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Présentée par

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PRIX DES ENERGIES ET MARCHES FINANCIERS: VERS UNE FINANCIARISATION DES MARCHES DE MATIERES PREMIERES

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Contents

Introduction générale

Le commencement de toutes les sciences, c'est l'étonnement que les choses sont ce qu'elles sont.

Aristote, in Metaphysics.

Les marchés des énergies, dans leur conception générale, englobent un certain nombre de commodités ayant chacune des spécificités propres. Nous pouvons généralement les classer en deux catégories distinctes:

- Les énergies de type "fuel": pétrole, gaz, charbon et leurs dérivés;
- Le marché de l'électricité.

La raison de cette classification tient autant à la nature spécifique de chacun de ces marchés, qu'au rythme historique avec lequel ils se sont ouverts à la concurrence. Les marchés de type "fuel", et plus précisément les marchés du pétrole et du gaz se sont transformés en des marchés concurrentiels de gros dans les années 1980. Le marché de l'électricité s'est quant à lui ouvert à la concurrence dans plusieurs pays au milieu des années 1990.

Malgré leurs différences fondamentales, ces marchés impliquent trois niveaux d'activités traditionnelles communs: production, distribution et consommation. Initialement, ces activités étaient organisées par une seule entité qui contrôlait l'ensemble du système local de distribution dans un contexte monopolistique. L'inefficience apparente de ce fonctionnement a donné lieu à une dérégulation progressive des différents marchés entrainant un dégroupage des services et la création de marchés jouant le rôle d'intermédiaire. L'objectif principal de cette initiative fût bien sûr de dissoudre les monopoles en assurant une sécurité d'approvisionnement de l'énergie à un prix abordable à tous les consommateurs dans le respect de la protection de l'environnement et de la promotion d'une concurrence non déloyale.[1]

Au-delà de ces aspects concurrentiels, ce processus de dérégulation a également donné lieu, pour l'ensemble des marchés énergétiques, au développement progressif de marchés dérivés et d'instruments de couverture très sophistiqués (*options*, *swaps*,...) rendant les transactions toujours plus complexes, et avec elles une participation croissante d'intervenants aux multiples horizons. En effet, aux prix comptants dits *spot*, représentant l'état du marché pour une transaction déterminée, en un lieu géographique et à un instant donnés sans présager des conditions futures, se sont ajoutés des marchés plus élaborés faisant intervenir la notion d'anticipation temporelle: les prix *futures* et *forward*. Le marché des *futures*, contrairement au marché *spot*, constitue une anticipation dans le futur du prix comptant compte tenu de l'information disponible à une date donnée. Ce marché standardisé apparaît être étroitement lié au marché du sous-jacent dans la mesure où la relation entre prix comptants et prix à terme est rendue possible par un phénomène de propagation des chocs d'un marché à l'autre. D'une manière générale, l'utilité de ces marchés *futures* réside dans leurs capacités de valorisation des livraisons futures conditionnelles à l'information disponible, dans l'amélioration de la gestion des stocks, mais aussi et surtout dans l'autorisation d'opérations de couverture de risques.[2] Un investisseur dit physique, actif sur le marché du pétrole, va alors pouvoir

[1] Voir Hansen et Percebois (2011).

[2] En effet, la base (la différence entre le prix au comptant et le prix à terme) tend à devenir nulle à mesure que l'on s'approche de l'échéance du contrat considéré. Les pertes sur le marché sous-jacent peuvent alors être compensées par les gains sur le marché à terme, et réciproquement.

effectuer des opérations de couverture en prenant position sur le marché physique tout en se couvrant sur les marchés *futures*.

Le prix *forward*, quant à lui, malgré de nombreuses similarités avec les futures, a la spécificité d'être plus opaque et plus sujet à des comportements de manipulation. En effet, contrairement aux prix *futures*, le marché *forward* n'est pas un marché où les transactions sont standardisées et où les prix sont publiquement et gratuitement disponibles. Ils se caractérisent davantage comme des échanges bilatéraux de contrats sur mesure. Il est alors fréquent d'avoir des situations où les opérateurs de marché de gré à gré prennent des positions en totale opacité. Le développement de ces différents marchés des dérivés s'est accompagné d'une modification des stratégies d'investissement. Aux investisseurs dits "commerciaux" qui produisent de l'énergie et utilisent les marchés dérivés pour se protéger contre les risques physiques, viennent s'ajouter des investisseurs "non commerciaux ou institutionnels", qui, n'ayant aucune considération fondamentale, se protègent via des instruments sophistiqués contre les fluctuations des marchés des actions en diversifiant leurs portefeuilles par des actifs de type commodités (Creti et al., 2013). Cela a parfois pour conséquence de rendre les prix des commodités en totale déconnexion de leurs fondamentaux.

De par l'uniformisation des contrats sur lesquels ils portent, les prix à terme servent cependant souvent de base à la valorisation des contrats sur les marchés physiques, au comptant comme en différé. En outre, la structure par terme des prix permet, pour un actif donné, l'existence d'une valorisation sur plusieurs maturités rendant le fontionnement des marchés des énergies similaire à celui des marchés financiers traditionnels. S'intéresser aux prix *forward* des commodités c'est alors mettre en exergue les liens potentiels existants entre le monde de l'énergie et le monde de la finance. Le développement de ces instruments et les phénomènes qui les accompagnent se trouvent dès lors au coeur de nombre de questions académiques et publiques récentes liant les marchés des commodités aux marchés financiers.

