in the middle regime. Concerning soybean and crude oil, lags of their futures prices are statistically significant in the lower and upper regimes, and the effect size is comparable among these two regimes for soybean, while for crude oil, the sign of the effect is different (positive in the lower regime and negative in the upper regime).

5.3. Optimal hedging strategies

In order to check the usefulness of futures markets as a tool for risk management, in this part of the paper, we focus on estimating optimal hedge ratios and evaluating the effectiveness of hedging. In fact, investors require information on the effectiveness of hedging in order to decide their appropriate positions in the futures markets, compensating for the risk from corresponding holdings in the spot market (Fan et al., 2016). Further, Chang et al. (2011) show that futures contracts are favored as a hedging tool because of their liquidity, speed, and lower transaction costs.

For this finality, we consider that, for each commodity, the return of a portfolio composed of spot and futures positions is given by the following equation:

$$R_t^{hedged} = R_t^{Spot} - \beta_t R_t^{Futures}, \tag{10}$$

where R_t^{hedged} is the return of the hedged portfolio at time t, R_t^{Spot} is the return of the spot position at time t, $R_t^{Futures}$ is the return of the futures position at time t, and β_t is the hedge ratio at time t.

In this paper, we adopt the minimum-variance hedge ratio as a hedging strategy in order to analyze the optimal weights and hedge ratios for spot and futures holdings.[17]

[17] An overview on econometric methods for computing the hedging ratio can be found in Lien and Tse (2002).

We consider a time-varying approach for the estimation of the hedge ratios by referring to previous findings, such as those of Kavussanos and Nomikos (2000), underlying that variance reduction is larger with conditional hedge ratios than static hedge ratios. A very recent study (Fan et al., 2016) provides more discussion on static (unconditional) and time-varying (conditional) models for hedge ratio estimation.

Then, the risk minimizing the hedge ratios for holding spot and futures positions for each one of the commodities considered (corn, soybean, and crude oil) is given by the following equation (Kroner and Sultan, 1993):

$$\beta_t^{Spot,Futures} = \frac{h_t^{Spot,Futures}}{h_t^{Futures}}, \tag{11}$$

where $h_t^{Futures}$ is the conditional variance of futures at time t, and $h_t^{Spot,Futures}$ is the conditional covariance between spot and futures at time t

For the estimation of these time-varying conditional volatilities and conditional covariance matrices, we apply the multivariate DCC-GARCH model of Engle (2002) in order to model the dynamics of the conditional variances and covariance matrices of spot and futures prices for each commodity. In fact, previous studies (e.g., Baillie and Myers, 1991; Myers, 1991) argue that the time variation of the optimal hedge ratios may come from the conditional heteroskedasticity in the spot and futures returns.

Our choice of the model is justified by the fact that commodity time series exhibit the phenomenon of volatility clustering (Jebabli et al., 2014) and the residuals show heteroskedasticity and autocorrelation, which can be better captured by the DCC-GARCH model. Moreover, we estimate this model in two steps, by estimating, first, the GARCH parameters and, then, the time-varying conditional correlations.[18]

[18] For more details about the different estimation steps, refer to Engle (2002).

The expression of the time-varying conditional covariance matrix in the DCC-GARCH model is given by the following equation:

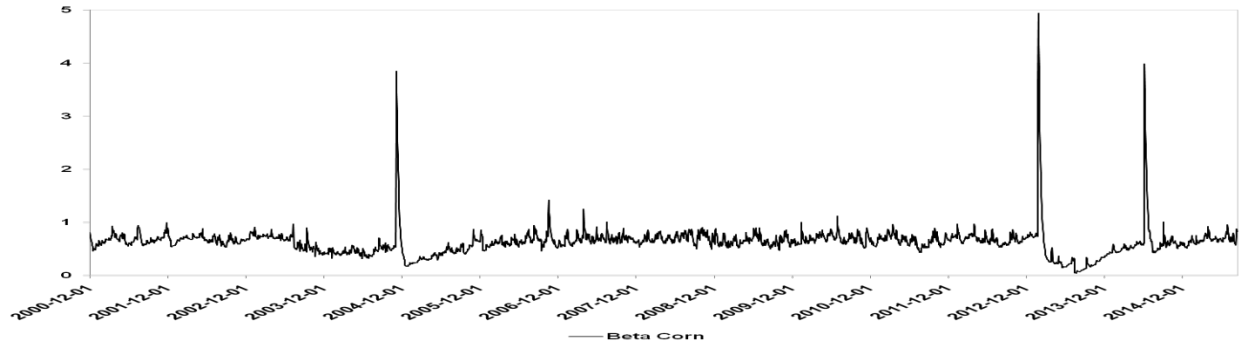
$$H_t = D_t R_t D_t, \quad (12)$$

where R_t is the conditional correlation matrix at time t, and D_t is the diagonal matrix with standard deviations at time t on the diagonal

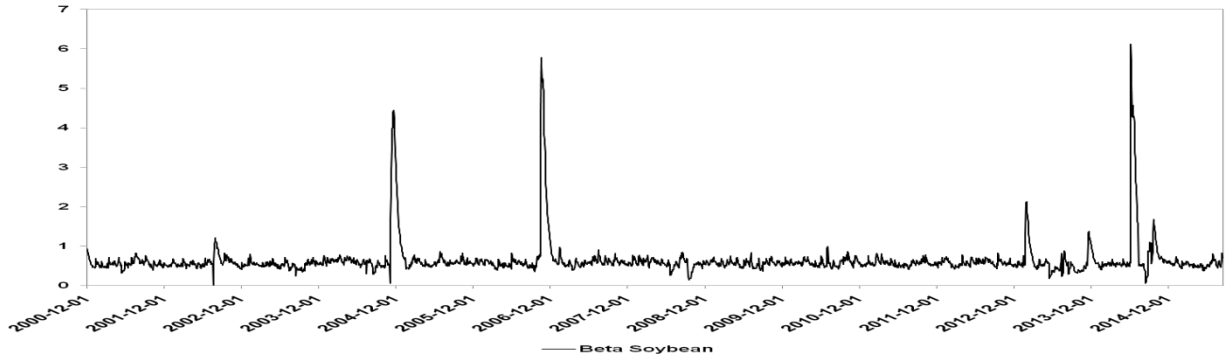
The estimated time-varying conditional volatilities and conditional covariance matrices are illustrated in figure A.2.5 in the Appendix,[19] while the optimal time-varying hedge ratios for each commodity are illustrated in figure 2.5 below.

[19] Details on the estimation of the DCC-GARCH model are not presented here for brevity, but can be provided per request.

Corn



Soybean



Crude oil

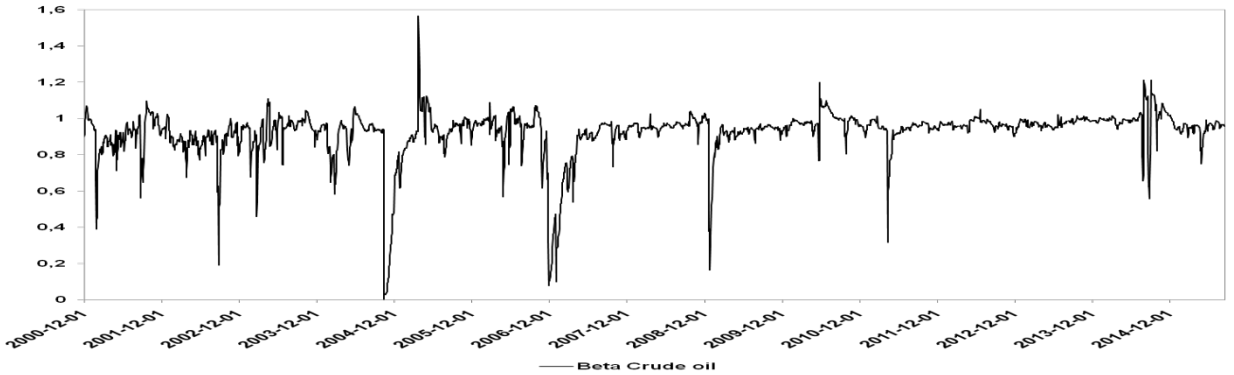


Figure 2. 5: **Time-varying optimal hedge ratios for each commodity**

The optimal hedge ratio results indicate that the percentage of spot contracts matched by futures positions that minimizes the variance of the hedged portfolio is varying over time for all commodities with similar patterns for corn and soybean commodities, while time-varying hedge ratios for crude oil show different patterns. The optimal hedge ratios for all commodities are positive, indicating that to hedge a long-spot position, hedgers have to go short on futures contracts.

Moreover, higher noticeable values (above 1) of hedge ratios are recorded for corn and soybean at common dates corresponding nearly to the end of 2004 year and middle of 2013, and are also recorded at the end of 2012 and 2006 for corn and soybean, respectively. Lower values (below 1) are noticeable for crude oil hedge ratios recorded namely at nearly the end of 2004, 2006, and 2008 years. The summary statistics of the hedge ratios for each commodity are outlined in table 2.11.

	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Corn	0.045	0.543	0.640	0.631	0.713	4.941
Soybean	-0.053	0.510	0.560	0.640	0.627	6.117
Crude oil	-0.023	0.913	0.955	0.924	0.981	1.567

Table 2. 11: Summary statistics of the hedge ratios for each commodity

Optimal hedge ratio means indicate comparable results for grains, while crude oil ratios are higher than those of grains, which can be partly explained by the fact that divergence between spot and futures grains is higher than for crude oil. Lower mean values for grains compared to crude oil suggest that futures grains provide better hedging effectiveness than do futures crude oil, which is in line with previous findings in the literature.

In order to estimate the optimal weights, in terms of risk reduction, of spot and futures positions to be held for each commodity (corn, soybean, and crude oil), we follow Kroner and Ng (1998). The optimal weights of spot positions are given by the following equation:

$$w_t^{Spot,Future} = \frac{h_t^{Spot} - h_t^{Spot,Future}}{h_t^{Future} - 2h_t^{Spot,Future} + h_t^{Spot}}, \quad (13)$$

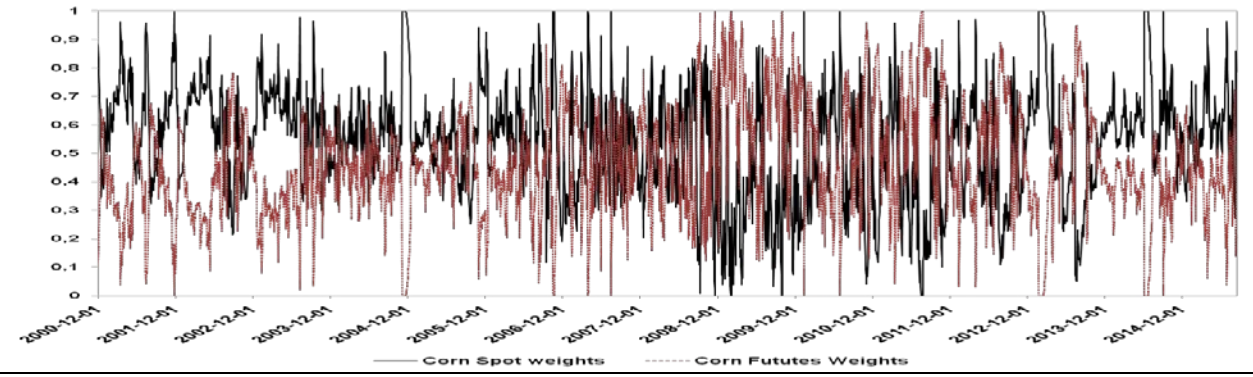
on the condition that:

$$w_t^{Spot,Future} = \begin{cases} 0 \; if \; w_t^{Spot,Future} < 0 \\ w_t^{Spot,Future} \; if \; 0 \leq w_t^{Spot,Future} \leq 1. \\ 1 \; if \; w_t^{Spot,Future} > 1 \end{cases}$$

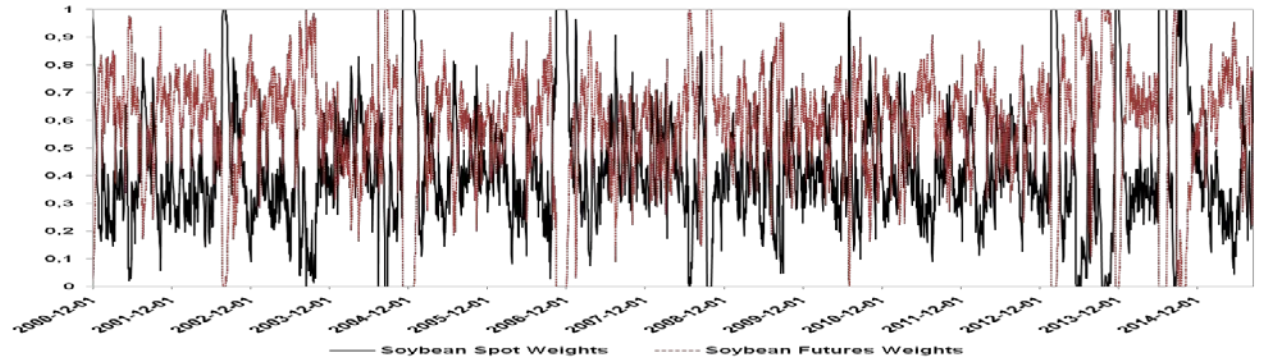
Further, the optimal weights of futures positions to be held are given by $1 - w_t^{Spot,Future}$.

The time-varying optimal weights of spot and futures prices for each commodity are presented in figure 2.6. The ratios between futures and spot weights and percentages of futures weights in a portfolio of spot and futures are presented for each commodity, respectively, in figures A.2.6 and A.2.7 in the Appendix. Our findings show that the optimal weights alternate over time between larger positions of spot and futures for each commodity, and that changes in spot position values are counterbalanced by changes in the value of an opposite futures position. We also notice that for grains, and contrary to crude oil, which shows opposite patterns, larger futures positions than spot had to be held during the 2008 financial crisis and during the eruption of the food price crisis (January 2007), while more spot positions than futures had to be held in 2004 when index investment started to flow into commodity markets.

Corn



Soybean



Crude oil

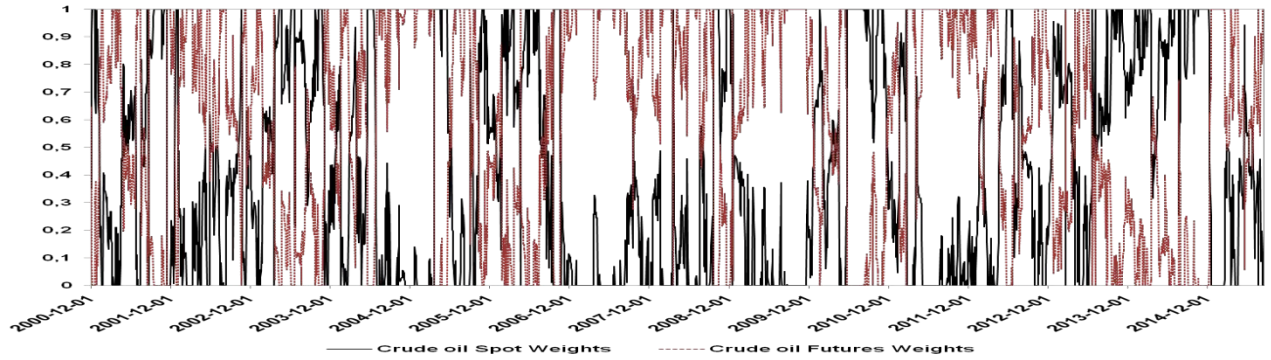


Figure 2. 6: **Time-varying optimal weights of spot and futures positions for each commodity**

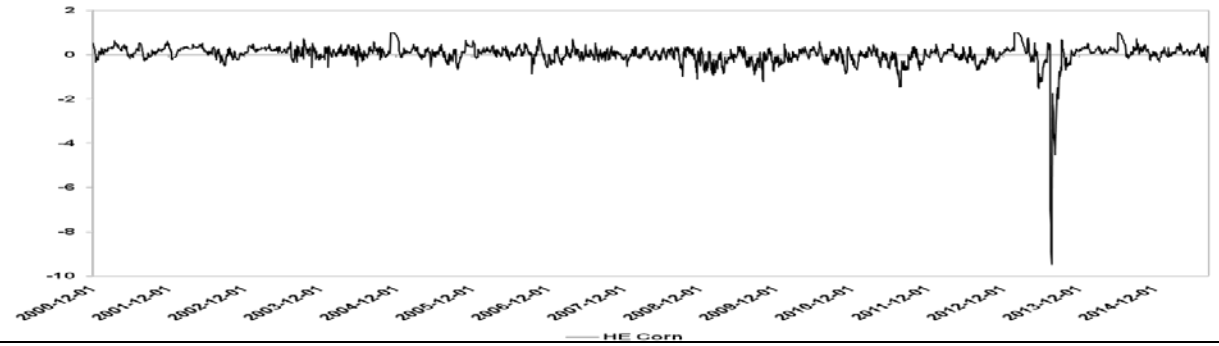
For the estimation of the hedging effectiveness index (in terms of variance reduction), we refer to Ku et al. (2007), who mention that a more accurate model of conditional volatility should also be superior in terms of hedging effectiveness:

$$HE_t = \frac{var_t^{unhedged} - var_t^{hedged}}{var_t^{unhedged}}, \quad (14)$$

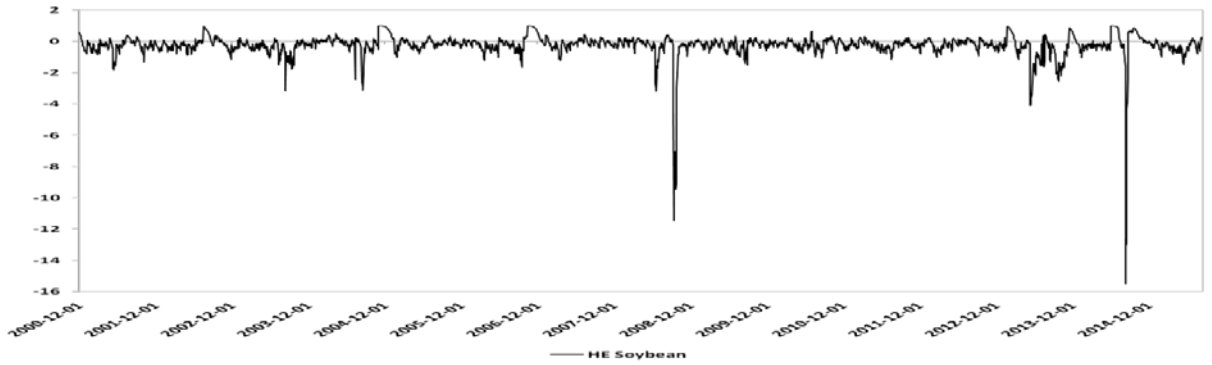
where $var_t^{unhedged}$ is the variance of spot returns at time t, and var_t^{hedged} is the variance of futures returns at time t.

The time-varying hedging effectiveness ratios are presented in figure 2.7 from which we can note that hedging is not effective during all periods of our sample, since we notice the presence of negative hedging effectiveness ratios on certain dates. The dates of negative hedging effectiveness correspond namely to periods of market inefficiency, meaning that divergence between spot and futures markets reduces the usefulness of hedging through futures markets. This finding emphasizes the positive link between the role played by commodity futures prices in price discovery and the futures hedging effectiveness.

Corn



Soybean



Crude oil

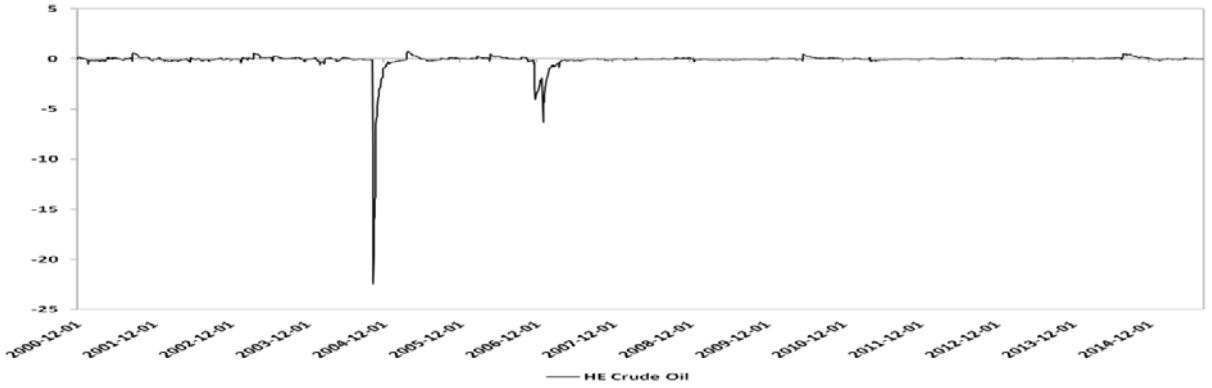


Figure 2. 7: **Time-varying hedge effectiveness ratios for each commodity**

We also observe that futures lose their usefulness, in terms of hedging, when hedge ratios are high. In terms of comparison between the effectiveness of the hedging of the different commodities, figure 2.8 indicates that grain futures provide better hedging effectiveness than do those of crude oil. The summary statistics of the hedge effectiveness for each commodity are recapitulated in table 2.12.

	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Corn	-947%	-12.4%	7.5%	0.9%	23.1%	99.8%
Soybean	-1,551%	-40.4%	-18.6%	-25.3%	2.5%	99.8%
Crude oil	-2,243%	-7.3%	-2.4%	-11.4%	3.7%	72.5%

Table 2. 12: Summary statistics of the hedge effectiveness for each commodity

6. Conclusion and policy implications

This paper highlights the importance of considering time-varying models in order to assess market efficiency dynamics since they allow taking into account the eventual presence of structural breaks in the time series. The results of the rolling Hurst exponent and TVECM estimation show that corn, soybean, and crude oil commodities exhibit long-run efficiency and inefficiency in the short-run.

Investigation of the presence of breakpoints among the estimated Hurst exponent series reveals the existence of multiple breakpoints explained by financial and economic events namely the 2008 global financial crisis and oil price fluctuations. In these breakpoints, futures prices are not unbiased estimators of future spot prices for each commodity.

TVECM allowed us to detect the presence of three regimes (lower, middle and upper) for each commodity depending on the gap values between spot and futures prices. A comparison of the estimated error-correction coefficients across the three regimes for each commodity reveals that adjustment process towards the long-run equilibrium is faster in the lower regime for corn spot prices, comparable among the three regimes for soybean spot prices and faster in the middle regime for crude oil spot prices. For spot equations, error correction term coefficients of the TVECM are significant in the three regimes for all the commodities.

Regarding the usefulness of futures in terms of hedge effectiveness, our findings underline the impact of the situation of market efficiency on the effectiveness of the futures hedge which is reduced during periods of inefficiency. Comparison across the hedging effectiveness of the different commodities reveals that grain futures provide better effectiveness of the hedging than crude oil futures. Optimal hedge ratios show that the percentage of spot contracts matched by futures positions that minimizes the variance of the hedged portfolio is varying over time for all the commodities with similar patterns for corn and soybean while crude oil shows different patterns. Positive optimal hedge ratios for all the commodities indicate that hedgers have to go short on futures contracts in order to hedge a long spot position. In terms of optimal weights to be held in order to minimize the portfolio risk, our findings underline the importance of alternation between spot and futures weights. We also note that, contrary to crude oil, more grain futures than spot have to be held during the 2008 financial crisis and in the period of eruption of food price crisis (January, 2007), which underline the usefulness of futures grain hedging during these periods of crisis, while more grain spot have to be held in the 2004 year when index investment started to flow into commodity markets.

Our findings have implications on investors' management strategies which have to be hybrid (passive and active management) in order to be adapted to the state of the market. In fact, since markets are efficient in long term, it is impossible to systematically beat them through active management. Thus, investors will prefer passive management which consists on investing by indexing the portfolio with the overall market in order to minimize investing fees. During periods of markets inefficiency, active managers will make specific investments with the goal of outperforming an investment benchmark index. Hence, short and mid-term benefits can be obtained for investors who allocate portions of their portfolios to commodities from an active investment strategy during recessions and exogenous shocks. They also have implications for policy makers who must establish adequate regulatory frameworks to address the detected inefficiencies in the future and, hence, ensure that the markets remain as efficient as possible and mitigate profit opportunities for arbitrageurs.

To put forward on this work, a larger set of food commodities types can be considered to check for their specificity and a depth analysis of exogenous factors that may disrupt the relationship between spot and futures prices for each commodity can be investigated.

Appendix

Corn	Soybean	Crude oil

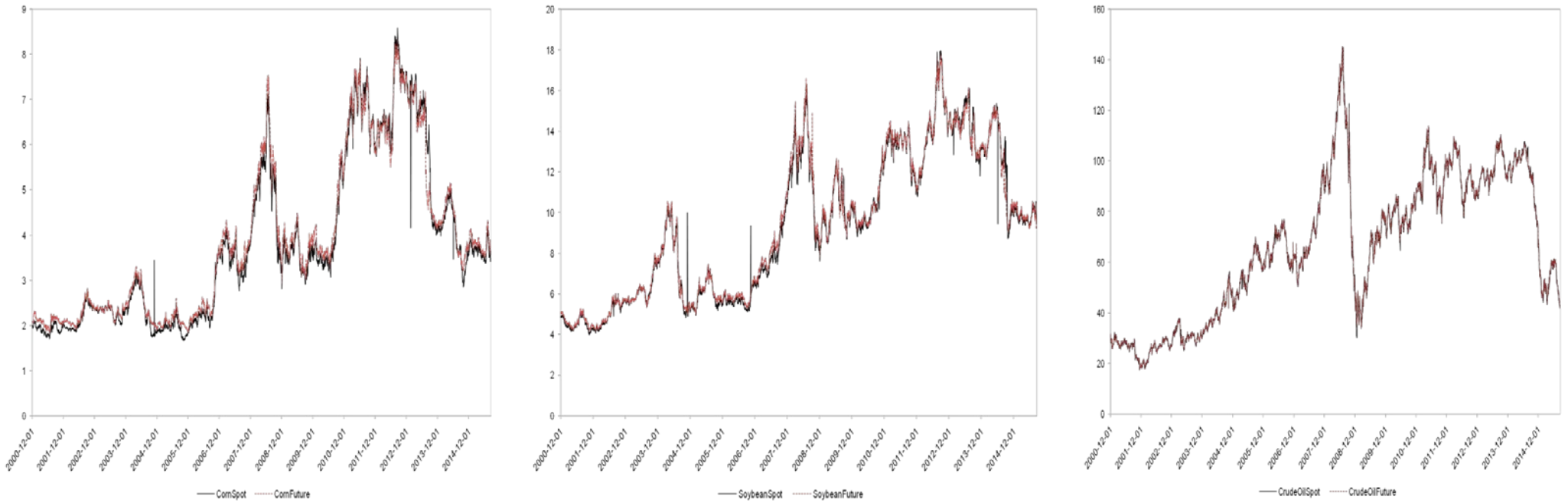


Figure A.2. 1: **Evolution of commodities spot and futures daily prices during the period December 2000-August 2015**

(Black continuous lines correspond to spot prices; futures prices are presented by dashed red lines)

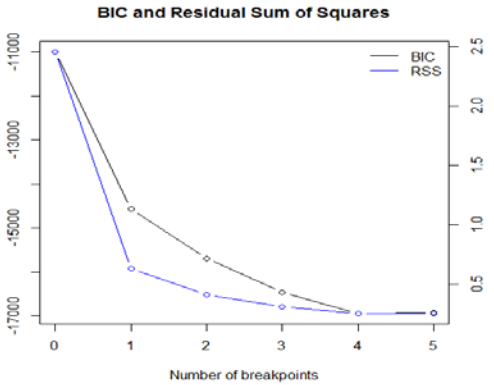
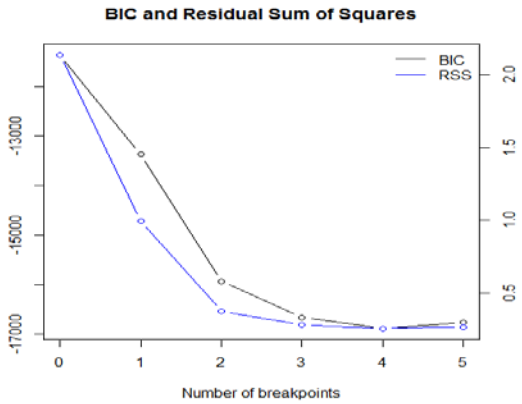
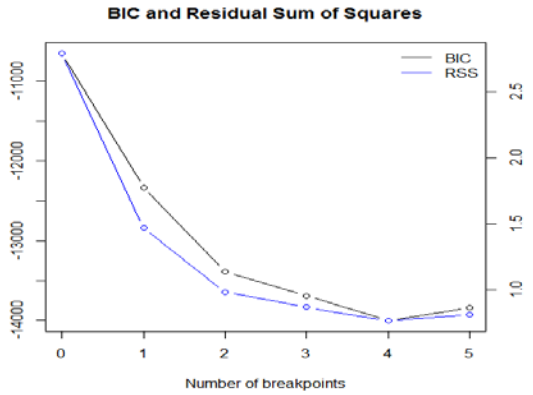
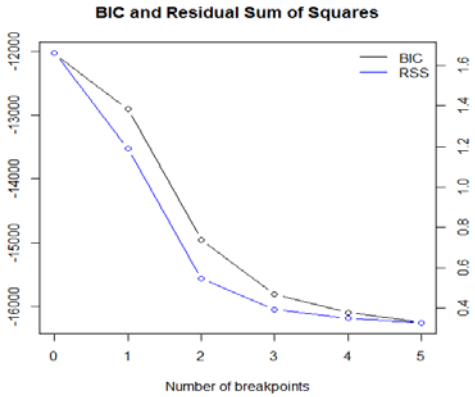
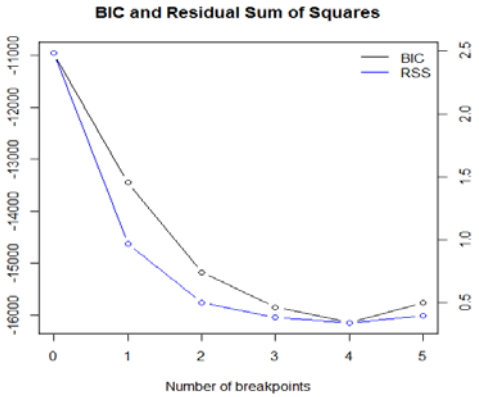
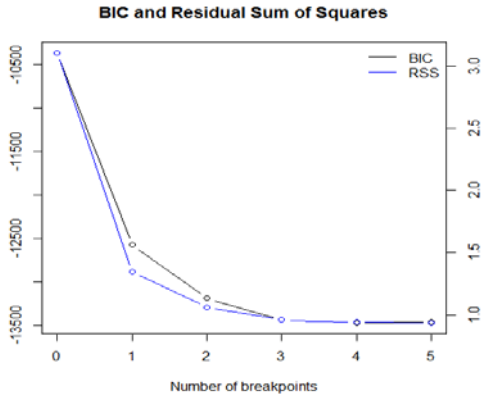
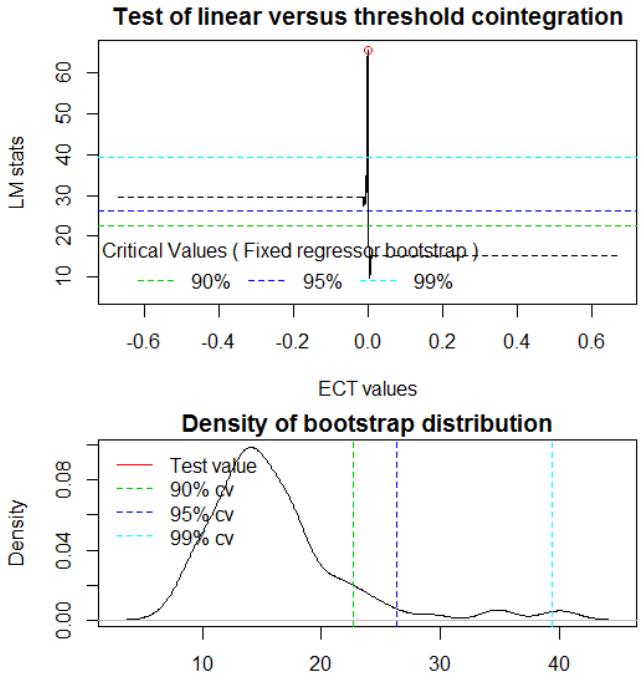
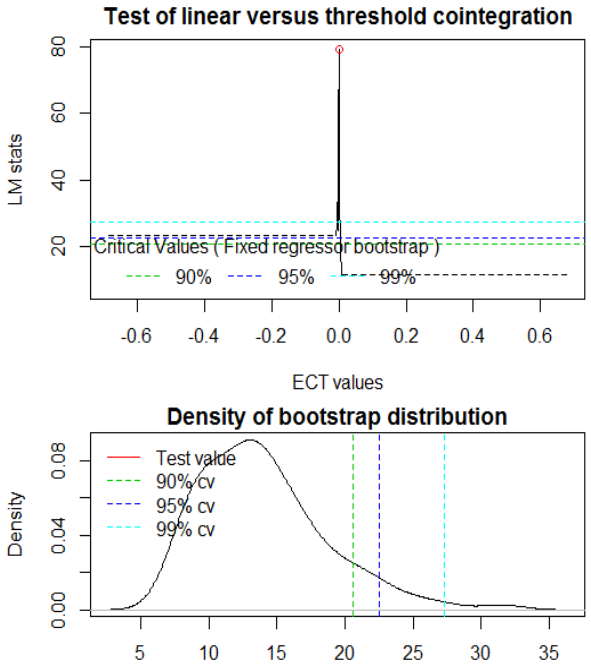
Corn spot	Soybean spot	Crude oil spot
		
Corn futures	**Soybean futures**	**Crude oil futures**
		

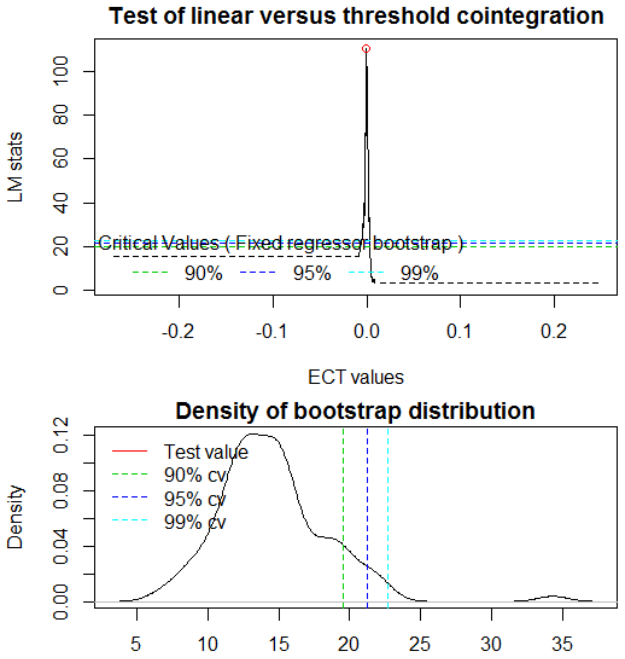
Figure A.2. 2: Number of breakpoints in the Hurst series for corn, soybean, and crude oil filtered returns



(a) Test of linear versus threshold cointegration for corn

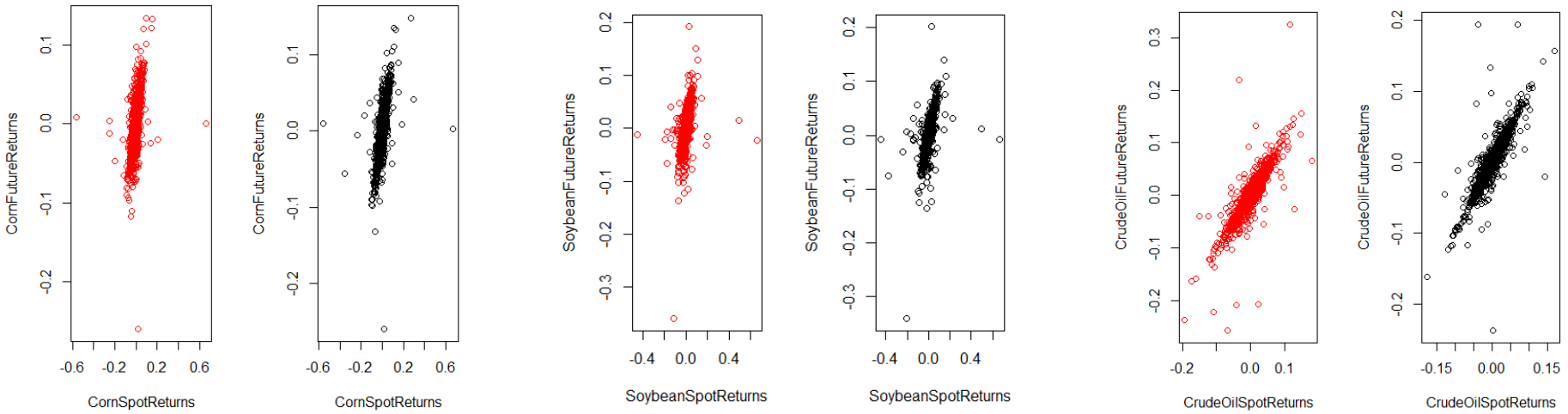


(b) Test of linear versus threshold cointegration for soybean



(c) Test of linear versus threshold cointegration for crude oil

Figure A.2. 3: Test of linear cointegration (VECM) versus threshold cointegration (TVECM)



(a) Residuals of corn (b) Residuals of soybean (c) Residuals of crude oil

Figure A.2. 4: Residuals of the estimated VECM (in black) and TVECM (in red) models

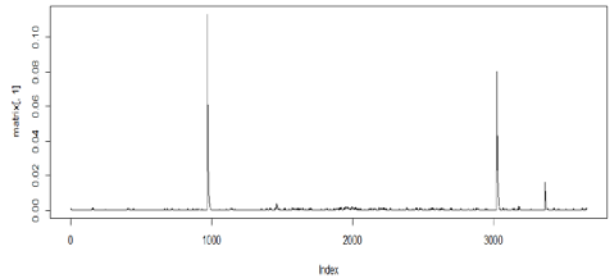
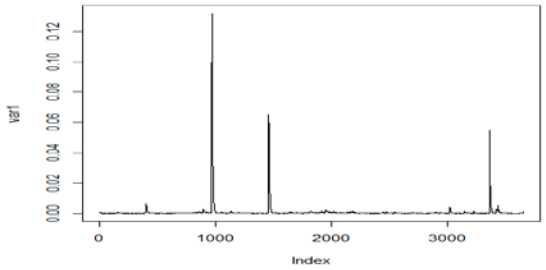
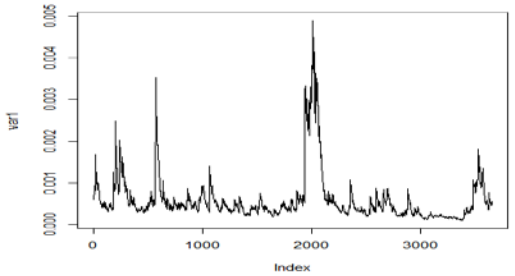
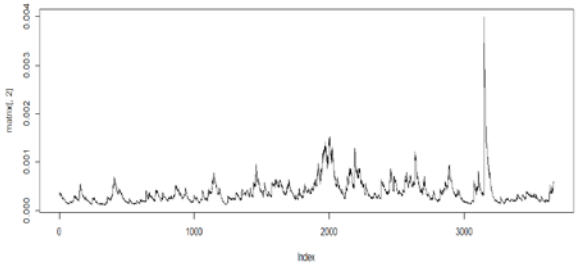
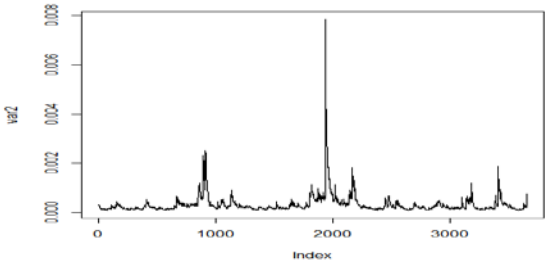
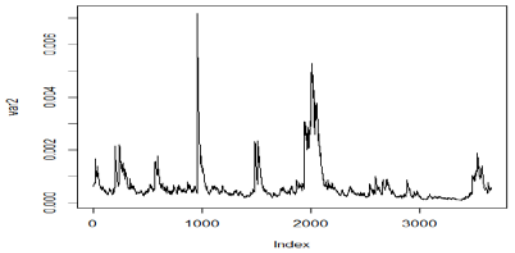
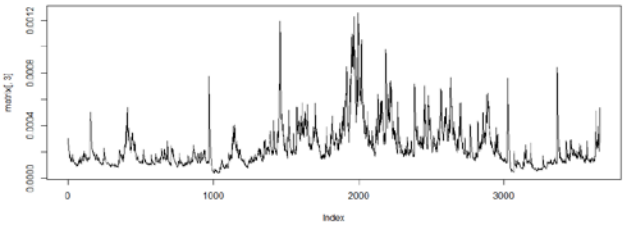
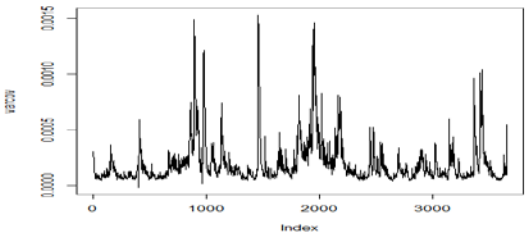
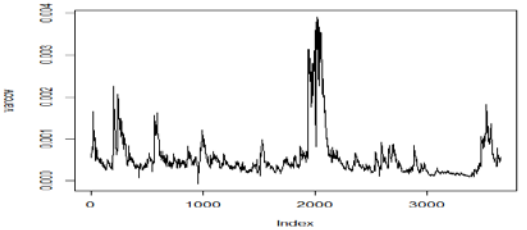
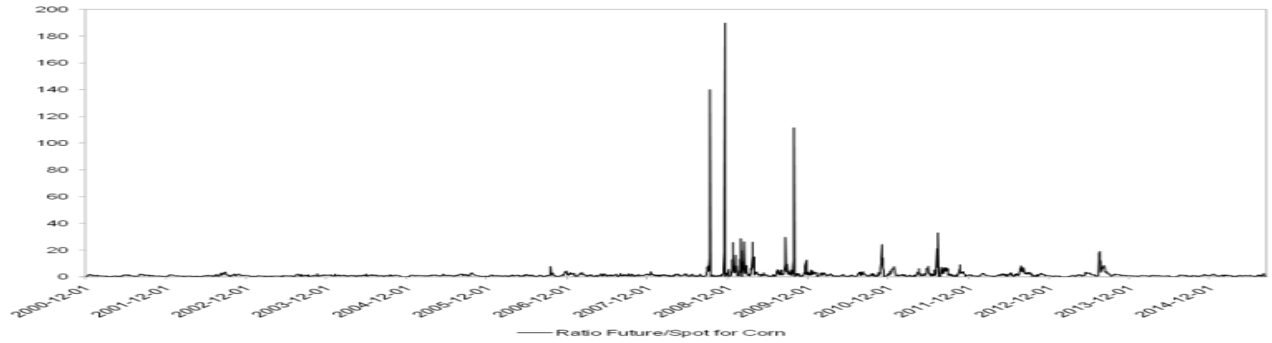
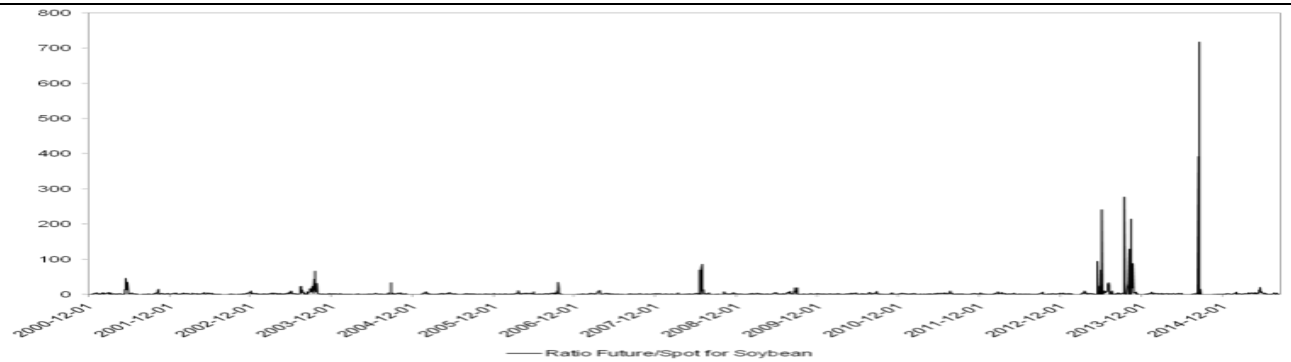
	Corn	Soybean	Crude oil
Commodity Spot conditional variance			
Commodity Future conditional variance			
Commodity conditional Variance Covariance			