Ce phénomène en marche au sein des marchés énergétiques tend à modifier la nature profonde et intrinsèque des prix. En effet, partant d'un constat historique, depuis plusieurs décennies, les prix des énergies *spot* et à terme sont sujets à une volatilité croissante[3] pesant considérablement sur l'ensemble de l'économie.[4] Comparée aux prix des autres matières premières (comme, par exemple, les métaux précieux, ou encore les produits agricoles), l'évolution des produits énergétiques et principalement celle du pétrole, du gaz et de l'électricité est apparue exceptionnellement incertaine, tant à long terme qu'à court terme. Comme illustrée par la Table 1, cette volatilité des prix énergétiques s'est accrue sensiblement sur l'ensemble de la période 1980-2010, et plus significativement depuis le début des années 2000 renforçant l'incertitude ambiante sur les marchés physiques, sans commune mesure avec les autres marchés de commodités. En comparaison, cette évolution est d'un ordre de grandeur supérieur à celles constatées pour certaines séries macroeconomiques ou financières, ainsi que l'illustrent les figures 0-1, 0-2, 0-3, et 0-4, retraçant respectivement la volatilité des séries de rendements du prix du pétrole WTI (West Texas Intermediate), du Nasdaq, du Standard & Poor's, ainsi que du taux de change dollar/euro depuis le début des années 2000. L'évolution comparée de la volatilité de chacune des séries met en lumière le caractère extrêmement erratique des prix du pétrole.

Couplée à cette intensité accrue, les prix des énergies et plus particulièrement ceux du pétrole présentent des mouvements brusques d'amplitudes très élévées. Ce phénomène d'envergure internationale semble s'étendre à d'autres matières premières généralement moins enclines à de fortes perturbations. Quelles pourraient être les raisons économiques expliquant cette dynamique? Dans un contexte économique global, cette question d'intérêt public acquiert toute son importance tant les dommages sur l'économie réelle d'une forte variation des prix des matières premières peuvent être conséquents

[3] Voir Regnier (2007).

[4] Nombre de travaux académiques ont en effet mis en avant l'impact des prix des énergies sur l'économie réelle (Sadorsky (1999), Hamilton (2003), Edelstein et Kilian (2007), Kilian (2008), ...).

(voir les travaux de Hamilton (2003), Edelstein et Kilian (2007), Kilian (2008)). D'un point de vue macroéconomique, les variations des prix des énergies peuvent agir sur les déséquilibres des comptes courants à l'échelle mondiale, ainsi que sur les positions extérieures nettes des pays. Une augmentation substantielle des prix du pétrole, par exemple, est identifiée comme un transfert de richesses des pays importateurs vers les pays exportateurs créant un déséquilibre courant entre offreurs et demandeurs via le canal commercial et les flux internationaux de capitaux. Ces déséquilibres sont d'autant plus importants compte tenu du contexte d'épuisabilité des ressources dans lequel ils s'inscrivent.[5]

En outre, l'impact relatif des prix des énergies sur l'économie réelle est aussi et surtout conditionné par le *mix*, la dépendance énergétique et l'intensité de la consommation et de la production des pays, ainsi que par la manière dont les économies s'ajustent à court comme à long terme suite à des chocs des prix de l'énergie. Pour des économies ouvertes telles que les économies de la Zone franc par exemple, cette volatilité des prix énergétiques et leurs capacités d'absorption des chocs constituent un enjeu majeur de politique économique, compte tenu des nombreuses implications, notamment sur la gestion des finances publiques ou la sécurité alimentaire. Cet enjeu est d'autant plus crucial que ces pays ne disposent généralement pas de la taille nécessaire pour influer sur la détermination des prix internationaux (situation de *price taker*) et en subissent donc directement les variations. L'importance des enjeux associés à cette extrême volatilité des prix et les causes profondes de ces mouvements expliquent la position adoptée par la France à ce sujet lors de sa présidence du G20 en 2011 .

Aux Etats-Unis, cette question fait également l'objet de nombreux et vifs débats au parlement américain, notamment depuis l'instauration en Juillet 2010 par le Président Obama du *Dodd-Frank Wall Street Reform and Consumer Protection Act* vis-

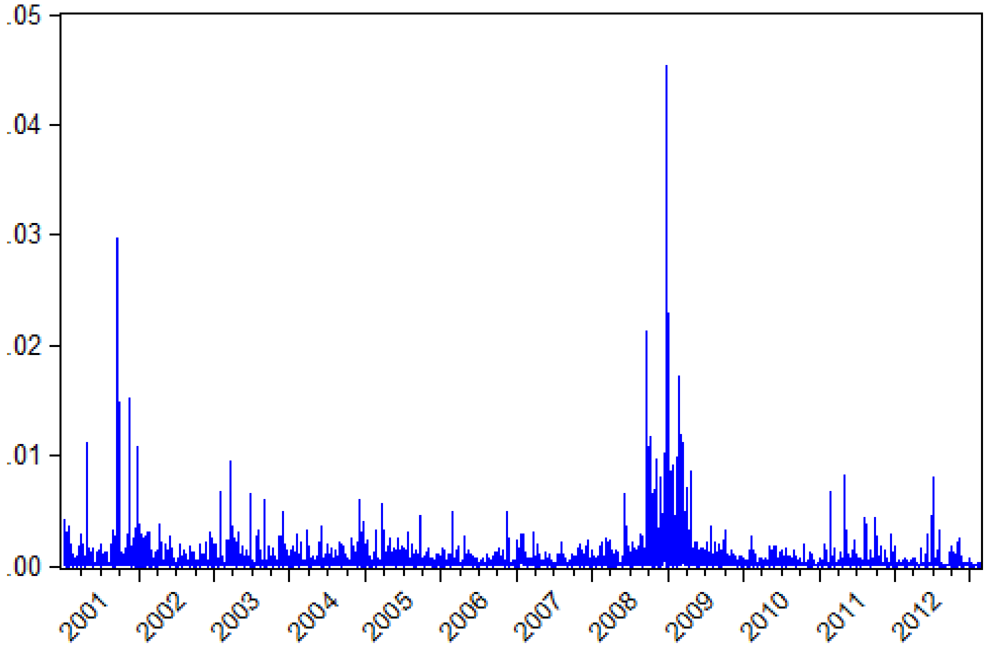
[5] Voir Brown et Yücel (2002), Jones, Leiby et Paik (2004), Lardic et Mignon (2006), et Lescaroux et Mignon (2008).

Table 1: **Evolution de la volatilité supra-annuelle des prix depuis 1980, par catégorie de produits (source FMI et Banque de France).**

	1980-1989	1990-1999	2000-2010
Produits énergétiques	19.43	18.32	34.90
Métaux	20.24	17.70	29.90
Produits agricoles	17.07	16.33	18.10

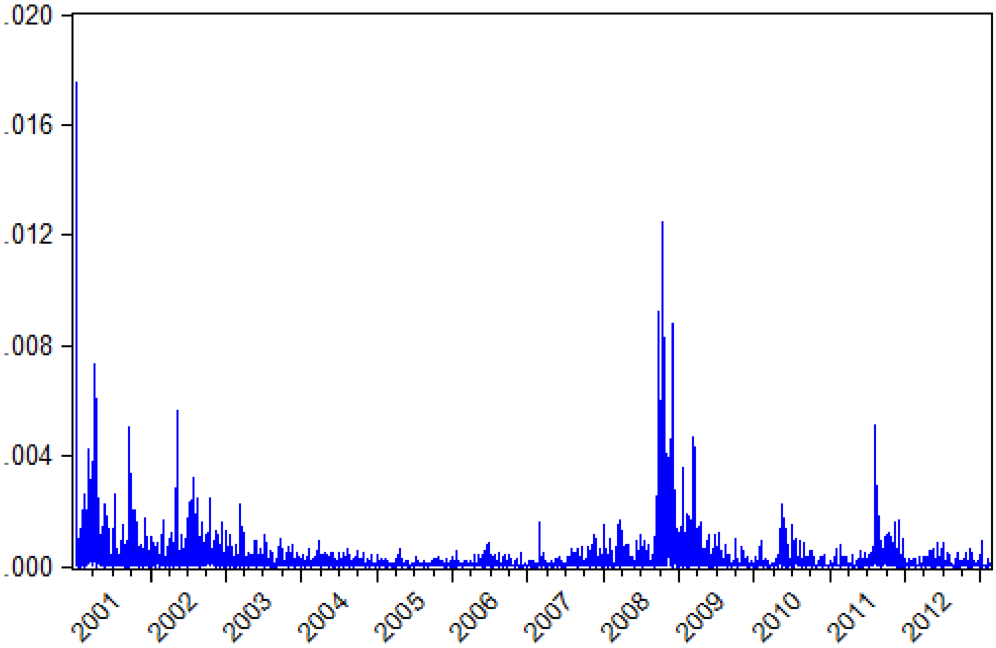
Notes: La volatilité supra-annuelle est calculée comme l'écart-type des taux de croissance annuels des prix calculé par sous-période de 5 ans. Sources: FMI et Banque de France

Figure 0-1: Volatilité des rendements des prix spot du pétrole brut WTI (03/01/2001-18/02/2013)



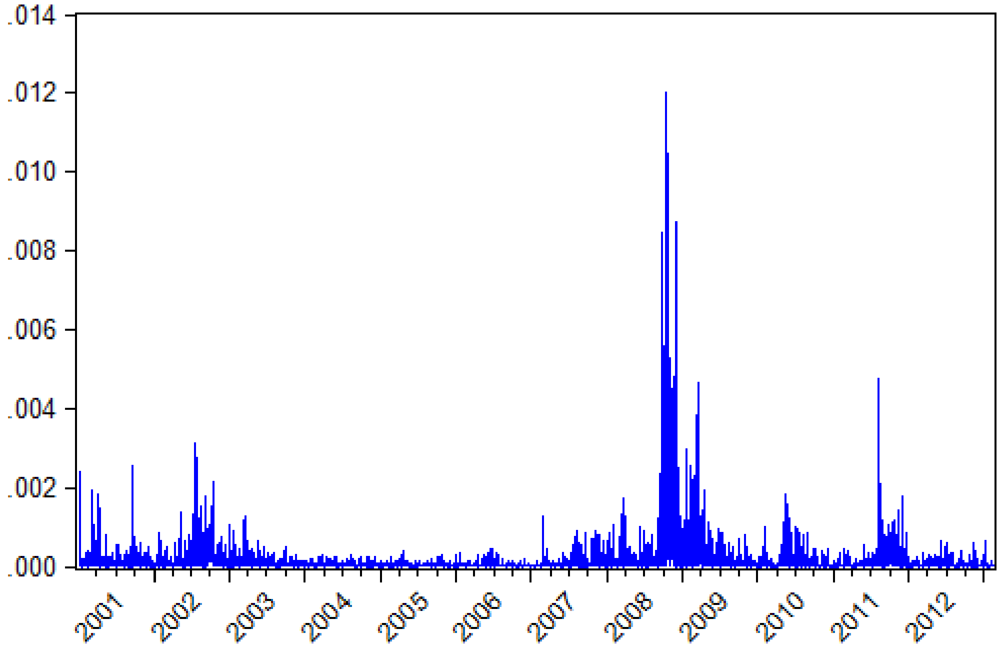
Source: Datastream. La volatilité est approximée par les rendements des prix au carré

Figure 0-2: Volatilité des rendements de l'indice Nasdaq (03/01/2001-18/02/2013)