Figure A.2. 5: Time-varying conditional variances and covariance matrices obtained from DCC-GARCH model

Corn



Soybean



Crude oil

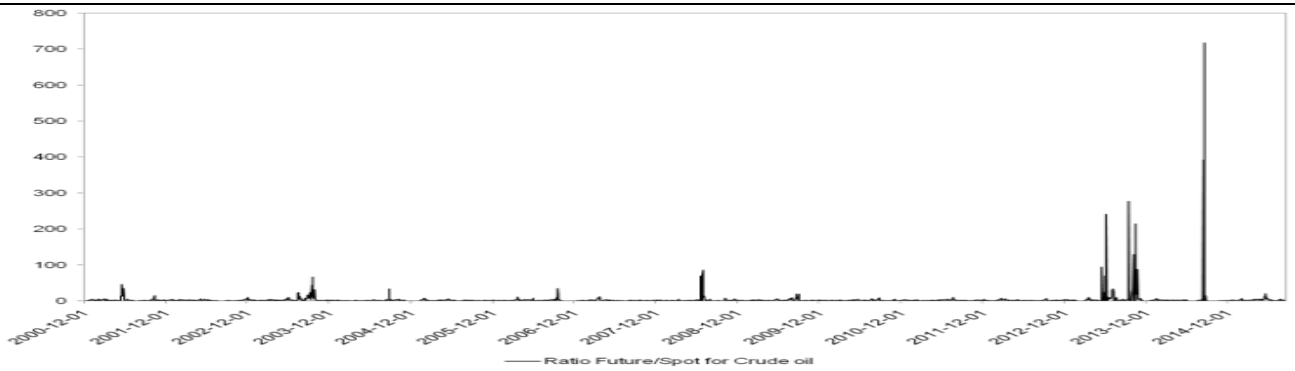
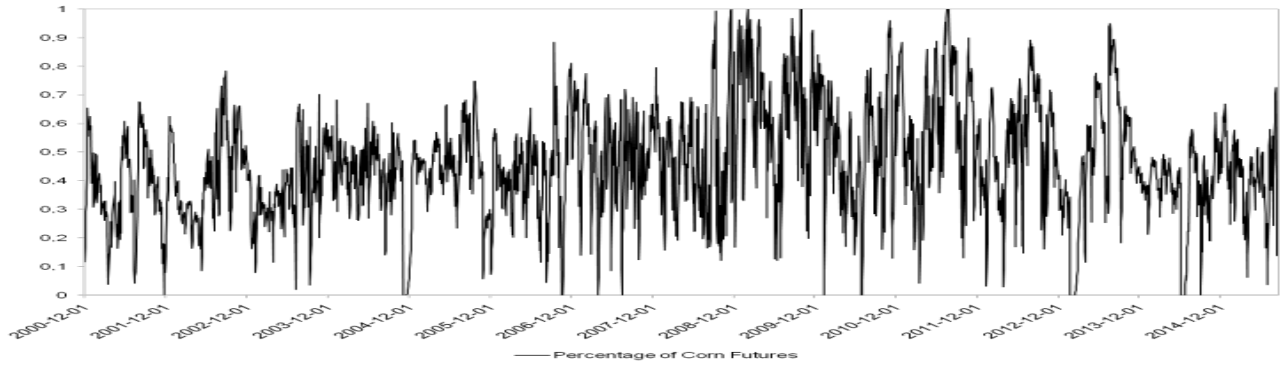
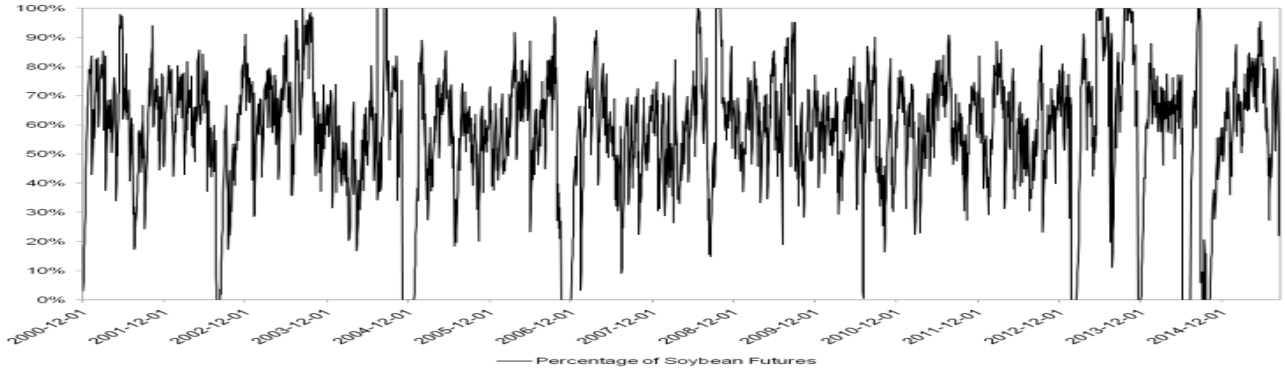


Figure A.2. 6: Time-varying ratios between futures and spot weights for each commodity

Corn



Soybean



Crude oil

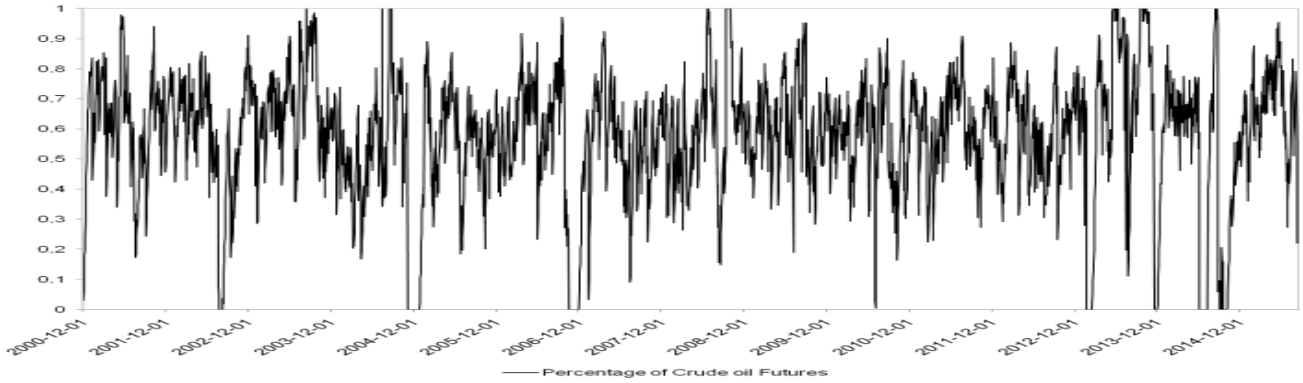


Figure A.2. 7: Time-varying percentages of futures weights for each commodity

Chapter 3

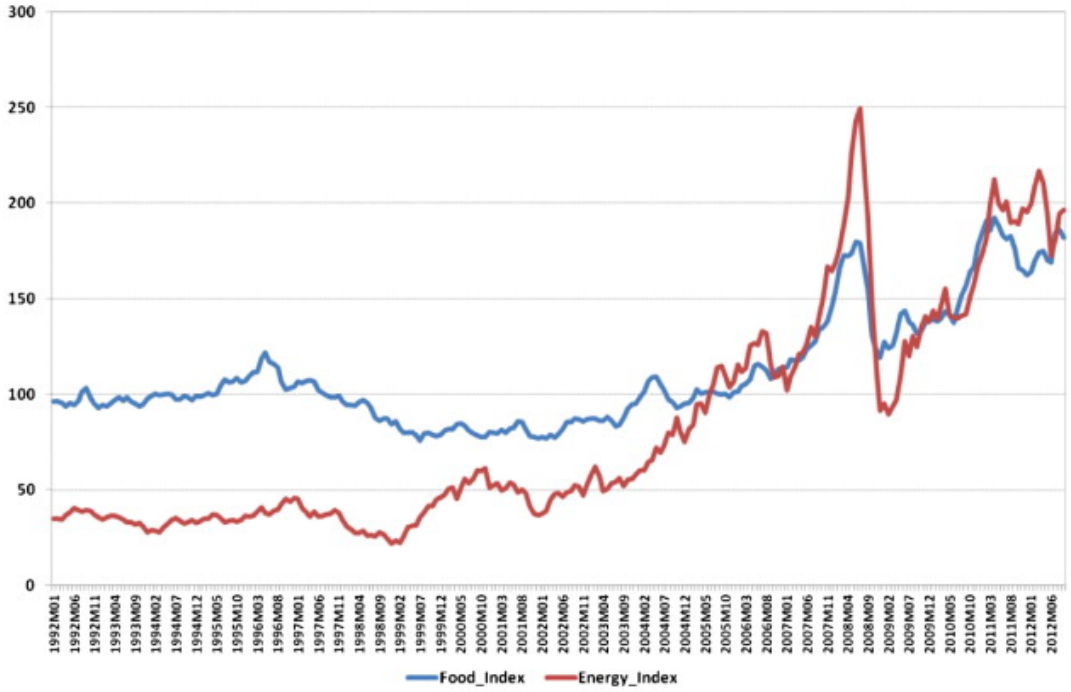
On the effects of world stock market and oil price shocks on food prices: An empirical investigation based on TVP-VAR models with stochastic volatility

This chapter is a version of paper co-authored with Mohamed Arouri and Frédéric Teulon published in Energy Economics.

1. Introduction

During the 2000s, world indices related to food prices and energy prices have shown simultaneous upward trends and volatilities. Figure 3.1, which represents the evolution over time of these two indices provided from the International Monetary Fund (IMF) database, illustrates this trend. This has led to think about shock and volatility transmission mechanisms between these two markets.

This topic has become a central issue for the global economy and has been widely discussed mainly since the financial crisis due to the significant rise in energy and food prices. Nevertheless, there is still less agreement about the causal factors of this shock and volatility transmission. It has been raised in the literature that volatility of agricultural commodities is no longer simply guided by rules of the fundamental factors related to supply and demand (Prakash and Gilbert, 2011). Different sources can explain this volatility which may be summed up in natural shocks related to climatic changes, stock levels, agricultural product demand and supply, growing links with energy and financial markets, and macroeconomic factors (exchange rates and interest rates).



Food_Index : Food Price Index, 2005 = 100, includes Cereal, Vegetable Oils, Meat, Seafood, Sugar, Bananas and Oranges Price Indices
Energy_Index : Fuel (Energy) Index, 2005 = 100, includes Crude oil, Natural Gas and Coal Price Indices

Figure 3. 1: Evolution of food and energy price indices

It is evident that understanding volatility transmission mechanisms is essential for both international investors and policy makers (Mensi et al., 2013). In fact, as commodity markets are increasingly viewed as alternative investment areas, existence and direction of spillovers must be carefully evaluated by investors. Investors need this type of information for the purpose of their portfolio risk management in order to develop their investment strategies for each market and to decide whether they can benefit from risk diversification. It is argued that food commodities are having as much interest in portfolio allocation as crude oil prices have (Gilbert, 2010).

Policy makers also require this information about volatility to settle on the appropriate policy namely by establishing the accurate pricing models and also to anticipate future actions and decisions (Deaton, 1999). Numerous studies have focused on commodity price stabilization policies that have to be carried out by governments. Most of these have dealt with agricultural prices (Wright, 2001). In their works, Gardner (1979) and Gouel (2013) have generalized the scope to deal with food prices. According to Gouel (2013), it is essential to identify the precise

economic motives for intervention and to design the policies accordingly given the pervasiveness of these policies and the potential cost of food price spikes for poor consumers. Many international organizations have investigated policy responses in order to manage food price volatility (Gilbert, 2012). Recommendations issued form these organizations[20] have been formulated in the 2011 G20 Summit on food security.

Special attention has been actually devoted to the source of food volatility related to the link between energy and financial markets. In a report from the Global Development and Environment Institute and the Institute for Agriculture and Trade Policy, Wise and Murphy (2012) have illustrated the paradigm shift between agriculture, energy and financial markets and mentioned that this paradigm is caused by the deepening integration of the three markets.

Recent empirical studies have analyzed the determinants of volatility in food commodity prices by resorting to different econometric methods and focusing on different data during various periods of time. These studies reveal a divergence between the findings obtained which makes this issue a topic of current discussions.

In fact, most of these studies highlight the significant volatility linkages between oil prices and most food commodity prices which are deepened through biofuel sector growth (among others: Akram, 2009; Baffes, 2007; Balcombe, 2011; Busse et al., 2011; Ciaian and Kancs, 2011a). These studies agree on the fact that oil price volatility translates into food price volatility through two key elements. The first one corresponds to transportation costs and fertilizer prices. The second element is related to biofuels and the expanding use of agricultural commodities as feedstocks for biofuel production. This agreement, taken alone, leads to think that transmission of oil price volatilities to crop prices may be more rapid.

The work of Baffes (2007) has been based on both food price indices and individual food price annual data for the 1960-2005 period analyzed through an ordinary least squares regression. Akram (2009) findings, obtained from structural VAR models, have been based on a larger sample covering the period 1990-2007 with data having a higher frequency (quarterly data) corresponding to real commodity prices. Balcombe (2011) analyzed monthly and annual prices during the period 1957-2009 covering various food commodities (wheat, maize, rice, soybean, rapeseed, palm, poultry, beef, pig meat, butter, cheese, cocoa, coffee, tea, sugar and cotton) through random parameters models with time varying volatility and a panel regression

[20] FAO, OECD, IFAD, IMF, UNCTAD, WFP, the World Bank, the WTO, IFPRI, and the UN HLT.

approach. A much larger sample has been used by Ciaian and Kancs (2011a) covering the period 1993-2010. This sample is composed of price series having a much higher frequency (weekly data) and corresponding to a wider variety of foods (corn, wheat, rice, sugar, soybeans, cotton, banana, sorghum and tea). The work of Ciaian and Kancs (2011a) has been characterized by the consideration of the structural breaks while studying price transmission between energy, bioenergy and food prices. For this purpose, Ciaian and Kancs (2011a) divided the sample into three periods (1993–1998, 1999–2004 and 2005–2010). The first one is characterized by the reduction in the OPEC spare capacity. The second period is related to the increase in bioenergy policy support in developed economies. The third one corresponds to the significant expansion of biofuel production. An analysis focusing on daily rapeseed future prices from 1999 to 2009 has been done by Busse et al. (2011) using the dynamic conditional correlation method.

Some other works indicate that volatility spillover from crude oil to food commodity prices is not always significant. For instance, we can cite the works of Du et al. (2011) and Nazlioglu et al. (2013). Du et al. (2011) findings indicate volatility spillover among crude oil, corn and wheat markets after the fall of 2006. Data considered by Du et al. (2011) correspond to futures prices weekly observed from 1998 to 2009. These data have been analyzed by applying stochastic volatility models and resorting to Bayesian econometric analysis for the estimation of the models' parameters. The same result has been shared by Nazlioglu et al., (2013) by extending the scope of agricultural commodities considered (wheat, corn, soybeans, and sugar) and raising their frequency to daily prices observed over a longer sample from 01 January 1986 to 21 March 2011. Nazlioglu et al. (2013) apply a different method which corresponds to the causality in variance test and impulse response functions. In order to identify the impact of food price crisis, Nazlioglu et al. (2013) divided the data into two sub-periods: the pre-crisis period (January 1986–31 December 2005) and the post-crisis period (01 January 2006–21 March 2011). Their findings mention that, with the exception of sugar, volatility spillover between oil and agricultural markets is absent in the pre-crisis period and is confirmed during the post-crisis period.

Nevertheless, some other studies reveal no volatility spillover effect between these two markets (among others: Kaltalioglu and Soytas, 2011 and Zhang et al., 2010).

The results of Zhang et al. (2010) indicate no direct long-run price relations between fuel and agricultural commodity prices and limited if any direct short-run relationships, except for sugar

which has an influence on increasing agricultural commodity prices through biofuel production affects. These results, obtained by means of cointegration estimation and a vector error correction model, are based on monthly price data of fuels (ethanol, gasoline and oil) and agricultural commodities (corn, rice, soybeans, sugar and wheat) for the period 1989–2008. Kaltalioglu and Soytas (2011) have extended the sample to include, in addition to agricultural commodities, other food commodities. Their sample is composed of price indices for the period from 1980 to 2008 observed monthly and covering fruits, vegetables, meat, poultry, fish, grocery food, and non-alcoholic beverages. For the purpose of volatility spillover investigation, they based their analysis on the Granger causality in variance approach developed by Cheung and Ng (1996).

Therefore, the literature review highlights Zilberman et al. (2013) statement which consists on the fact that the relationship between fuels and food commodity prices depends, among others, on commodities considered for each one of these two markets, the specification of the models used for this finality and the frequency of considered data.

Concerning volatility transmission between financial and food markets, most of the previous works have considered the S&P 500 index. We can list hereafter, as summary and not exhaustive review, some of the recent relevant work that has been done. Mensi et al. (2013) investigate the return links and volatility transmission between S&P 500 and commodity price indices for energy, food, gold and beverages over the period from 2000 to 2011 by resorting to a VAR-GARCH model. Their findings indicate a significant volatility transmission among commodity markets and the S&P 500. Creti et al. (2013) findings confirm this by means of the dynamic conditional correlation GARCH methodology applied to data observed during the period 2001–2011 covering, among other commodities, energy, agricultural, food, oleaginous, exotic and livestock commodities. Creti et al. (2013) also highlight the role played by the 2007–2008 financial crisis in emphasizing the links between commodities and stock market and the financialization of commodity markets.

The recent work of S. L. Chen et al. (2014) identifies two common factors which are responsible for changes in international commodity prices. This work is based on a factor analysis procedure (Panel Analysis of Nonstationarity in Idiosyncratic and Common Components) developed by Bai and Ng (2004) which is applied to a panel of 51 international commodity prices, including non-fuel commodity indices, food index, beverage index, and agricultural raw material index, from January 1980 to December 2009. The results provide strong evidence that

the most important common factor that drives the persistent movement of international commodity prices corresponds to the US nominal exchange rate. The second common factor shows stable fluctuations which may be consistent with stationarity and may be closely related to some economic conditions such as the excess demand for certain commodities. The works conducted by Roache (2010) and Gilbert (1989) emphasize that commodity prices can be influenced by exchange rates via international purchasing power and the effects on margins for producers with non-American dollar costs.

In this paper, we focus on volatility transmission between crude oil prices, MSCI index prices and a large panel of food commodity prices differing in terms of their production topology (crops, livestock products and plantation and forestry products). We explore also whether MSCI index and crude oil prices have a role in driving food prices. To the extent of our knowledge, we focus here for the first time on real prices of livestock products and MSCI stock index market. We resort in our analysis to a time varying parameter VAR (TVP-VAR) model with stochastic volatility which allows taking into account the economy structure evolution and the volatility of the shocks. Total and directional volatility spillovers are assessed based on a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering.

The remaining of this paper evolves as follows. Next section introduces the methodology adopted in this paper. The following one presents the characteristics of our data and a preliminary analysis of these data. The penultimate section discusses empirical findings related to total and directional volatility spillovers, impulse responses and portfolio diversification. The last one concludes and points to some directions for future research.

2. Methodology

Most of the methods used in the literature in order to analyze commodity price volatility are based on GARCH models which allow for rich insights into the volatility structure of time series and provide information about the conditional correlation between the changes of different price series in their multivariate versions. However, GARCH models do not offer a clear unified methodology to uncover volatility dynamics operating between the involved variables and to recognize structural changes. Multivariate GARCH models share the main

problem which consists on the difficulty, in many cases, to obtain convergence of the optimization algorithms used to estimate the parameters.

Since there are similarities between GARCH and VAR models, we generalize VAR models to allow for stochastic time-varying volatilities and extend impulse response functions to the analysis of shocks in volatility. Compared to previous works discussed above, this article provides a new look at the transmission of shocks between food, financial and energy markets and provides original findings on the impact of independent shock on volatility. This choice has been based on the studies of Primiceri (2005) and Koop et al. (2009) which mention that both the transmission mechanism and the variance of the exogenous shocks have changed over time. Koop and Korobilis (2009) also highlight that the issue of the appropriate modeling of the error covariance matrix in multivariate time series models has led to the incorporation of multivariate stochastic volatility in many empirical papers. Hence, understanding the macroeconomic policy issues should be based on multivariate models where both the VAR coefficients and the error covariance matrix can potentially change over time. This reflects both time variation of the simultaneous relations among the variables of the model and heteroskedasticity of the innovations.

More precisely, we build on the multivariate time-varying parameter vector autoregressive (TVP-VAR) model introduced recently by Primiceri (2005) and especially used in analyzing macroeconomic issues for the empirical research of price volatility behavior. The TVP-VAR model has an advantage over the constant parameter VAR models in the sense that it does not need to divide data into subsamples to confirm the change of the structure of the model (Nakajima et al., 2011). Thus, we avoid the risk of losing information based on the entire sample and having results which depend on the arbitrary choice of the sub-samples. In fact, instead of splitting the sample into several sub-samples, time variation in the parameters enables exact dating of the transition. Time-varying variances capture the change in the impact and nature of the shocks, enabling us to model the apparent decline in volatility.

The standard VAR model with constant parameters allows drawing impulse responses only for a set of two variables under the assumption that parameters do not change over the horizon of impulse responses. With the TVP-VAR model, an additional dimension corresponding to time can be added which permits to check responses at different points in time. As we will explain below, this major advantage of the TVP-VAR model family is very useful to investigate transmission of volatility shocks between different markets.

In order to be able to capture possible changes in underlying structure of the considered markets in a flexible and robust manner, we build on Omori et al. (2007) and extend the TVP-VAR model of Primiceri (2005) by incorporating stochastic volatility. Thus, our model allows reflecting both time variation of the simultaneous relations among the variables which can be due to variations in the structural dynamic interrelations among macroeconomic variables and heteroskedasticity of the innovations which can be due to changes in the size of exogenous shocks or their impact on macroeconomic variables (D'Agostino et al., 2013).

According to Primiceri (2005), Omori et al. (2007) and Nakajima (2011), the TVP-VAR model is constructed form the basic structural VAR model by allowing the parameters to change over time.

We consider a basic structural VAR model defined as:

$$Ay_t = F_1 y_{t-1} + \cdots + F_s y_{t-s} + u_t, \qquad t = s+1, \ldots, n \tag{1}$$

where:

$$\begin{cases} y_t \text{is } a\ k \times 1 \text{ vector of observed variables} \\ A, F_1, \ldots, F_s \text{ are } k \times k \text{ matrices of coefficients} \\ u_t \text{ is } a\ k \times 1 \text{ structural shock with } u_t \sim N(0, \sum\sum) \end{cases}$$

$$\sum = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix}$$

$$A = \begin{pmatrix} 1 & 0 & \ldots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \ldots & a_{k,k-1} & 1 \end{pmatrix}$$

The reduced form of this model can be written as follows:

$$y_t = B_1 y_{t-1} + \cdots + B_s y_{t-s} + A^{-1}\sum\varepsilon_t, \qquad \varepsilon_t \sim N(0, I_k) \tag{2}$$

where $B_i = A^{-1}F_i, \quad i = 1, \ldots, s$

This form can be written in this way:

$$y_t = X_t\beta + A^{-1}\sum\varepsilon_t \quad (3)$$

with:

$$\begin{cases}\beta \text{ is a } (k^2 s \times 1) \text{ vector obtained by stacking the elements in the rows of the } B_i's \\ X_t = I_s \otimes \left(y'_{t-1}, \dots, y'_{t-s}\right)\end{cases}$$

The expression of this model to the TVP-VAR model with stochastic volatility is given by:

$$y_t = X_t\beta_t + A_t^{-1}\sum_t \varepsilon_t \,,\ t = s+1, \dots, n \quad (4)$$

For simplicity, a number of assumptions are done for the specification of the TVP-VAR model[21]. First, the matrix A_t is assumed to be a lower-triangular matrix. Second, the parameters are supposed to follow a random walk process as follows:

$$\begin{cases}\beta_{t+1} = \beta_t + u_{\beta t} \\ a_{t+1} = a_t + u_{at} \\ h_{t+1} = h_t + u_{ht}\end{cases}$$

with:

$h_t = (h_{1t}, \dots, h_{kt})'$where $h_{kt} = log\sigma_{jt}^2 \,, j = 1, \dots, k, t = s+1, \dots, n$

$\beta_{s+1} \sim N\left(\mu_{\beta_0}, \sum_{\beta_0}\right)$

$a_{s+1} \sim N\left(\mu_{a_0}, \sum_{a_0}\right)$

$h_{s+1} \sim N\left(\mu_{h_0}, \sum_{h_0}\right)$

[21] For a discussion of these assumptions, please see Christiano et al. (1999).

The variance covariance matrix of the model's innovations is block diagonal.

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \sum_{\beta} & 0 & 0 \\ 0 & 0 & \sum_{a} & 0 \\ 0 & 0 & 0 & \sum_{h} \end{pmatrix}\right)$$

where $\sum_a$ and $\sum_h$ are assumed to be diagonal matrixes.

The assumption of random walk process allows for both temporary and permanent shifts in the coefficients. In this specification, possible non-linearity such as a gradual change or a structural break can be estimated.

TVP regression forms the state space model for which different estimation methods have been developed. In case of constant volatility, the standard Kalman filter for a Gaussian state space model is used. Implementation of this method in case of stochastic volatility is not easy since the model forms a non-linear state space model. As stated by Koop and Korobilis (2009), macroeconomists are facing the challenge of the choice of models which allow representing key data features and at the same time are not over-parameterized. It is argued that shrinkage enables to resolve the over-parameterization issue. Thereby, recourse to Bayesian methods use has increased since priors constitute a way of introducing this shrinkage. Therefore, Bayesian inference will be introduced as an alternative to overcome the over-parameterization problem.

In this paper, we resort to the Markov Chain Monte Carlo (MCMC) method which is appropriate for several reasons. The first reason corresponds to intractability of the likelihood function because the model includes the non-linear state equations of stochastic volatility. The second is the opportunity offered by this method to make inference for the state variables with the uncertainty of the unknown parameters. This method allows also estimating the function of the parameters such as an impulse response function with the uncertainty of the unknown parameters. As stated by Primiceri (2005) and Copy (2011), MCMC method delivers smoothed estimates of the parameters of interest based on the entire available set of data. These estimates are more efficient than the filtered estimates in case of interest in the evolution of the unobservable states over time, which is the case for the issues that we address in this paper.

We thereby start by setting in advance certain prior probability densities similarly to Primiceri (2005). For a discussion about the different methods for the settlement of priors, we refer to the

work by Koop and Korobilis (2009). Based on these priors, we assess through the MCMC algorithm the joint posterior distributions of the parameters of interest.

The MCMC algorithm involves the following steps:

1. Initialize β, a, h and w
2. Sample β from $p(\beta|a, h, \sum_{\beta}, \mathrm{y})$
3. Sample $\sum_{\beta}$ from $p(\sum_{\beta}|\beta)$
4. Sample a from $p(a|\beta, h, \sum_{a}, \mathrm{y})$
5. Sample $\sum_{a}$ from $p(\sum_{a}|\mathrm{a})$
6. Sample h from $p(h|\beta, a, \sum_{h}, \mathrm{y})$
7. Sample $\sum_{h}$ from $p(\sum_{h}|\mathrm{h})$
8. Go back to 2

In order to generate the VAR parameters β, we use the equations below :

$$\begin{cases} y_t = X_t\beta_t + A_t^{-1}\sum_t \varepsilon_t, t = s+1, \dots, n \\ \beta_{t+1} = \beta_t + u_{\beta t}, \qquad t = s, \dots, n-1 \\ \text{where} \beta_s = \mu_{\beta_0} \text{and } \mu_{\beta_s} \sim N(0, \sum_{\beta_0}) \end{cases}$$

Simulation smoother introduced by De Jong and Shephard (1995), Durbin and Koopman (2002) is employed to speed the convergence of the Markov chain.

To sample the covariance states a, we use the equations below to implement the simulation smoother :

$$\begin{cases} \hat{y}_t = \hat{X}_t a_t + \sum_t \varepsilon_t, & t = s+1, \dots, n \\ a_{t+1} = a_t + u_{at}, & t = s, \dots, n-1 \end{cases}$$

$$\text{where } a_s = \mu_{a_0},\ \mu_{a_s} \sim N\left(0, \sum_{a_0}\right)$$

$$\hat{y}_t = y_t - X_t \beta_t$$

and for $t = s+1, \dots, n$:

$$\hat{X}_t = \begin{pmatrix} 0 & \dots & & & & & & 0 \\ -\hat{y}_{1t} & 0 & 0 & \dots & & & & \vdots \\ 0 & -\hat{y}_{1t} & -\hat{y}_{2t} & 0 & \dots & & & \\ 0 & 0 & 0 & -\hat{y}_{1t} & \dots & & & \\ \vdots & & & & \ddots & 0 & \dots & 0 \\ 0 & \dots & & & 0 & -\hat{y}_{1t} & \dots & -\hat{y}_{k-1,t} \end{pmatrix}$$

In order to draw stochastic volatility states h, we make the inference for $\{h_{jt}\}_{t=s+1}^{n}$ separately for $j = 1, \dots, k$.

The *i*-th element of $A_t \hat{y}_t$ can be written as :

$$y_{it}^{*} = exp\left(\frac{h_{it}}{2}\right)\varepsilon_{it}, t = s+1, \dots, n$$

$$h_{i,t+1} = h_{it} + \eta_{it}, t = s, \dots, n-1$$

$$\begin{pmatrix} \varepsilon_{it} \\ \eta_{it} \end{pmatrix} \sim N\left(0, \begin{pmatrix} 1 & 0 \\ 0 & v_i^2 \end{pmatrix}\right)$$

where:

$\eta_{is} \sim N(0, v_{i0}^2)$, v_i^2 the *i*-th diagonal elements of $\sum_h$, v_{i0}^2 the *i*-th diagonal elements of $\sum_{h0}$ and η_{it} the *i*-th element of u_{ht}.

To sample $(h_{i,s+1}, \dots, h_{i,n})$, the multi-move sampler is used (Shephard and Pitt, 1997 and Watanabe and Omori, 2004).

3. Data and preliminary analysis

To study volatility shock transmission between food, energy and financial markets, we consider, based on Deaton (1999) and Baffes (2007) recommendation, series of individual commodity prices rather than price indices. Thus, we avoid the aggregation bias of commodity prices and the weighting rule to combine them into indices (Hadri et al., 2013).

All these prices are expressed in American dollar and cover a long period of more than three decades (1980–2012) on a monthly basis. Food and energy prices are obtained from the International Monetary Fund (IMF). Food commodities covered by these data are different in terms of production topology: crops (maize, barley and rapeseed oil), livestock products (lamb, beef and fish), and plantation and forestry products (banana, cocoa beans and ground nuts). This large panel of different types of commodities will give us the opportunity to check whether they constitute a homogeneous asset class in the matter of their links with energy and stock markets. For energy market, we consider in this paper crude oil. A brief description of the indicator price of these commodities is given in Appendix A. As for the financial market, we consider the MSCI world stock market index for the same period obtained from the Morgan Stanley Capital International (MSCI) company database.

Figure B.3.2 in Appendix B presents commodity prices and MSCI stock market index during our sample period. Similar to financial time series, commodity prices exhibit time varying volatility (volatility clustering) and fat tails as mentioned in the distribution of returns presented in figure B.3.1 in Appendix B.

A visual inspection of price evolutions suggests links between food, energy and stock markets. Especially, a strong increase in commodity prices emerged until the 2008 financial crisis. To better understand market dynamics that affect food commodities, their interrelationships, and their link to crude oil and MSCI index, an analysis of volatility is required.

We test, for the first time, the stationarity properties of our series using the augmented Dickey–Fuller (ADF) test where the alternative hypothesis is stationary. The ADF test reveals, as mentioned in table 3.1, non-stationarity in prices where the null hypothesis of the existence of a unit root cannot be rejected for any series. However, the return series show stationarity at 10% significance level, implying that they are integrated of order 1.

	Prices		Returns	
	p-value	**Test statistic**	**p-value**	**Test statistic**
Banana	0.160	-2.988	0.01	-11.139
Barley	0.441	-2.323	0.01	-6.804
Beef	0.986	-0.395	0.01	-7.999
CocoaBeans	0.519	-2.137	0.01	-7.095
Rapeseed Oil	0.069	-3.309	0.01	-6.829
Fish	0.625	-1.887	0.01	-6.379
Ground Nuts	0.120	-3.082	0.01	-7.590
Lamb	0.272	-2.723	0.01	-6.938
Maize	0.765	-1.554	0.01	-7.798
Crude Oil	0.788	-1.500	0.01	-8.486
MSCI	0.159	-2.990	0.01	-6.605

Table 3. 1: Augmented Dickey-Fuller Test

According to the AIC, FPE, HQ and SC criterion, the optimal lag number is p = 1. Residuals are found to be white noise when the lag length is set to 1. Diagnostic plots of VAR(1) are not produced in this paper for brevity. Thus, we estimate the VAR, structural vector autoregression (SVAR) and TVP-VAR models based on one lag length.

4. Empirical results

In this section, we consider each time a three-variable TVP-VAR model in order to assess volatility transmission between energy, financial and food markets and check if the magnitude of the impacts varies over time. Price returns are used to ensure stationary.

The estimation of the parameters of the TVP-VAR model requires that priors be fixed in advance. Taking account of our data, we assume the following priors:

$$\begin{cases} \sum_{\beta} \sim IW(80, 0.01I) \\ (\sum_{a})_{i}^{-2} \sim G(4, 0.02) \\ (\sum_{h})_{i}^{-2} \sim G(4, 0.02) \end{cases}$$

where $(\sum_{a})_{i}^{-2}$ and $(\sum_{h})_{i}^{-2}$ are the i-*th* diagonal elements in $\sum_{a}$ and $\sum_{h}$ respectively, and IW and G denote the inverse Wishart and Gamma distributions respectively.

Table 3.2 presents the estimation results computed using the MCMC algorithm (posterior means, standard deviations, 95% credible intervals, Geweke convergence diagnostics statistics

and inefficiency). Based on Geweke statistics, the null hypothesis of the convergence to the posterior distribution in the estimated result is not rejected for the parameters of the TVP-VAR model at the 5% significance level. In addition, the inefficiency factors are quite low and the 95% confidence intervals include the estimated posterior mean for each of the parameters estimated. Therefore, the results show that posterior draws are efficiently produced by the MCMC algorithm. Figure B.3.3 in Appendix B presents the estimation results of the TVP-VAR model with stochastic volatility.

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
$(\sum_{\beta})_1$	0.0045	0.0003	0.0039	0.0052	0.036	11.20
$(\sum_{\beta})_2$	0.0046	0.0003	0.0040	0.0053	0.607	11.88
$(\sum_{a})_1$	0.0498	0.0101	0.0334	0.0723	0.595	88.92
$(\sum_{a})_2$	0.0518	0.0103	0.0349	0.0753	0.372	52.11
$(\sum_{h})_1$	0.3963	0.0601	0.2940	0.5286	0.800	35.33
$(\sum_{h})_2$	0.4186	0.0825	0.2797	0.6044	0.240	70.45

(a) Estimates for the set (crude oil, maize, MSCI)

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
$(\sum_{\beta})_1$	0.0045	0.0003	0.0039	0.0052	0.032	5.85
$(\sum_{\beta})_2$	0.0045	0.0003	0.0039	0.0052	0.678	7.21
$(\sum_{a})_1$	0.0573	0.0130	0.0368	0.0863	0.406	84.96
$(\sum_{a})_2$	0.0515	0.0105	0.0347	0.0763	0.001	65.15
$(\sum_{h})_1$	0.3962	0.0571	0.2921	0.5195	0.141	36.60
$(\sum_{h})_2$	0.4545	0.0791	0.3135	0.6246	0.450	48.93

(b) Estimates for the set (crude oil, barley, MSCI)

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
$(\sum_{\beta})_1$	0.0045	0.0003	0.0039	0.0052	0.454	8.58
$(\sum_{\beta})_2$	0.0045	0.0003	0.0039	0.0052	0.871	7.92
$(\sum_{a})_1$	0.0526	0.0115	0.0345	0.0785	0.116	65.75
$(\sum_{a})_2$	0.0490	0.0100	0.0333	0.0730	0.979	53.06
$(\sum_{h})_1$	0.3905	0.0594	0.2827	0.5182	0.407	49.36
$(\sum_{h})_2$	0.3068	0.0584	0.2095	0.4373	0.000	69.22

(c) Estimates for the set (crude oil, cocoa beans, MSCI)

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
$(\sum_{\beta})_1$	0.0045	0.0003	0.0039	0.0052	0.339	6.36
$(\sum_{\beta})_2$	0.0045	0.0003	0.0039	0.0052	0.001	6.60
$(\sum_{a})_1$	0.0412	0.0071	0.0297	0.0573	0.389	52.80
$(\sum_{a})_2$	0.0482	0.0099	0.0327	0.0723	0.824	72.07
$(\sum_{h})_1$	0.3902	0.0548	0.2898	0.5091	0.061	27.98
$(\sum_{h})_2$	0.4210	0.0665	0.3020	0.5616	0.610	39.48

(d) Estimates for the set (crude oil, beef, MSCI)

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
$(\sum_{\beta})_1$	0.0045	0.0003	0.0039	0.0052	0.561	8.49
$(\sum_{\beta})_2$	0.0045	0.0003	0.0039	0.0052	0.000	12.56
$(\sum_{a})_1$	0.0441	0.0080	0.0304	0.0614	0.000	51.03
$(\sum_{a})_2$	0.0515	0.0115	0.0336	0.0783	0.001	52.07
$(\sum_{h})_1$	0.3892	0.0550	0.2881	0.5031	0.001	29.20
$(\sum_{h})_2$	0.5122	0.0847	0.3639	0.7040	0.740	45.58

(e) Estimates for the set (crude oil, fish, MSCI)

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
$(\sum_{\beta})_1$	0.0045	0.0003	0.0039	0.0052	0.992	11.52
$(\sum_{\beta})_2$	0.0045	0.0003	0.0039	0.0052	0.568	5.00
$(\sum_{a})_1$	0.0482	0.0097	0.0335	0.0714	0.924	48.79
$(\sum_{a})_2$	0.0497	0.0108	0.0338	0.0765	0.944	67.62
$(\sum_{h})_1$	0.4056	0.0581	0.2978	0.5278	0.974	27.61
$(\sum_{h})_2$	0.6282	0.0814	0.4771	0.7963	0.629	23.61

(f) Estimates for the set (crude oil, rapeseed oil, MSCI)

Parameter	Mean	Stdev	95%L	95%U	Geweke	Inef.
$(\sum_{\beta})_1$	0.0045	0.0003	0.0039	0.0052	0.535	6.67
$(\sum_{\beta})_2$	0.0045	0.0003	0.0039	0.0052	0.050	8.74
$(\sum_{a})_1$	0.0430	0.0075	0.0307	0.0598	0.522	54.53
$(\sum_{a})_2$	0.0514	0.0104	0.0347	0.0747	0.536	69.62
$(\sum_{h})_1$	0.3881	0.0577	0.2862	0.5136	0.750	42.87
$(\sum_{h})_2$	1.0828	0.1108	0.8801	1.3112	0.472	42.18

(g) Estimates for the set (crude oil, ground nuts, MSCI)

Table 3. 2: Estimation results of selected parameters in the TVP-VAR model

(**Mean :** posterior means, **Stdev :** standard deviations, **95%L :** 95% Lower credible interval limit, **95%U :** 95% Upper credible interval limit, **Geweke :**Geweke convergence diagnostics statistics, **Inef :** inefficiency)

As stated before, a TVP-VAR model will allow us to assess effects at different time periods. Hence, this will avoid us to estimate a model for each significant time period (Alom et al., 2011).

4.1. Stochastic volatility estimation

Figure 3.2 presents the dynamics of the estimated stochastic volatilities of commodity price return series over time $\sigma_{it}^2 = \exp(h_{it})$ based on the posterior mean and 95% credible intervals. This figure shows that volatility varies significantly in the time which reinforces the use of the TVP-VAR model with stochastic volatility to avoid biased estimation since posterior estimates

of stochastic volatilities are significant. This observation confirms the evidence introduced in the literature on the topic of this point.

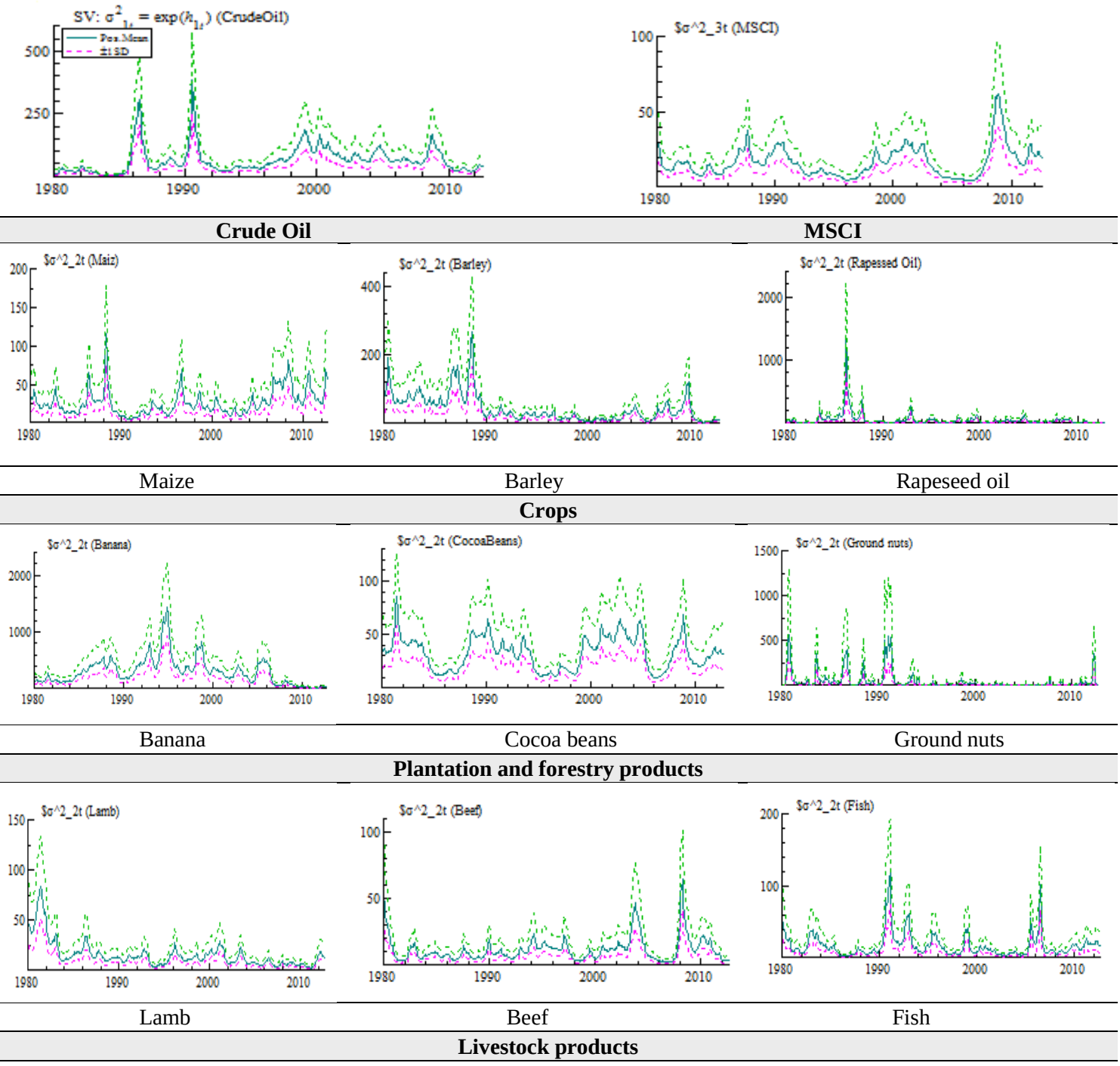


Figure 3. 2: Posterior estimates of stochastic volatility of structural shock

Three key important dates for stochastic volatilities of most of food series are observed (1980, 1990 and 2008) and cyclical ups and downs are detected. These observations are in line in particular with those of Stock and Watson (2002) who qualify the 1980 period as the Great Moderation period, Koop and Korobilis (2009), Ciaian and Kancs (2011a) and Creti et al., (2013). As stated by Creti et al. (2013), the relative increase in food volatility during the 2007–2008 financial crisis reveals the phenomenon of commodity market financialization.

We observe that stochastic volatility of most of food series has some sub-periods with similar evolutions as the MSCI and crude oil. In fact, often when high volatilities are observed for MSCI index and crude oil prices, volatilities in food commodity returns are observed, but with different magnitudes. This observation suggests that there is volatility transmission from MSCI and crude oil to food commodities. Our approach allows us to test for that.

Figure 3.2 also illustrates that agricultural products are more volatile than livestock products. This can be explained by the fact that production in agriculture takes time, so the supply cannot respond much to price changes in short term, unless stocks are available.

4.2. Impulse response estimation

Impulse responses for the TVP-VAR model are computed by fixing an initial shock size equal to the time-series average of stochastic volatility for each commodity over the whole sample period and then using the simultaneous relations at each point in time. Hence, time-varying volatility contributes to VAR estimation, identifying the structural shock with appropriate variance of the shock size.

Simultaneous relations of the structural shock are presented in figure B.3.4 in Appendix B. Posterior means and ± 1 standard deviation confidence intervals show that the simultaneous relations of the structural shock are not significantly time varying in all cases.

Figures from 1 to 9 in Appendix D show the impulse responses for food commodity price returns following a shock on crude oil price returns and MSCI stock index price returns obtained from the constant parameter VAR model, SVAR model and TVP-VAR model. Time varying responses to shocks for 3 month, 6 month and one year horizons are presented[22]. Horizontal

[22] The red, purple and green lines respectively in charts of posterior means correspond to these time horizons.

axes indicate the number of months after a shock and vertical axes represent the standardized responses to shocks for each variable. It is clear that there is significant variation of the impulse responses over time which supports applying the TVP-VAR model.

Results illustrated through these figures emphasize those of Deaton (1999) and Baffes (2007) regarding the adoption of individual commodity prices instead of indices. In fact, although there are some common features between the different food commodities, some differences issued from particularities of each food can be detected among them. This is in accordance with Creti et al. (2013) findings that agree on the fact that the different types of commodities cannot be aggregated in a homogeneous asset class (Creti et al., 2013).

General findings observed for all food commodities can be stressed. The first one corresponds to the immediate impact of a shock, either of crude oil returns or of MSCI index returns, on food returns and its low amplitude. This impact is a short-term one since it is absorbed within a period of six months. Our results support in part those of Nazlioglu et al. (2013) which show that the responses of a selection of agricultural commodity prices (wheat, corn, soybeans, and sugar) to oil price shocks are immediate and not permanent (they are absorbed in about a month). This lack of return persistence to a shock indicates a rapid market response mitigating a shock's effect. Such a response supports the theory indicating that decentralized perfectly competitive markets are efficient in responding to price signals (Zhang et al., 2010).

Mainly two important dates have been identified for most of food commodities during which the impact on food commodity returns of either crude oil or MSCI index return shocks is stressed. The first one is related to the great moderation period (the beginning of the 1980s). The second one corresponds to the financial crisis (2008 year) which highlights the phenomenon of food commodity financialization. Increases on the impact of crude oil shocks in most of food commodities in 2008 year are also explained by the significant expansion of biofuel production. These findings are in line with most of previous works, in particular those of Ciaian and Kancs (2011a).

For all food commodities, it is shown that the impacts of shocks can be biased if assessed through VAR model with constant parameters and constant volatility. The big 95% confidence intervals show that impulse responses obtained by applying constant VAR and SVAR models are not significant in all cases. Hence, the assumption of constant parameters over the horizon of the impulse responses induced by a constant VAR model biased the results. This observation

outlines the importance of considering a VAR model with time varying parameters and stochastic volatility.

The implementation of the TVP-VAR model with stochastic volatility has allowed identification of structural shocks with the appropriate variance of shocks' size. This is illustrated through the amplitude of the impacts which is more significant once evaluated based on the TVP-VAR model with stochastic volatility. Hence, recourse to the TVP-VAR model with stochastic volatility has allowed us to avoid misspecification of the dynamics of VAR model parameters.

4.3. Volatility spillover estimation

In order to assess volatility spillovers, we follow the approach adopted by Diebold and Yilmaz (2012) based on a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering. This approach is a revision of the previous version based on traditional orthogonalized impulse response function through Cholesky decomposition of variance-covariance matrix of error terms (Diebold and Yilmaz, 2009). It allows measuring both total and directional volatility spillovers (from/to a particular market).

We consider n-variable VAR(p) model defined by the following equation:

$$X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \epsilon_t , \qquad t = 1, \dots, T \tag{5}$$

where : X_t is a vector of dimension n

Φ_i $n \times n$ coefficient matrices

ϵ_t an $n \times 1$ i.i.d error vector with $E(\epsilon_t) = 0$ and $E(\epsilon_t \epsilon_t{}') = \Sigma$ where Σ is a positive definite variance-covariance matrix

The process defined by this equation is assumed to meet the condition that all the eigenvalues λ satisfying the equation below are $|\lambda| < 1$.

$$\left| I_n \lambda^p - \Phi_1 \lambda^{p-1} - \Phi_2 \lambda^{p-2} - \cdots - \Phi_{p-1} \lambda - \Phi_p \right| = 0$$

Under this condition, the process defined in equation (5) can be transformed into an infinite order moving average MA(∞) representation.

$$X_t = \sum_{i=0}^{\infty} \mathrm{A}_i \epsilon_{t-i} \tag{6}$$

with $\mathrm{A_i}$ $n \times n$ coefficient matrices $\mathrm{A_i} = \Phi_1 \mathrm{A_{i-1}} + \Phi_2 \mathrm{A_{i-2}} + \cdots + \Phi_p \mathrm{A_{i-p}}$

where: $\mathrm{A_0}$ is an $n \times n$ identity matrix and

$\mathrm{A_i} = 0$ for $\mathrm{i} < 0$

Based on the generalized impulse responses, the H-step ahead forecast error variance decomposition is given by:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e'_i A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} (e'_i A_h \Sigma A'_h e_i)} \tag{7}$$

where : σ_{jj} the standard deviation of the error term for the *j-th* equation

e_i is an $n \times 1$ selection vector which takes 1 for the *i-th* element and 0 otherwise

Each element of the variance decomposition matrix is normalized by the row sum as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{n} \theta_{ij}^{g}(H)}$$

where $\sum_{j=1}^{n} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^{g}(H) = n$

The total volatility spillover index is given by:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{n} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^{g}(H)} \times 100 \tag{8}$$

Directional volatility spillovers received by market i from all other markets j are given by:

$$S_{i\cdot}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{n} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^{g}(H)} \times 100 \quad (9)$$

Directional volatility spillovers transmitted by market i to other markets j are measured by:

$$S_{\cdot i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{n} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ji}^{g}(H)} \times 100 \quad (10)$$

Net volatility spillovers from market i to all other markets j allow to have an information about the contribution of each market to the volatility in other markets and are defined by:

$$S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H) \quad (11)$$

Net pairwise volatility spillovers are defined as:

$$S_{ij}^{g}(H) = \frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{n} \times 100 \quad (12)$$

4.3.1. The full-sample volatility spillovers

Table 3.3 presents volatility spillover tables in a static environment based on single fixed parameters.

	MSCI	Maize	Crude Oil	Directional form others
MSCI	99.41%	0.014%	0.57%	0.58%
Maize	1.85%	97.47%	0.67%	2.52%
Crude oil	2.00%	0.13%	97.87%	2,13%
Directional to others	3.85%	0.14%	1.24%	
Directional including own	103.26%	97.61%	99.11%	Total spillover index 1.74%

	MSCI	Barley	Crude Oil	Directional form others
MSCI	99.22%	0.29%	0.49%	0.78%
Barley	3.23%	95.91%	0.87%	4.10%
Crude oil	1.92%	1.74%	96.34%	3.66%
Directional to others	5.15%	2.03%	1.36%	
Directional including own	104.37%	97.94%	97.7%	Total spillover index 2.85%

	MSCI	Rapeseed Oil	Crude oil	Directional form others
MSCI	99.40%	0.03%	0.56%	0.59%
Rapeseed oil	0.89%	99.08%	0.03%	0.92%
Crude oil	2.04%	0.83%	97.13%	2.87%
Directional to others	2.93%	0.86%	0.59%	
Directional including own	102.33%	99.94%	97.72%	Total spillover index 1.46%

	MSCI	Banana	Crude oil	Directional form others
MSCI	99.37%	0.08%	0.56%	0.64%
Banana	0.80%	99.19%	0.01%	0.81%
Crude oil	2.03%	0.57%	97.40%	2.6%
Directional to others	2.83%	0.65%	0.57%	
Directional including own	102.2%	99.84%	97.97%	Total spillover index 1.35%

	MSCI	Cocoa Beans	Crude Oil	Directional form others
MSCI	99.22%	0.28%	0.50%	0.78%
Cocoa beans	0.23%	99.72%	0.05%	0.28%
Crude oil	2.07%	1.45%	96.48%	3.52%
Directional to others	2.30%	1.73%	0.55%	
Directional including own	101.52%	101.45%	97.03%	Total spillover index 1.53%

	MSCI	Ground nuts	Crude oil	Directional form others
MSCI	98.84%	0.76%	0.4%	1.16%
Ground nuts	1.00%	98.94%	0.06%	1.06%
Crude oil	2.17%	2.70%	95.13%	4.87%
Directional to others	3.17%	3.46%	0.46%	
Directional including own	102.01%	102.4%	95.59%	Total spillover index 2.36%

	MSCI	Lamb	Crude oil	Directional form others
MSCI	99.39%	0.02%	0.59%	0.61%
Lamb	1.09%	97.47%	1.44%	2.53%
Crude oil	2.02%	0.68%	97.30%	2.70%
Directional to others	3.11%	0.70%	2.03%	
Directional including own	102.5%	98.17%	99.33%	Total spillover index 1.95%

	MSCI	Beef	Crude oil	Directional form others
MSCI	99.40%	0.05%	0.55%	0.60%
Beef	1.96%	97.66%	0.38%	2.34%
Crude oil	2.01%	1.40%	96.59%	3.41%
Directional to others	3.97%	1.45%	0.93%	
Directional including own	103.37%	99.11%	97.52%	Total spillover index 2.12%

	MSCI	Fish	Crude oil	Directional form others
MSCI	99.21%	0.24%	0.54%	0.78%
Fish	3.23%	96.60%	0.17%	3.4%
Crude oil	1.97%	0.28%	97.74%	2.25%
Directional to others	5.20%	0.52%	0.71%	
Directional including own	104.41%	97.12%	98.45%	Total spillover index 2.14%

Table 3. 3: Full sample volatility spillover tables

For each table, the *ij*th entry represents the estimated contribution to the forecast error variance of market *i* coming from innovations to market *j*. It is clear from this table that both total and

directional volatility spillovers are low. Directional to others rows of the volatility spillover table show that gross directional volatility spillovers are comparable. Directional from others columns of the volatility spillover table show that gross directional volatility spillovers from other markets are not very different. Directional volatility spillovers from crude oil to foods range between 0.01% (for banana) and 1.44% (for lamb). Those from MSCI to foods are between 0.23% (for cocoa beans) and 3.23% (for barley and fish). Total volatility spillover, which is a distillation of the various directional volatility spillovers into a single index, indicates that, on average, a percentage comprised between 1.35% and 2.85% of the volatility forecast error variance in all three markets comes from spillovers.

Our results confirm findings in the literature stating that oil prices have been mentioned as an additional shock to food price via supply and demand channels (Thompson et al., 2009). In fact, an increase in oil prices results in an increase in input costs (like fertilizers, irrigation, and transportation) and an increase in demand for grains as biofuels having as a consequence an increase in food commodity prices.

4.3.2. The rolling-sample volatility spillovers

4.3.2.1. Total volatility spillovers

As mentioned above, results found through assessing only one single index for the full sample period indicate low total and directional spillovers. However, application of this approach to markets which are volatile over time probably can lead to not considering potentially important cyclical movements in spillovers.

We propose then to assess dynamic volatility spillovers over different time intervals through applying a rolling window approach. To do this, we estimate volatility spillovers using 72-month rolling samples. In order to check for the robustness of our results regarding the choice of this window length, we have considered different window lengths (60 and 84 months) and results were qualitatively similar to those obtained with a 72-month window length.

Our results for the total (non-directional) volatility spillover index over time presented in figure C.3.1 in Appendix C allow measuring the contribution of spillovers of volatility shocks across the three types of asset classes to the total forecast error variance.

This figure and table 3.4 show that total volatility spillovers range roughly between 1% and 30% for most of the sets considered composed each time of 3 types of assets (oil, food and

MSCI stock). Average values are comparable for the different sets and are approximately between 5% and 10%. Even though there are significant volatility spillover fluctuations in all the sets during the sample period, they were quite limited until mid-2008. Nearly all the sets exhibit the same episodes of either important increases or decreases of the total volatility spillover index. Several cycles can be identified namely in 1980 and 1990 and the most important one corresponds to the financial crisis period (2007–2009). Indeed, the most important jumps in total volatility spillovers have been recorded in 01/10/2008 after the failure of Lehman Brothers as it is shown in table 3.5. It is also clear from figure C.3.1 that total volatility spillovers become more and more important with the intensification of the crisis. The general observation that we can conclude from this is that total volatility spillovers generally increase during times of crisis.

	MSCI Maize Crude oil	MSCI Barley Crude oil	MSCI Rapeseed oil Crude oil	MSCI Banana Crude oil	MSCI Cocoa Beans Crude oil	MSCI Ground Nuts Crude oil	MSCI Lamb Crude oil	MSCI Beef Crude oil	MSCI Fish Crude oil
Mean	8.09%	7.90%	7.93%	5.85%	7.92%	9.76%	8.74%	6.91%	8.22%
Minimum	1.79%	1,75%	1.04%	1.04%	1.25%	2.18%	1.94%	1.43%	1.98%
Maximum	27.3%	27.49%	26.92%	15.88%	23.91%	29.61%	27.63%	21.83%	21.38%
Std. Dev.	6.24%	6.46%	6.33%	3.26%	5.17%	7.43%	6.22%	4.78%	4.69%

Table 3. 4: Descriptive statistics of the 72-month rolling sample total volatility spillover indices for each set composed of 3 assets during the total sample span

	MSCI Maize Crude oil	MSCI Barley Crude oil	MSCI Rapeseed oil Crude oil	MSCI Banana Crude oil	MSCI Cocoa Beans Crude oil	MSCI Ground nuts Crude oil	MSCI Lamb Crude oil	MSCI Beef Crude oil	MSCI Fish Crude oil
01/09/2008	4.82%	3.39%	5.98%	3.28%	6.61%	10.12%	4.19%	3.20%	5.51%
01/10/2008	25.37%	22.08%	19.95%	12.84%	14.33%	25.86%	13.45%	13.06%	15.99%

Table 3. 5: Jumps of the 72-month rolling sample total volatility spillover indices for each set composed of 3 assets during the period 01/09/2008-01/10/2008

Thus, our results confirm the fact that it is unlikely that total volatility spillovers presented in table 3.3 hold for the whole sample period during which the global economy has witnessed some major changes. Dynamic volatility spillovers found through applying the rolling window approach are then more meaningful since they allow taking into account evolution of these spillovers over time.

4.3.2.2. Directional volatility spillovers

In order to take into account directional information, we estimate directional volatility spillovers from other and directional spillovers to other indices by applying the rolling window approach with the same length of window (72 months).

Directional volatility spillovers to each one of the assets coming from other assets are presented in figure C.3.2 in Appendix C. These spillovers vary obviously over time. Directional volatility spillovers to foods and oil markets are sharply increasing in turbulent times.

Figure C.3.3 in Appendix C shows the directional volatility spillovers from each one of the assets (corresponding to energy, food and stocks markets) to others. These spillovers vary greatly over time. It is clear that, since mid-2008, volatility spillovers from MSCI stock markets have become more important than those from food and energy markets.

4.3.2.3. Net volatility spillovers

To check the difference between gross volatility shocks transmitted to and those transmitted from all other markets, we compute net volatility spillovers which are presented in figure C.3.4 in Appendix C. It is clear from this figure that net volatility spillover patterns after mid-2008 differ from the previous periods. For all the sets, and in almost all periods of time, MSCI is a net transmitter of volatility shocks namely after mid-2008 while crude oil and foods are net receivers of volatility spillovers. Ground nuts appear to be the strongest volatility receiver among all food commodities. Null values of net volatility spillovers indicate equal spillover effects from/to both assets.

4.3.2.4. Net pairwise volatility spillovers

In order to consider the difference between volatility shocks transmitted from market *i* to market *j* and those transmitted from market *j* to *i*, we estimate the net pairwise volatility spillovers between these two markets. Results are presented in figure C.3.5 in Appendix C. During most of our sample span, namely after mid-2008, net pairwise volatility spillovers from MSCI stock to foods are positive and those from crude oil to foods are negative. This observation reinforces again the previous finding that MSCI is a net transmitter of volatility shocks while crude oil is a net receiver of volatility shocks.

Net pairwise volatility spillovers show that volatilities from MSCI stock market reach their highest values after mid-2008 and are transmitted during this period with similar ranges to each

type of food with most important volatilities transmitted to maize for crops, to ground nuts for plantation and forestry products and to lamb for livestock products. After mid-2008, crude oil is receiving volatility shocks from crops more than from other types of foods.

4.4. Implications for portfolio diversification

Based on the fact that benefits of diversification are most appreciated when risk market rises and investors tend to choose commodities as refuge instruments, we propose in this part to study the implications of food commodities' sensitivity to oil and MSCI shocks on decisions taken by investors regarding the risk management of their portfolios. We consider two hedged portfolios. The first one is a hedged portfolio of crude oil and food commodities. The second one is a hedged portfolio of MSCI and food commodities.

To determine the optimal weights of the portfolios and hedging ratios, we use the results issued from our TVP-VAR model on the subject of the variance-covariance matrix. We base our work on Kroner and Ng (1998) regarding the optimal weight of holding food commodities in a portfolio constructed of either crude oil or MSCI at time *t*.

In their work, El Hedi Arouri et al. (2011) adopt the same approach in order to analyze the optimal weights and hedge ratios for oil-stock portfolio holdings.

We consider the following equation for the optimal weight of a portfolio composed of food and crude oil.

$$w_t^{Oil,Food} = \frac{h_t^{Oil} - h_t^{Oil,Food}}{h_t^{Food} - 2h_t^{Oil,Food} + h_t^{Oil}} \quad (13)$$

on condition:

$$w_t^{Oil,Food} = \begin{cases} 0 \; if \; w_t^{Oil,Food} < 0 \\ w_t^{Oil,Food} \; if \; 0 \leq w_t^{Oil,Food} \leq 1 \\ 1 \; if \; w_t^{Oil,Food} > 1 \end{cases}$$

where:

$$\begin{cases} h_t^{Oil} : \text{conditional volatilityof crude oil at time } t \\ h_t^{Food} : \text{conditional volatility of food at time } t \\ h_t^{Oil,Food} : \text{conditional covariance between crude oil and food at time } t \end{cases}$$

The weight of food commodities in a portfolio constituted of food commodities and crude oil is equal to $1 - w_t^{Oil,Food}$.

The risk minimizing the hedge ratios for the portfolio composed of crude oil and food commodities, following Kroner and Sultan (1993) work, is considered as:

$$\beta_t^{Oil,Food} = \frac{h_t^{Oil,Food}}{h_t^{Food}} \quad (14)$$

The same thing is applied for the portfolio composed of food and MSCI stock assets.

$$w_t^{MSCI,Food} = \frac{h_t^{MSCI} - h_t^{MSCI,Food}}{h_t^{Food} - 2h_t^{MSCI,Food} + h_t^{MSCI}} \quad (15)$$

$$\beta_t^{MSCI,Food} = \frac{h_t^{MSCI,Food}}{h_t^{Food}} \quad (16)$$

Figures from 1 to 9 in Appendix E show the time-varying optimal hedge ratios. These hedge ratios are not stable and have large fluctuations, requiring the hedgers to frequently adjust their futures positions. In table 3.6, we summarize average values obtained regarding optimal portfolio weights and hedge ratios along time.

		$w_t^{Oil,Food}$	$\beta_t^{Oil,Food}$	$w_t^{MSCI,Food}$	$\beta_t^{MSCI,Food}$
Crops	Maize	0.628	- 0.045	0.430	0.013
	Barley	0.560	0.103	0.297	0.085
	Rapeseed oil	0.512	0.032	0.347	0.014
Plantation and forestry products	Banana	0.176	- 0.032	0.087	- 0.010
	Cocoa beans	0.600	0.169	0.356	- 0.002
	Ground nuts	0.632	0.058	0.476	0.015
Livestock products	Lamb	0.693	0.243	0.538	0.136
	Beef	0.711	0.159	0.594	0.039
	Fish	0.679	0.193	0.516	0.139

Table 3. 6: Optimal portfolios weights and hedge ratios

As shown in table 3.6, hedge ratios are typically low, suggesting that hedging effectiveness involving food and crude oil or food and stocks is quite good. They underline the fact that oil and stock assets should be an integral part of a diversified portfolio of food. Thus, inclusion of crude oil or stocks in a diversified portfolio of food commodities increases the risk-adjusted performance of the resulting portfolio.

In a 1$ portfolio of crude oil and food, optimal weights range from 17.6% (banana) to 71.1% (beef). It means that for a 1$ portfolio of crude oil and banana, 17.6 cents should be invested in crude oil and the remainder (82.4 cents) should be invested in banana. However in a 1$ portfolio of crude oil and beef, the majority of investment has to be done in crude oil (71.1 cents). Table 3.6 shows also that the optimal portfolio weights for a portfolio composed of crude oil and food are comparable for each type of food, except for the plantation and forestry products where investment in banana is much more important than that in cocoa beans and ground nuts.

In a 1$ portfolio of stocks and food, optimal weights are comprised between 8.7% (banana) and 59.4% (beef). It is also notable, when comparing optimum weights of the two portfolios that investors have to invest more in crude oil than in stocks. We notice also a similarity of the estimates of optimal portfolio weights into each category of food, except for banana.

Hedge ratios are negative for portfolios composed of crude oil and maize, crude oil and banana, stocks and banana, and stocks and cocoa beans. This reflects the fact that spot and futures prices may move in opposite directions in short run (Tong, 1996). It requires the hedger to go long in futures market to hedge the long spot position.

In order to check the effectiveness of portfolio diversification, we study the realized hedging errors determined by Ku et al. (2007):

$$HE = \left(\frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \right) \quad (17)$$

where:

$$\begin{cases} Var_{hedged}: \text{variance of the returns on the oil} - \text{food} \\ \qquad\qquad \text{or MSCI} - \text{food portfolios} \\ Var_{unhedged}: \text{variance of the returns on the oil} \\ \qquad\qquad \text{or MSCI portfolios} \end{cases}$$

We use, for the allocation of each portfolio, the optimum weights previously determined.

Table 3.7 summarizes results obtained for hedge effectiveness.

		Oil-food portfolio		**MSCI-food portfolio**	
		Variance (%)	**HE (%)**	**Variance (%)**	**HE (%)**
Crops	Maize	0.345	0.560	0.345	- 0.747
	Barley	0.532	0.322	0.532	- 1.694
	Rapeseed oil	0.740	0.057	0.740	-2.748
Plantation and forestry products	Banana	3.28	- 3.181	3.28	- 15.611
	Cocoa beans	0.372	0.526	0.372	- 0.884
	Ground nuts	0.652	0.169	0.652	- 2.302
Livestock products	Lamb	0.184	0.765	0.184	0.068
	Beef	0.143	0.818	0.143	0.276
	Fish	0.228	0.709	0.228	- 0.155

Table 3. 7: Hedge effectiveness

A higher HE ratio indicates greater hedging effectiveness in terms of the portfolio's variance reduction, which thus implies that the associated investment method can be deemed as a better hedging strategy.

The highest hedge effectiveness ratio obtained for a portfolio composed of (crude oil, crops) is reached with the introduction of maize (56%). Thus, we can say that maize provides the most useful risk management tool for hedging and for portfolio diversification among the crops considered in this paper. Hedge effectiveness for portfolios composed of (crude oil, livestock products) are comparable and high (from 70.9% to 81.8%). This indicates that introduction of livestock products into a portfolio of crude oil allows the significant improvement of its risk return characteristics. Negative estimated hedge effectiveness has been found for the (crude oil, banana) portfolio and for almost all the (MSCI, food) portfolios. This may be because of higher futures return variance.

5. Conclusion

This paper highlights that time-varying volatility contributes to VAR estimation since it allows identifying the structural shock with the appropriate variance of the shock size. Therefore, the adoption of a TVP-VAR model where sources of time variation are both the coefficients and the variance covariance matrix of the innovations has allowed us to avoid biased estimation of the parameters. A general finding from this paper points to the fact that, although there are some common features between the different food commodities, some differences issued from particularities of each food can be detected among them.

The findings identify the presence of low volatility spillovers from crude oil or MSCI returns to most of food returns. Hence, policy makers and investors can forecast food prices and their volatilities through the information about crude oil or MSCI index. In terms of shocks' transmission from crude oil or MSCI to food commodities, impulse responses show that the impact of these shocks is immediate and a short one since it is absorbed within a six month period. This indicates a rapid market response mitigating a shock's effect. Results highlight also the key role played by the 2007–2008 financial crisis in emphasizing shocks' transmission from crude oil or stock markets to foods. The most important jumps in total volatility spillovers have been recorded in 01/10/2008 and total volatility spillovers become more and more important with the intensification of the crisis. Before this date, volatility spillovers were quite limited. In

terms of net volatility spillovers, patterns became different after mid-2008 from the previous periods. For all the sets, and in almost all periods of time, MSCI is a net transmitter of volatility shocks while crude oil and foods are net receivers. Volatility spillovers from MSCI stock market reach their highest values after mid-2008 and are transmitted during this period with similar ranges to each type of food. After mid-2008, crude oil is receiving volatility shocks from crops more than from other types of foods.

Certainly understanding these shock transmission and volatility spillovers among different markets provides investors with useful information which can be considered in their decisions related to optimal portfolio allocation.

Regarding portfolio diversification, hedge ratios are found to be not stable and have large fluctuations, requiring the hedgers to frequently adjust their futures positions. Mean values indicate typically low hedge ratios, suggesting that hedging effectiveness involving food and crude oil or food and stocks is quite good. Thus, inclusion of crude oil or stocks in a diversified portfolio of food commodities increases the risk-adjusted performance of the resulting portfolio.

Construction of dynamic volatility spillovers by using as input the variance covariance matrix issued from a TVP-VAR model could constitute potential avenues for further research. An extension to this work could also be through the adoption of large TVP-VAR models or TVP-FAVAR (factor augmented VAR) models. To put forward on this work, a study of price transmission between different food commodities and cross countries can be achieved. The present work can also be extended in order to discuss about the different drivers of food commodity prices which can be summarized on market-specific factors, broad macroeconomic determinants, speculative components, and weather variables and in order to quantify their impact.

Appendix A

Commodities list:

- Bananas, Central American and Ecuador, FOB U.S. Ports, US$ per metric ton,
- Barley, Canadian no.1 Western Barley, spot price, US$ per metric ton,
- Beef, Australian and New Zealand 85% lean fores, CIF U.S. import price, US cents per pound,
- Cocoa beans, International Cocoa Organization cash price, CIF US and European ports, US$ per metric ton,
- Rapeseed oil, crude, fob Rotterdam, US$ per metric ton,
- Fishmeal, Peru Fish meal/pellets 65% protein, CIF, US$ per metric ton,
- Groundnuts (peanuts), 40/50 (40 to 50 count per ounce), cif Argentina, US$ per metric ton,
- Lamb, frozen carcass Smithfield London, US cents per pound,
- Maize (corn), U.S. No.2 Yellow, FOB Gulf of Mexico, U.S. price, US$ per metric ton,
- Crude Oil (petroleum), Price index, 2005 = 100, simple average of three spot prices.

Appendix B

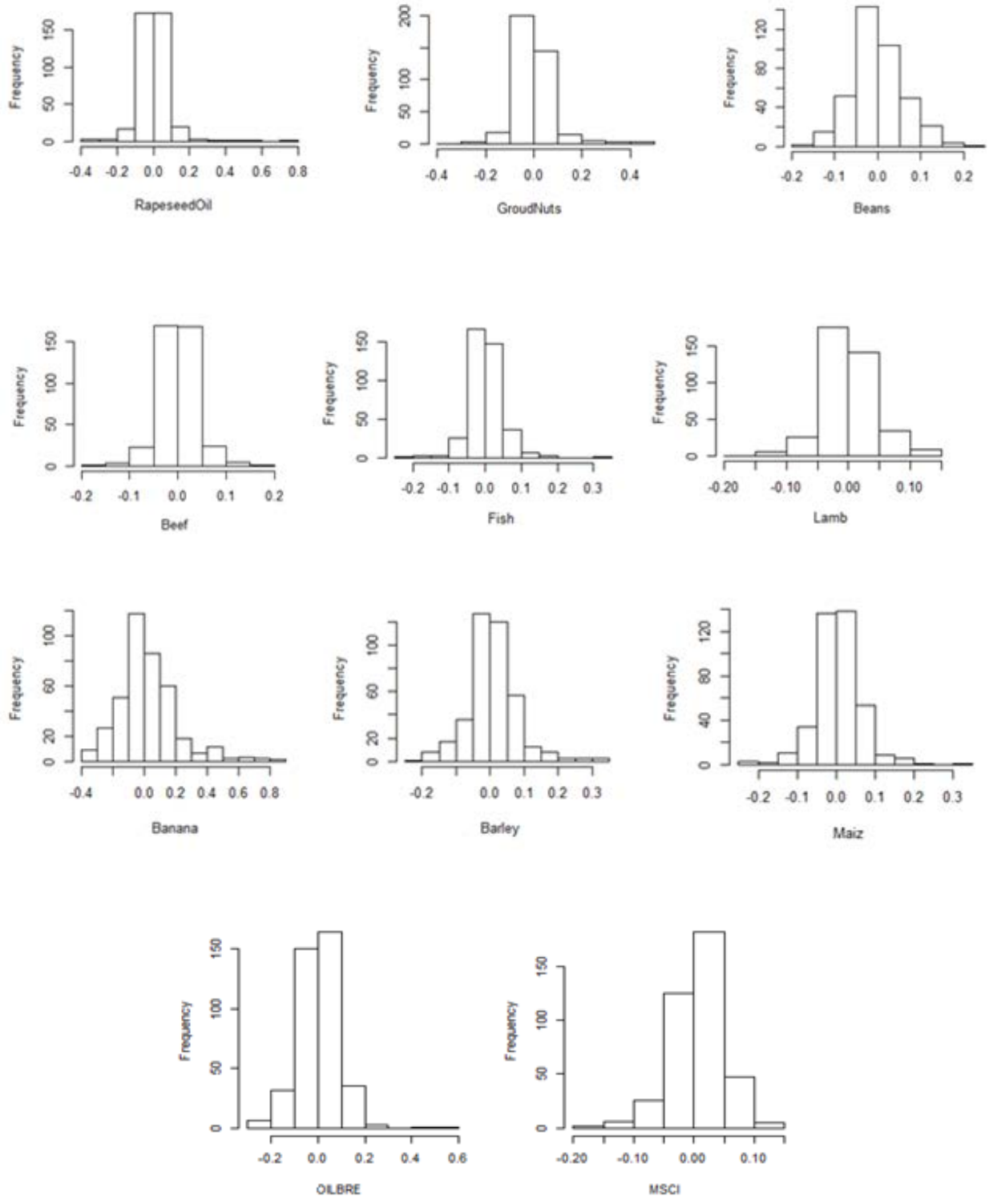


Figure B.3. 1: Histogram of return series

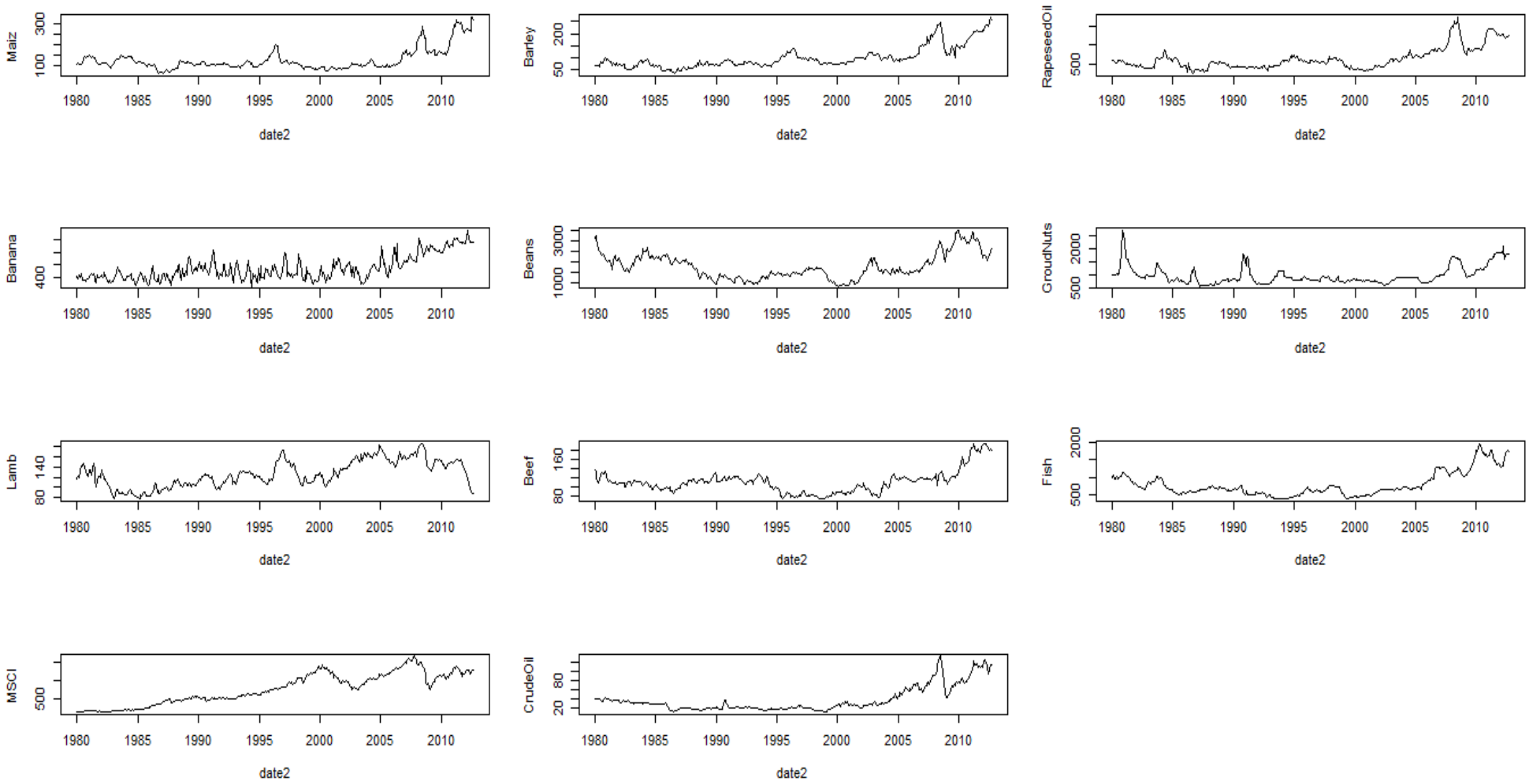


Figure B.3. 2: Food commodities, energy commodities and MSCI index prices for the period 1980-2012

(Source: IMF and MSCI Company)

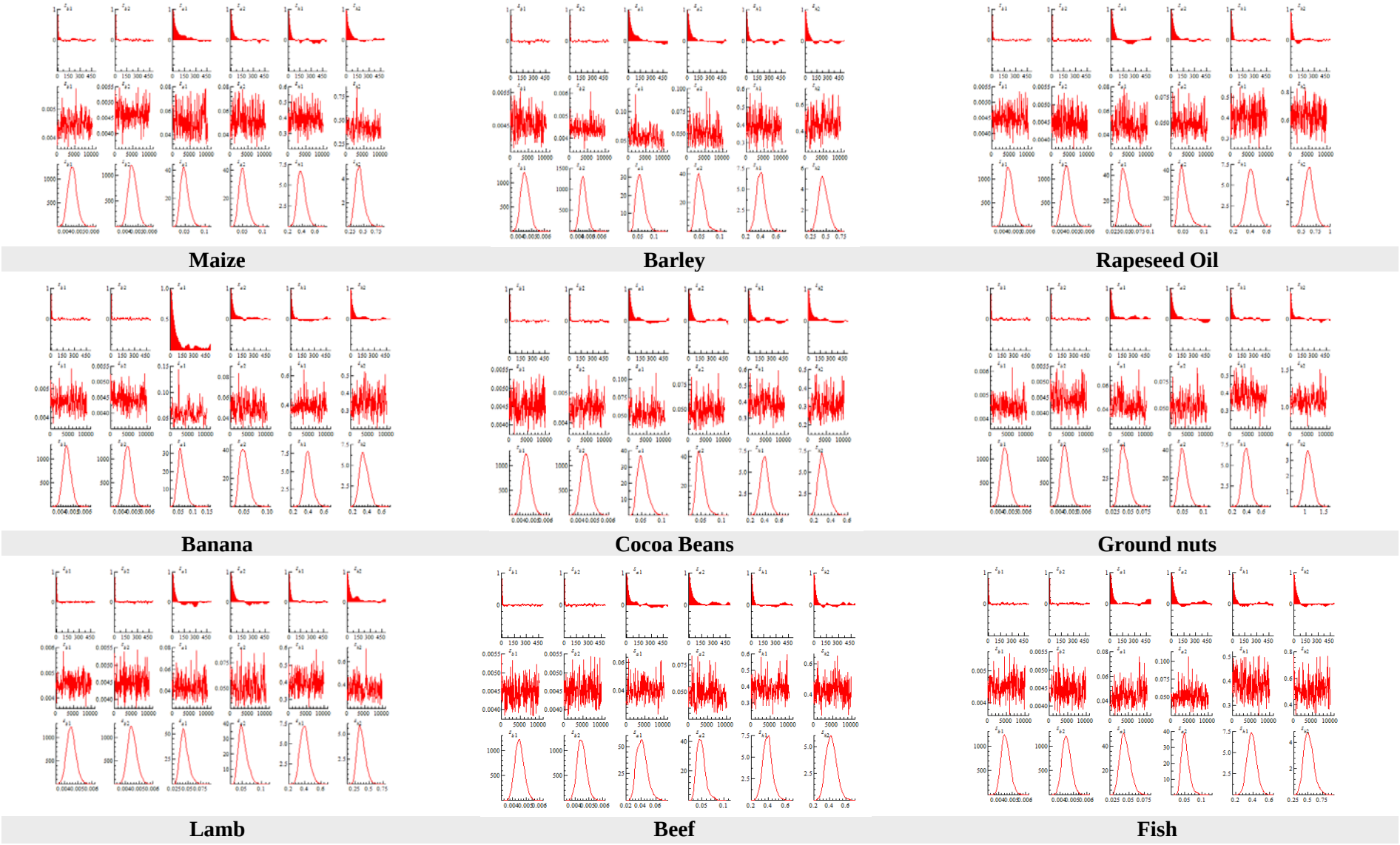
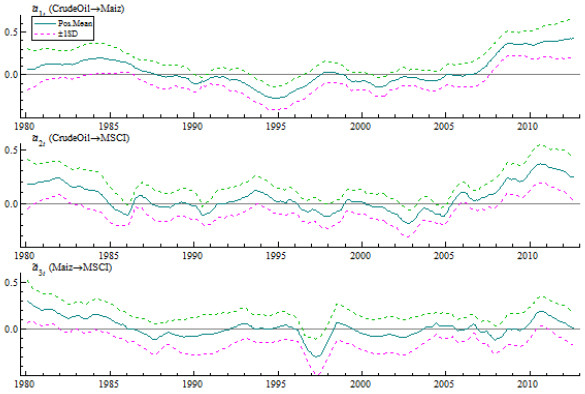
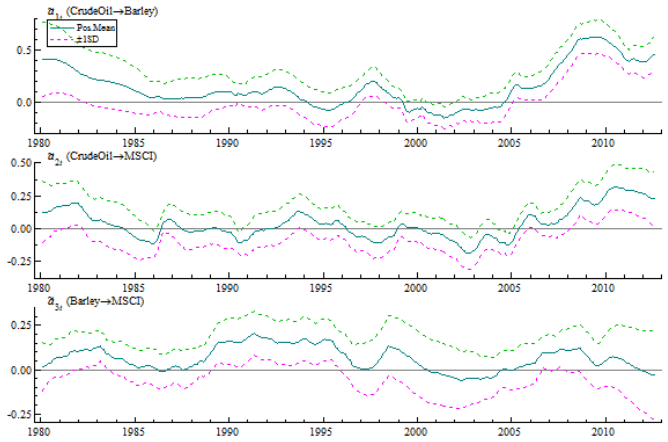