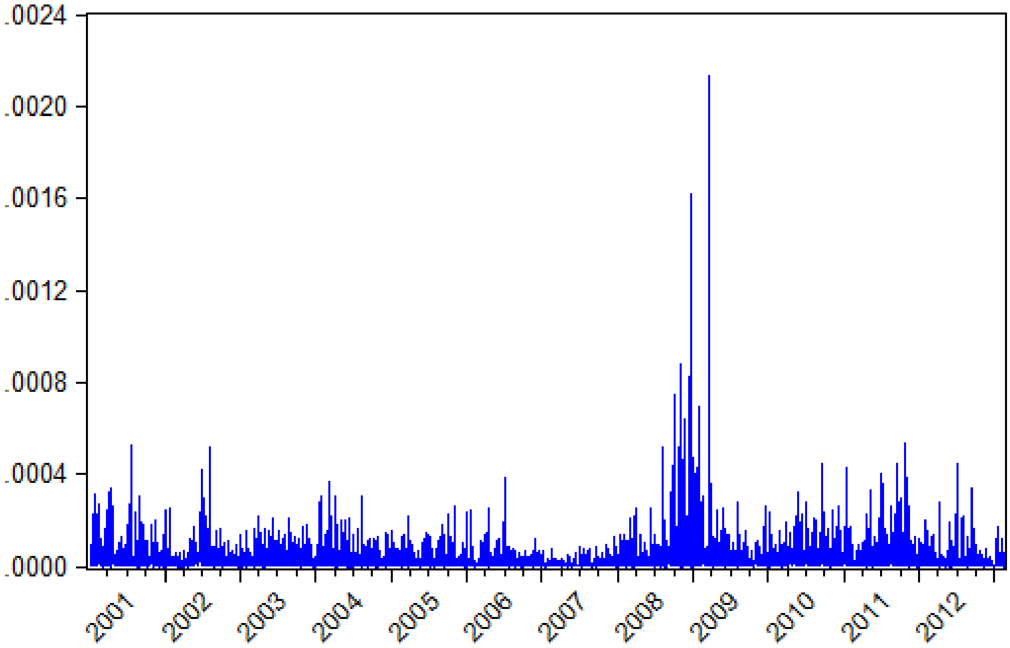
Source: Datastream. La volatilité est approximée par les rendements des prix au carré.

Figure 0-3: Volatilité des rendements de l'indice Standard & Poor's 500 (03/01/2001-18/02/2013)



Source: Datastream. La volatilité est approximée par les rendements des prix au carré.

Figure 0-4: Volatilité des rendements du taux de change US$/euro (03/01/2001-18/02/2013)



Source: Datastream. La volatilité est approximée par les rendements des prix au carré.

ant à limiter les mouvements extrêmes de prix des matières premières en restreignant l'utilisation d'instruments d'investissement sophistiqués. En Europe, elle se pose avec une acuité toute aussi particulière en raison du processus de libéralisation des marchés dans lequel elle s'inscrit. Cette ouverture progressive à la concurrence a, comme nous l'avons signalé précédemment, incité de nouvelles opportunités d'échanges au travers d'instruments financiers complexes, favorisant un contexte de financiarisation croissante des marchés énergétiques.
Nombreuses et cruciales sont alors les questions que se posent les pouvoirs publics et les académiques. Parmi ces questions figurent celles (i) du mécanisme de formation des prix des énergies aux niveaux international et européen; (ii) de la place des marchés financiers dans le changement profond qui s'opère dans le paysage énergétique mondial; (iii) de la véritable nature des mouvements des prix des énergies, ou encore (iv) de l'évolution des marchés énergétiques et des matières premières vers des marchés financiers traditionnels. Plus généralement, quel est le rôle joué par les différents acteurs économiques et financiers dans cette mutation? Y-a-t'il réellement une financiarisation des marchés de l'énergie? Dans l'affirmative, est-elle dommageable en termes de bien être social? Ces questions en appellent bien d'autres, que ce soit en termes de politique énergétique, transfert de technologies, politique environnementale ou régulation financière face auxquelles il convient de trouver des réponses.

Face à ces évolutions majeures sur les marchés énergétiques, nombreux sont les défis qui se posent aux chercheurs concernant la compréhension conjointe des mécanismes et des dynamiques des marchés énergétiques et financiers dans un contexte environnemental toujours plus instable. Force est de constater que, jusqu'à présent, la recherche existante s'inscrit dans un cadre dichotomique cloisonné séparant ces différents aspects, que sont les marchés des énergies, les politiques macroéconomiques et industrielles, et les institutions financières. Mieux, la plupart des études sur le sujet ne s'accordent pas sur les causes profondes des fluctuations des prix. Les principales

divergences se caractérisent dans les fondements même de l'analyse, certains auteurs évoluant dans un cadre de complète rationalité où les agents économiques ont une connaissance totale de l'information dont ils disposent et l'utilisent de manière optimale (Büyüksahin et al. (2009, 2010a,b, 2011a,b), Silvennoinen et Thorp (2010), Kilian et Murphy (2012), Baumeister et Kilian (2012), Creti et al. (2013),...) alors que d'autres envisagent une rationalité limitée où les fluctuations des prix peuvent être le résultat d'une non représentativité des comportements (Reitz et Westerhoff (2009), Reitz et Slopek (2009), Ellen et Zwinkels (2010),...).
Ainsi, au-delà même de la complexité du phénomène de financiarisation, cette analyse rend la compréhension encore plus difficile et paradoxale puisque ne reposant pas sur un cadre structurel global. Ce paradoxe peut donner lieu à des situations "indécidables" économiquement (voir figure 0-5), puisque trop contradictoires et trop restrictives en terme d'approche. **Notre objectif dans cette thèse est d'analyser le rôle de la finance dans la dynamique des marchés énergétiques et de clarifier cette question de fond qu'est la financiarisation des commodités et les phénomènes qui l'accompagnent**. Plus généralement, notre thèse cherche à apporter un cadre d'analyse global combinant économie de l'énergie, théories macroéconomique et financière, et techniques quantitatives. Bien entendu, nous ne prétendons pas répondre à l'ensemble des interrogations auxquelles nous faisons face, mais nous ambitionnons d'analyser les éléments factuels caractérisant la formation des prix des matières premières.