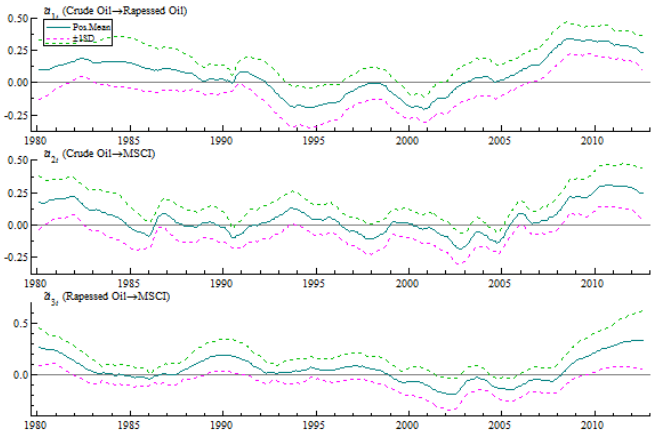
Figure B.3. 3: MCMC estimation results (sample autocorrelations, sample paths and posterior densities)



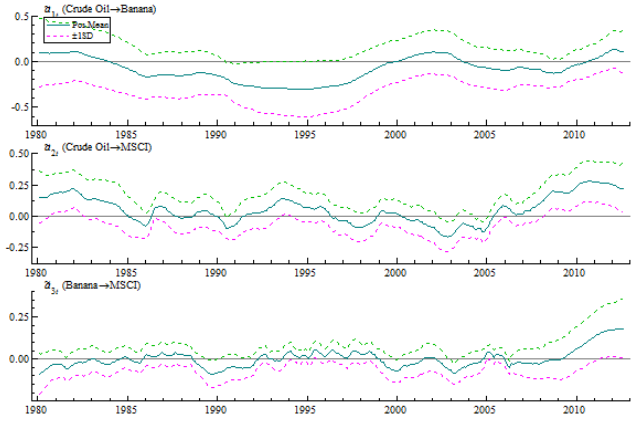
Crude oil, Maize, MSCI



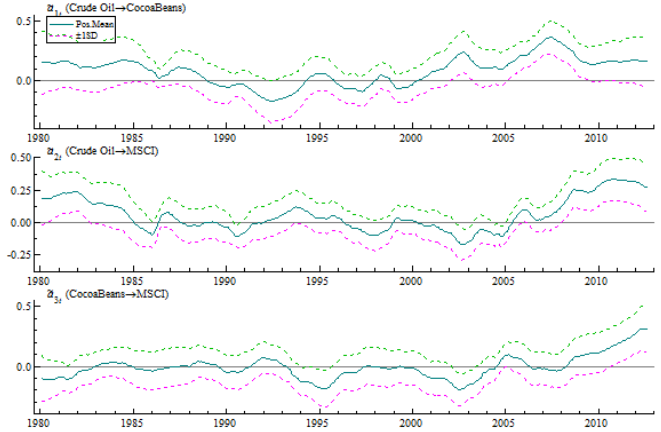
Crude oil, Barley, MSCI



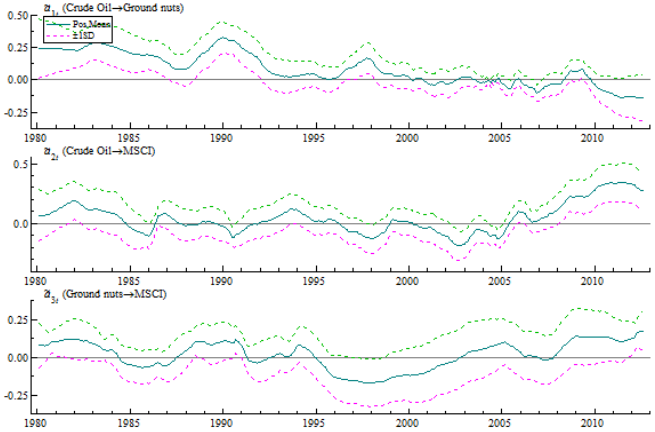
Crude oil, Rapeseed Oil, MSCI



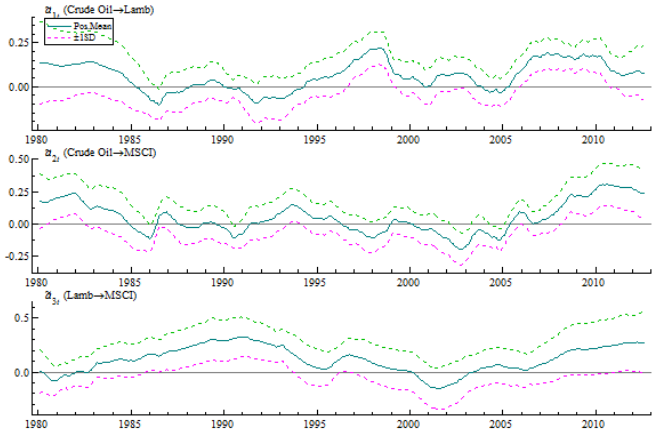
Crude oil, Banana, MSCI



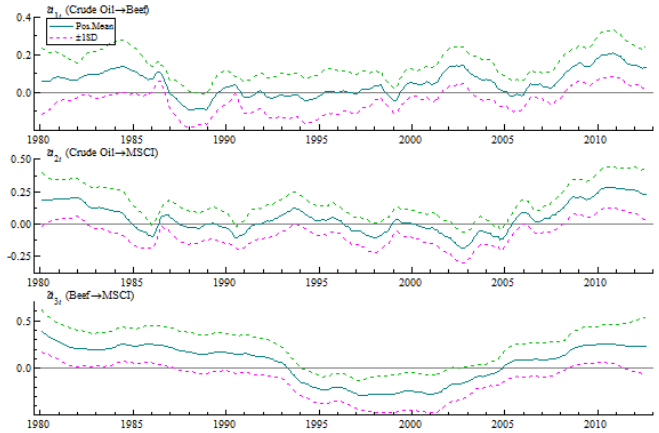
Crude oil, Cocoa Beans, MSCI



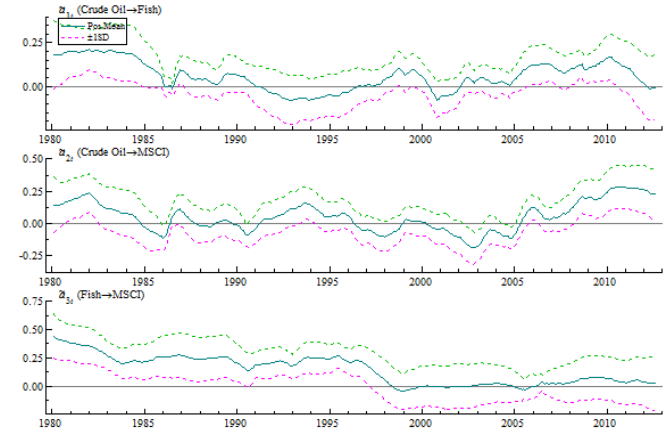
Crude oil, Ground nuts, MSCI



Crude oil, Lamb, MSCI



Crude oil, Beef, MSCI



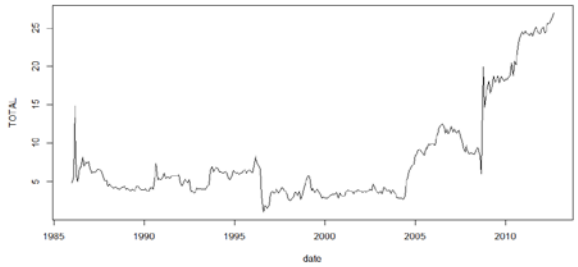
Crude oil, Fish, MSCI

Figure B.3. 4: Simultaneous relation posterior estimates

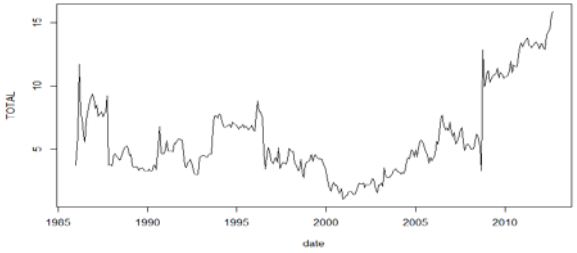
Appendix C

Total volatility spillovers (Crude oil, Maize, MSCI)

Total volatility spillovers (Crude oil, Barley, MSCI)

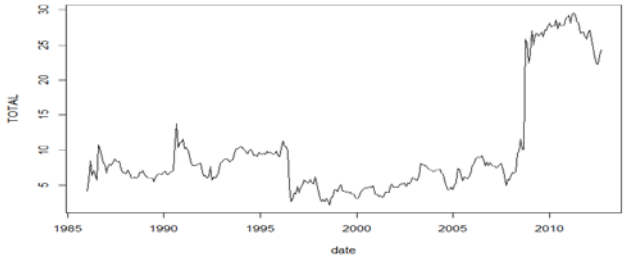


Total volatility spillovers (Crude oil, Rapeseed Oil, MSCI)

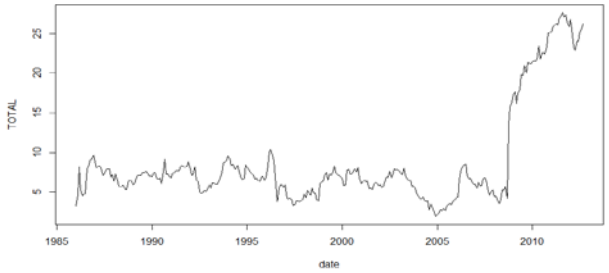


Total volatility spillovers (Crude oil, Banana, MSCI)

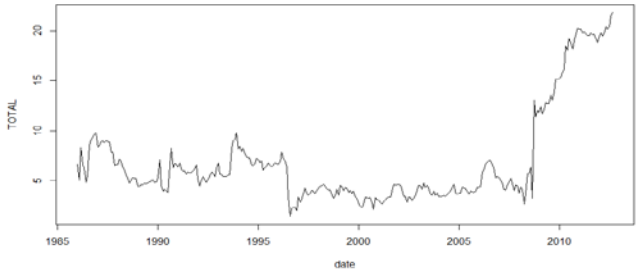
Total volatility spillovers (Crude oil, Cocoa Beans, MSCI)



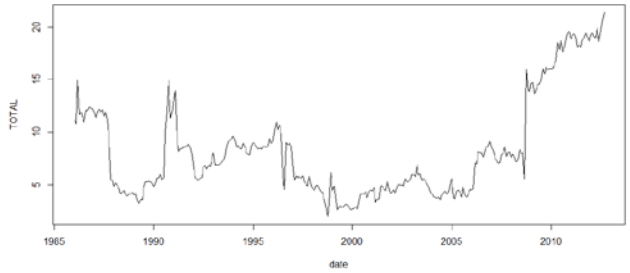
Total volatility spillovers (Crude oil, Ground nuts, MSCI)



Total volatility spillovers (Crude oil, Lamb, MSCI)

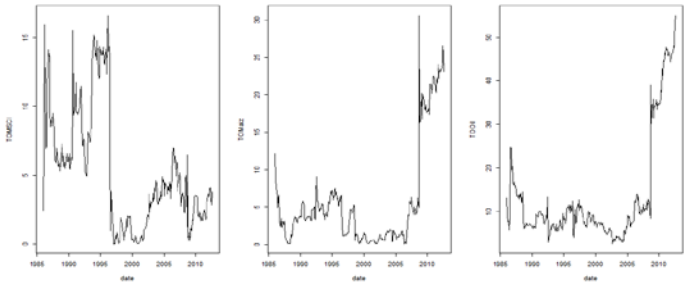


Total volatility spillovers (Crude oil, Beef, MSCI)



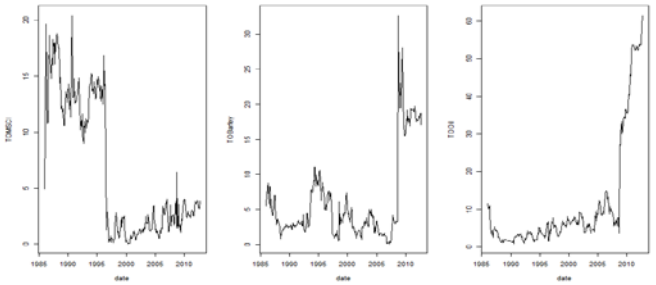
Total volatility spillovers (Crude oil, Fish, MSCI)

Figure C.3. 1: Total volatility spillovers expressed as a percentage (in each set composed of 3 types of asset classes: Energy, Food and Stocks)



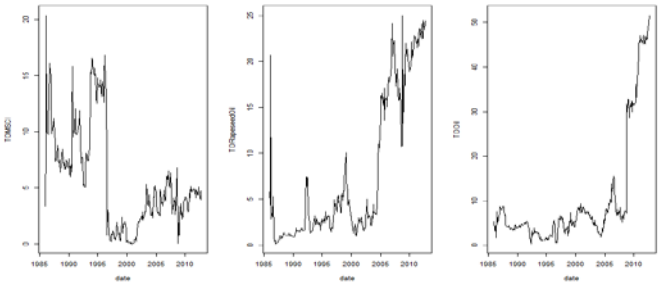
To MSCI To Maize To crude oil

Directional volatility spillovers to each asset of the set
(Crude oil, Maize, MSCI)



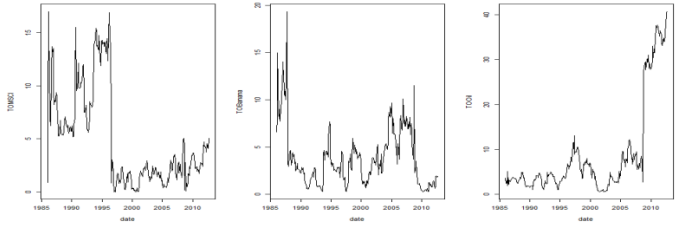
To MSCI To Barley To crude oil

Directional volatility spillovers to each asset
(Crude oil, Barley, MSCI)



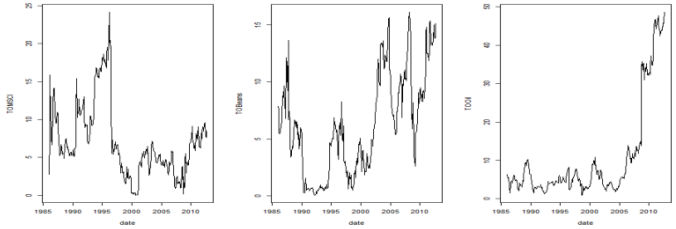
To MSCI To Rapeseed oil To crude oil

Directional volatility spillovers to each asset
(Crude oil, Rapeseed Oil, MSCI)



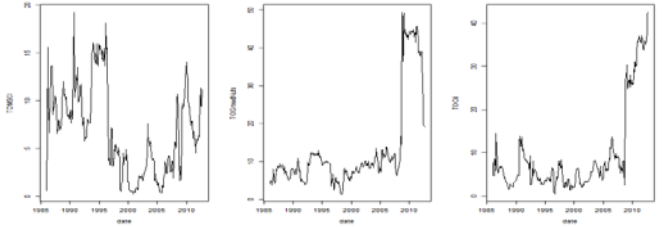
To MSCI To Banana To crude oil

Directional volatility spillovers to each asset from others
(Crude oil, Banana, MSCI)



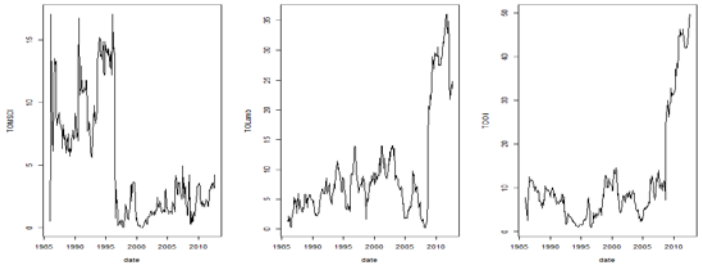
To MSCI To Cocoa Beans To crude oil

Directional volatility spillovers to each asset from others
(Crude oil, Cocoa Beans, MSCI)



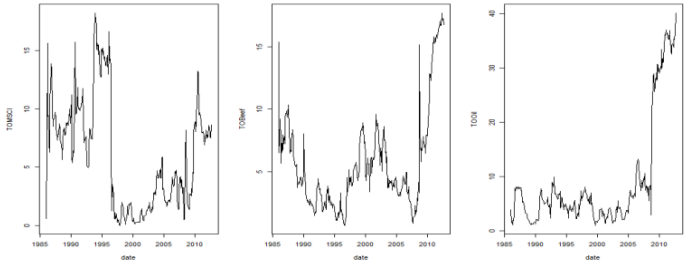
To MSCI To Ground nuts To crude oil

Directional volatility spillovers to each asset from others
(Crude oil, Ground nuts, MSCI)



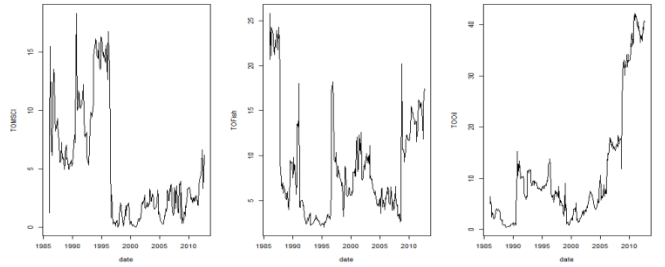
To MSCI To Lamb To crude oil

Directional volatility spillovers to each asset from others
(Crude oil, Lamb, MSCI)



To MSCI To Beef To crude oil

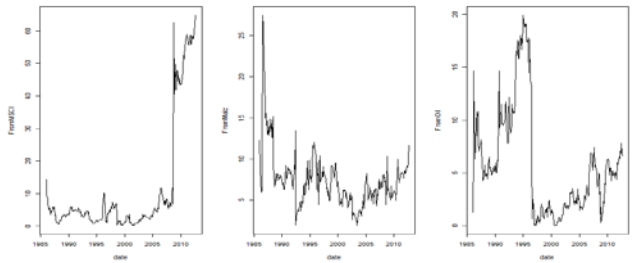
Directional volatility spillovers to each asset from others
(Crude oil, Beef, MSCI)



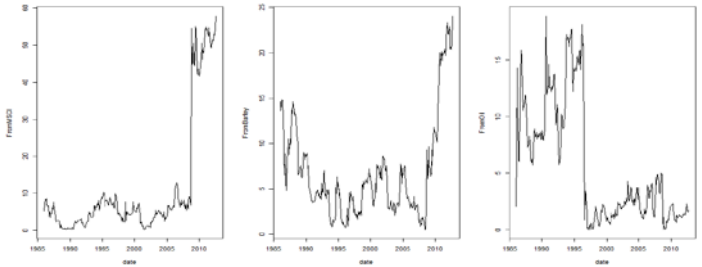
To MSCI To Fish To crude oil

Directional volatility spillovers to each asset from others
(Crude oil, Fish, MSCI)

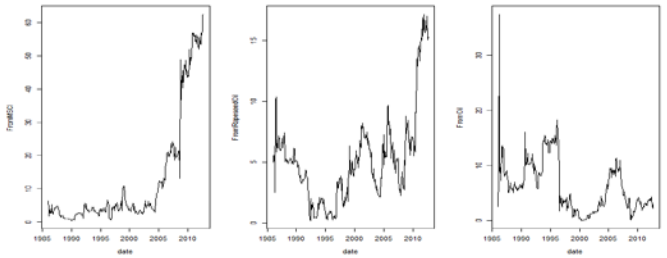
Figure C.3. 2: Directional volatility spillovers to each asset from others expressed as a percentage



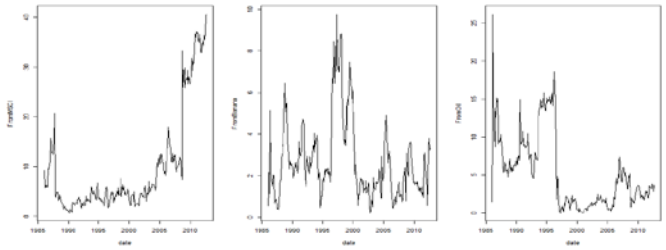
From MSCI From Maize From Crude oil
Directional volatility spillovers from each assetto others
(Crude oil, Maize, MSCI)



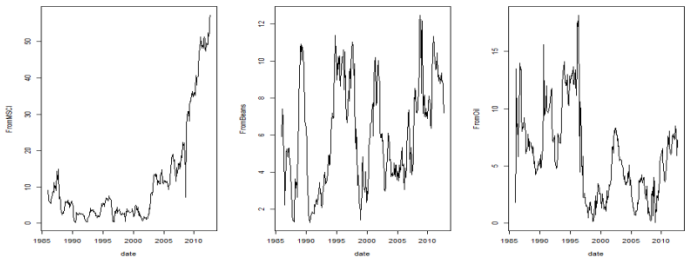
From MSCI From Barley From Crude oil
Directional volatility spillovers from each assetto others
(Crude oil, Barley, MSCI)



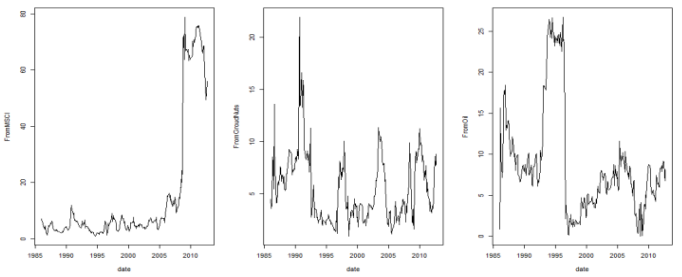
From MSCI From Rapeseed oil From Crude oil
Directional volatility spillovers from each assetto others
(Crude oil, Rapeseed Oil, MSCI)



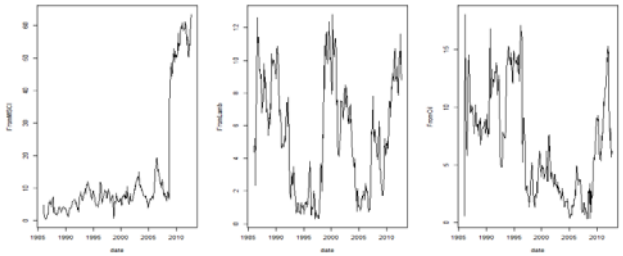
From MSCI From Banana From Crude oil
Directional volatility spillovers from each assetto others
(Crude oil, Banana, MSCI)



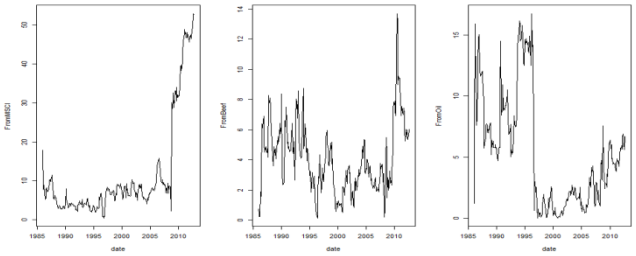
From MSCI From Cocoa Beans From Crude oil
Directional volatility spillovers from each assetto others
(Crude oil, Cocoa Beans, MSCI)



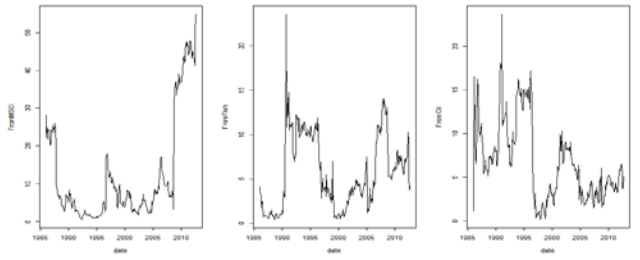
From MSCI From Ground nuts From Crude oil
Directional volatility spillovers from each assetto others
(Crude oil, Ground nuts, MSCI)



From MSCI From Lamb From crude oil
Directional volatility spillovers from each assetto others
(Crude oil, Lamb, MSCI)

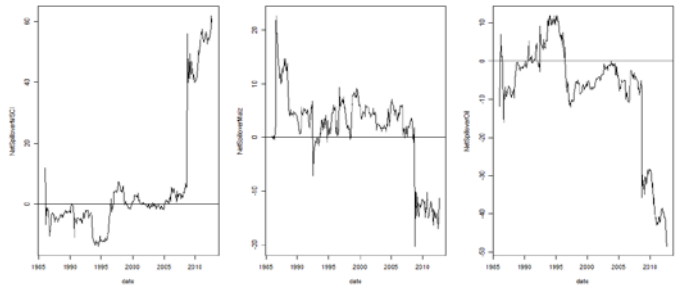


From MSCI From Beef From crude oil
Directional volatility spillovers from each assetto others
(Crude oil, Beef, MSCI)

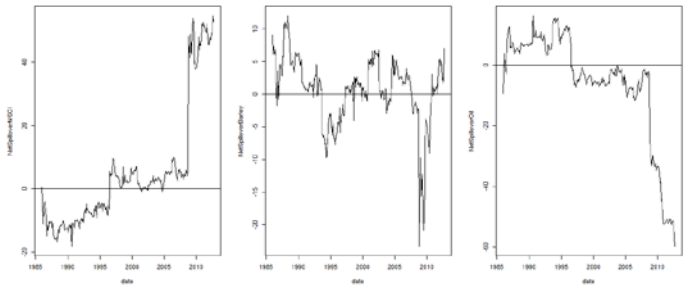


From MSCI From Fish From crude oil
Directional volatility spillovers from each assetto others
(Crude oil, Fish, MSCI)

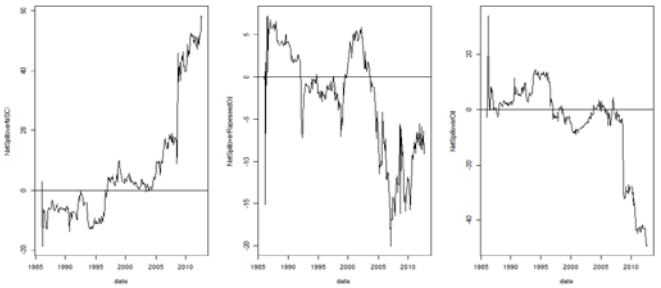
Figure C.3. 3: Directional volatility spillovers from each asset to others expressed as a percentage



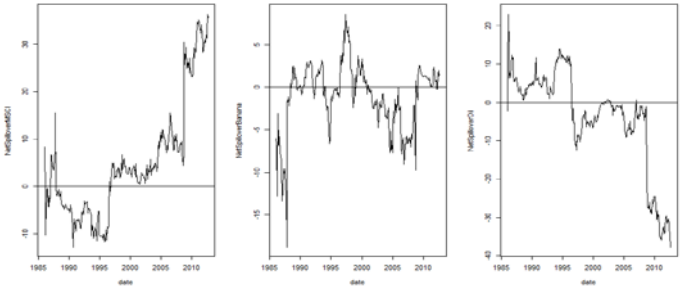
Net volatility spillovers
(Crude oil, Maize, MSCI)



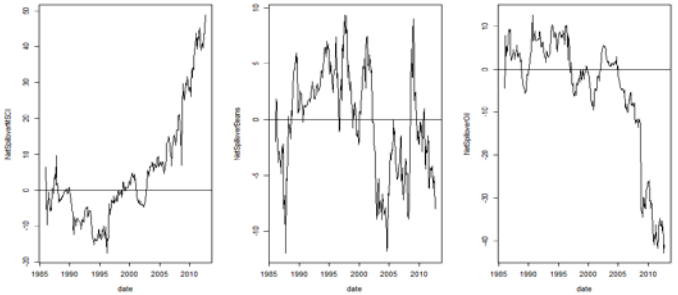
Net volatility spillovers
(Crude oil, Barley, MSCI)



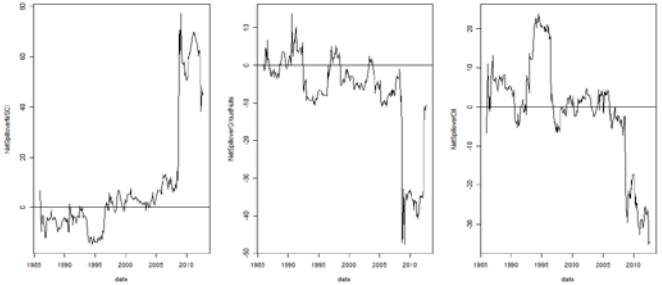
Net volatility spillovers
(Crude oil, Rapeseed Oil, MSCI)



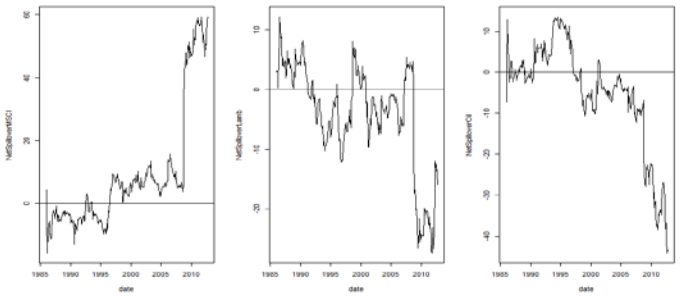
Net volatility spillovers
(Crude oil, Banana, MSCI)



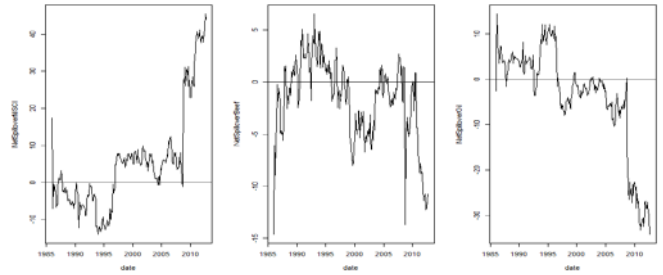
Net volatility spillovers
(Crude oil, Cocoa Beans, MSCI)



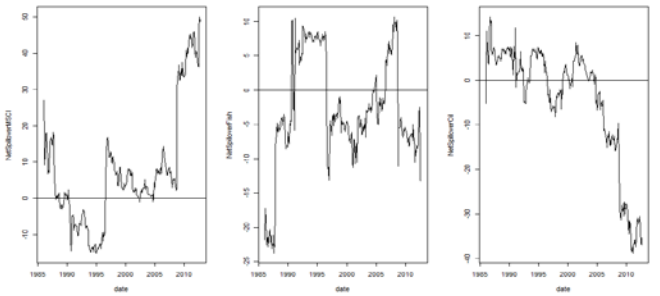
Net volatility spillovers
(Crude oil, Ground nuts, MSCI)



Net volatility spillovers
(Crude oil, Lamb, MSCI)



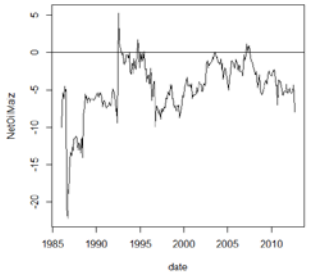
Net volatility spillovers
(Crude oil, Beef, MSCI)



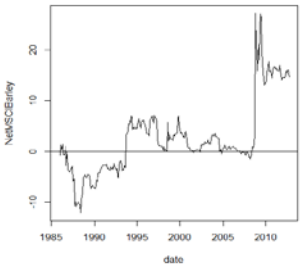
Net volatility spillovers
(Crude oil, Fish, MSCI)

Figure C.3. 4: Net volatility spillovers expressed as a percentage

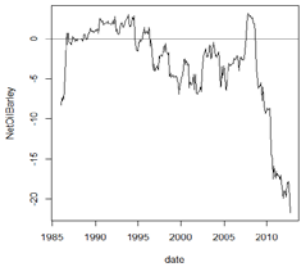
Net pairwise volatility spillovers (MSCI, Maize)



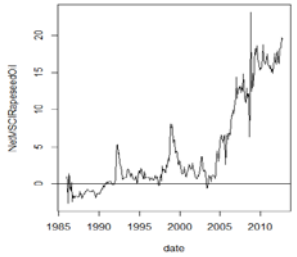
Net pairwise volatility spillovers (Crude oil, Maize)



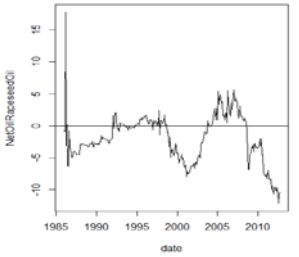
Net pairwise volatility spillovers (MSCI, Barley)



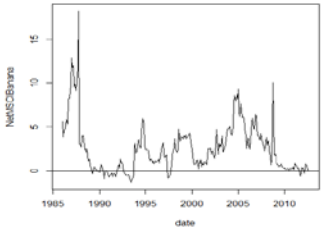
Net pairwise volatility spillovers (Crude oil, Barley)



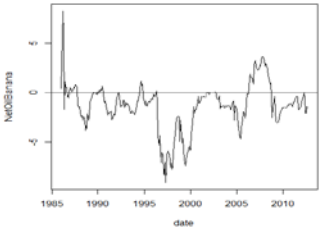
Net pairwise volatility spillovers (MSCI, Rapeseed oil)



Net pairwise volatility spillovers (Crude oil, Rapeseed oil)

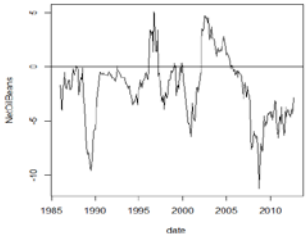


Net pairwise volatility spillovers (MSCI, Banana)

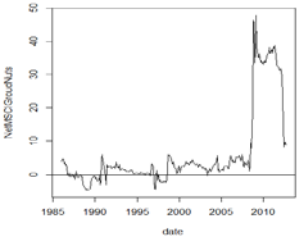


Net pairwise volatility spillovers (Crude oil, Banana)

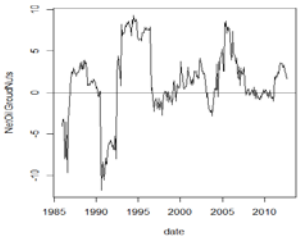
Net pairwise volatility spillovers (MSCI, Cocoa Beans)



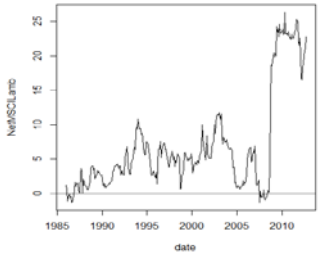
Net pairwise volatility spillovers (Crude oil, Cocoa Beans)



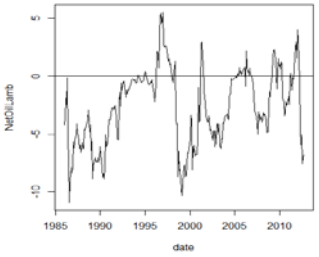
Net pairwise volatility spillovers (MSCI, Ground nuts)



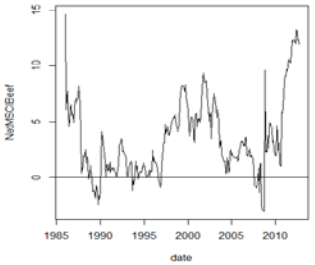
Net pairwise volatility spillovers (Crude oil, Ground nuts)



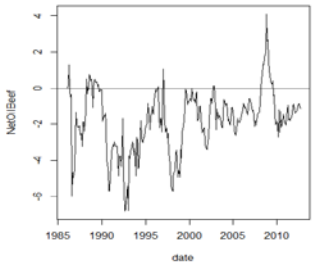
Net pairwise volatility spillovers (MSCI, Lamb)



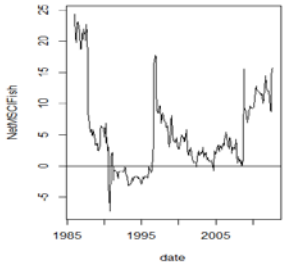
Net pairwise volatility spillovers (Crude oil, Lamb)



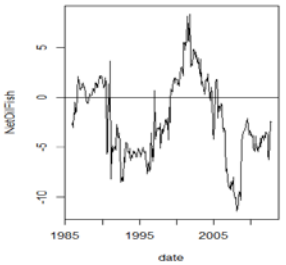
Net pairwise volatility spillovers (MSCI, Beef)



Net pairwise volatility spillovers (Crude oil, Beef)



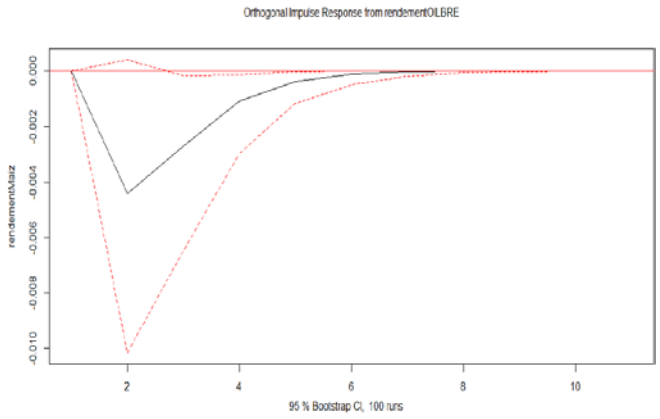
Net pairwise volatility spillovers (MSCI, Fish)



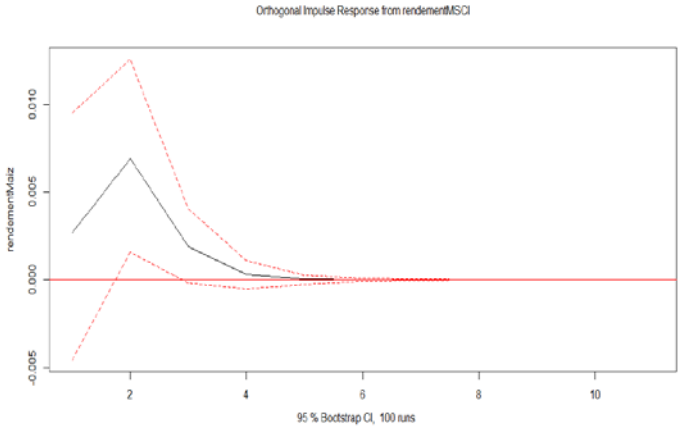
Net pairwise volatility spillovers (Crude oil, Fish)

Figure C.3. 5: Net pairwise volatility spillovers expressed as a percentage

Appendix D

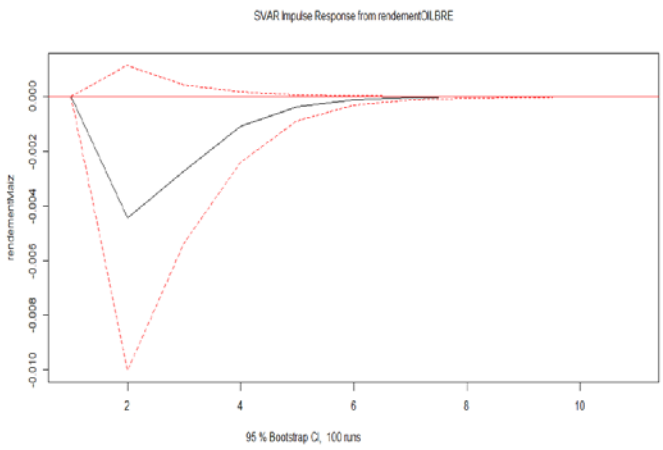


Orthogonal impulse response from crude oil

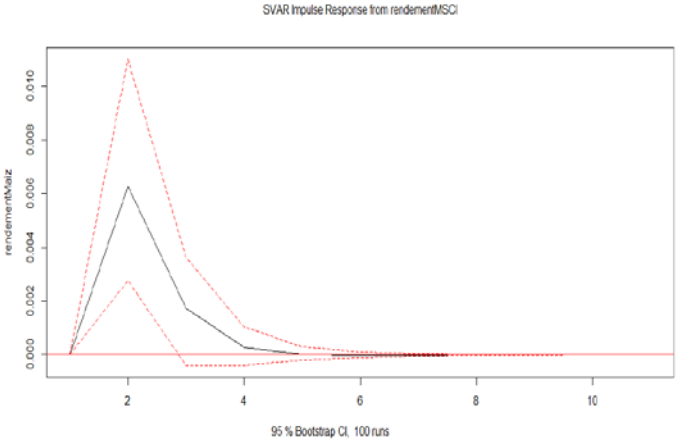


Orthogonal impulse response from MSCI

(a) Constant VAR model

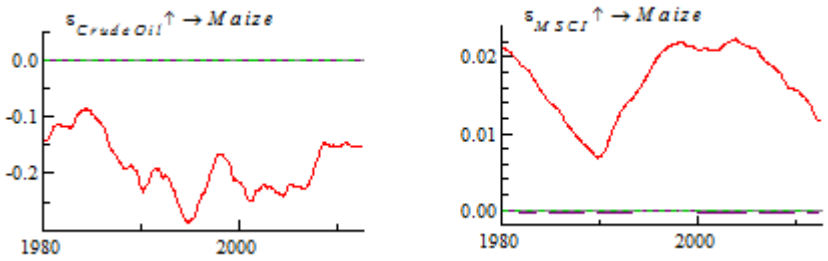


SVAR impulse response from crude oil



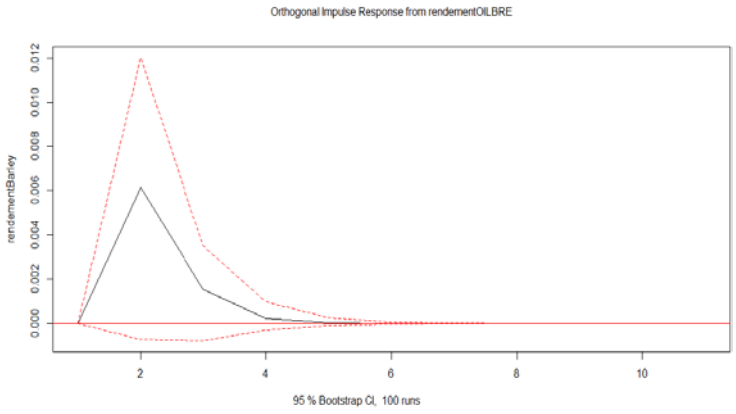
SVAR impulse response from MSCI

(b) Constant SVAR model

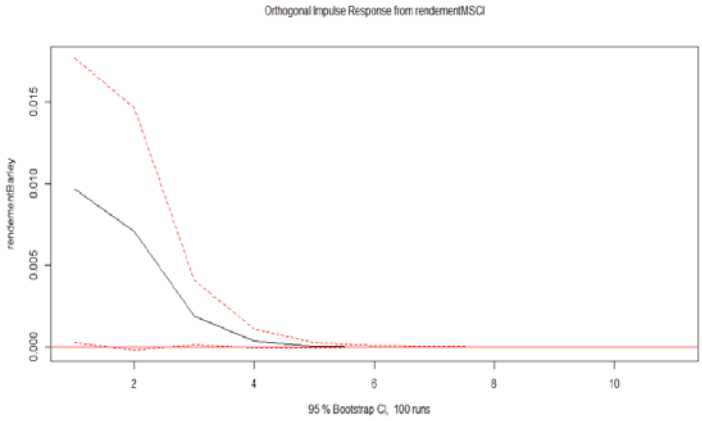


(c) TVP-VAR model

Figure D.3. 1: Impulse responses for the set Crude oil, Maize, MSCI

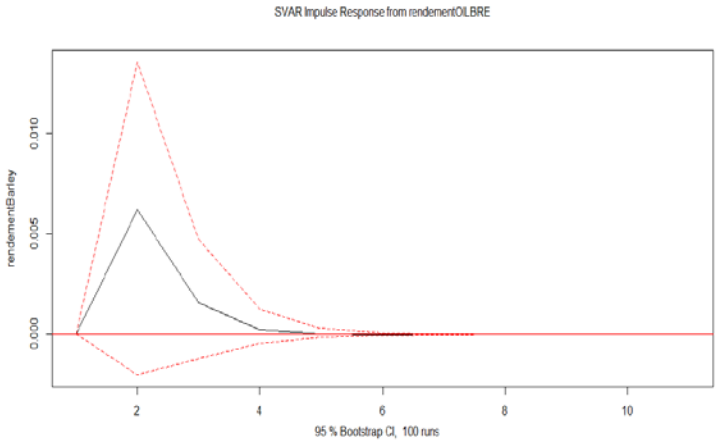


Orthogonal impulse response from crude oil

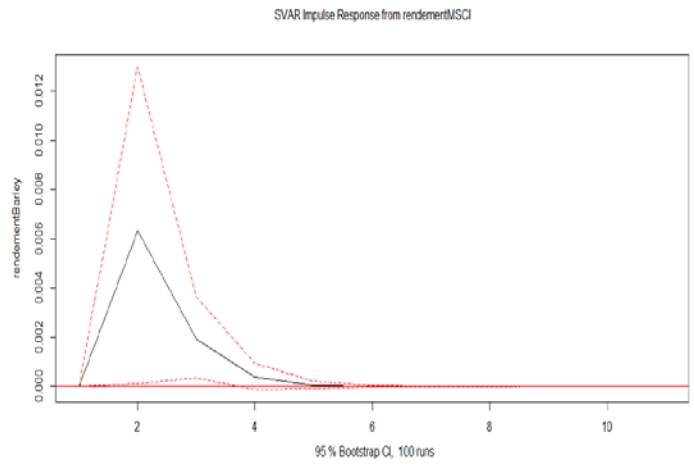


Orthogonal impulse response from MSCI

(a) Constant VAR model

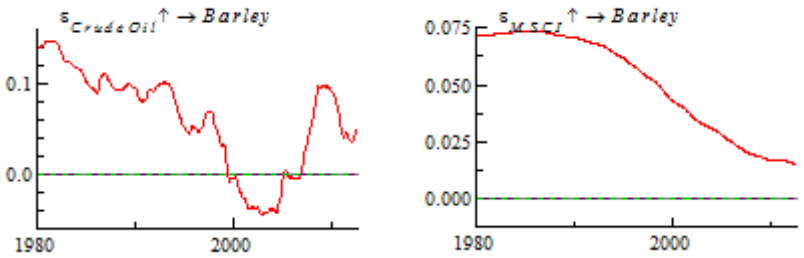


SVAR impulse response from crude oil



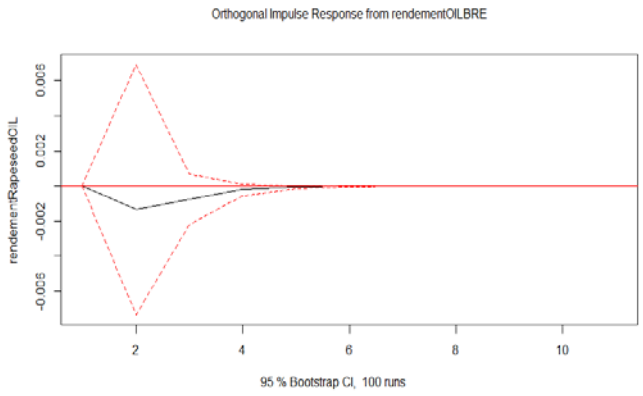
SVAR impulse response from MSCI

(b) Constant SVAR model

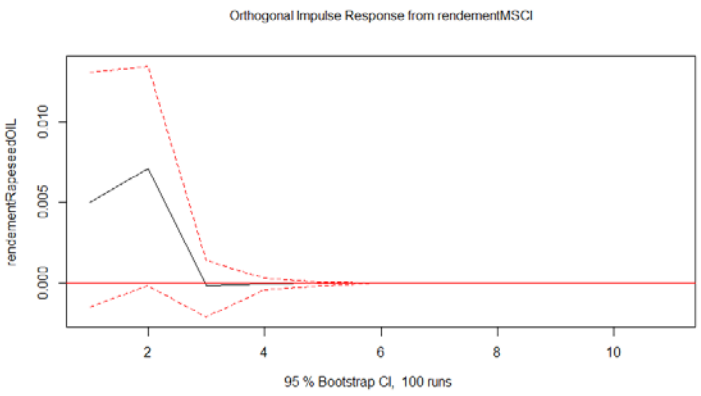


(c) TVP-VAR model

Figure D.3. 2: Impulse responses for the set Crude oil, Barley, MSCI

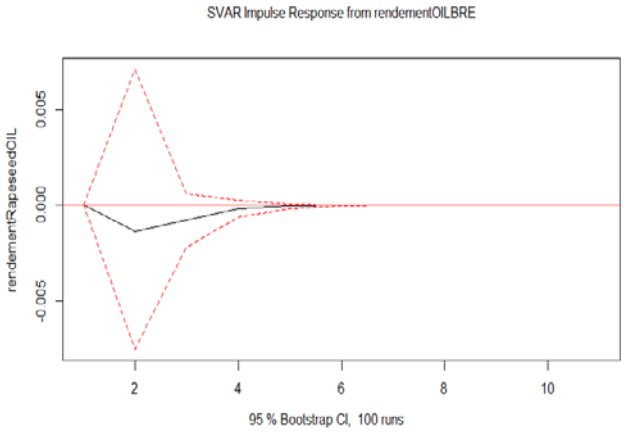


Orthogonal impulse response from crude oil

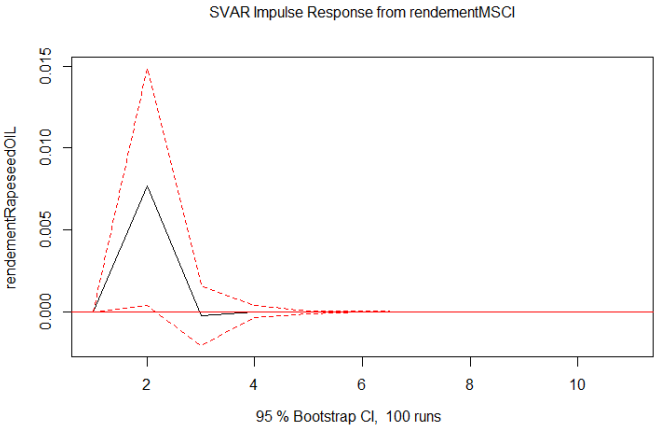


Orthogonal impulse response from MSCI

(a) Constant VAR model

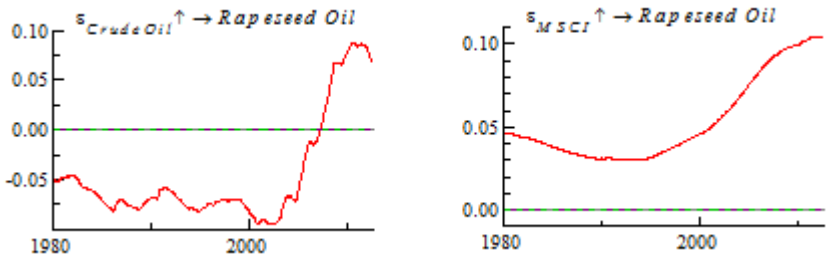


SVAR impulse response from crude oil



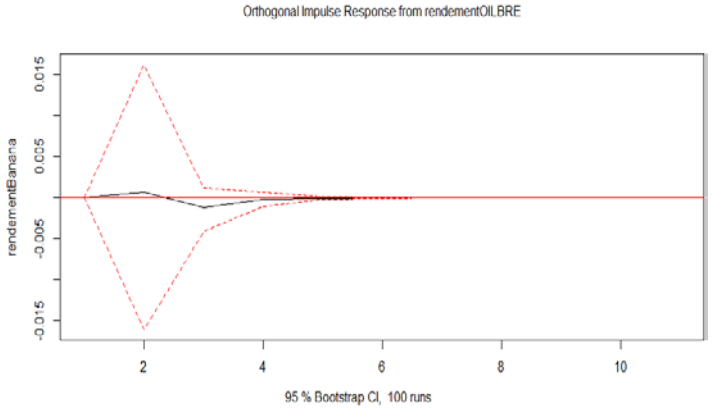
SVAR impulse response from MSCI

(b) Constant SVAR model

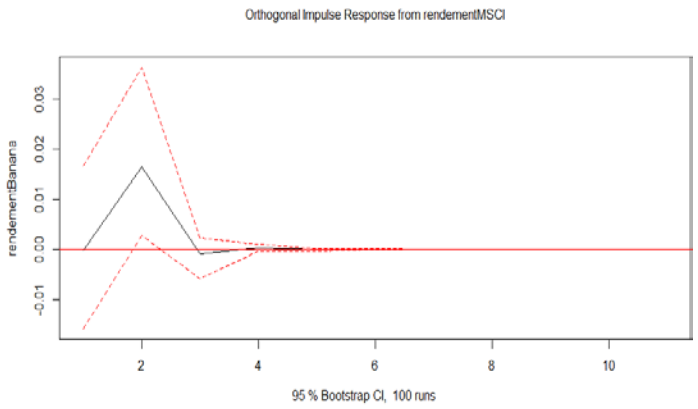


(c) TVP-VAR model

Figure D.3. 3: Impulse responses for the set Crude oil, Rapeseed oil, MSCI

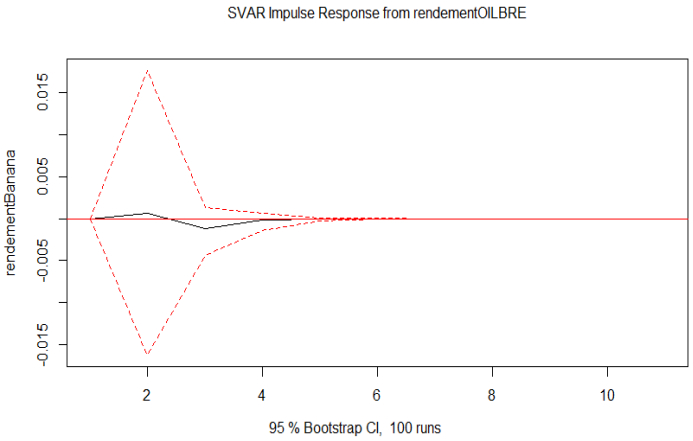


Orthogonal impulse response from crude oil

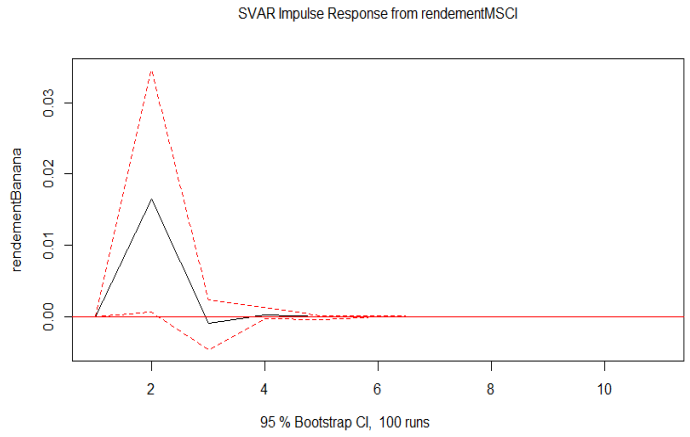


Orthogonal impulse response from MSCI

(a) Constant VAR model

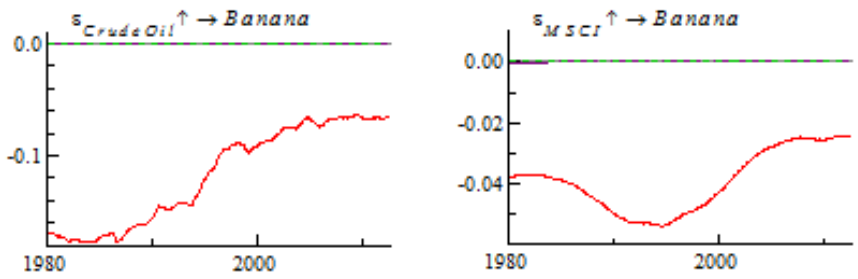


SVAR impulse response from crude oil



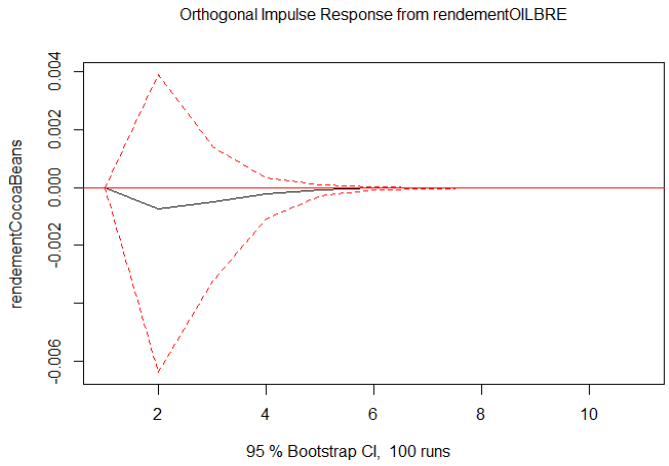
SVAR impulse response from MSCI

(b) Constant SVAR model

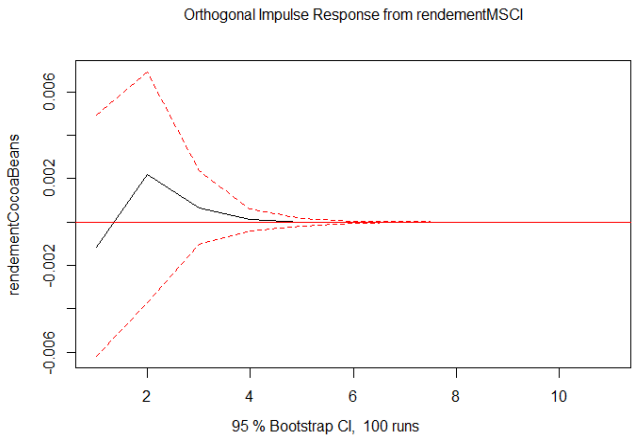


(c) TVP-VAR model

Figure D.3. 4: Impulse responses for the set Crude oil, Banana, MSCI

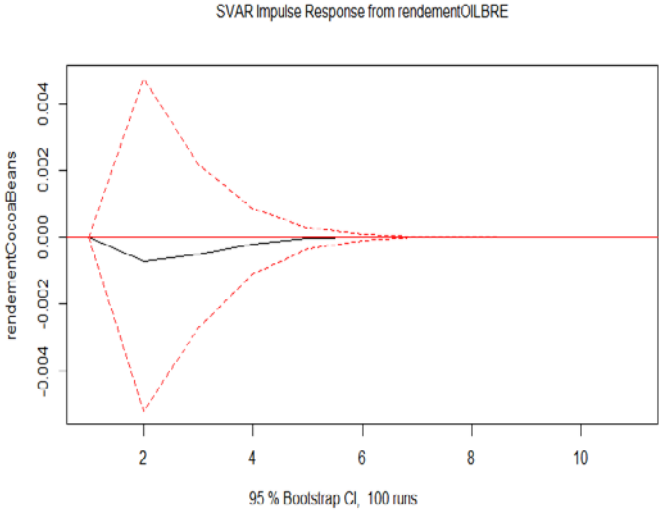


Orthogonal impulse response from crude oil

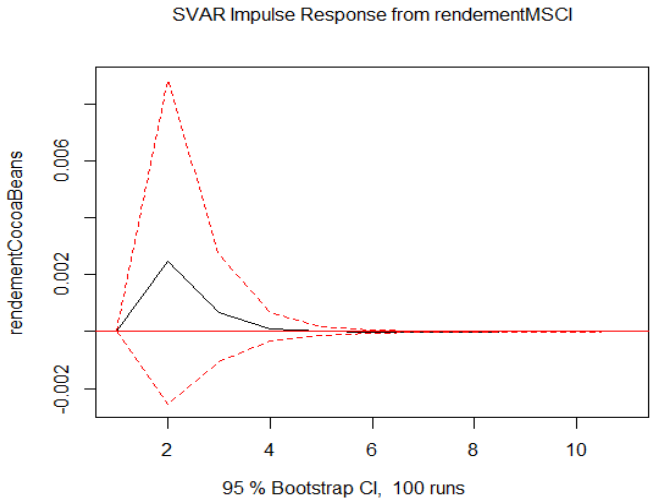


Orthogonal impulse response from MSCI

(a) Constant VAR model

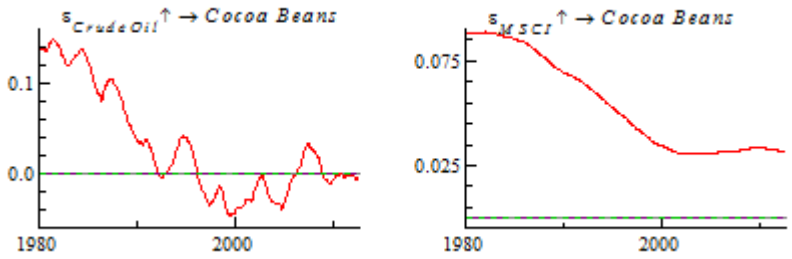


SVAR impulse response from crude oil



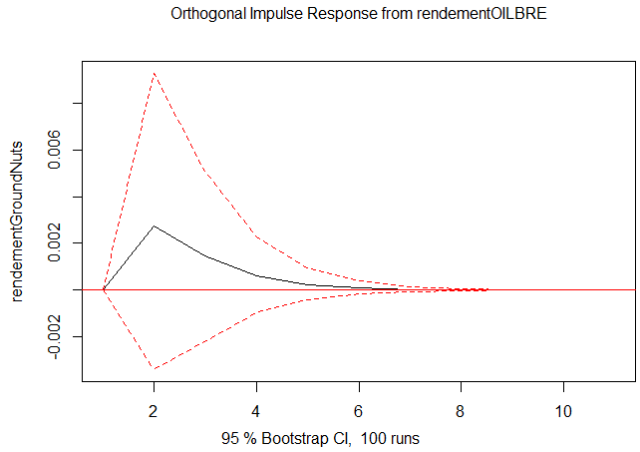
SVAR impulse response from MSCI

(b) Constant SVAR model

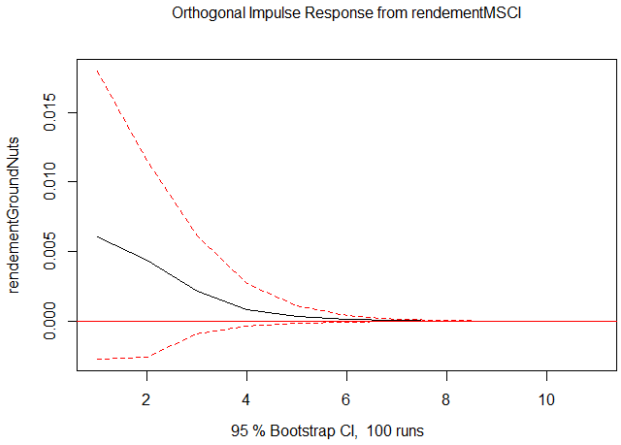


(c) TVP-VAR model

Figure D.3. 5: Impulse responses for the set Crude oil, Cocoa beans, MSCI

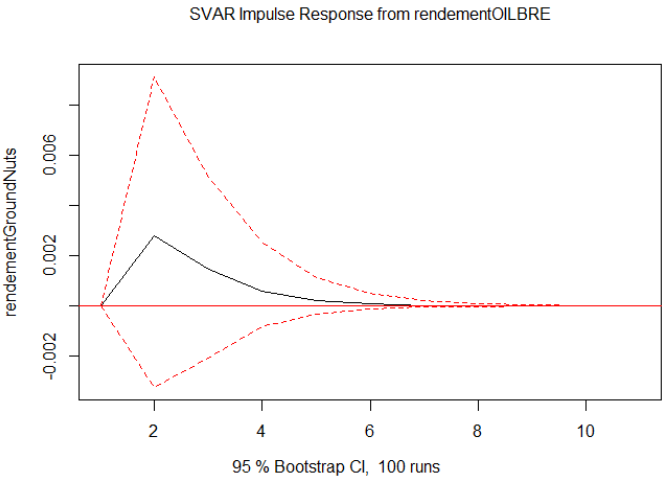


Orthogonal impulse response from crude oil

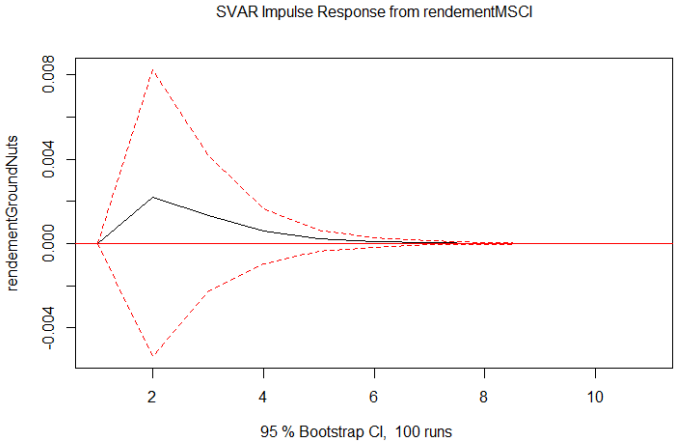


Orthogonal impulse response from MSCI

(a) Constant VAR model

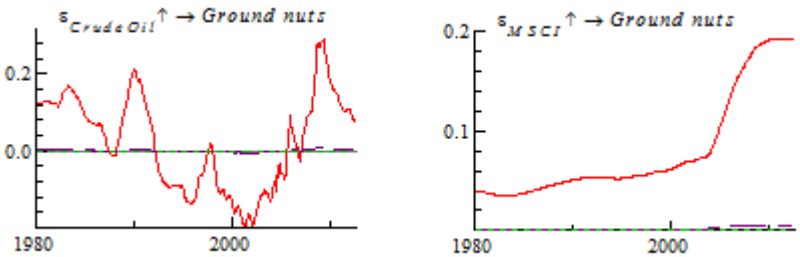


SVAR impulse response from crude oil



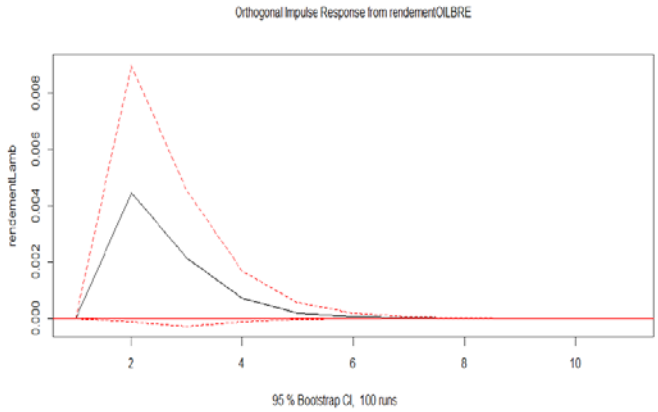
SVAR impulse response from MSCI

(b) Constant SVAR model

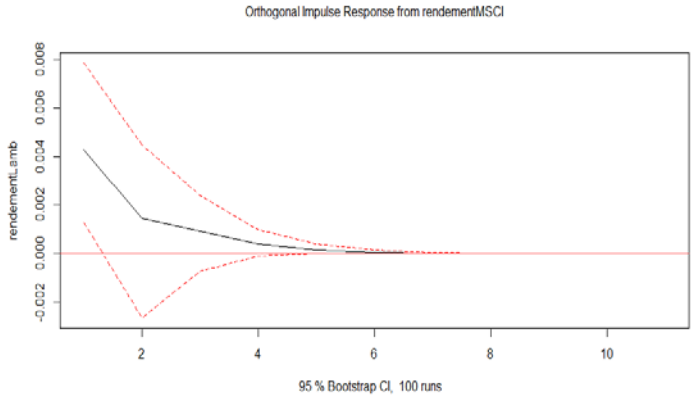


(c) TVP-VAR model

Figure D.3. 6: Impulse responses for the set Crude oil, Ground nuts, MSCI

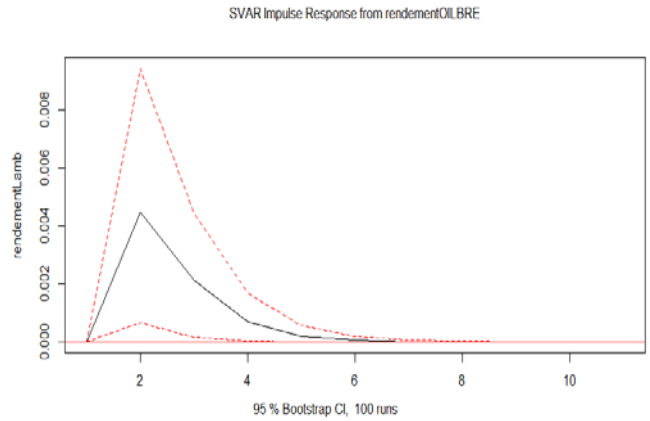


Orthogonal impulse response from crude oil

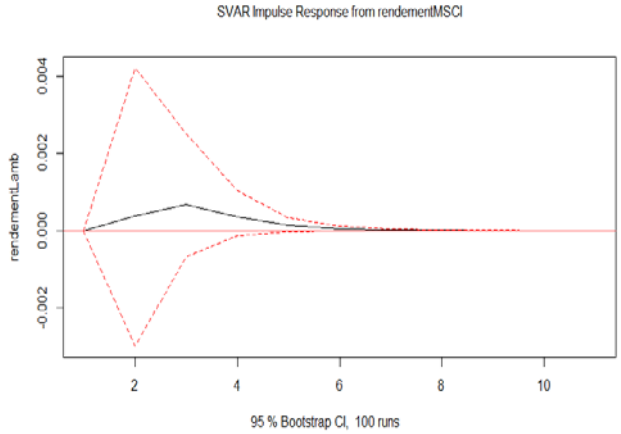


Orthogonal impulse response from MSCI

(a) Constant VAR model

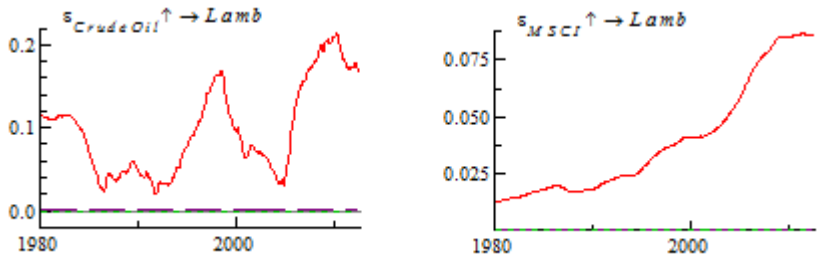


SVAR impulse response from crude oil



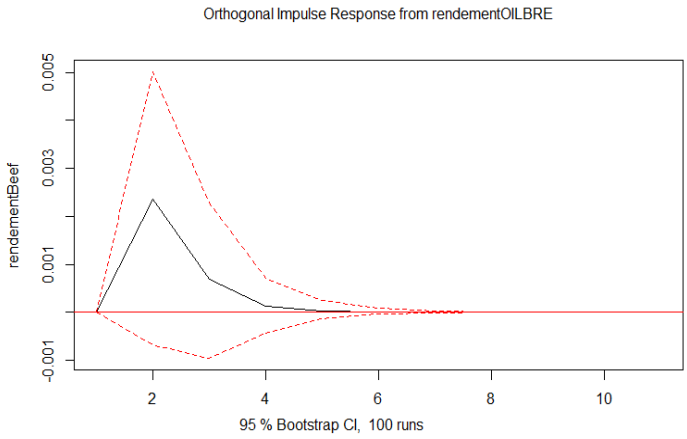
SVAR impulse response from MSCI

(b) Constant SVAR model

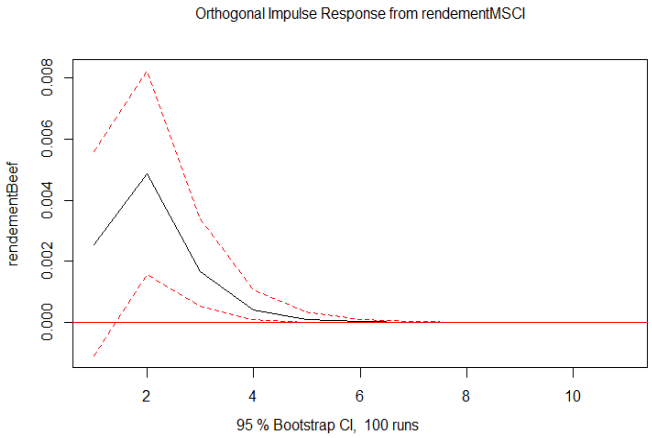


(c) TVP-VAR model

Figure D.3. 7: Impulse responses for the set Crude oil, Lamb, MSCI

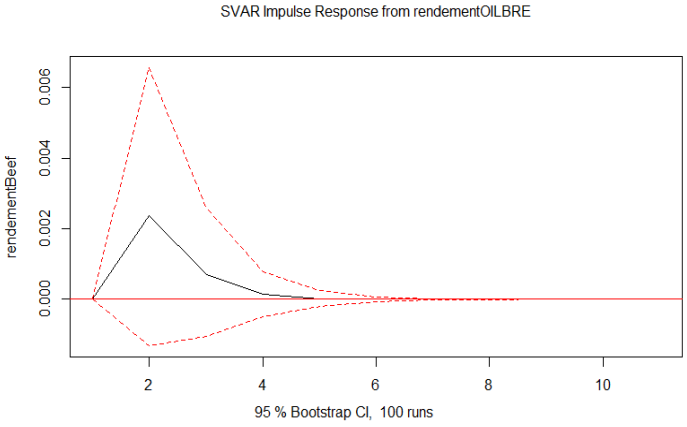


Orthogonal impulse response from crude oil

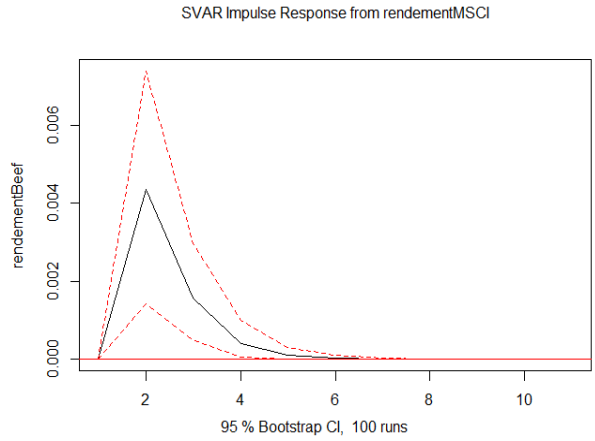


Orthogonal impulse response from MSCI

(a) Constant VAR model

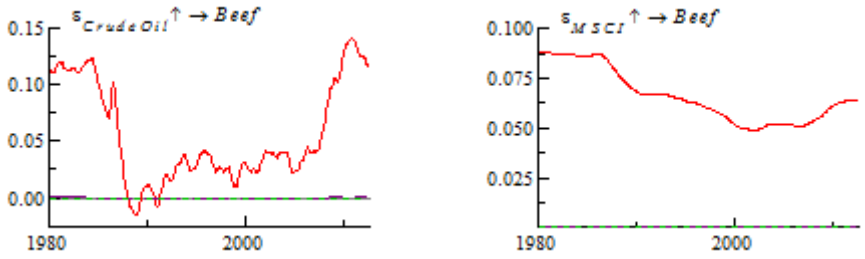


SVAR impulse response from crude oil



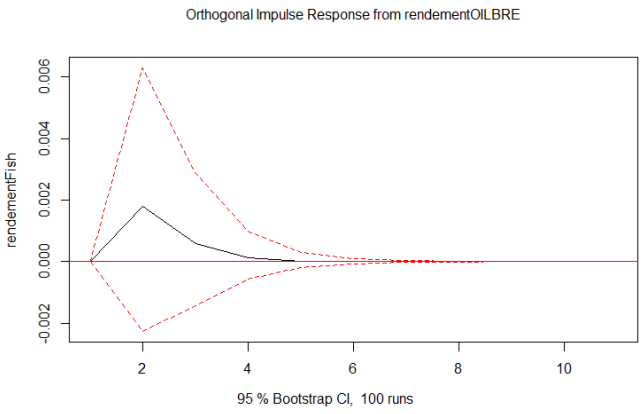
SVAR impulse response from MSCI

(b) Constant SVAR model

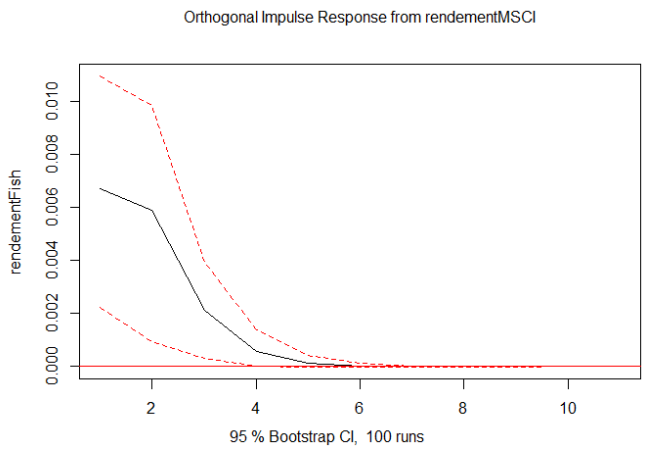


(c) TVP-VAR model

Figure D.3. 8: Impulse responses for the set Crude oil, Beef, MSCI

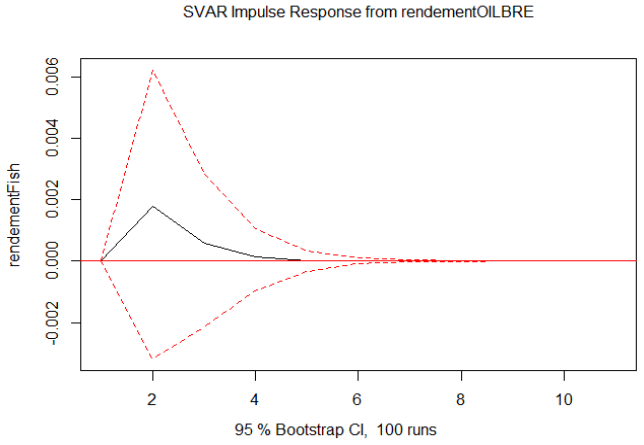


Orthogonal impulse response from crude oil

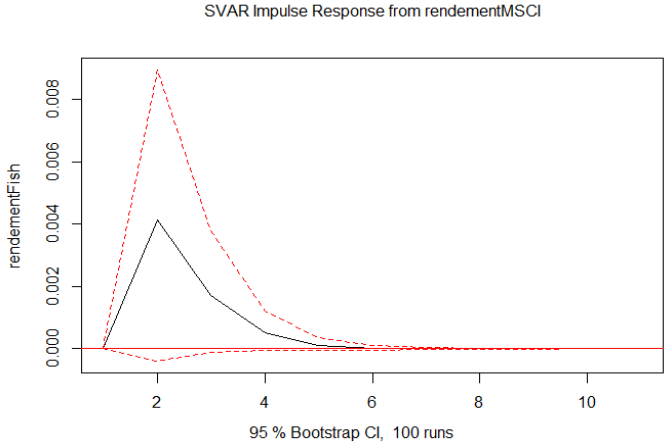


Orthogonal impulse response from MSCI

(a) Constant VAR model

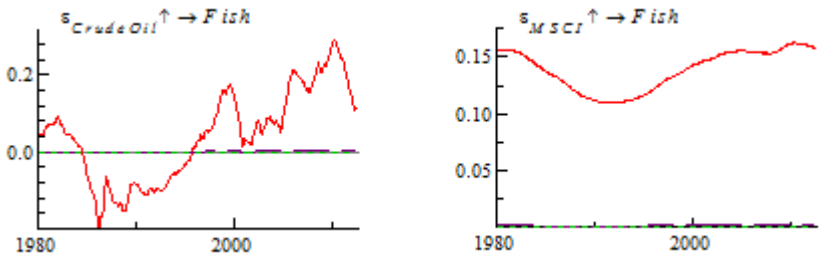


SVAR impulse response from crude oil



SVAR impulse response from MSCI

(b) Constant SVAR model



(c) TVP-VAR model

Figure D.3. 9: Impulse responses for the set Crude oil, Fish, MSCI

Appendix E

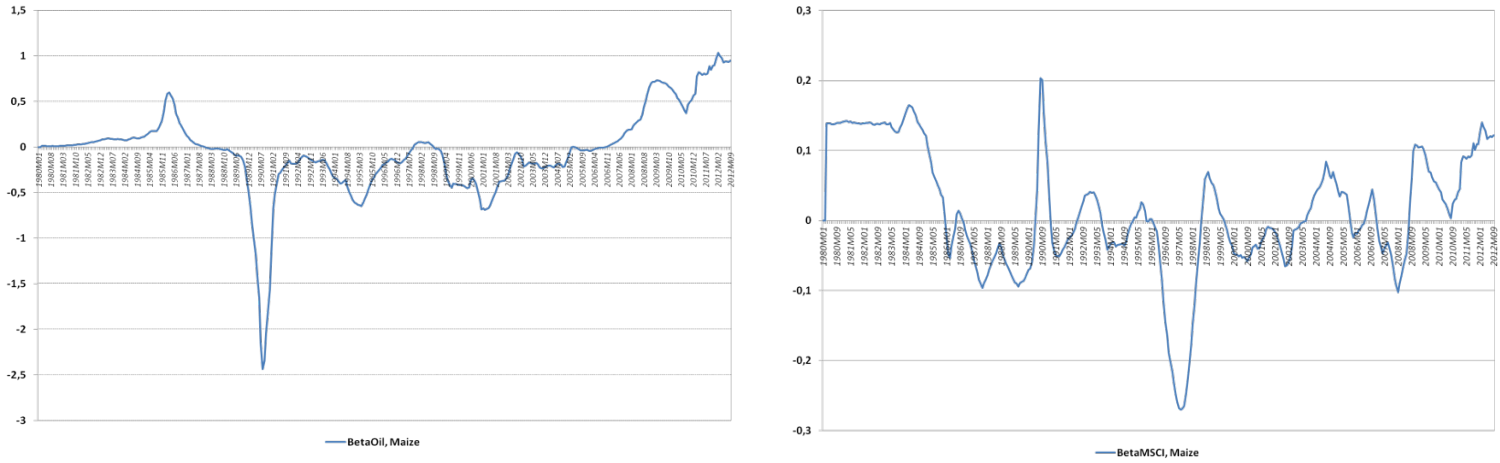


Figure E.3. 1: Dynamic hedge ratios of the portfolio Crude oil/MSCI, Maize

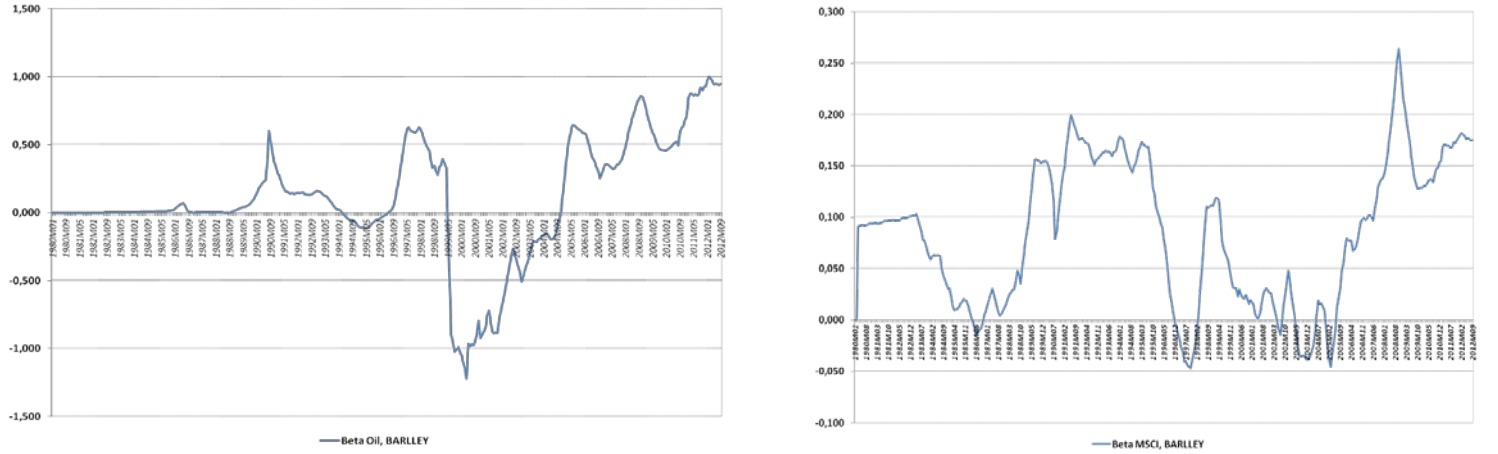


Figure E.3. 2: Dynamic hedge ratios of the portfolio Crude oil/MSCI, Barley

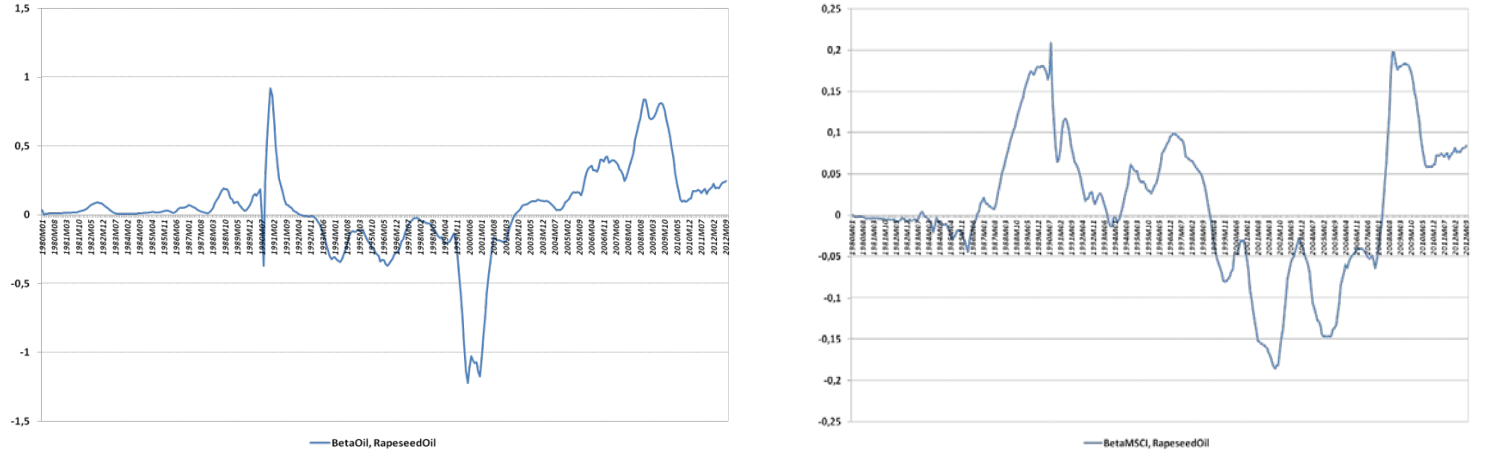
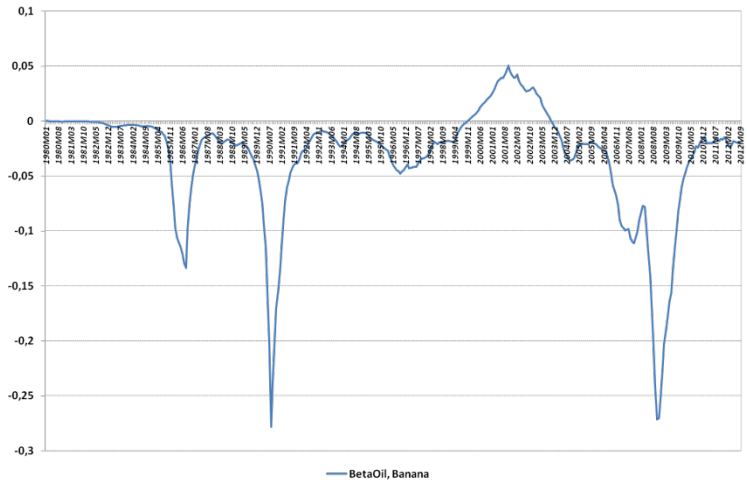