Plus formellement, notre thèse cherche à comprendre la nature profonde des marchés et va au-delà du cadre restreint proposé jusqu'à présent. **L'objet est ainsi d'analyser les relations étroites entre énergie et finance, d'abord d'un point de vue rationnel et systématique à travers des techniques quantitatives sophistiquées, puis en s'éloignant du cadre tradtionnel par une analyse comportementale et émotionnelle des marchés.** En nous écartant progressivement du cadre économique traditionnel afin de tenir compte du "caractère humain" des marchés, nous ambitionnons d'avoir une réflexion "décidable" économiquement (voir figure 0-6), à même d'expliquer la particularité des prix des énergies. De manière rigoureuse, au-delà d'une analyse détaillée des dynamiques conjointes pouvant exister entre energie et finance, notre thèse cherche à montrer si des comportements "d'éxubérance irrationnelle et émotionnelle" existent dans le processus de formation des prix. Si tel est le cas, cela justifierait que les marchés des énergies, malgré leur caractère physique, peuvent à maints égards se comporter comme des marchés financiers traditionnels et être sujets à nombre d'anomalies. Cela appelle bien sûr un cadre conceptuel élargi de l'économie de l'énergie, en perpetuelle évolution, et une reflexion moins concessive qu'à l'ordinaire cherchant à relever le défi de trouver les réponses aux questions en unissant les savoirs dans les différents champs de l'énergie, de l'économétrie, de la finance et de la psychologie.

Afin de répondre à cet objectif, notre thèse s'articule autour de trois thèmes: d'une part la relation entre les prix des différentes énergies et leurs propriétés financières est analysée, d'autre part les aspects émotionnels et comportementaux des marchés sont étudiés, enfin les liens directs entre marchés boursiers et marchés des commodités sont abordés. Ces trois thèmes s'organisent en cinq chapitres.

Le premier chapitre étudie les relations de long terme entre les prix *forward* européens du pétrole, du gaz, du charbon et de l'électricité sur plusieurs maturités à travers l'utilisation de techniques de cointégration non linéaire en panel. A cet effet, nous considérons un panel de 35 maturités et une variable de contrôle, le *Dow Jones Euro Stoxx 50* proxy de l'environnement économique et financier. Les estimations économétriques nous révèlent que les prix du pétrole, du gaz et du charbon sont liés positivement, alors que la relation négative entre les prix du pétrole et de l'électricité est cohérente avec un effet de substitution entre les deux énergies à long terme. Les estimations du modèle de regression à transition lisse en panel (*Panel Smooth Transition Regression* (PSTR)) mettent en évidence un ajustement des prix *forward* du pétrole non linéaire et asymétrique, ce qui révèle le rôle important des anticipations auto-réalisatrices et de la spéculation.

Le deuxème chapitre s'inscrit dans le prolongement du précédent puisqu'il s'intéresse aux co-mouvements entre les prix des énergies. Il propose une nouvelle procédure d'évaluation des causalités à court terme basée sur l'approche traditionnelle de Granger pour plusieurs niveaux de risque dans les queues de distribution.[6] Les propriétés asymptotiques et d'échantillon du test sont proposées et ce dernier est appliqué à deux problématiques en économie de l'énergie: (i) l'intégration des marchés du pétrole, et (ii) la transmission entre les prix *forward* des énergies.
Concernant l'hypothèse d'intégration des marchés internationaux du pétrole, notre test de causalité nous permet de répondre à deux questions: (i) si les différents marchés du pétrole sont plus ou moins intégrés durant les périodes d'extrêmes fluctuations des prix, et (ii) si les propriétés des *price setter* changent durant cette période. Nos résultats révèlent que le niveau d'intégration des différents marchés du pétrole diminue durant les périodes d'extrême fluctuation des prix, conduisant à des situations de diversification potentiellement plus profitables. Par ailleurs, le comportement des marchés *price-setter* apparaît être différent selon l'intensité des fluctuations.
La problématique relative aux co-mouvements entre les prix des énergies est evoquée dans un second temps. La question sous-jacente ici abordée concerne les propriétés financières des prix des énergies. Nous cherchons à déterminer si les mécanismes de transmission entre les prix *forward* européens à différentes maturités sont plus ou moins importants durant les phases d'extrêmes fluctuations des prix comparées aux périodes dites "calmes" des marchés. Il apparaît alors une absence de lien causal entre les marchés durant les périodes de "calmes", alors qu'une étroite relation semble exister durant les périodes d'extrêmes fluctuations à la baisse. Plus précisemment, cette causalité semble être davantage significative à une courte maturité (prix *forward* à 1 mois)

[6] Techniquement, ce test est une extension en multivarié de l'approche proposée par Hong et al. (2009).

qu'à des maturités plus éloignées (prix *forward* à 10, 20 et 30 mois), témoignant d'un effet de type Samuelson dans la courbe à terme des prix. Les stratégies de diversification seraient alors plus efficientes à mesure que les maturités augmentent.