Figure E.3. 3: Dynamic hedge ratios of the portfolio Crude oil/MSCI, Rapeseed oil



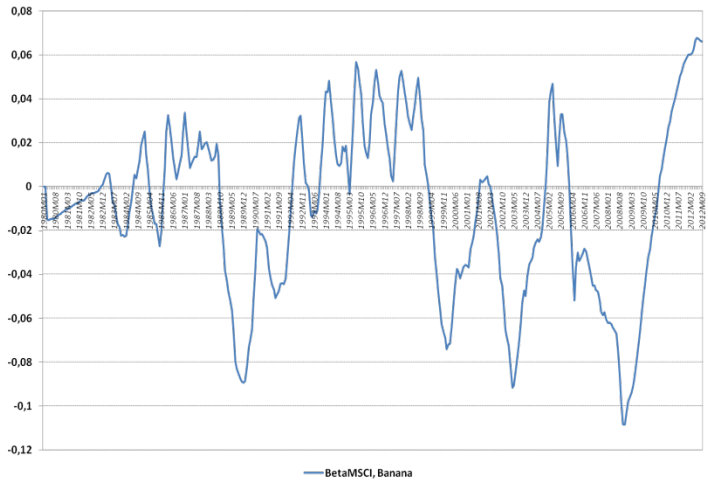
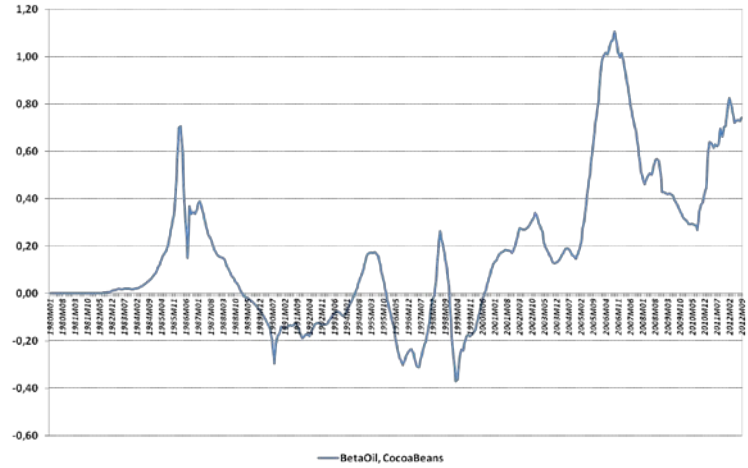


Figure E.3. 4: Dynamic hedge ratios of the portfolio Crude oil/MSCI, Banana



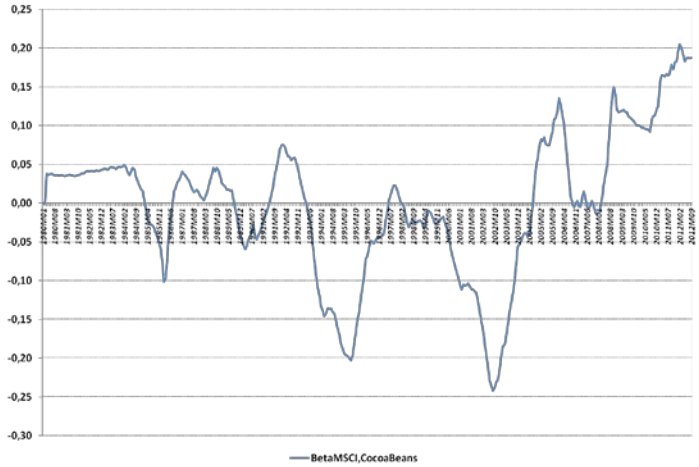
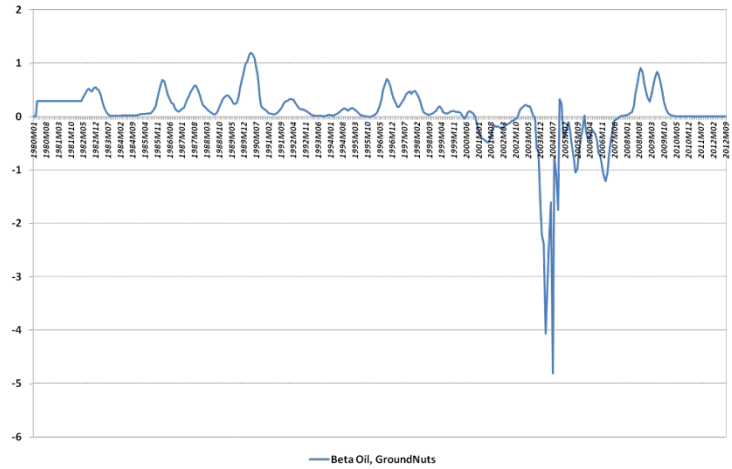


Figure E.3. 5: Dynamic hedge ratios of the portfolio Crude oil/MSCI, Cocoa Beans



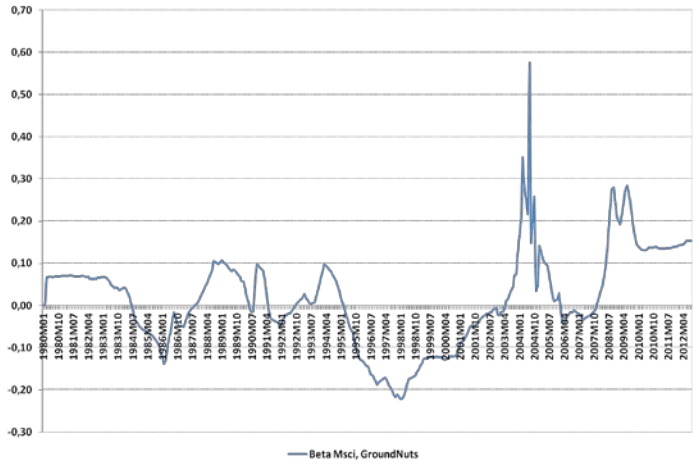


Figure E.3. 6: Dynamic hedge ratios of the portfolio Crude oil/MSCI, Ground nuts

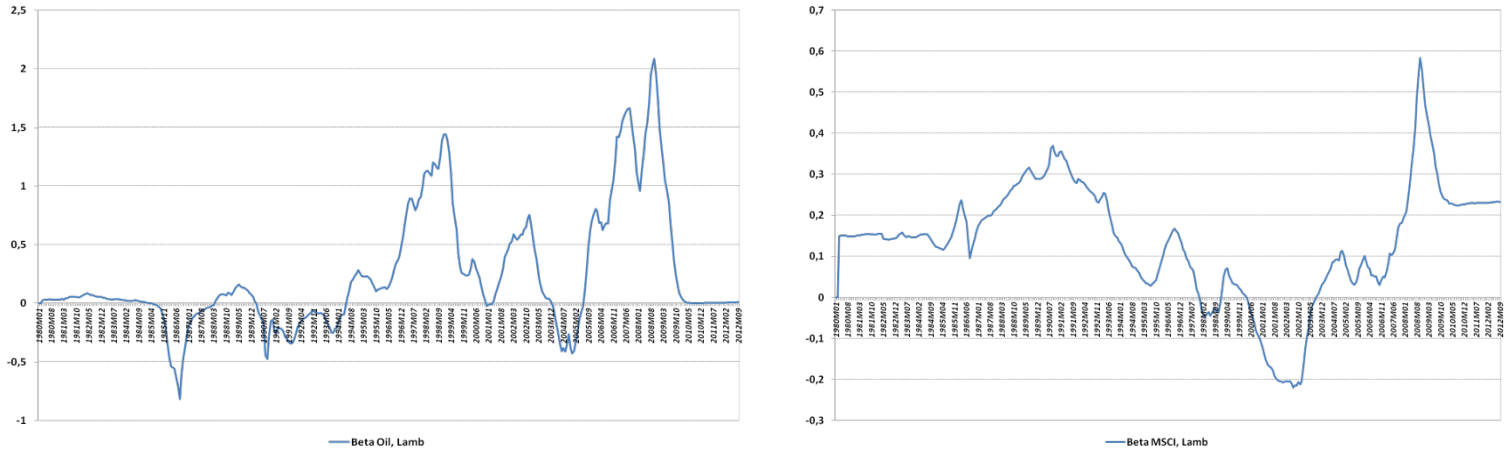


Figure E.3. 7: Dynamic hedge ratios of the portfolio Crude oil/MSCI, Lamb

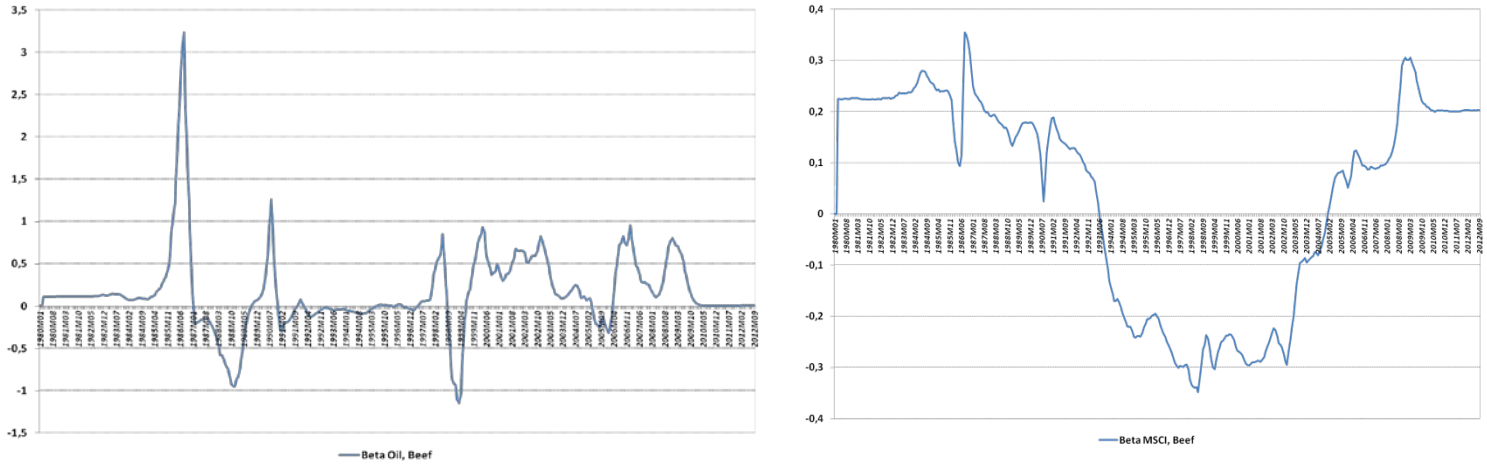


Figure E.3. 8: Dynamic hedge ratios of the portfolio Crude oil/MSCI, Beef

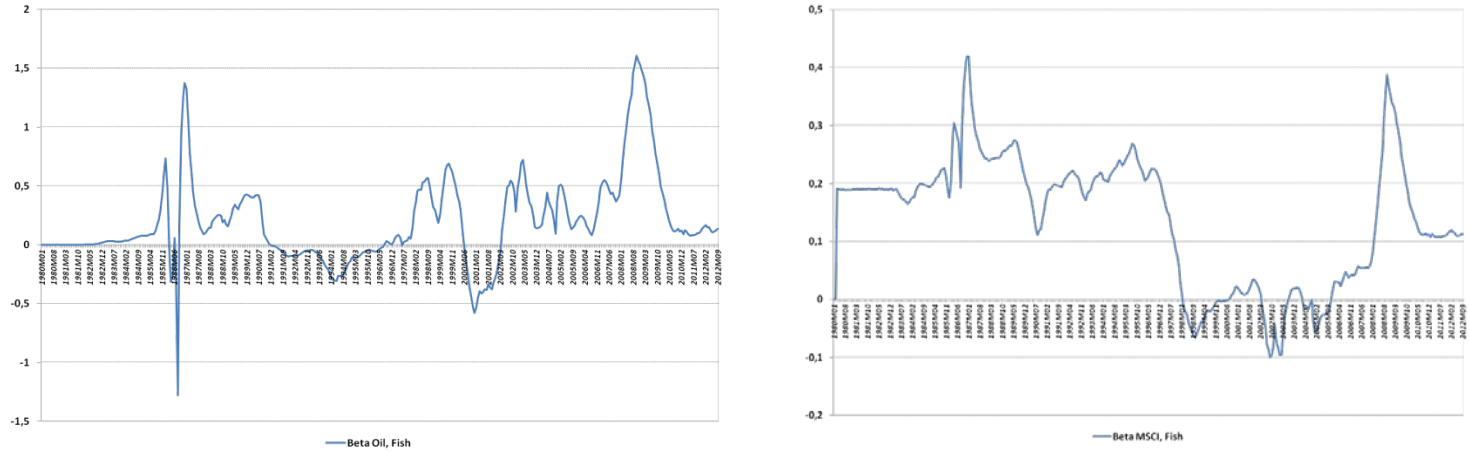


Figure E.3. 9: Dynamic hedge ratios of the portfolio Crude oil/MSCI, Fish

Chapter 4

Multivariate extreme dependence between food, energy and financial markets: Analysis through Vine Copula methods

This chapter is a version of paper co-authored with David Roubaud.

1. Introduction

Previous studies reveal that food, energy, and financial markets are characterized by the presence of many breaks (Arouri et al., 2012; Chen et al., 2010; Reboredo, 2012) and crises of different sources and proportions (Aloui et al., 2014). We can cite such an example and not a limited list the works focusing on the food crisis dated January 2006 (Nazlioglu et al., 2013), on the Brent oil bubble (Fan and Xu, 2011), on the June 2006 implementation of the RFS Policy (Abbott et al., 2009; Avalos, 2014; De Gorter et al., 2013), and on the effect of the 2008 financial crisis (Jebabli et al., 2014). Focusing on the structural properties of the price dependencies in energy and agricultural commodity markets (corn, soybean and wheat) during the period 2000-2014, Han et al. (2015) conclude that global financial crisis corresponds to the most influential exogenous shock on the links between energy and agricultural markets prices.

The occurrence of these extreme events can have major adverse impacts (Sarris, 2014), which makes crucial the interest on extreme dependence and tails behavior in order to assess whether markets are dependent or independent during booms and crashes. Literature agrees on the fact that these tails have to be well studied because structural breaks in tail dependence are an actual dimension of the phenomenon of contagion (Han et al., 2015; Rodriguez, 2007). Tail behavior is affected namely by stochastic volatility and jumps which are the characteristic of

commodities and financial markets (Jondeau, 2016; Merener, 2016). In fact, recent studies focusing on the simultaneous increases recorded in the prices of these markets during the 2000s reveal that volatility spillovers between them are more important with the intensification of the crises and namely the 2008 financial crisis (Jebabli et al., 2014)

Literature review points out that previous studies dealing with dependence among different commodities mostly ignore the asymmetric impacts. While asymmetric dependence of stock markets was well investigated and reveals that dependence across stock returns may be stronger in bearish markets than in bullish markets but without evidence if this asymmetric dependence really implies an asymmetric dependence in the tails of the distribution, this issue was not well investigated for commodities. In fact, few previous studies have considered the asymmetric aspect in commodities in order to check whether the dependence structure is significantly different in case of a joint upswing or downswing in the market. There is little evidence that food and biofuel price increases have the same interactions as price decreases (Serra and Zilberman, 2013) . However, recent studies controvert this evidence.

Results on dependence structures between food and energy markets have been explained in the previous works by a series of drivers. In fact, increases in oil prices lead to increased demand for agricultural commodities for biofuel production purposes. The usage of oil for agriculture production leads to an increase in their prices following an increase in oil prices. In addition, this can be explained by other drivers like increase in market inelasticity, weather, stock levels and macroeconomic factors like the dollar value which is correlated with other macroeconomic factors that can affect commodity prices through the dollar value channel.

Some studies focusing on dependence of these markets can be cited hereafter as examples and not a limited list of works (e.g. Allen et al., 2014; Boonyanuphong et al., 2013; Boonyanuphong and Sriboonchitta, 2014; Han et al., 2015; Koirala et al., 2015; Reboredo, 2012; Reboredo and Ugando, 2014; Wen et al., 2012).

Allen et al. (2014) analyze the changes in the co-dependencies of ten major European stock market indices and the composite STOXX50 index for three periods spanning the GFC: pre-GFC (Jan 2005- July 2007), GFC (July 2007-Sep 2009) and post-GFC periods (Sep 2009-Dec 2011). They resort to the recently developed R Vine copula methods. Their findings underline the complex change in the dependencies in different economic circumstances and the evidence of greater reliance on the Student t copula, in the copula choice within the tree structures, for the GFC period, which is consistent with the existence of larger tails in the distributions of

returns. Boonyanuphong et al. (2013) focus on dependence structure between crude oil and agricultural commodity future prices. They apply copula-based GARCH models to daily data for the period from February 28, 2008 to December 15, 2011. Their results underline the presence of a relatively low symmetrical tail dependence between crude oil and agricultural commodity prices for all pairs which is very volatile over time. Boonyanuphong and Sriboonchitta (2014) study the structure of interdependencies between energy (crude oil), biofuel (ethanol) and agricultural commodity markets (corn, soybeans and sugar) using daily futures returns covering the period from March 23, 2005 to January 1, 2013. They apply the C-vine copula based ARMA-GARCH model. Their results underline the presence of symmetrical tail dependence between energy, biofuel and agricultural commodities and a dynamic dependence especially the dependence between the ethanol and agricultural commodity futures returns conditional to crude oil and ethanol futures returns. Han et al. (2015) findings underline the importance of focusing on tail dependence structure when considering price dependencies among commodity assets. Their study focuses on detecting the structural properties of the price dependencies in energy and agricultural commodity markets (corn, soybean and wheat). Daily futures returns covering the period 2000-2014 are used and different sub-periods are considered in this study corresponding to five points (January 5, 2004 : significant index investment started to flow into commodity markets; July 29, 2005 : the Energy Policy Act of 2005 was passed; January 3, 2007: the food price crisis erupted; September 15, 2008: Lehman Brothers filed for bankruptcy, which marked the full-blown of the financial crisis; October 17, 2012: the EU launched new rules for biofuels, indicating that crop-based biofuels would not be subsidized in the future). In regards to tail dependence, Han et al. (2015) findings indicate that the occurrence of a significant increase in tail dependence is recorded only during the financial crisis and that their levels (either for lower or upper tail dependence) are more important than during the other periods. During the biofuel policy and financial crisis periods, lower tail dependence is much stronger than upper tail dependence. Koirala et al. (2015) investigate dependence between agricultural (corn, soybean, cattle) and energy commodities futures prices (crude oil, natural gas, gasoline, diesel, biodiesel). They use both the Clayton and the Clayton-Gumbel mixture copulas applied to daily data covering the period from March 2011 to September 2012. The main findings of their paper indicate that agricultural commodities and energy futures prices are highly correlated and exhibit positive and significant relationship. In his paper, Reboredo (2012) focuses on dependence structure between world oil prices and global prices for three key agricultural commodities (corn, soybean and wheat). In addition to average movements across marginals, he deals with upper and lower tail dependence allowing thus to check for joint

extreme movements. Copula models with different conditional dependence structures and time-varying dependence parameters are applied in his paper to weekly data for the period from 9 January 1998 to 15 April 2011. His main findings underline the neutrality hypothesis at the extremes of the joint distribution for the overall sample, the presence of structural breaks and the increase in dependence during the last three years of the sample mainly for corn and soybean. In their paper, Reboredo and Ugando (2014) study the dependence between US dollar exchange rate and food markets (corn, wheat, soybeans, rice) by resorting to different copula specifications with different conditional dependence structures and time-varying dependence parameters applied to weekly data observed for the period January 1998-October 2012. Their main results indicate the absence of extreme dependence between US dollar exchange rate and corn, wheat and rice foods which confirm that price spikes for these foods were not caused by extreme US dollar exchange rate depreciation. However, they find asymmetric tail dependence for soybeans. Wen et al. (2012) apply time-varying copulas to investigate whether a contagion effect existed between energy and stock markets during the recent financial crisis. Using the WTI oil spot price, the S&P 500 index, the Shanghai stock market composite index and the Shenzhen stock market component index returns, they find evidence of a significantly increasing dependence between crude oil and stock markets after the failure of Lehman Brothers. Tail dependencies are found to be increasing and symmetric for all the paired markets underlining the fact that crude oil and stock prices are linked to the same degree regardless of whether markets are booming or crashing during the sample period. Through the application of threshold analysis to daily data of biofuels and agricultural commodities during the period 2007-2011, Apergis et al. (2017) find the presence of two different regimes separated by the 2008 commodity price spikes period.

The purpose of this paper is to investigate conditional dependence structure between food, energy and financial markets namely tail dependence (upper or lower) in order to understand transmission channels between these markets during extreme events corresponding either to booms or crashes. Different commodities are considered for each market (corn, wheat and live cattle for food market, crude oil and natural gas for energy market and MSCI world stock market for financial market). Our analysis takes also into consideration a macroeconomic factor corresponding to U.S. exchange rate. We base our empirical study on Vine copula models which allow to model with flexibility the dependence structures and to capture different types of tail behavior. To the best of our knowledge, it is for the first time that all these variables are used to study multivariate extreme dependence between food, energy and financial markets.

The remaining of this paper evolves as follows. The next section introduces the methodology used in this paper. The following one presents data used in this paper and their preliminary analysis. Section 4 discusses results found regarding the extreme dependence between markets by focusing on lower and upper tails. The penultimate section is reserved to the implications of our results for portfolio risk management. The last one concludes and presents the main policy implications of this work.

2. Methodology

2.1. Presentation of copulas:

In this paper, we resort to copula models in order to analyze dependence between food, energy and financial markets and namely extreme dependence. We select the multivariate copula-GARCH approach. Our choice is justified by the advantages of this method in analyzing dependence (Aloui et al., 2014; Embrechts et al., 2003; Jondeau and Rockinger, 2006; Lee and Long, 2009).

In fact, commodity returns have a behavior similar to financial returns which is characterized by non-normal distribution, asymmetry, excess kurtosis, the presence of stylized facts and tail dependencies referring to the dependence during extreme events; which makes the linear correlation coefficient not suitable for the measure of dependence (Artzner et al., 1999).

However, copulas are more flexible in modeling the volatility and dependence structures since they allow a separate modeling of the marginal behavior and dependence structures. Moreover, copulas are invariant to increasing and continuous transformations (Reboredo, 2012). Copula function provides information on both the degree and structure of dependence contrary to simple linear correlation analyses which only look at how prices move together on average across marginal distributions assuming multivariate normality[23].

[23] For more details, see Embrechts et al. (2003).

The concept of copula was first developed by Sklar (1959). It is based on the hypothesis that for a random vector $X = (X_1, X_2, \dots, X_n)'$ having F as the n-dimensional distribution function with marginal distributions $F_1, F_2, \dots, F_n$, there exists a copula C such that :

$$F(x_1, x_2, \dots, x_n) = C(F_1(x_1), F_2(x_2), \dots, F_n(x_n)) \quad (1)$$

If F is an absolutely continuous function and $F_i, i = 1, \dots, n$ are strictly increasing, then the copula can be separately decomposed into two parts in terms of copula density, one related to the modeling of the marginal densities and the other part corresponding to the dependency part.

$$f(x_1, x_2, \dots, x_n) = \left[\prod_{i=1}^{n} f_i(x_i)\right] \times c\big(F_1(x_1), F_2(x_2), \dots, F_n(x_n)\big) \quad (2)$$

where c is the copula density function

Copulas allow also to identify tail dependence measuring thus the probability that two variables are in the lower or upper joint tails of bivariate distributions.

For two continuous random variables X_1 and X_2 having marginal distribution functions F_{X_1} and F_{X_2}, the coefficients for upper and lower tail dependence are defined respectively as follows :

$$\lambda_u(X_1, X_2) = lim_{\alpha \to 1} P\left(X_2 > {F_{X_2}}^{-1}(\alpha) | X_1 > {F_{X_1}}^{-1}(\alpha)\right) \quad (3)$$

$$\lambda_l(X_1, X_2) = lim_{\alpha \to 0} P\left(X_2 \leq {F_{X_2}}^{-1}(\alpha) | X_1 \leq {F_{X_1}}^{-1}(\alpha)\right) \quad (4)$$

For the bivariate case, there is a rich variety of copula families with distinct features allowing to capture different patterns of tail dependence (Joe, 1997; Nelsen, 2006). Table 4.1 below summarizes tail characteristics of some bivariate Elliptical and Archimedean copula families.

	N	t	C	G	F	J	BB1	BB7	RC	RG
Positive dependence	√	√	√	√	√	√	√	√	-	-
Negative dependence	√	√	-	-	√	-	-	-	√	√
Tail asymmetry	-	-	√	√	-	√	√	√	√	√
Lower tail dependence	-	√	√	-	-	-	√	√	-	-
Upper tail dependence	-	√	-	√	-	√	√	√	-	-

Notation of copula families : **N**=Gaussian, **t**=Student's, **C**=Clayton, **G**=Gumbel, **F**=Frank, **J**=Joe, **BB1**=Clayton-Gumbel, **BB7**=Joe-Clayton, **RC**=rotated Clayton (90°), **RG**=rotated Gumbel (90°)

Source: Brechmann and Czado (2013)

Table 4. 1: Tail characteristics of some Bivariate Elliptical and Archimedean copula families

From this table, it is clear that Gaussian and Frank copulas cannot capture tail dependence. Student-t copula allows for symmetric non-zero dependence in the tails dependence with the same probability of occurrence both positive and negative. Investigation of asymmetric tail dependence can be done either through Clayton copula (to catch lower tail dependence) or Gumbel or Joe copulas (to catch upper tail dependence). BB1 and BB7 copulas provide nonzero upper and lower tail dependencies.

For multivariate cases, flexible multivariate distributions are needed. However, standard multivariate copulas suffer from rather inflexible structures for accurately modeling the dependence among larger numbers of variables due to the imposition of strong restrictions on equal dependence with all pairs of variables[24]. In order to overcome such limitations, we resort to vine copulas which perform well compared to standard multivariate copulas and allow accurate estimation of the dependence structure (Bartels and Ziegelmann, 2016; Bekiros et al., 2015; Jondeau, 2016; Nikoloulopoulos et al., 2012).

2.2. Vine copulas:

Vine copulas are one of the most empirically successful tools for studying multivariate dependence. The concept of vines was initially proposed by Joe (1996) and developed in more

[24] More details about drawbacks of multivariate copula modeling with standard classes copulas can be found in Savu and Trede (2010).

detail by Bedford and Cooke (2001, 2002) and Kurowicka and Cooke (2006). It consists on describing multivariate copulas through flexible graphical models. Combined with copulas, vines have proven to be a flexible tool in high-dimensional dependence modeling.

Vine copulas are able to model complex dependency patterns by benefiting from the rich variety of bivariate copulas as building blocks based on the pair-copula construction in which $\frac{n(n-1)}{2}$ pair-copulas are arranged in $n-1$ trees so that to form connected acyclic graphs with nodes and edges allowing to explore multiple dependencies. Hence, this pair-wise construction allows capturing different types of tail behavior and dependency at different levels in the tree. Their statistical breakthrough was due to Aas et al. (2009) who described statistical inference techniques for two classes of regular vines corresponding to Canonical vines (C-vines) and Drawable vines (D-vines). Dißmann (2010) has pointed the direction for constructing regular vines (R-vines) using graph theoretical algorithms.

2.2.1. R-vine copulas:

For R-vines, an efficient method is required in the joint density function for storing the indices of the pair copulas. A method of proceeding has been recently suggested by Kurowicka (2011) and Dißmann (2010). This method consists on specifying a lower triangular matrix and its density is given by:

$$f(x_1,\dots,x_n)=\left[\prod_{k=1}^{n} f(x_k)\right]\times\left[\prod_{i=n-1}^{1}\prod_{j=n}^{i+1} c_{m_{i,i},m_{j,i}|m_{j+1,i},\dots,m_{n,i}}\right] \quad (4)$$

where:

$\left(m_{i,j}\right)_{i,j=1,\dots,n}$ refers to element (i,j) in the matrix representation of the R-vine

More details about theoretical background of regular vines and their properties can be found in the works of Bedford and Cooke (2002), Dißmann et al. (2013), and Kurowicka (2011).

2.2.2. C-vine copulas:

Each tree in a C-vine is a star with one unique node that connects to all other nodes. Considering its structure, C-vine copula is then useful for variables ordering by importance

(Aas et al., 2009). At the start of the first C-vine tree, the first root node models the dependence using bivariate copulas for each pair with respect to one particular variable that is known or analyzed to govern the dependence structure among the other variables in the data set. Conditional on this variable, pairwise dependencies with reference to a second variable are modeled (the second root node). The tree is developed in this way; a root node is chosen for each tree and all pairwise dependencies with respect to this node are modeled conditional on all previous root nodes. In total, there are $^{n!}/_{2}$ different canonical vines. The joint density function with a C-vine decomposition can be written as follows:

$$f(x_1, \dots, x_n) = \left[\prod_{k=1}^{n} f(x_k)\right] \times \left[\prod_{i=1}^{n-1} \prod_{j=1}^{n-i} c_{i,i+j|1:(i-1)}\right] \quad (5)$$

where:

$$\begin{cases} c_{i,i+j|1:(i-1)} \text{bivariate copula densities with parameters } \theta_{i,i+j|1:(i-1)} \\ \text{index } i \text{ passes through the edges in each level of trees} \\ \text{index } j \text{ specifies the level of the tree} \end{cases}$$

2.2.3. D-vine copulas:

A similar process of construction is followed by D-vines by choosing a specific order for the variables. The first tree models the dependence through using pair copulas of the first and second variables, of the second and third variables and so on. In the second tree, the co-dependence analysis can proceed by modeling the conditional dependence of the first and third variables given the second variable and so forth. The same process will be followed for the next tree. Hence, each D-vine tree has a path structure which is useful for temporal variables ordering.

The D-vine density can be constructed as follows:

$$f(x_1, \dots, x_n) = \left[\prod_{k=1}^{n} f(x_k)\right] \times \left[\prod_{i=1}^{n-1} \prod_{j=1}^{n-i} c_{j,j+i|(j+1):(j+i-1)}\right] \quad (6)$$

3. Data

In order to investigate dependence between energy, financial and food markets, we select, for each one of these markets, certain commodities according to data availability. For food market, we consider agricultural commodities which constitute the main products for food in the world and the main crops used as raw materials for biofuel products (corn and wheat) and livestock commodities (live cattle). We look at both crops and livestock because there are concerns over fuel prices driving up feed grain prices and leading to increased input prices for livestock producers. Energy market is represented through crude oil and natural gas commodities. MSCI world stock is considered for financial market. We consider also U.S. exchange rate as a macroeconomic factor since this currency is widely used in international financial transactions and international trading of food, agriculture commodities and crude oil.

Daily prices expressed in U.S dollar of each one of these commodities are observed for the period from 02/12/2005 to 24/04/2015 allowing thus an explanation of the dependence in different economic circumstances. These data are obtained from EcoWin database[25]. Data related to U.S exchange rate are selected by adopting EcoWin database definition which considers this variable as a weighted average of the foreign exchange values of the U.S dollar against the currencies of a large group of major U.S trading partners. The evolution over time of daily prices is presented in figure 4.1 below.

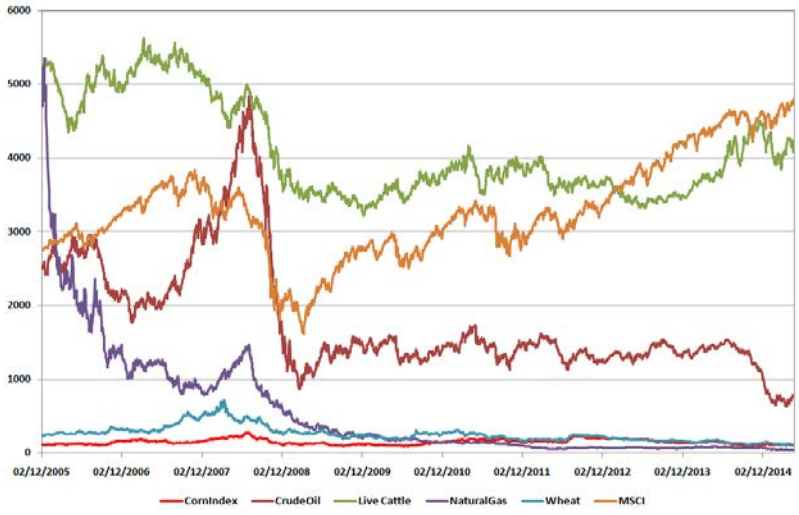


Figure 4. 1: Evolution of daily price series over time

[25] Details about the data considered from this database are indicated in Appendix A.

To make our data series stationary, we transform these data to their returns by applying log first difference. Figure 4.2 below illustrates evolution of these return series over time.

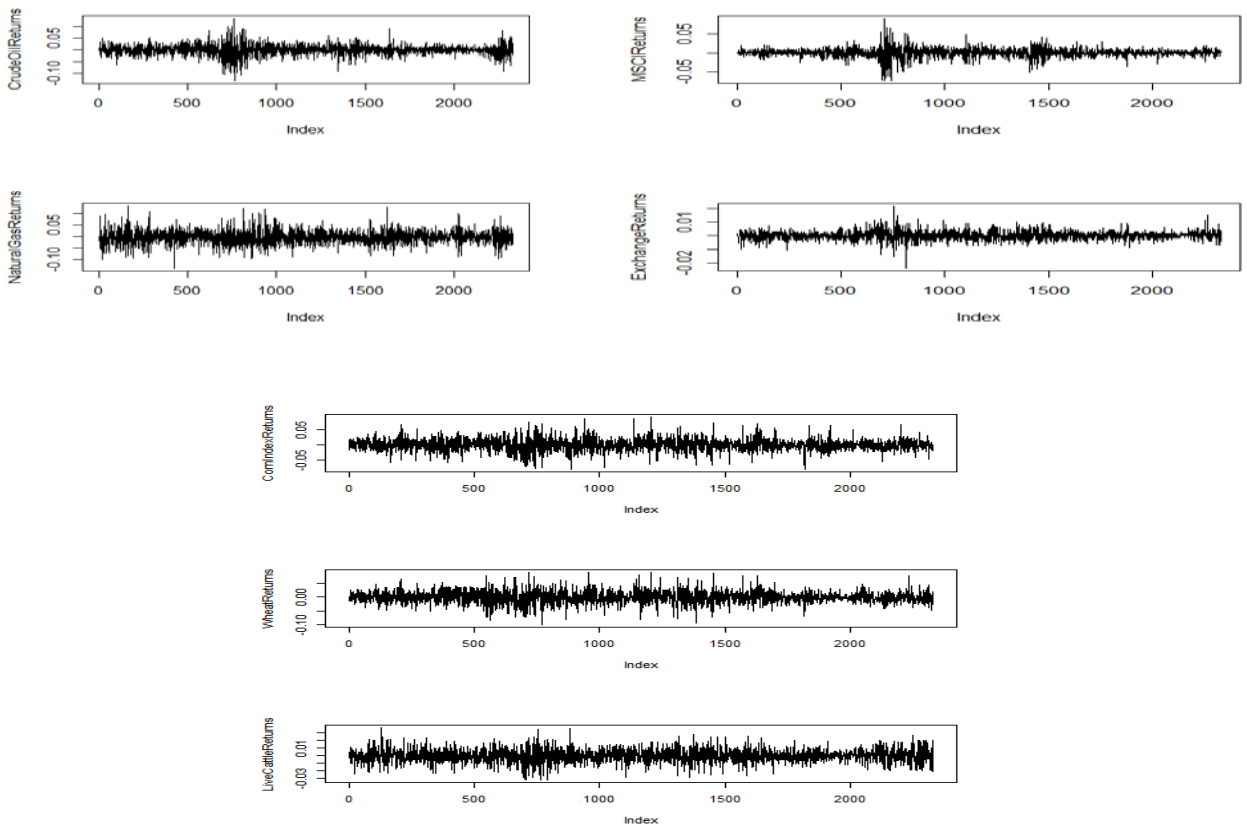


Figure 4. 2: Evolution of daily return series over time

Table 4.2 below provides a statistic description of these returns.

		U.S. Exchange rate	MSCI	Crude Oil	Wheat	Natural Gas	Corn	Live Cattle
Minimum		-2.395e-02	-0.073	-0.131	-0.1	-0.14	-8.128e-02	-3.238e-02
1st quantile		-1.543e-03	-0.004	-0.012	-0.013	-0.02	-1.105e-02	-5.236e-03
Median		0	0.001	0.0003	-0.0007	-0.002	0	4.150e-06
Mean		1.084e-05	0.0002	-0.0005	-0.0003	-0.002	-2.056e-05	-9.413e-05
3rd quantile		1.540e-03	0.005	0.011	0.012	0.016	1.142e-02	4.968e-03
Maximum		2.188e-02	0.090	0.133	0.088	0.134	9.174e-02	3.712e-02
Standard deviation		0.003	0.011	0.029	0.022	0.009	0.02	0.022
Skewness		0.076	-0.475	0.112	-0.239	-0.06	0.035	0.007
Kurtosis		4.215	8.242	1.4	3.67	1.051	1.682	1.593
Jarque-Bera test	**Test statistic**	1729	6689	195.4	1331	108.8	275.3	246.5
	p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16
Augmented Dickey-Fuller test	**Test statistic**	-12.39	-12.89	-12.6	-11.09	-13.83	-12.29	-12.5
	p-value	0.01	0.01	0.01	0.01	0.01	0.01	0.01
ARCH LM test	**Test statistic**	155.3	727.3	169.7	494.5	125.9	138.1	129.3
	p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

Table 4. 2: Descriptive statistics of daily return series

Kurtosis values summarized in table 4.2 show that returns series exhibit leptokurtosis revealing the presence of fat tails. This asymmetry suggests that a decrease in returns is followed by an upsurge in volatility greater than the volatility caused by a rise in returns. MSCI, wheat and natural gas returns are negatively skewed (with long left tail), implying that there is a propensity to generate negative returns with greater probability than suggested by a symmetric distribution; contrary to the rest of commodities which are positively skewed.

Dickey-Fuller test shows that all return series are stationary at 1% significance level. Test for the presence of autoregressive conditional heteroskedasticity is applied through Lagrange Multiplier test. Results indicate that the null hypothesis of no ARCH effects is rejected at 1% significance level. From table 4.2, it is clear that return series are skewed and highly leptokurtic with respect to the normal distribution. Results of Jarque-Bera test also reject the null hypothesis of normality of the returns distributions and imply that the distributions are both leptokurtic and fat tailed. Multivariate normal distribution cannot then be used to analyze return series. Our conclusion is also confirmed by the normal QQ-plots (figure 4.3 below) which illustrate the presence of heavy-tails for each return series. Hence, the tails of the distributions

are of particular importance and have to be studied carefully in order to study the occurrence of extreme movements.

These findings underline the fact that the assumption of independent and identically distributed (iid) sample is not verified which justify our recourse to GARCH model in order to take into account the presence of heteroskedasticity in the marginal series.

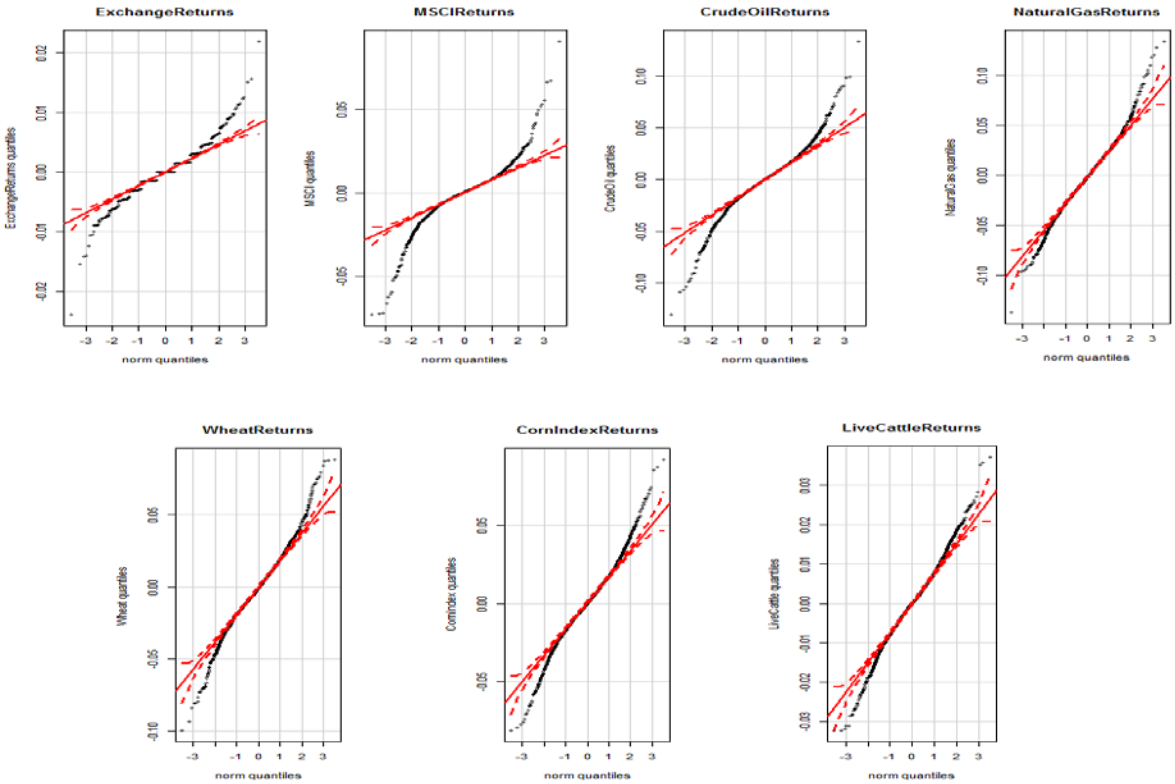


Figure 4. 3: Normal QQ-plots of daily returns

4. Results and discussion

In order to model the dependencies between our markets, we follow two steps. First, we estimate the marginal distribution functions that suit the data. Then, we select a copula that describes the dependence.

We also analyze the results for the overall sample and for two sub-periods (before and after the crisis)[26] allowing thus to check the impact of the most important structural break point corresponding to the 2008 financial crisis on dependence structure.

4.1. Estimation of the marginal distributions

The marginal distributions of each return series will be constructed by ARMA-GARCH model allowing to consider the characteristics of the conditional mean and the conditional variance. In fact, this model is suitable for capturing the stylized facts in returns including mean reversion and seasonality. Each one of our index return series is defined by the following equations.

$$\begin{cases} r_{i,t} = \mu_i + \sum_{j=1}^{p} \emptyset_{i,j} r_{i,t-j} + \sum_{k=1}^{q} \psi_{i,j} \varepsilon_{i,t-k} + \varepsilon_{i,t} \\ \varepsilon_{i,t} = \eta_{i,t} \sqrt{h_{i,t}} \\ h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-i}^2 + \beta_i h_{i,t-i} \end{cases} \quad (8)$$

where μ_i and $h_{i,t}$ are, respectively, the conditional mean and variance given past information

$\varepsilon_{i,t} \rightsquigarrow skewed\ t(\nu_i, \lambda_i)$ to capture the characteristics of asymmetric heavy tail dependence

Hence, for each index, returns are decomposed into a mean μ_i and an error term $\varepsilon_{i,t}$ defined as the product between conditional variance $h_{i,t}$ and a residual $\eta_{i,t}$. We look for many feasible models and select the most suitable one according to AIC criteria. The best model which fits our data is the GARCH(1,1). Then, we use rank method to transform standardized residuals to uniforms so that to obtain uniform marginal distributions.

Table 4.3 below shows results of the estimation of the GARCH(1,1) model for the overall sample. Results related to the GARCH model estimation for the pre-crisis and post-crisis periods are not provided here for brevity but can be provided under request.

[26] The pre-crisis period considered ends on 01/01/2008. The post-crisis period considered is from 02/01/2008 to 24/04/2015 including thus the period of crisis.

Parameter	Commodity	Estimate	Std. Error	t value	Pr(>|t|)
mu	U.S. Exchange rate	-1.23e-06	5.529e-05	-0.022	0.9822
	MSCI	8.7e-04	1.477e-04	5.884	4.00e-09 ***
	Crude Oil	1.8e-04	3.341e-04	0.525	0.5993
	Wheat	-6.7e-04	3.790e-04	-1.764	0.0777
	Natural Gas	-1.6e-03	5.285e-04	-3.075	0.00210 **
	Corn Index	-2.04e-05	3.507e-04	-0.058	0.9536
	Live Cattle	9.77e-06	1.593e-04	0.061	0.9511
omega	U.S. Exchange rate	3.25e-08	1.400e-08	2.324	0.0201 *
	MSCI	1.04e-06	3.594e-07	2.894	0.00381 **
	Crude Oil	1.94e-06	1.008e-06	1.929	0.0537
	Wheat	2.38e-06	1.267e-06	1.882	0.0599
	Natural Gas	1.23e-05	4.301e-06	2.859	0.00425 **
	Corn Index	5.67e-06	2.480e-06	2.286	0.0222 *
	Live Cattle	3.73e-07	2.120e-07	1.759	0.0786
alpha1	U.S. Exchange rate	3.31e-02	4.773e-03	6.944	3.81e-12 ***
	MSCI	9.94e-02	1.505e-02	6.608	3.90e-11 ***
	Crude Oil	5.93e-02	9.816e-03	6.043	1.51e-09 ***
	Wheat	4.7e-02	8.755e-03	5.372	7.77e-08 ***
	Natural Gas	5.9e-02	9.478e-03	6.223	4.86e-10 ***
	Corn Index	5.97e-02	1.217e-02	4.904	9.41e-07 ***
	Live Cattle	3.53e-02	6.208e-03	5.684	1.32e-08 ***
beta1	U.S. Exchange rate	9.64e-01	4.790e-03	201.269	< 2e-16 ***
	MSCI	8.96e-01	1.454e-02	61.633	< 2e-16 ***
	Crude Oil	9.38e-01	1.016e-02	92.390	< 2e-16 ***
	Wheat	9.49e-01	9.332e-03	101.729	< 2e-16 ***
	Natural Gas	9.3e-01	1.145e-02	81.034	< 2e-16 ***
	Corn Index	9.3e-01	1.568e-02	59.166	< 2e-16 ***
	Live Cattle	9.61e-01	6.743e-03	142.515	< 2e-16 ***
shape	U.S. Exchange rate	-	-	-	-
	MSCI	6.3e+00	8.448e-01	7.496	6.55e-14 ***
	Crude Oil	1.0e+01	1.760e+00	5.683	1.33e-08 ***
	Wheat	8.9e+00	1.450e+00	6.124	9.11e-10 ***
	Natural Gas	1.0e+01	1.645e+00	6.078	1.21e-09 ***
	Corn Index	7.19e+00	9.751e-01	7.375	1.65e-13 ***
	Live Cattle	9.16e+00	1.794e+00	5.109	3.24e-07 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 4. 3: Results of GARCH(1,1) model estimation for the overall sample

More detail about the results of this estimation, namely the ACF and QQS-Plot of standardized residuals, are provided in appendix B.

Results of ARCH LM test applied to the standardized residuals issued from the estimation of GARCH(1,1) model for the overall sample indicate that there is no evidence of remaining ARCH effects as it is summarized in table 4.4 below. Results for each one of the two periods (pre-crisis and post-crisis) are not illustrated here for brevity[27].

		U.S. Exchange rate	Corn Index	Crude Oil	Live Cattle	Natural Gas	Wheat	MSCI
ARCH LM-test	**Test statistic**	5.909	10.485	14.446	8.228	25.866	14.667	18.128
	p-value	0.921	0.573	0.273	0.767	0.011	0.260	0.112

Table 4. 4: Test of autoregressive conditional heteroskedasticity on standardized residuals of the overall sample

Goodness-of-fit test of our marginal distributions are verified through the application of Box-Ljung and Kolmogrov Smirnov (K-S) tests[28] which indicate that marginal distributions are independent and uniform and, hence, correctly specified.

4.2. Estimation of copulas

Having correctly specified our uniform margins, we estimate dependence structures by trying different copulas. The best copula fitting our data is selected based on AIC and BIC criteria.

We start by R-vine copulas by selecting in a first step the regular vine tree structure defining which conditioned and unconditioned pairs will be used and we apply it to the overall sample.[29] R-vine trees are selected using maximum spanning tress with absolute values of pairwise Kendall's tau as weights[30], i.e., the following optimization problem is solved for each tree:

[27] These results can be provided under request.

[28] Results are not presented here for brevity. However, they can be provided under request.

[29] For more detail, refer to works of Dißmann et al. (2013); MORALES NAPOLES (2010); Morales-Nápoles et al. (2010) detailing how a triangular matrix can be used to store a regular vine.

[30] More details on the sequential construction method can be found in Brechmann (2010).

$$max \sum_{\substack{edges\ e_{ij}\ in \\ spanning\ tree}} |\hat{\tau}_{ij}| \quad (9)$$

where $\hat{\tau}_{ij}$ the pairwise empirical Kendall's tau

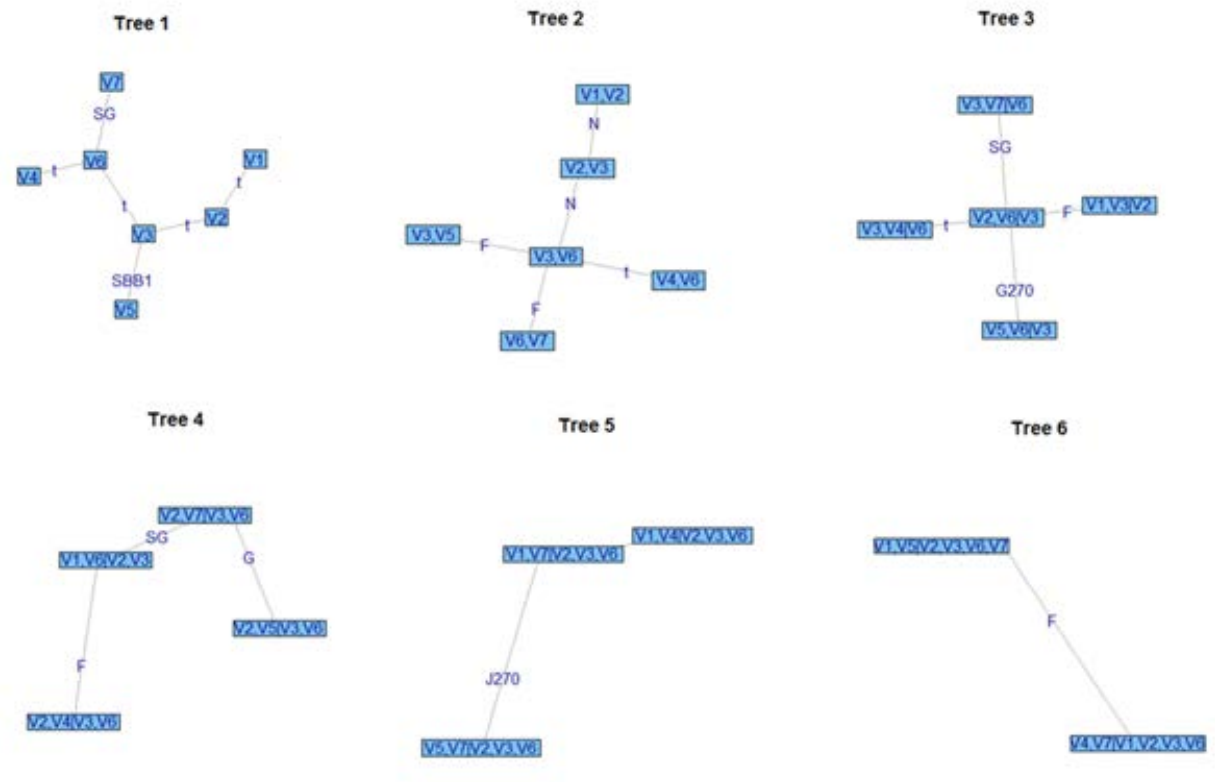
Once our tree structure is selected using vines, we select a bivariate copula family for each pair of variables and use AIC information criterion to determine the copula that best fits the data. Then, we estimate our copula parameters and evaluate the model.

Parameter estimates for the R-vine copulas applied to the overall sample and their tree plots are presented in table 4.5 and figure 4.4 below. Each tree allows to have an additional information about the dependence structure between the variables constituting our sample.

Tree	Pair copula	Copula	Par1	Par2	λ_U	λ_L	τ
T1	$R_{1,2}$	Student	-0.27	13.42	0.0002	0.0002	-0.18
	$R_{2,3}$	Student	0.38	6.19	0.114	0.114	0.25
	$R_{3,5}$	Survival BB1	0.12	1.1	0.122	0.532	0.14
	$R_{3,6}$	Student	0.26	18.2	0.003	0.003	0.17
	$R_{4,6}$	Student	0.66	8.48	0.195	0.195	0.46
	$R_{6,7}$	Survival Gumbel	1.11	0	0.133	0	0.11
T2	$R_{1,3\|2}$	Gaussian	-0.06	0	0	0	-0.03
	$R_{2,6\|3}$	Gaussian	0.08	0	0	0	0.05
	$R_{3,4\|6}$	Student	0.05	14.93	0.0016	0.0016	0.04
	$R_{5,6\|3}$	Frank	0.6	0	0	0	0.07
	$R_{3,7\|6}$	Frank	0.76	0	0	0	0.08
T3	$R_{2,4\|3,6}$	Student	0.04	15.5	0.0012	0.0012	0.03
	$R_{2,7\|3,6}$	Survival Gumbel	1.04	0	0.053	0	0.04
	$R_{1,6\|2,3}$	Frank	-0.36	0	0	0	-0.04
	$R_{2,5\|3,6}$	Rotated Gumbel (270 degrees)	-1.02	0	0	0	-0.03
T4	$R_{1,4\|2,3,6}$	Frank	-0.38	0	0	0	-0.04
	$R_{1,7\|2,3,6}$	Survival Gumbel	1.03	0	0.04	0	0.03
	$R_{5,7\|2,3,6}$	Gumbel	1.01	0	0	0.014	0.01
T5	$R_{4,7\|1,2,3,6}$	Clayton	0.04	0	2.98e-08	0	0.02
	$R_{1,5\|2,3,6,7}$	Rotated Joe (270 degrees)	-1.03	0	0	0	0
T6	$R_{4,5\|1,2,3,6,7}$	Frank	0.09	0	0	0	0.01

1=U.S. Exchange rate, 2=MSCI, 3=Crude Oil, 4=Wheat, 5=Natural Gas, 6=Corn Index, 7=Live cattle

Table 4. 5: Results of the parameter estimates of R-vine copulas



1=U.S. Exchange rate, 2=MSCI, 3=Crude Oil, 4=Wheat, 5=Natural Gas, 6=Corn Index, 7=Live cattle

Figure 4. 4: R-vine copulas tree plots

From tree 1, we detect the presence of two groups, one corresponding to food markets and the other to financial and energy markets. These two groups are linked through crude oil and corn index variables being at the center of the graph. This result is in line with findings in the literature mentioning that crude oil is the best candidate for the transmission of price shocks to both agricultural and financial markets (Lautier and Raynaud, 2012). Dependence between crude oil and corn index variables is positive and low (0.17) and is presented by means of Student t-copula indicating a symmetric tail dependence which is low (0.003). It is revealed from tree 2 that the low positive dependence between MSCI and corn (0.05) passes through crude oil and does not present tail dependencies. However, dependence between crude oil and MSCI presented by means of Student copula is bigger (0.25) and shows symmetric tail dependencies (0.114) either for boom or crash market conditions, which is in line with previous results revealing that crude oil is the most related commodity to stock markets (Filis et al., 2011; Hammoudeh et al., 2004; Jones and Kaul, 1996).

Next, we deal with two particular cases of R-vine copula methods corresponding to C-vine and D-vine copulas which we apply to both the overall sample and the two sub periods previously defined.

Findings issued from C-vine copulas for both the overall sample and the two sub-periods (pre-crisis and post-crisis) are summarized in table 4.6 below and figure B.4.8 in Appendix B for each block. These findings allow us to identify, in each tree, an additional information about the dependence structure between the variables constituting our sample. The division of the sample into two sub- periods allows us to check the change in dependence structure and values after the 2008 financial crisis.

We notice from tree 1 of C-vine copula models that U.S. exchange rate is presented in the middle of the tree meaning that all the other variables depend on it. This finding is in line with results found in the literature mentioning that U.S. exchange rate is a key variable which plays a role in the linkage between agricultural and crude oil prices. Kendall's tau values found in tree 1 show that dependencies between U.S. exchange rate and the rest of commodities are low and negative indicating that a change in prices of these commodities is slightly negatively related to a change in U.S exchange rate explained through the decrease in demand following U.S. dollar exchange rate appreciation. We notice that these dependencies are more important during the post-crisis than the pre-crisis period[31].

Dependencies between U.S exchange rate and MSCI are presented through Student t-copula characterized by symmetric tail dependencies having the same probability of occurrence both positive and negative either during the pre-crisis or the post-crisis period. However, results reveal no extreme market dependence between the pairs U.S exchange rate-crude oil, U.S exchange rate-natural gas and U.S exchange rate-corn which implies the absence of systematic risk in times of extreme USD depreciation. These results are in line with those of Reboredo and Ugando (2014) which underline the utility of the USD in food investments given that it enhances hedging effectiveness and reduces portfolio risk by reducing value at risk and achieving better performance in terms of the investor's loss function with respect to a food-only portfolio. Dependence between U.S exchange rate and wheat is presented by means of Student-t copula during the pre-crisis period showing symmetric upper and lower tail dependencies while these tail dependencies are absent during the post-crisis period where the relation is

[31] Except for natural gas.

presented through Gaussian copula. On the contrary, U.S exchange rate and live cattle present no tail dependencies in the pre-crisis period and symmetric tail dependencies during the post-crisis period, indicating a symmetric dependence either markets are booming or crashing.

Trees from 2 to 6 of C-vine copula models allow us to determine the conditional dependencies between variables.

From tree 2 of C-vine copula models, we note that all dependencies conditional to U.S exchange rate are positive and become stronger during the post-crisis period. Conditional to U.S exchange rate, dependencies between MSCI and crude oil from one side, and between MSCI and wheat from the other side, are presented by means of Student-t copula in the post crisis-period, indicating the presence of low symmetric tail dependencies while these tail dependencies are null during the pre-crisis period. Our findings are in line with those of Paraschiv et al. (2015) dealing with risk measurement of commodity markets which underline the increase in the probability for joint extremes due to the financialization of commodity markets. From the same tree, we find that, conditioned by U.S. exchange rate, there are no tail dependencies between MSCI and corn which relation is presented by means of Gaussian copula. Asymmetric tail dependencies conditional to U.S. exchange rate are detected for the pair MSCI-live cattle which are presented by means of Gumbel copula during the pre-crisis period indicating the presence of upper tail dependence and no lower tail dependence, contrary to the post-crisis period characterized by dependence on the lower tail and no dependence for the upper tail. These asymmetric tail dependencies reveal the presence of dependence in boom market situations during the pre-crisis period while the post-crisis period is characterized by dependence when markets are crashing.

Tree 3 of C-vine copula models shows that dependencies between crude oil and the rest of commodities conditional to U.S. exchange rate and MSCI are positive and are intensified during the post-crisis period[32]. Conditional to U.S. exchange rate and MSCI, dependencies between the pairs crude oil-corn and crude oil-live cattle are presented by means of Frank copula, revealing the absence of tail dependencies during the pre-crisis and post-crisis period. However, for the pair crude oil-wheat, symmetric low tail dependencies are detected during the post-crisis period and are absent for the pre-crisis period.

[32] Except for the dependence between crude oil and natural gas.

Results issued from the application of D-vine copula method for each tree, either for the overall sample or the two sub-periods, are summarized in table 4.7 and figure B.4.9 in Appendix B.

Results of D-vine copula estimation indicate that dependence between MSCI and crude oil is positive, more important for the post-crisis period than the pre-crisis period and is characterized by symmetric tail dependencies for the post-crisis period and no tail dependence during the pre-crisis period. The same dependence structure is found between crude oil and wheat but with lower dependencies. Conditional to crude oil, dependence between MSCI and wheat is positive, with a stronger impact in the post-crisis period and is characterized by the absence of tail dependencies (either lower or upper) for both the pre-crisis and post-crisis periods.

From tree 3, we can observe that, conditional to MSCI and crude oil, dependence between U.S. exchange rate and wheat is negative and is characterized by independence in the tails corresponding to either bearish or bullish extreme situations during the post-crisis period while symmetric tail dependencies are detected for the pre-crisis period.

Tree	Pair copula	Copula family			Par1			Par2			λ_U			λ_L			τ		
		Overall sample	Pre-crisis	Post-crisis	Overall sample	Pre-crisis	Post-crisis	Overall sample	Pre-crisis	Post-crisis	Overall sample	Pre-crisis	Post-crisis	Overall sample	Pre-crisis	Post-crisis	Overall sample	Pre-crisis	Post-crisis
T1	$C_{1,2}$	Student	Student	Student	-0.268	-0.213	-0.279	13.42	9.881	14.714	0.0002	0.002	7.9e-05	0.0002	0.002	7.9e-05	-0.173	-0.137	-0.180
	$C_{1,3}$	Student	Gaussian	Rotated Gumbel (270 degrees)	-0.161	-0.109	-1.117	22.38	0	0	8.05e-06	0	0	8.05e-06	0	0	-0.103	-0.070	-0.105
	$C_{1,4}$	Rotated Gumbel (270 degrees)	Student	Gaussian	-1.078	-0.029	-0.143	0	5.913	0	0	0.031	0	0	0.031	0	-0.072	-0.019	-0.091
	$C_{1,5}$	Rotated Gumbel (90 degrees)	Rotated Clayton (270 degrees)	Rotated Gumbel (90 degrees)	-1.03	-0.090	-1.030	0	0	0	0	0	0	0	0	0	-0.03	-0.043	-0.030
	$C_{1,6}$	Frank	Frank	Gaussian	-0.653	-0.134	-0.123	0	0	0	0	0	0	0	0	0	-0.072	-0.015	-0.079
	$C_{1,7}$	Student	Frank	Student	-0.007	0.052	-0.012	19.24	0	15.708	0.0002	0	0.001	0.0002	0	0.001	-0.004	-0.006	-0.008
T2	$C_{2,3\|1}$	Student	Frank	Student	0.36	0.831	0.425	6.49	0	5.497	0.1002	0	0.153	0.1002	0	0.153	0.235	0.092	0.280
	$C_{2,4\|1}$	Student	Frank	Student	0.131	0.299	0.161	12.31	0	10.310	0.007	0	0.015	0.007	0	0.015	0.083	0.033	0.103
	$C_{2,5\|1}$	Survival Gumbel	Gumbel	Survival Gumbel	1.028	1.016	1.035	0	0	0	0	0.021	0	0.038	0	0.046	0.027	0.015	0.034
	$C_{2,6\|1}$	Gaussian	Gaussian	Gaussian	0.149	0.130	0.159	0	0	0	0	0	0	0	0	0	0.095	0.083	0.102
	$C_{2,7\|1}$	Clayton	Gumbel	Survival Gumbel	0.165	1.031	1.104	0	0	0	0	0.042	0	0.015	0	0.126	0.076	0.030	0.094
T3	$C_{3,4\|1,2}$	Frank	Frank	Student	1.003	0.772	0.159	0	0	15.366	0	0	0.003	0	0	0.003	0.110	0.085	0.102
	$C_{3,5\|1,2}$	Survival BB1	Gaussian	Survival BB7	0.104	0.366	1.108	1.102	0	0.110	0.124	0	0.002	0.533	0	0.130	0.137	0.238	0.105
	$C_{3,6\|1,2}$	Frank	Frank	Frank	1.340	1.249	1.344	0	0	0	0	0	0	0	0	0	0.146	0.137	0.147
	$C_{3,7\|1,2}$	Frank	Frank	Frank	0.8	0.582	0.825	0	0	0	0	0	0	0	0	0	0.088	0.064	0.091

T4	$C_{4,5\|1,2,3}$	Gumbel	Rotated Clayton (270 degrees)	Gaussian	1.040	-0.103	0.113	0	0	0	0.053	0	0	0	0	0	0.039	-0.049	0.072
	$C_{4,6\|1,2,3}$	Student	Student	Student	0.635	0.532	0.664	9.17	7.408	10.938	0.162	0.146	0.147	0.162	0.146	0.147	0.438	0.357	0.462
	$C_{4,7\|1,2,3}$	Frank	Rotated Clayton (270 degrees)	Frank	0.67	-0.032	0.863	0	0	0	0	0	0	0	0	0	0.074	-0.016	0.095
T5	$C_{5,6\|1,2,3,4}$	Frank	Survival Joe	Frank	0.47	1.064	0.493	0	0	0	0	0	0	0	0.082	0	0.052	0.036	0.055
	$C_{5,7\|1,2,3,4}$	Gumbel	Gaussian	Clayton	1.012	-0.058	0.046	0	0	0	0.017	0	0	0	0	2.90e-07	0.012	-0.037	0.022
T6	$C_{6,7\|1,2,3,4,5}$	Survival BB8	Gaussian	Survival BB8	1.358	-0.010	1.378	0.718	0	0.787	0	0	0	0	0	0	0.060	-0.007	0.078

1=U.S. Exchange rate, 2=MSCI, 3=CrudeOil, 4=Wheat, 5=NaturalGas, 6=CornIndex, 7=Live cattle

Table 4. 6: Results of the parameter estimates of C-vine copulas

Tree	Pair copula	Copula			Par1			Par2			λ_U			λ_L			τ		
		Overall sample	Pre-crisis	Post-crisis	Overall sample	Pre-crisis	Post-crisis	Overall sample	Pre-crisis	Post-crisis	Overall sample	Pre-crisis	Post-crisis	Overall sample	Pre-crisis	Post-crisis	Overall sample	Pre-crisis	Post-crisis
T1	$D_{1,2}$	Student	Student	Student	-0.268	-0.213	-0.279	13.42	9.881	14.714	0.0002	0.002	7.9e-05	0.0002	0.002	7.94e-05	-0.173	-0.137	-0.180
	$D_{2,3}$	Student	Frank	Student	0.383	0.900	0.450	6.18	0	5.549	0.115	0	0.162	0.115	0	0.162	0.250	0.099	0.297
	$D_{3,4}$	Student	Frank	Student	0.208	0.787	0.227	8.42	0	7.995	0.033	0	0.041	0.033	0	0.041	0.133	0.087	0.146
	$D_{4,5}$	Student	Rotated Jo (90 degrees)	Student	0.110	-1.066	0.147	16.08	0	17.930	0.002	0	0.001	0.002	0	0.001	0.070	-0.036	0.094
	$D_{5,6}$	Gaussian	Clayton	Gaussian	0.152	0.089	0.178	0	0	0	0	0	0	0	0.0004	0	0.097	0.042	0.114
	$D_{6,7}$	Survival Gumbel	Frank	Survival Gumbel	1.109	0.108	1.148	0	0	0	0	0	0	0.133	0	0.171	0.099	0.012	0.129
T2	$D_{1,3\|2}$	Gaussian	Rotated Clayton (270 degrees)	Rotated Gumbel (270 degrees)	-0.059	-0.089	-1.031	0	0	0	0	0	0	0	0	0	-0.037	-0.043	-0.030
	$D_{2,4\|3}$	Frank	Clayton	Frank	0.516	0.049	0.618	0	0	0	0	0	0	0	7.9e-07	0	0.057	0.024	0.068
	$D_{3,5\|4}$	Student	Gaussian	Survival Gumbel	0.21	0.371	1.103	25.235	0	0	0.0003	0	0	0.0003	0	0.126	0.134	0.242	0.094
	$D_{4,6\|5}$	Student	Survival BB1	Student	0.65	0.298	0.680	9.219	1.374	10.563	0.173	0.604	0.165	0.173	0.344	0.165	0.453	0.367	0.476
	$D_{5,7\|6}$	Gumbel	Frank	Frank	1.018	-0.149	0.326	0	0	0	0.024	0	0	0	0	0	0.017	-0.016	0.036
T3	$D_{1,4\|2,3}$	Frank	Student	Gaussian	-0.48	-0.019	-0.090	0	6.095	0	0	0.030	0	0	0.030	0	-0.053	-0.012	-0.057
	$D_{2,5\|3,4}$	Rotated Gumbel (270 degrees)	Rotated Clayton (90 degrees)	Rotated Gumbel (270 degrees)	-1.021	-0.043	-1.020	0	0	0	0	0	0	0	0	0	-0.020	-0.021	-0.019
	$D_{3,6\|4,5}$	Frank	Gaussian	Frank	0.971	0.162	0.958	0	0	0	0	0	0	0	0	0	0.107	0.104	0.106
	$D_{4,7\|5,6}$	Clayton	Rotated Clayton (270 degrees)	Gaussian	0.046	-0.022	0.043	0	0	0	0	0	0	2.8e-07	0	0	0.022	-0.011	0.027

T4	$D_{1,5\|2,3,4}$	Rotated Joe (90 degrees)	Rotated Clayton (270 degrees)	Joe	-1.023	-0.051	1.012		0	0		0	0.016		0	0	-0.013	-0.025	0.007
	$D_{2,6\|3,4,5}$	Survival Clayton	Survival Gumbel	Gaussian	0.045	1.068	0.011	0	0	0	2.2e-07	0	0	0	0.087	0	0.022	0.064	0.007
	$D_{3,7\|4,5,6}$	Frank	Gaussian	Student	0.713	0.105	0.122	0	0	28.380	0	0	4.4e-05	0	0	4.4e-05	0.079	0.067	0.078
T5	$D_{1,6\|2,3,4,5}$	Rotated Clayton	Frank	Frank	-0.006	0.314	-0.097	0	0	0	0	0	0	0	0	0	-0.003	0.035	-0.011
	$D_{2,7\|3,4,5,6}$	Survival Gumbel	Joe	Survival Gumbel	1.035	1.043	1.042		0	0		0.057	0	0.047	0	0.055	0.034	0.024	0.040
T6	$D_{1,7\|2,3,4,5,6}$	Survival Gumbel	Frank	Survival Gumbel	1.032	0.183	1.040		0	0		0	0	0.043	0	0.052	0.031	0.020	0.038

1=U.S. Exchange rate, 2=MSCI, 3=CrudeOil, 4=Wheat, 5=NaturalGas, 6=Corn Index, 7=Live cattle

Table 4. 7: Results of the parameter estimates of D-vine copulas

5. Implications for portfolio risk management

Based on previous section results related to dependence structure of multivariate commodity markets estimated through vine copula-based ARMA-GARCH model, we focus here on the prevision of the maximum possible loss of a portfolio composed of different types of commodities at a certain quantile level $1-\alpha$ through a commonly used risk measure in financial markets (VaR) defined as follows:

$$VaR_t^{\alpha} = \arg\min_{x\in\mathbb{R}}\{x: P(r_t \leq x) \geq \alpha\},\ 0 < \alpha < 1$$

where r_t is the return of the portfolio at time t defined as $r_t = \sum_{i=1}^{n} w_i\, r_{i,t}$
with w_i the weight of each commodity in the portfolio
and $r_{i,t}$ the return of each commodity in the portfolio at time t

Our choice is argued through previous works in the literature stressing the efficiency and accuracy of this method in systemic risk analysis. As underlined by Paraschiv et al. (2015), adequate risk management tools are compulsory since institutional investors are more and more interested by commodity markets which is manifested by a growth in their investment in commodity indices.

Literature related to the prediction of the portfolio's VaR gets improvement through the use of copula functions for VaR prediction allowing thus to consider the nonlinear correlation of variables composing the portfolio (Cheng et al., 2007; Huang et al., 2009). Vine copula models has the advantage of allowing to describe the relationship among multiple variables contrary to the traditional binary copula functions, which allows to predict the *VaR* of a portfolio composed of multiple variables.

We can list hereafter, as an example and not a limited list, some of the recent studies that have discussed the application of Vine copula in financial risk management and have underlined the accuracy of Vine copula models in VaR forecasting. Hofmann and Czado (2010) find that D-vine copulas provide a better fit since they allow to consider either positive or negative dependencies. They also show that VaR forecasts obtained through the application of D-vine copula model have better accuracy than those obtained from multivariate Student copula model. Maugis and Guégan (2010) show that Vine copula method gives the best portfolio VaR forecasting results compared with traditional GARCH type models and underline its usefulness

in risk management of high dimensional portfolios. Vaz de Melo Mendes et al. (2010) are among the first authors focusing on the applications of pair-copulas in finance for risk management purposes in particular for the construction of efficient portfolio frontiers and the assessment of VaR. Brechmann et al. (2012) discuss how Vine copula models can be employed for active and passive portfolio management.

Arreola Hernandez (2014) combines vine copula (C-Vine) and optimization methods through nonlinear mean-variance quadratic portfolio optimization in order to estimate the minimum risk optimal portfolios of two energy portfolios from the Australian market in the context of the global financial crisis of 2008-2009. His findings indicate that C-vine copula model allows to better capture the overall dependence of the energy portfolios. Bangzheng Zhang et al. (2014) find that historical simulation, mean-variance and multivariate DCC-GARCH methods are not suitable for forecasting the VaR of a portfolio composed of 10 international stock market indices with daily returns observed during the period 2006-2013; contrary to Vine copula models which provide sufficiently accurate VaR forecasts with a superiority of D-Vine copula model compared to the other Vine copula models.

For the prevision of the Vine copula-VaR, we follow different steps. Starting from our results of fitting vine copulas to the multivariate data, we generate 1000 simulations u_i for each commodity using the fitted vine models in order to forecast a day ahead VaR where u_i follows the uniform distribution of (0,1). Then, we convert these simulated uniform marginals to standardized residuals by applying the inverse distribution function $x_i = F_i^{(-1)}(u_i)$. In a further step, we use these standardized residuals for the simulation of returns for each commodity. In the last step, we compute the VaR of the portfolio.

Our results for the prediction of one day ahead Vine Copula ARMA-GARCH VaR at 99% confidence level (either for each commodity alone or for an equal-weighted portfolio) are provided in figure 4.5 below.

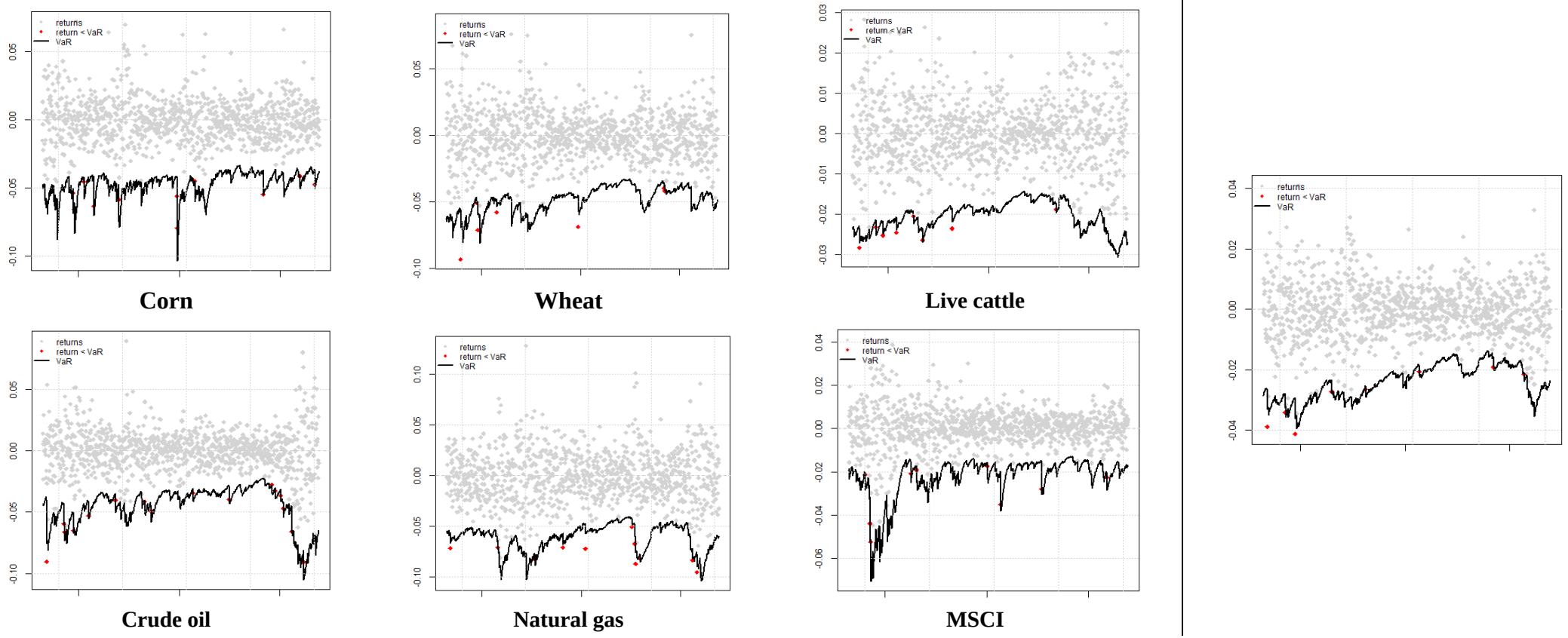


Figure 4. 5: One day ahead VaR at the 99% confidence level estimated through Vine Copula ARMA-GARCH approach

A well-specified VaR model should produce statistical meaningful VaR forecasts. Thus, the proportion of exceedances should approximately equal the VaR confidence level (unconditional coverage) while the exceedances should not occur in clusters but instead independently. In order to check the accuracy of the VaR forecasts, we test if the violation sequence (i.e. the portfolio losses exceeding the VaR forecast) satisfies the unconditional coverage criteria proposed by Kupiec (1995) and the duration-based Weibull test of independence of Christoffersen and Pelletier (2004).

The unconditional coverage test measures whether the number of exceedances is consistent with the confidence level α. The likelihood-ratio test statistic is given by:

$$LR_{uc} = -2log\left[\frac{\alpha^{n_1}(1-\alpha)^{n_0}}{\hat{\pi}^{n_1}(1-\hat{\pi})^{n_0}}\right]$$

where n_1 the number of exceedances, n_0 the number of non-exceedances, α the confidence level at which VaR measures are estimated, and $\hat{\pi}$ the observed failure rate estimated by $n_1/(n_0+n_1)$.

However, this test considers only the frequency of exceedances without taking into account the time when they occur which may lead to reject a model which suffers from clustered exceedances. To encounter this limit, we rely, in addition to this test, on the duration-based Weibull test which allows to take into account clustered exceedances. This test allows to check that duration of time between VaR violations are independent and not cluster.

Results of the unconditional coverage and the duration-based Weibull tests to check the accuracy of the one day ahead VaR at 99% confidence level estimated through Vine Copula ARMA-GARCH are summarized in table 4.8. They underline the accuracy of this approach in the estimation of the VaR with respect to several backtesting criteria.

	Forecasts and outcomes		Unconditional Coverage test		Duration-based Weibull test	
			Null hypothesis (H0): Correct Exceedances		Null hypothesis (H0): Duration between exceedances have no memory	
1% VaR	**Expected Exceedances**	**Actual Exceedances**	**p-value**	**Decision**	**p-value**	**Decision**
Corn	10	11	0.754	Failure to reject H0	0.364	Failure to reject H0
Wheat	10	7	0.314	Failure to reject H0	0.273	Failure to reject H0
Live cattle	10	8	0.510	Failure to reject H0	0.283	Failure to reject H0
Crude oil	10	16	0.079	Failure to reject H0	0.114	Failure to reject H0
Natural gas	10	11	0.754	Failure to reject H0	0.560	Failure to reject H0
MSCI	10	9	0.746	Failure to reject H0	0.513	Failure to reject H0

Table 4. 8: Results of the accuracy tests of VaR estimated through Vine Copula ARMA-GARCH

6. Conclusion

Vine copulas used in this paper have allowed us to study in a flexible manner multivariate dependence, namely extreme dependence, between food, energy and financial markets considering U.S exchange rate.

Our results underline the fact that dependencies between these markets are low, higher during the post-crisis period and pass through crude oil commodity which is the best candidate to the transmission of price shocks to both agricultural and financial markets. Tail dependence behavior is different across markets and between pre-crisis and post-crisis periods. We underline that there is no evidence of symmetric tail dependence between these markets.

Our main findings indicate that dependence between corn and crude oil is characterized by symmetric tail dependence, while, conditional to crude oil, no tail dependence is detected neither in the dependence between corn and MSCI stock market nor in the dependence between wheat and MSCI stock market.

Dependencies conditional to U.S exchange rate reveal the absence of tail dependence between MSCI and corn, the presence of symmetric tail dependence between MSCI and crude oil from one side and between MSCI and wheat from the other side during the post-crisis period, and an

asymmetric tail dependence between MSCI and live cattle characterized by an upper tail dependence during the pre-crisis period and a lower tail dependence in the post-crisis period.

Conditional to U.S exchange rate and MSCI stock market, there are no tail dependencies either between crude oil and corn or between crude oil and live cattle during the pre-crisis and the post-crisis periods, revealing the absence of extreme dependencies. Nevertheless, a symmetric tail dependence between crude oil and wheat is revealed during the post-crisis period, indicating that upper and lower tails have the same probability of occurrence during this period.

Dependence results have important implications for policy makers and investors. In fact, this information is useful in risk management issues since it can be used by investors for a better allocation and optimization of their portfolios (Hedi Arouri and Khuong Nguyen, 2010). As stated by Ang and Bekaert (2002), Das and Uppal (2004), and Rodriguez (2007), asset allocation should take into account changes in tail dependence. Policy makers need it to formulate the appropriate policies namely to ensure food security.

As regard to the prevision of the risk of a portfolio composed of different types of commodities, we underline the accuracy of the Vine copula ARMA-GARCH approach in the prevision of the VaR with respect to several backtesting criteria.

The present work can be extended through the application of vine copulas with time-varying parameters and the consideration of other exogenous factors for the analysis of dependence between these markets.

Appendix A

Data considered[33] **:**

- World, Spot Rates, USD/XDR (SDR Special Drawing Rights), Close
- World, MSCI, Net, World, USD
- World, GSCI, Crude Oil Index, Total Return, Close, USD
- World, GSCI, Wheat Index, Total Return, Close, USD
- World, GSCI, Natural Gas Index, Total Return, Close, USD
- Corn, World, GSCI, Corn Index, Total Return, Close, USD
- World, GSCI, Live Cattle Index, Total Return, Close, USD

[33]Obtained from EcoWin database.