Le troisième chapitre s'intéresse, par une approche biorhytmique, à la relation entre les émotions et les prix *forward* européens du pétrole, du gaz, du charbon et de l'électricité durant les périodes "calme" et d'extrême fluctuation des prix. Pour ce faire, nous utilisons la variable SAD (*Seasonal Affective Disorder*) proposée par Kamstra et al. (2003) comme proxy des émotions pour évaluer cet impact sur la dynamique des marchés énergétiques. Nos résultats révèlent que les tendances saisonnières ont un impact significatif sur les prix uniquement durant les périodes d'extrêmes mouvements. Une étude plus approfondie montre un effet asymétrique de la variable SAD entre les phases de hausse ou de baisse des marchés. Finalement, nous évaluons les propriétés *out-of-sample* de cette variable SAD dans la prévision des fluctuations des prix et nous montrons que cette dernière surperforme de manière significative le modèle utilisé comme benchmark.[7]

Le quatrième chapitre s'intéresse plus spécifiquement à l'impact potentiel de la financiarisation sur la dynamique des prix énergétiques en fournissant un modèle théorique comportemental et émotionnel, où différentes catégories d'agents (*i.e.* fondamentalistes et chartistes) co-existent sur les marchés énergétiques et sont soumis au regret et à l'incertitude. Le modèle théorique est ensuite estimé sur les prix *forward* européens des énergies (pétrole, gaz, charbon et électricité) durant les périodes de calme et d'extrêmes fluctuations des prix. Nos résultats montrent que les marchés des énergies sont composés d'agents hétérogènes qui se comportent différemment selon l'intensité des fluctuations et le dégré d'incertitude. En particulier, durant les périodes de "calme", les prix des énergies apparaîssent être gouvernés par des fondamentalistes et chartistes neutres

[7] Le modèle de comparaison est un modèle "macroéconomique" où les prix sont expliqués par le taux de change euro/dollar US et l'indice boursier *Dow Jones Euro Stoxx* 50.

à l'incertitude, en revanche ils semblent davantage dictés par des chartistes irrationnels averse à l'incertitude pendant les phases d'intenses mouvements. Dans cette perspective, les fluctuations récentes observées sur les marchés pourraient être, en partie, la conséquence d'une exhubérance irrationnelle. En terme de prévision, notre modèle comportemental et émotionnel surperforme la marche aléatoire.

Le cinquième et dernier chapitre adopte une conception plus traditionnelle de l'économie et s'intéresse aux relations existantes entre marchés boursiers et marchés des matières premières. Nous considérons alors une gamme plus large de marchés des commodités, regroupant 25 secteurs différents[8] sur la période janvier 2001 à novembre 2011. Par une approche multivariée de type DCC-GARCH, nous montrons que les corrélations dynamiques entre les marchés des commodités et l'indice Standard & Poor's sont extrêmement volatiles, particulièrement durant la période 2007-2008 de crise financière. Plus précisémment, ce phénomène semble être de plus ou moins grande ampleur selon les phases de hausse ou de baisse des marchés financiers, particulièrement pour les séries du pétrole, du café et du cacao. En outre, le marché de l'or semble conserver son rôle de valeur refuge car ses corrélations avec le marché des actions sont négatives et diminuent durant les périodes de baisse de l'indice. Certaines commodités apparaîssent alors être caractérisées par un phénomène de spéculation.

[8] Les marchés considérés correspondent aux secteurs suivants: énergie, métaux précieux, agro-industriel, métaux non-ferreux, alimentaire, oléagineux, exotique et bétail.

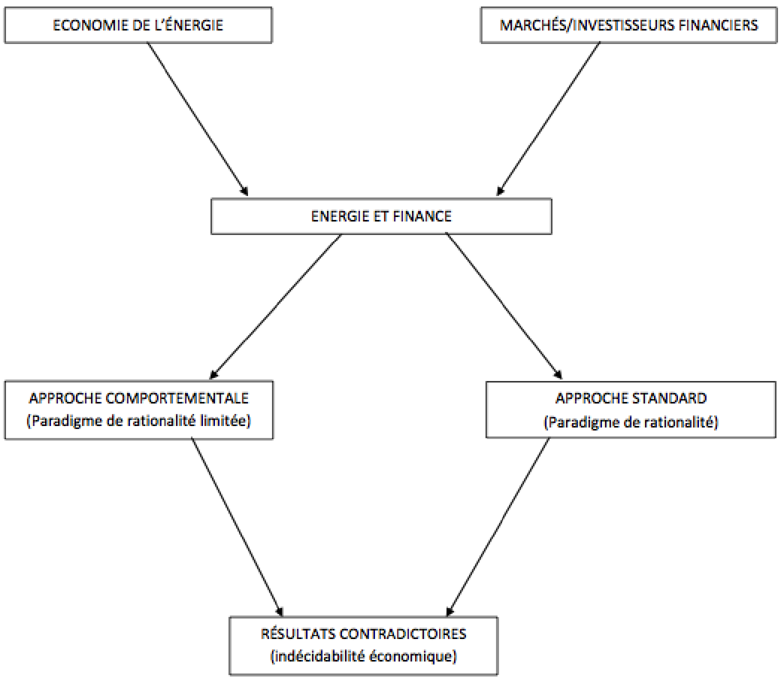


Figure 0-5: Schéma d'indécidabilité économique

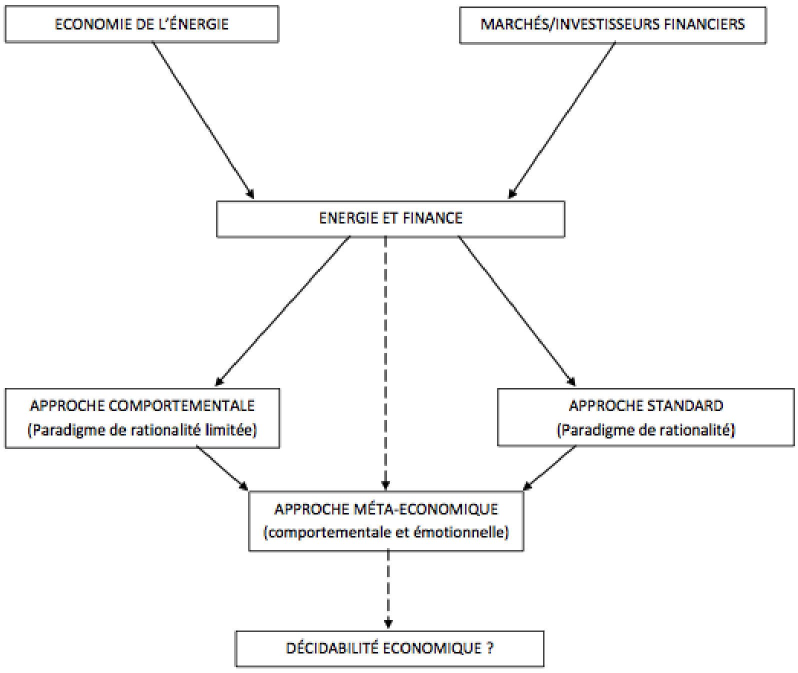


Figure 0-6: Schéma de décidabilité économique

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Chapter 1

On the link between forward energy prices: A nonlinear panel cointegration approach