Appendix B

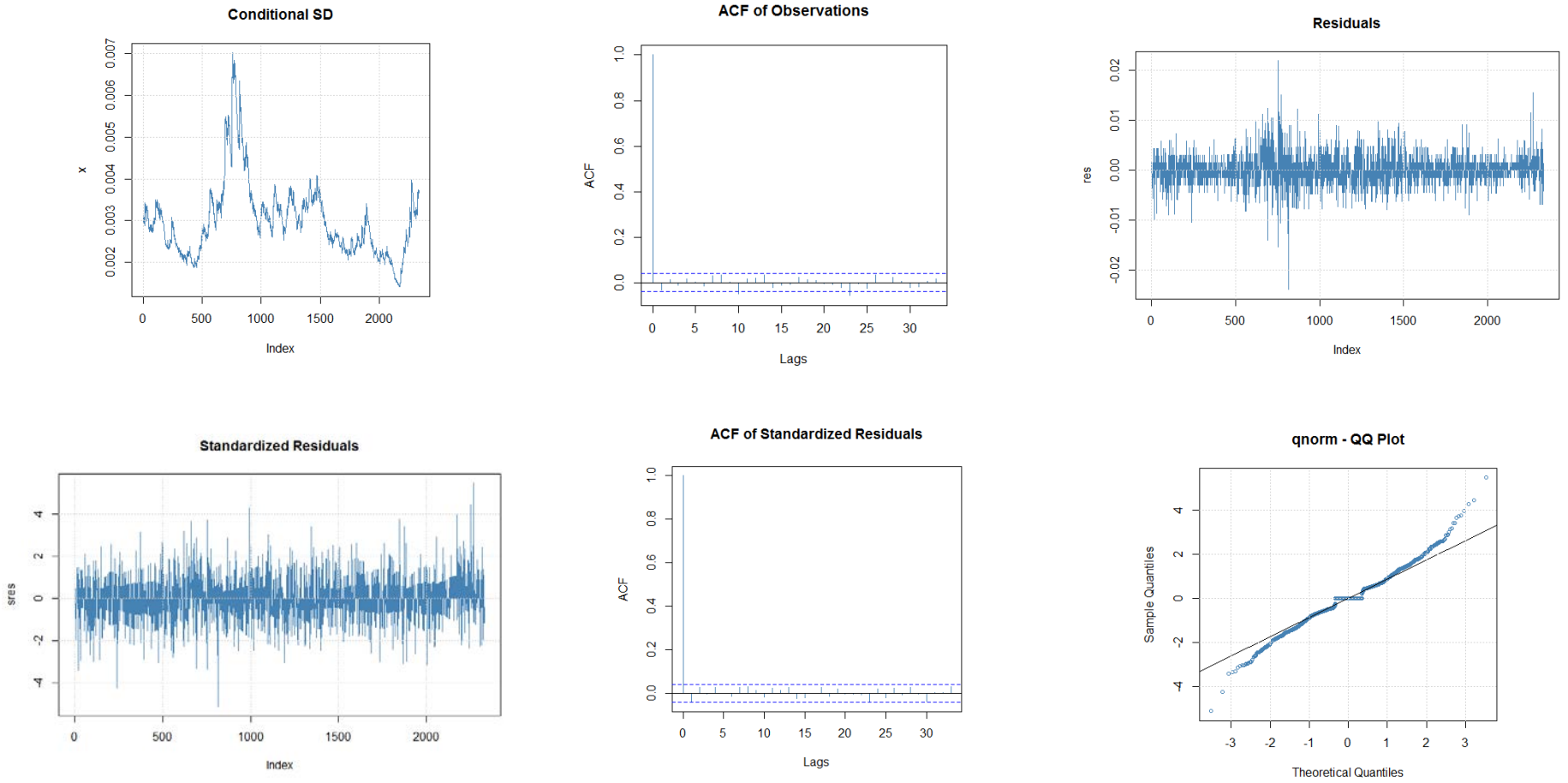


Figure B.4. 1: Results of GARCH(1,1) estimation for U.S. exchange rate returns series

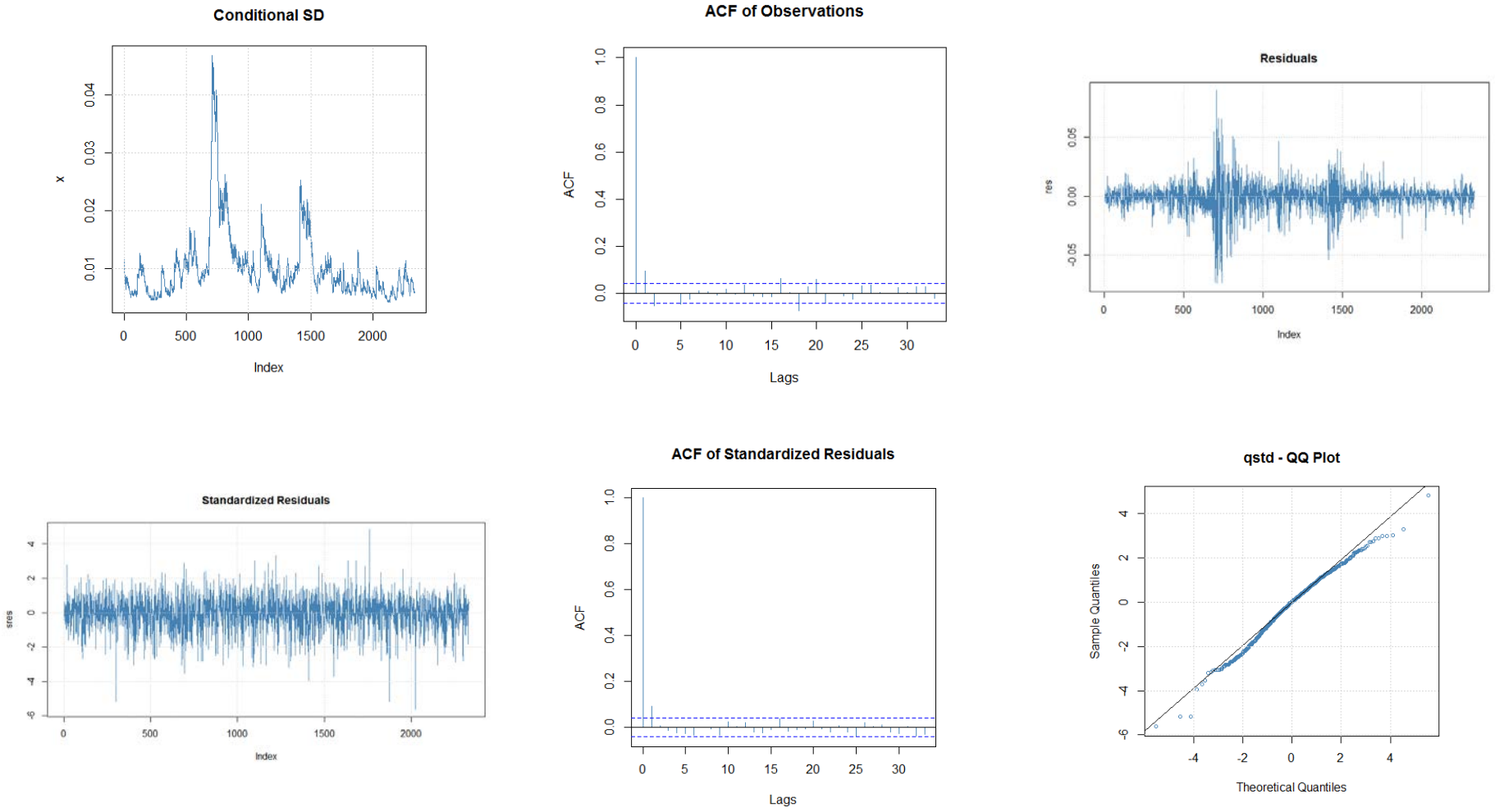


Figure B.4. 2: Results of GARCH(1,1) estimation for MSCI returns series

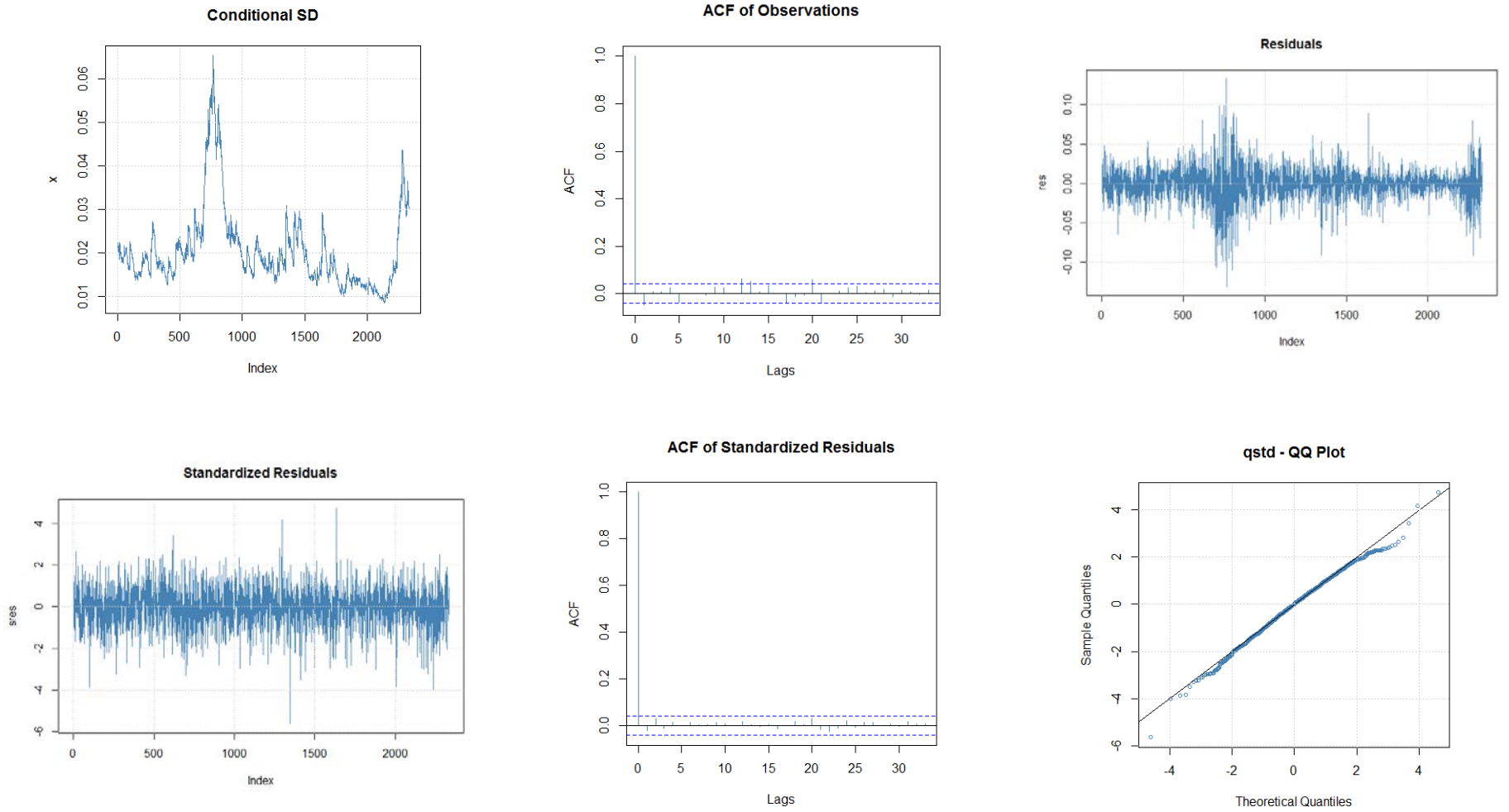


Figure B.4. 3: Results of GARCH(1,1) estimation for Crude Oil returns series

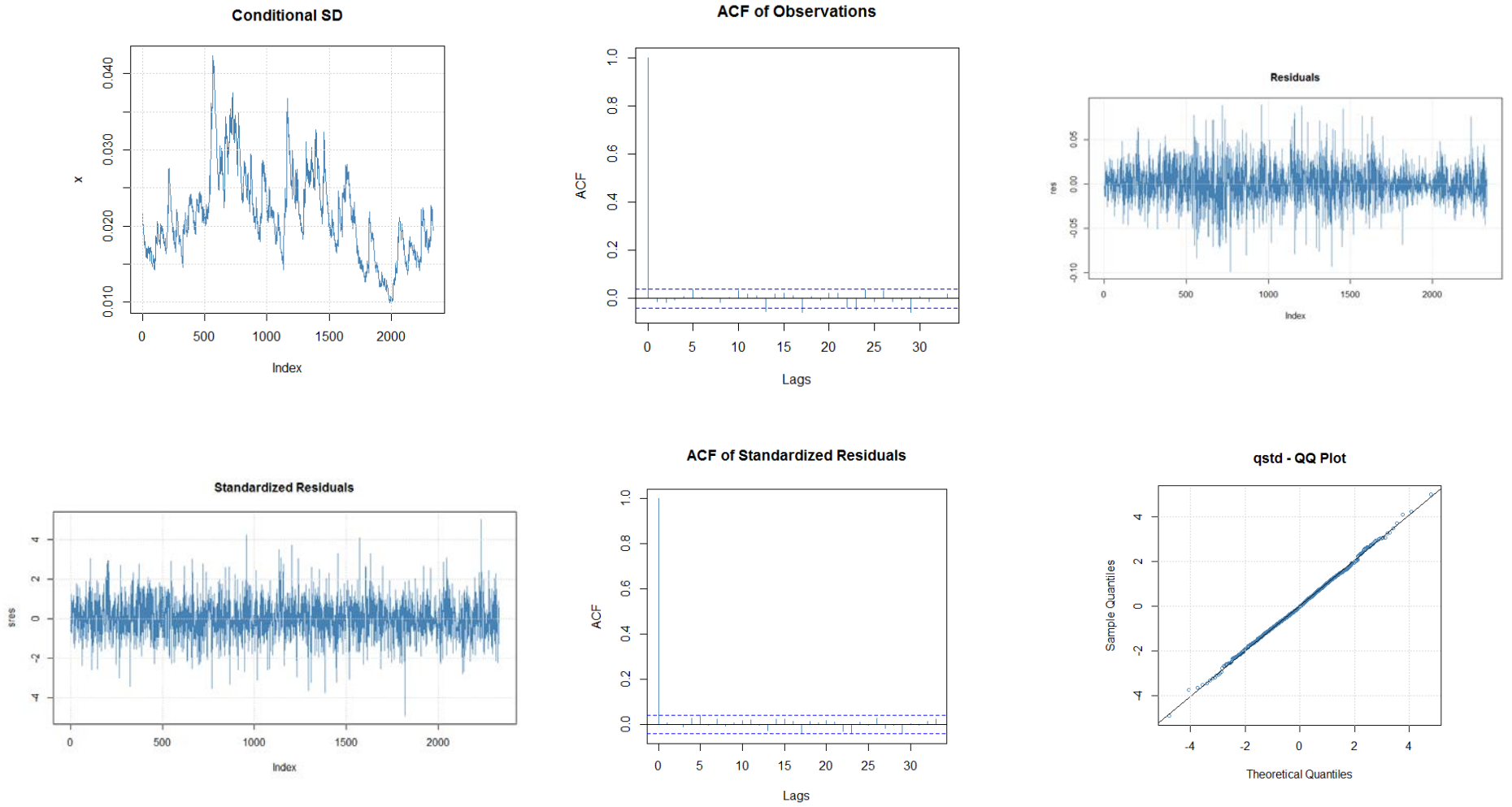


Figure B.4. 4: Results of GARCH(1,1) estimation for Wheat returns series

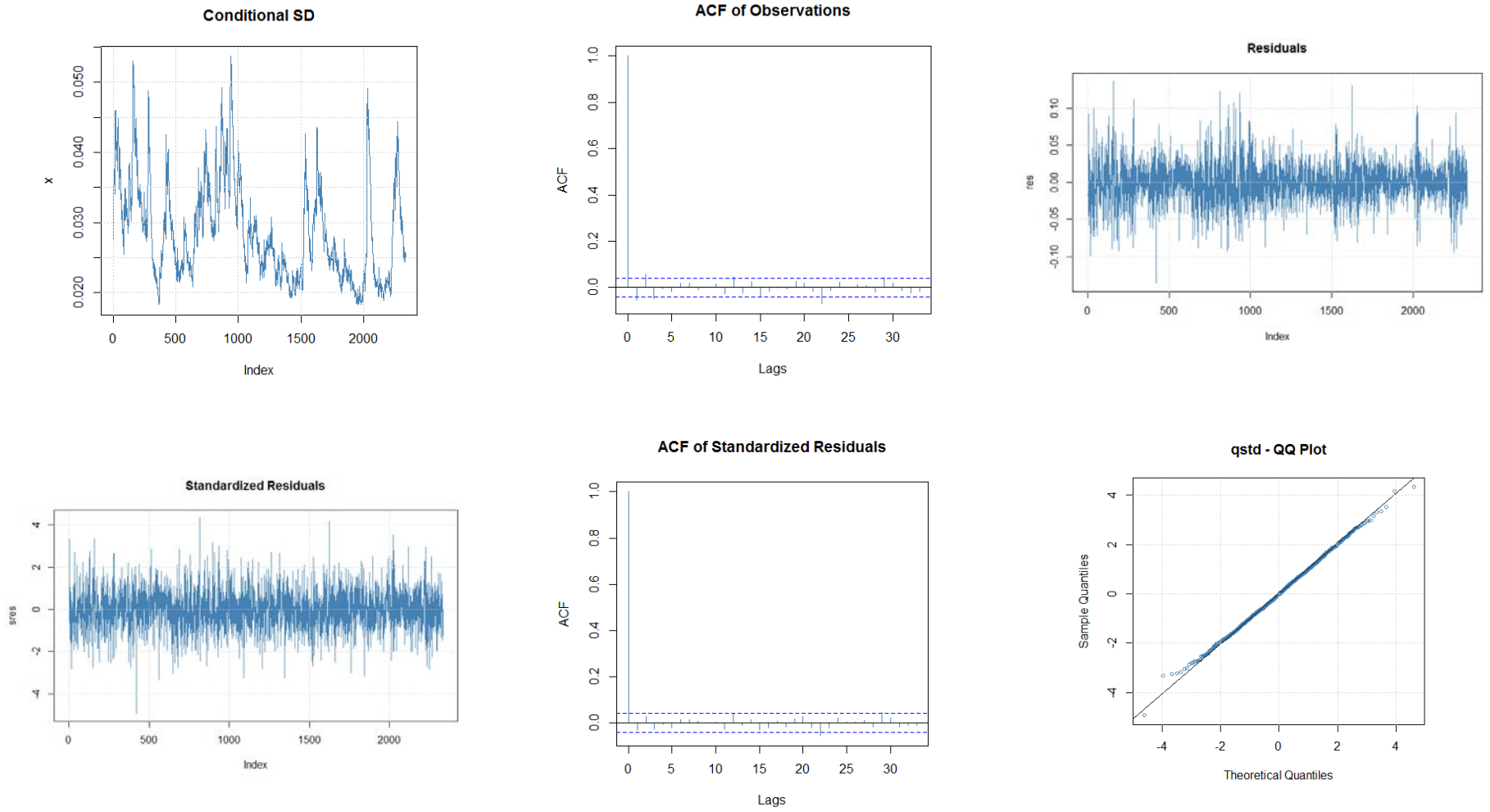


Figure B.4. 5: Results of GARCH(1,1) estimation for Natural gas returns series

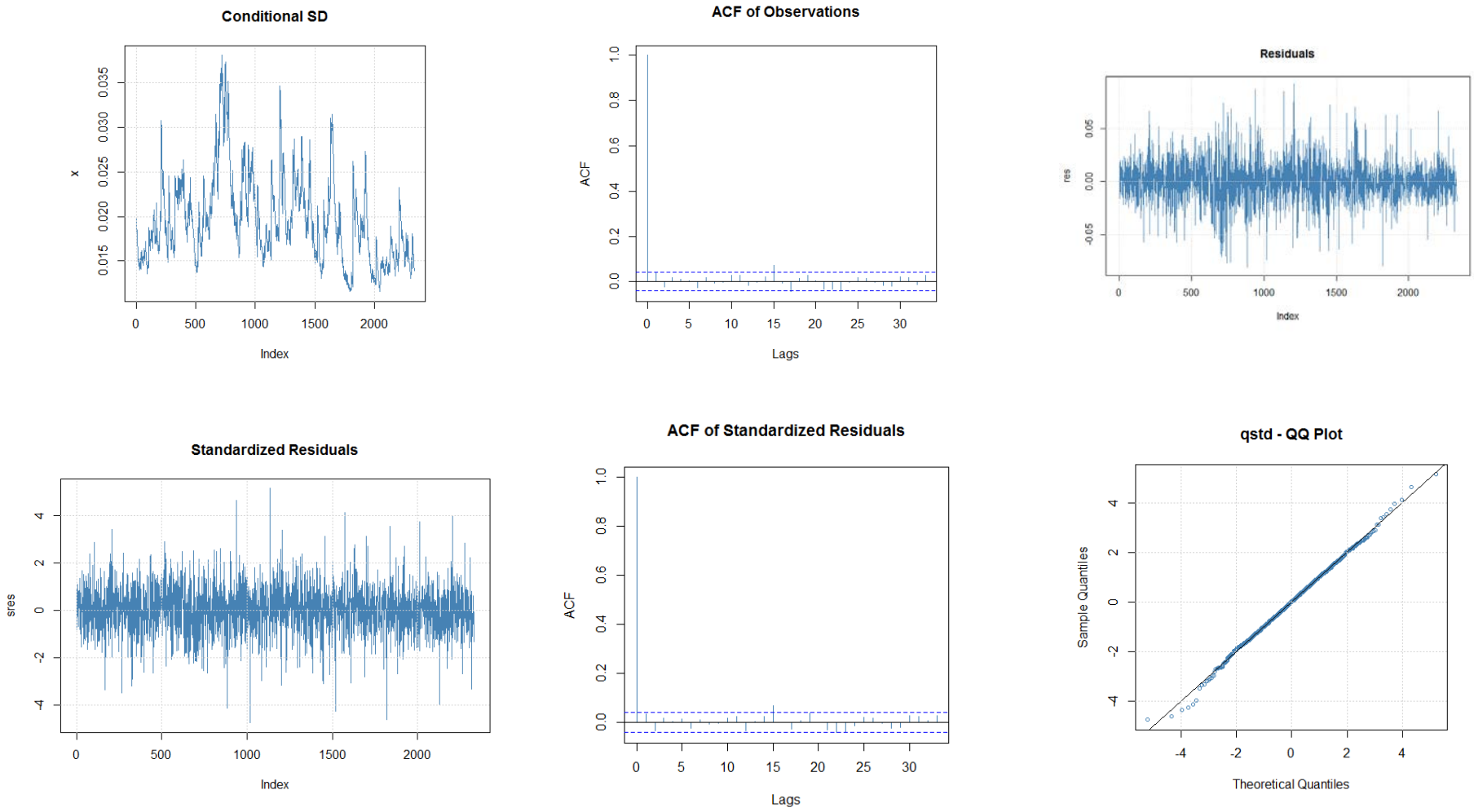


Figure B.4. 6: Results of GARCH(1,1) estimation for Corn index returns series

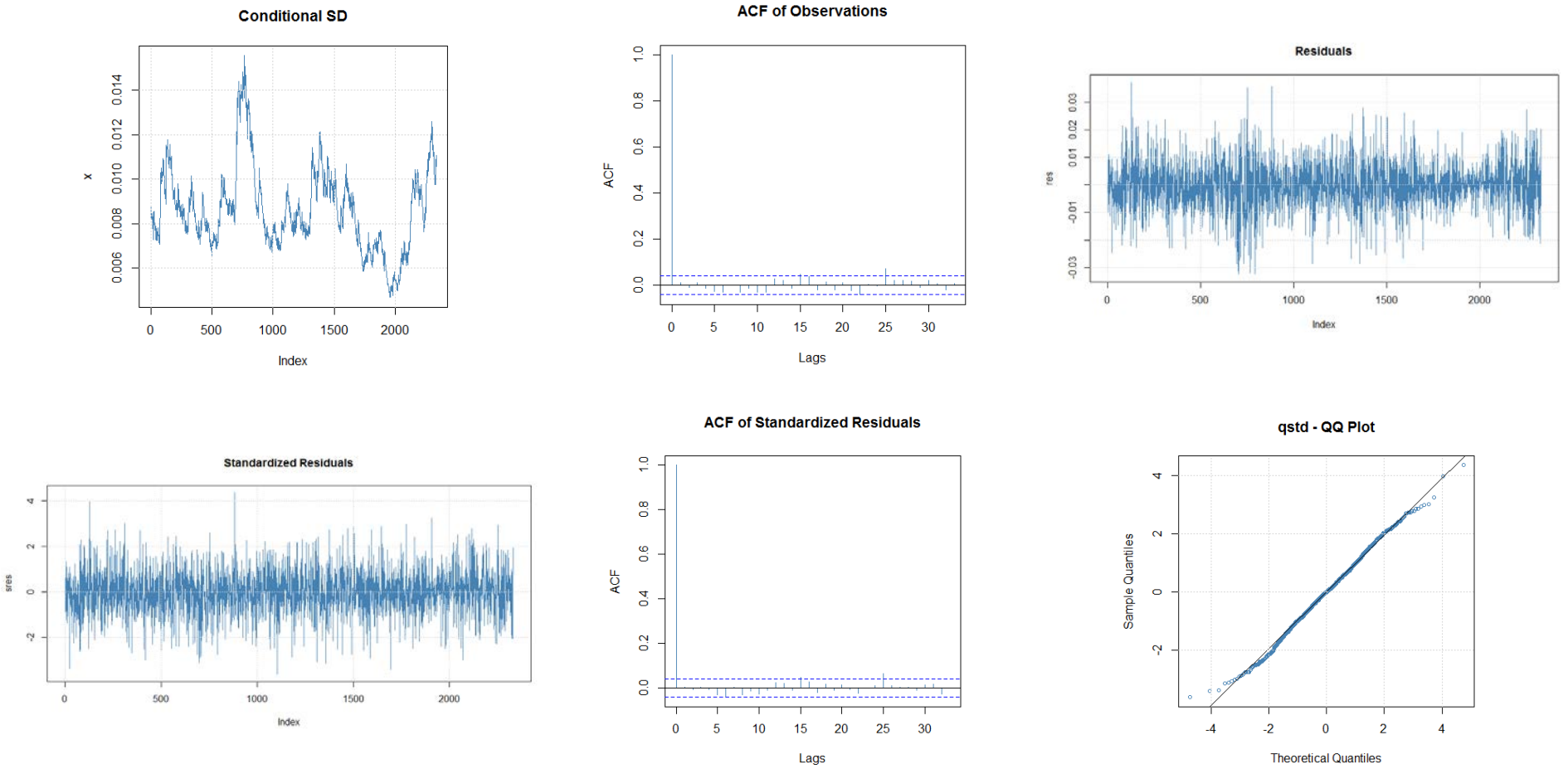
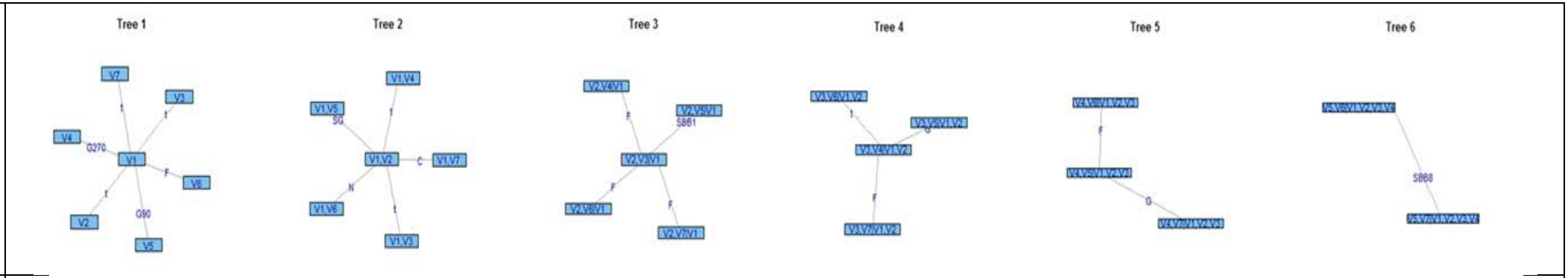
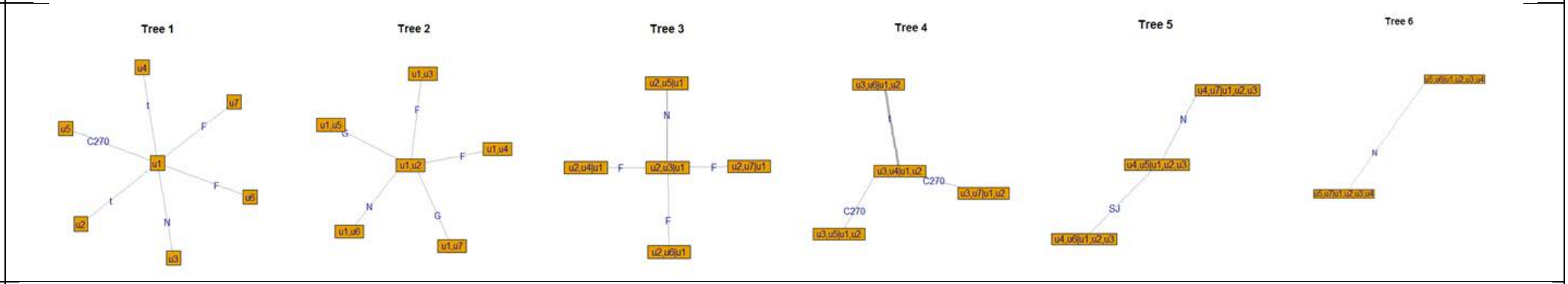
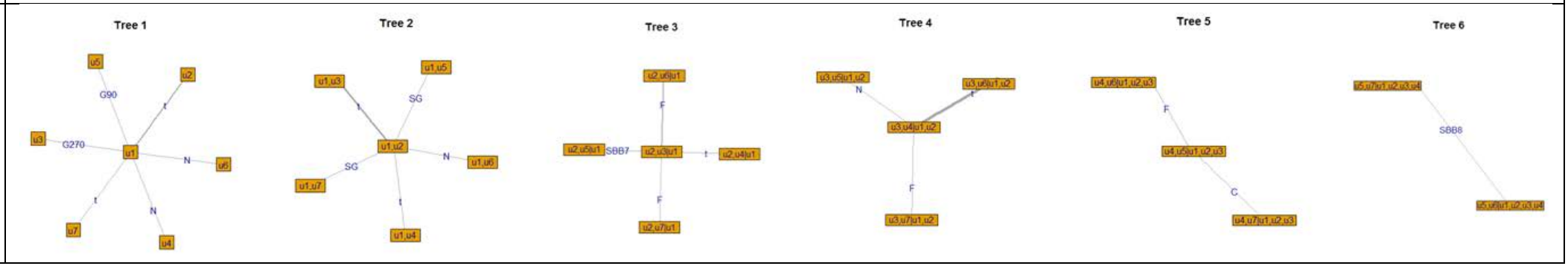
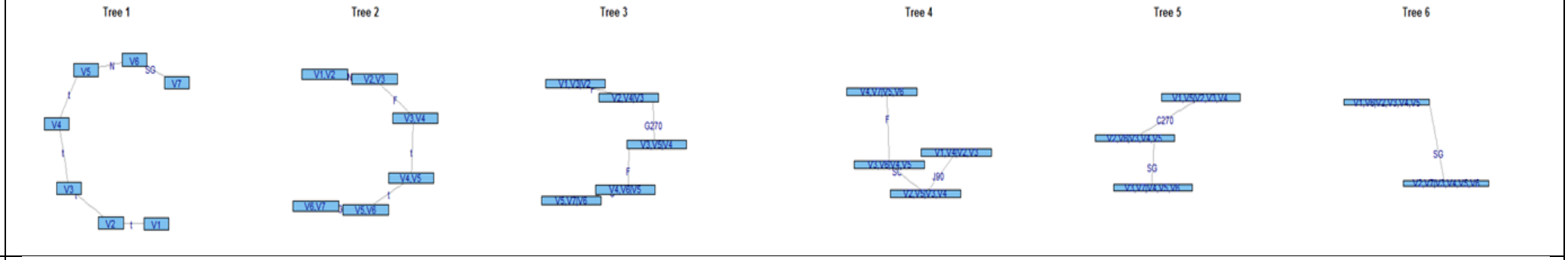
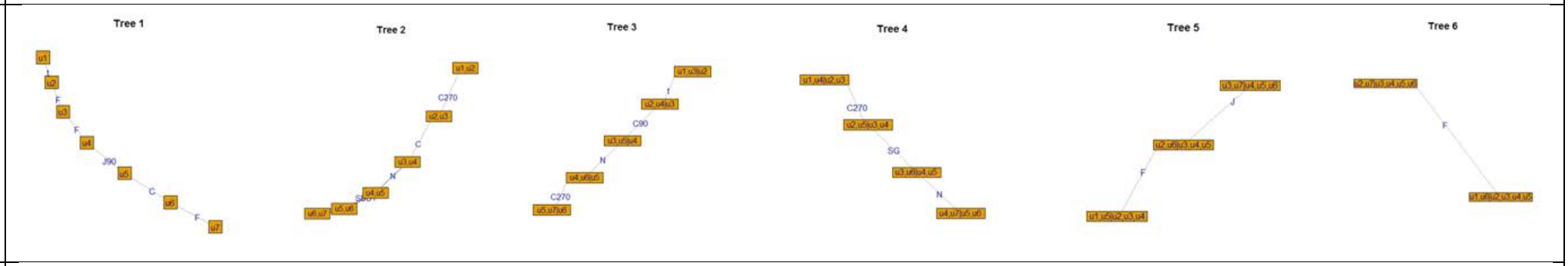
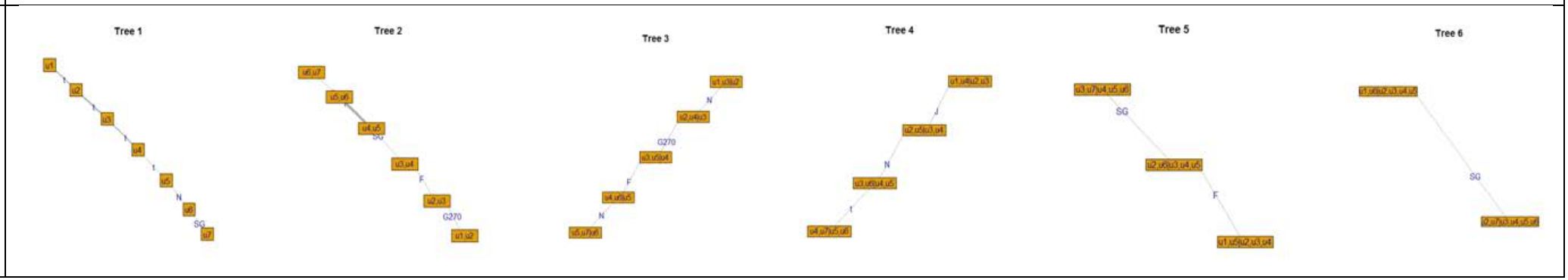


Figure B.4. 7: Results of GARCH(1,1) estimation for Live cattle returns series

Overall Sample	
Pre-crisis	
Post-crisis	

1=U.S. Exchange rate, 2=MSCI, 3=CrudeOil, 4=Wheat, 5=NaturalGas, 6=CornIndex, 7=Live cattle

Figure B.4. 8: C-vine copulas tree plots

Overall Sample	
Pre-crisis	
Post-crisis	

1=U.S. Exchange rate, 2=MSCI, 3=CrudeOil, 4=Wheat, 5=NaturalGas, 6=CornIndex, 7=Live cattle

Figure B.4. 9: D-vine copulas tree plots

General conclusion

This thesis is an attempt to investigate the links between food, energy and financial markets in terms of shocks transmission, which is becoming an important issue namely after the 2008 financial crisis during which sudden changes in price levels and volatilities for these markets have been recorded.

We start the thesis by a general introduction analyzing the situation of these markets characterized namely by a high and similar volatility throughout most of 2008. We also provide some social and economic reasons behind the interest on these markets and their links both for policy makers and investors.

The first chapter reviews some of the main previous works in the literature focusing on the links between energy, financial and food markets.

Some divergences are detected on the links between energy and food markets and are explained by the type of commodities considered, the frequency of data, the time period and the methods applied for the analysis of these links. Transmission of prices between these markets is explained namely by the input and biofuel channels in addition to macro-economic variables. The input channel is related to the use of oil in the production of food commodities (fertilizers, chemical materials, irrigation, fuel and transportation). The biofuel channel is associated to the use of agricultural commodities as feedstock for biofuel production. Exchange rates and financialization are among the macro-economic factors explaining the transmission channels between energy and food markets prices.

With regard to transmission channels between financial and food markets, two polarized views were distinguished (the bubble view and the business-as-usual view). The bubble view explains these channels through commodities financialization, while the business-as-usual view considers that these channels are due to the evolution of market fundamentals. Economic mechanisms linking financial and food markets were mainly explained by the speculative storage, the information discovery role of commodity futures, and the risk sharing function of commodity markets.

Owing to commodity prices volatility, appropriate instruments for price discovery are necessary. Futures contracts are considered as one of these instruments. Hence, the relationship between spot and futures prices is of particular interest. Therefore, we deal in the second chapter with the efficiency of food compared to energy markets during the period 2000-2015. For this finality, and in order to check the eventual presence of structural break points, we apply time varying Hurst exponent and threshold cointegration model to daily spot and futures prices of grains (corn and soybean) and energy markets. We consider 1-month futures contracts since they are in most cases heavily traded, in contrast to far month futures contracts. Our findings in this chapter underline the time-varying characteristic of markets efficiency in presence of structural break points. Results of the rolling Hurst exponent and TVECM estimation show that corn, soybean, and crude oil commodities exhibit long-run efficiency and inefficiency in the short-run. Short-run inefficiencies correspond to the presence of structural break points in the Hurst exponent series explained by financial and economic events namely the 2008 global financial crisis and oil price fluctuations. Depending on the convergence level between spot and futures prices, TVECM reveal the presence of three regimes (lower, middle and upper) for each commodity where the higher divergences between spot and futures prices are recorded in the upper regime.

In order to check the usefulness of futures markets as a tool for risk management, we analyze optimal weights and hedge ratios for spot and futures holdings through the minimum-variance hedge ratio as a hedging strategy. We find a decrease in the hedge effectiveness of futures during periods of inefficiency corresponding to turmoil market conditions. Comparison between grains and crude oil reveals that grain futures provide better effectiveness of the hedging than crude oil futures.

The third chapter is devoted to the investigation of volatilities in these markets and how these volatilities spill over between financial, energy and food markets. It also focuses on shocks transmission in level between these markets. To answer these questions, we resort to a TVP-VAR model with stochastic volatility in addition to volatility spillover indices based on a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering applied to monthly data covering the period 1980-2012. Different types of food commodities are considered (crops, livestock, plantation and forestry) to check if there are particularities for each commodity type.

Concerning volatility spillovers, findings in this chapter underline that stochastic volatilities of the returns of the different types of commodities (food/oil/MSCI) are time-varying with cyclical

ups and downs and similarities in the evolution for some sub-periods even if magnitudes of these evolutions are different. Directional volatility spillovers reveal that volatility spillovers from MSCI stock market have become more important than those from food and energy markets since mid-2008. Net volatility spillovers show different patterns before and after mid-2008. MSCI is found to be a net transmitter of volatility shocks while crude oil and food commodities are net receivers, suggesting that the information about MSCI volatilities can help improve forecast accuracy of crude oil and food commodities. Volatility spillovers from MSCI stock market reach their highest values after mid-2008 and are transmitted during this period with similar ranges to each type of food. After mid-2008, crude oil is receiving volatility shocks from crops more than from other types of foods. Dynamic volatility spillovers highlight the key role played by the 2007-2008 financial crisis in the intensification of volatility spillovers with a most important jump in total volatility spillovers recorded in 01/10/2008 after the failure of Lehman Brothers. Before this date, volatility spillovers were quite limited.

In terms of shocks' transmission from crude oil or MSCI to food commodities, impulse responses show that the impact of these shocks is immediate and a short term one since it is absorbed within a six month period. This indicates a rapid market response mitigating a shock's effect. The impact of shocks of either crude oil returns or MSCI returns on food commodities shows that two main important dates can be identified characterized by increase in this impact corresponding to the great moderation period (the beginning of the 1980s) and the financial crisis (2007-2008). We find that shocks on MSCI stock market returns are positively transmitted to food commodities, underlying the evolution of food and stock returns in the same direction. However, the magnitude of these returns spillovers is low.

Understanding transmission of returns shocks and volatility spillovers among the different markets provides investors with useful information which can be considered in their decisions related to optimal portfolio allocation. To illustrate how this information can be exploited, we look for portfolio diversification by considering two hedged portfolios where the first one is a hedged portfolio of oil and food commodities and the second one is a hedged portfolio of MSCI and food commodities. We find non stable hedge ratios with large fluctuations, requiring the hedgers to frequently adjust their futures positions. Mean values indicate typically low hedge ratios, suggesting that hedging effectiveness involving food and crude oil or food and stocks is quite good; which underlines the diversification benefits provided by food commodities. Thus, inclusion of crude oil or stocks in a diversified portfolio of food commodities increases the risk-adjusted performance of the resulting portfolio. Average values of optimal weights indicate

that, inside each type of food commodity (crops or plantation and forestry products or livestock products), conclusions regarding either more investment has to be done in either food commodities or in oil/MSCI are similar with comparable optimal weights (except for banana). For optimal portfolios composed of oil and food commodities, our results reveal that the majority of the investment has to be done in oil (except for banana). Optimal weights of portfolios composed of food and MSCI stocks show that for crops and plantation and forestry products, investment in these types of food has to be more important than investment in MSCI stock, while conclusions for livestock products are different. In terms of effectiveness of the hedging, our results reveal that, among the crops considered, maize provides the most useful risk management tool for hedging and for diversification of a portfolio composed of oil and food commodities, followed by barley.

In order to investigate extreme dependence between food, energy and financial markets, we resort in chapter four to Vine copulas (R-Vine, C-Vine and D-Vine copulas) allowing us to study in a flexible manner multivariate dependence. We consider daily data of agricultural, livestock and energy commodities in addition to MSCI stock market and U.S exchange rate covering the period 2005-2015. To check the eventual change in dependence structure surrounding the 2008 financial crisis, we divide our sample into two periods (pre-crisis and post-crisis). We find that dependencies between these markets are low and higher during the post-crisis period. Our main findings reveal that there is no evidence of symmetric tail dependence between these markets, contrary to most of previous works in the literature and allow to conclude that crude oil is the best candidate for the transmission of price shocks to both agricultural and financial markets and that dependence between food and MSCI stock market passes through crude oil. Tail dependence behavior is different across markets and between pre-crisis and post-crisis periods. Our main findings indicate that dependence between corn and crude oil is characterized by symmetric tail dependence, while, conditional to crude oil, no tail dependence is detected neither in the dependence between corn and MSCI stock market nor in the dependence between wheat and MSCI stock market. Dependencies conditional to U.S exchange rate reveal the absence of tail dependence between MSCI and corn, the presence of a symmetric tail dependence between MSCI and crude oil from one side and between MSCI and wheat from the other side during the post-crisis period, and an asymmetric tail dependence between MSCI and live cattle characterized by an upper tail dependence during the pre-crisis period and a lower tail dependence in the post-crisis period. Conditional to U.S exchange rate and MSCI stock market, there are no tail dependencies either between crude oil and corn or between crude oil

and live cattle during the pre-crisis and the post-crisis periods, revealing the absence of extreme dependencies. Nevertheless, a symmetric tail dependence between crude oil and wheat is revealed during the post-crisis period, indicating that upper and lower tails have the same probability of occurrence during this period.

Our findings have implications for international investors and portfolio risk managers who have to adapt adequate management tools allowing a dynamic and multivariate analysis of the spillovers among these markets in order to undertake appropriate decisions in terms of portfolios diversification and risk hedging in the different states of the markets. Implications of these results are also noticeable for policymakers who have to implement appropriate policies to react to information transmission namely during turmoil periods of the markets and to take appropriate measures to improve transparency of the tariffs of the different commodities. Owing to the spillovers of volatilities and prices between food, energy and financial markets in the financial crisis period, policy makers are required to create sufficient modeling frameworks for monitoring food markets using indicators on energy and financial markets.

However, this thesis presents some limitations that lie namely in the lack of consideration of other exogenous shocks, such as macro-economic factors, stocks levels, and climatic changes factors that could impact the links between the food, energy and financial markets. The integration of these variables will allow us to obtain a more in-depth analysis of our results.

In perspective, this work can be enriched by the incorporation of these exogenous shocks. It may also be expanded by a study of the links between international and regional food markets prices across countries. Assessment of the socio-economic impact of these findings on the welfare of individuals could also constitute a potential avenue for further research.

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Essais sur la transmission de chocs entre les marchés financier, énergétique et alimentaire : Canaux de transmission, mesure, effets et gestion

Résumé :

Cette thèse par essais a pour objectif de contribuer à une meilleure compréhension de la transmission au marché alimentaire des chocs provenant des marchés financier et énergétique. Le premier essai étudie l'efficience des marchés de céréales comparée à celle du marché énergétique. Les résultats indiquent une efficience des marchés à long terme et une inefficience à court terme expliquée par les conditions économiques globales notamment la crise financière mondiale de 2008, la financiarisation des marchés de commodités et les fluctuations des prix du pétrole. Ils montrent également que les prix à terme des céréales permettent une efficacité de couverture contre le risque meilleure que celle offerte par le pétrole. Le deuxième essai examine les transmissions de rendements et de volatilités entre les trois marchés en considérant différents types de commodités alimentaires. Il révèle l'impact de la crise financière de 2007-2008 dans l'intensification des transmissions de volatilités et de prix entre ces marchés. L'impact des chocs de prix est immédiat et de court terme. Les résultats suggèrent l'efficacité de la couverture du risque par la construction de portefeuilles diversifiés notamment durant la période de la crise financière. S'agissant du troisième essai, il s'intéresse à l'analyse de la dépendance extrême entre ces marchés. Les résultats révèlent des dépendances faibles amplifiées par la crise financière de 2008 et des structures différentes de dépendance de queue selon les commodités alimentaires.

Mots clés: Alimentaire, énergie, financier, efficience, crise financière, financiarisation, efficacité de couverture, risque, portefeuille diversifié, transmission de volatilités, chocs de prix, dépendance extrême.

Essays on the transmission of shocks between financial, energy and food markets: Transmission channels, measurement, effects and management

Abstract:

The aim of this three essays thesis is to contribute to a better understanding of the transmission of shocks from energy and financial markets to food market commodities. The first essay investigates the efficiency of grains compared to energy market. Findings indicate a long-term markets efficiency and show the presence of short-term inefficiencies explained by global economic conditions namely the 2008 global financial crisis, commodities markets financialization, and crude oil prices fluctuations. They also show that grains futures allow a better hedge effectiveness than crude oil futures. The second essay studies returns and volatilities transmission between these markets considering different types of food commodities. Results underline the impact of the 2007-2008 financial crisis in the intensification of returns and volatilities transmissions between these markets. Price shocks are immediate and short-term. Results suggest hedge effectiveness by the construction of diversified portfolios namely during the financial crisis period. On the third essay, extreme dependence between these markets is analyzed. Results suggest low dependencies intensified by the 2008 financial crisis and different tail dependence structures according to food commodities.

Key words: Food, Energy, Financial, efficiency, financial crisis, financialization, hedge effectiveness, risk, diversified portfolio, volatilities spillovers, prices shocks, extreme dependence.

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