Introduction [1]

Investigating the interactions between energy markets if of crucial importance to correctly apprehend and understand their price dynamics. Indeed, energy prices are obviously connected through the production process, and economic theory suggests that a relationship should exist between input and output prices. Besides, oil—due to its physical properties and the importance of its market—is often viewed as an economic "driver" influencing the other energy prices, such as coal, gas, and electricity.

However, energy markets recently experienced significant developments that are likely to modify the potential interactions between energy prices. European gas and electricity markets have freshly known a liberalization process allowing the emergence of new contracts making prices more likely to be influenced by market participants rather than regulators (Mjelde and Bessler, 2009). While various studies[2] have investigated the links between energy prices on spot markets, they generally do not consider the financial dimension of energy markets. This may be viewed as an important limitation since along with these major evolutions in the field of energy, the development of new products promotes the financialization of the energy markets. The long-term challenge of these changes then becomes crucial because such financialization is likely to have a significant impact on price dynamics. Indeed, apart from any physical considerations, oil, like gas, electricity and coal, can be considered as a financial asset. Speculators seeking significant profits would then intervene in these markets and would maintain high prices through their long positions.

In this chapter, we account for the term structure of energy prices through an analysis of forward prices. More specifically, we consider forward prices of oil, coal, gas and electricity at 35 maturities, and aim at modelling the relationship between these four energy sources for all maturities in a panel data cointegration setting. Relying on forward prices presents several advantages. First, this approach allows us to study the links within and between heterogeneous maturities by accounting for arbitrage investors' behavior over the long run—the contracts being not only traded by agents who need physical energy delivery, but also by speculators with purely financial motivation. Second, while relying on spot models based on long-term price relationships often requires knowledge of the convenience yield for risk-neutral valuation which is not observable and difficult to obtain, this is not the case for forward price models (Eydeland and Wolyniec, 2003). Third, in addition to these economic arguments, using various maturities provides more observations, which is useful when implementing unit

[1] A first version of this chapter has been published as Joëts, M. and Mignon, V., 2011, On the link between forward energy prices: A nonlinear panel cointegration approach, Energy Economics, 33, 1170-1175.

[2] See references in Section 1.1.

root and cointegration tests.

It is worth mentioning that, given the various factors that may influence energy markets, the dynamics of energy prices is likely to be characterized by nonlinearities. Such nonlinearities may come from both fundamental factors or speculative forces. Regarding the first point, the recent huge increase in the Chinese oil demand coupled with an unexpected halt of non-OPEC production, as well as the loss of OPEC spare capacity since 2004 (Kaufmann, 2011) are examples of fundamental shocks that may generate nonlinearities and regime-switching. Turning to the speculative factors, investors may hold long-run positions that encourage increasing energy prices, and switch between investment strategies (Ellen and Zwinkels, 2010). These elements play in favor of nonlinear, regime-switching models.

Various specifications exist in the class of nonlinear regime-switching models. In addition to the category of (stochastic) Markov-switching models, the most popular models are (deterministic) threshold processes. These models are characterized by two (or more) regimes, determined by a threshold variable and a threshold value. The observations in the panel are then divided into these two regimes, depending on whether the threshold variable is lower or larger than the threshold value. In the panel threshold regression (PTR) model introduced by Hansen (1999), the transition from one regime to the other is abrupt and the model implicitly supposes that the two sub-samples of observations are clearly identified and distinguished, which is not always feasible in practice. To overcome this difficulty and to allow for possible smooth and gradual transitions, we consider here the panel smooth transition regression (PSTR) model introduced by González et al. (2005). These models are particularly appropriate for our purpose since they allow us to model the nonlinear behavior of the forward energy prices adjustment process to the equilibrium value, by accounting for gradual changes rather than abrupt ones. It seems indeed reasonable to think that smooth transitions are more suitable than abrupt ones in our case, since changes in energy markets are generally not sudden and tend to take some time.

To sum up, and given the key role played by oil in energy markets, the aim of this chapter is to investigate the nonlinear adjustment process of the forward oil price toward its equilibrium value given by the estimated long-term relationship between oil, gas, coal and electricity forward prices. To our best knowledge, our contribution is the first to account for interactions between energy prices at various maturities in a nonlinear panel data framework.

The rest of the chapter is organized as follows. Section 1.1 presents some stylized facts and reviews the literature on the links between energy prices. Data and results of panel unit root and cointegration tests are displayed in Section 1.2. Section 1.3 reports the estimation results, and Section 1.4 concludes the article.

1.1 Relationships between energy prices: stylized facts and literature review

The natural gas market is often considered to be potentially linked to other primary energy sources by different ways. Technically, gas is extracted from the soils either alone ("dry gas"), or associated with the oil exploration ("associated gas"). Consequently, natural gas and oil have the same extraction/exploration process, and oil producers are often gas producers too, creating an implicit link between prices. Usually, the natural gas is used for domestic needs and as an input to the electricity production process. However, it has no captive use and is in constant competition with other energy sources (with domestic and heavy fuel oil in domestic needs, and with coal in the power production). These characteristics explain the existence of (i) an input-output relationship between natural gas and electricity, and (ii) competitive relation between oil, gas, and coal. Despite the close relationship between energy markets, the entry of the gas market in the liberalization process is likely to exacerbate short-run decorrelation between oil and gas prices. Indeed, long-term gas contracts are no longer indexed to oil contracts, but to spot and futures prices, rending prices more sensitive to the behavior of market participants.

Turning to coal, due to its apparent abundance,[3] it is dominant in two specific sectors: manufacture of cement and steel, and electricity generation (IEA, 2010a and British Petroleum, 2010). It is the main input to the electricity production, making energy prices potentially connected through an input-output relationship. However, coal being extremely pollutant, it is in competition with gas and oil in the power production, likely to create substitution effects. Besides, due to its solid state and its inert nature, coal transportation is very expensive[4] because it requires seaborne trade. Then, coal prices strongly depend on the variability of the freight rates, which are significantly variable since the 1950s (Lundgren, 1996). Consequently, oil and coal prices may be indirectly related each other through the fluctuations of the transport fuel derived from oil.

Unlike oil, natural gas and coal, electricity is not a fossil energy. It can be produced either as primary energy from natural sources (like hydro, wind, solar, ...), or as secondary energy from the heat of nuclear fission, the geothermal and solar thermal heat, or by the combustion of fossil fuels (coal, natural gas, and oil) (IEA, 2010b). Accordingly, and as previously mentioned, electricity prices may be related to its products through an input-output relationship. Moreover, power energy is used for most human activities (heating, lighting, computers, powering machines, transport, ...) and

[3]The reserves/production ratio is equal to 145 years (British Petroleum, 2010), and reserves are also well distributed (no cartel exists).

[4]This is one of the reasons explaining the fact that the coal market was initially regional.

in several sectors (transformation and energy sectors, transmission and distribution of electricity sectors, and final consumption[5]). Thus, in addition to an obvious relation through the production process, electricity, gas, oil and coal prices may be interrelated by competition and substitution links.

On the whole, various factors may explain the interactions between energy prices. Turning to the empirical literature, Serletis and Rangel-Ruiz (2004) investigate the strength of shared dynamics between North American daily spot Henry Hub gas and WTI crude oil prices over the period after the deregulation, from January 1991 to April 2001. They found that while the US market deregulation has 'decoupled' the prices' relationship, North American natural gas prices are largely defined by the US Henry Hub prices trends. Focusing on the UK, Panagiotidis and Rutledge (2007) examine whether oil and gas prices 'decoupled' during the post market deregulation period (1996-2003). Using cointegration techniques, they show that a cointegrating relationship is present throughout the sample period, especially between 1999 and 2000. Relying on daily ICE futures prices of gas and Brent for five contracts, Westgaard et al. (2011) find that a long-term relationship exists between prices depending on the length of the contracts.

Considering more energy sources, Bachmeier and Griffin (2006) investigate the degree of integration between crude oil, coal, and natural gas markets. Using data from January 1990 to August 2003, and relying on the estimation of bivariate error correction models, they find a weak degree of integration between energy markets. Investigating the relationship between weekly spot prices among US electricity and its major fuel inputs (natural gas, uranium, coal and crude oil) over the period from June 6, 2001 to April 23, 2008, Mjelde and Bessler (2009) put forward that electricity prices influence natural gas prices, which in turn affect crude oil prices. Ma and Oxley (2010) investigate energy prices comovements in China from January 1995 to December 2005, and show that coal and electricity prices have comoved since 1997. Finally, one can mention the study by Chevallier (2012) concerning time-varying correlations between oil, gas and CO_2 markets using CCC, BEKK and DCC-GARCH models.

To sum up, the previous literature globally puts forward some links between energy markets, depending on the market location and the type of energy considered. However, most of them deal with spot prices. Consequently, they do not investigate the potential relationships at various maturities, a fact that is of considerable importance when one wishes to account for the financial dimension of energy markets. Furthermore, relying on spot models based on long-term price relationships often requires knowledge of the convenience yield for risk-neutral valuation. However, the later is not observable and difficult to deduce, whereas this is not the case for forward prices models (Eydeland and Wolyniec, 2003). For these reasons, and to account for the financial dimension of

[5]The final consumption sector represents the main sector for electricity consumption.

energy markets, it seems particularly relevant to focus on forward prices data, which is the aim of the present contribution.

1.2 Data, unit root and cointegration tests

We consider daily data over the January 3, 2005 to December 31, 2010 period. We rely on European forward prices of oil, gas, coal, and electricity for 35 maturities.[6] Using such a large sample of maturities allows us to account for possible heterogeneity in the relationship between energy prices,[7] as well as long-run arbitrage behavior of market participants. Energy price data are extracted from the Platt's Information Energy Agency. To control for the economic and financial environment that may impact all energy price series, we rely on a European equity futures price index—which has the advantage of being available at a daily frequency. This variable also allows considering oil as a financial asset and controls for the recent financial turmoil. Our retained equity variable is the Dow Jones Euro Stoxx 50, the European leading stock index for futures contracts, extracted from Datastream. All price series are in logarithms.

We start by estimating the equilibrium value of forward oil price, given the values of the other forward energy prices and the equity futures price index. More specifically, we estimate the following long-term relationship:

$$p_{i,t}^{oil} = a_i + b_1 p_{i,t}^{elec} + b_2 p_{i,t}^{gas} + b_3 p_{i,t}^{coal} + b_4 p_{i,t}^{Stoxx} + \epsilon_{i,t} \tag{1.1}$$

where $i = 1, ..., 35$ denotes the maturity, and $t = 1, ..., T$ the time. $p_{i,t}^{oil}$, $p_{i,t}^{elec}$, $p_{i,t}^{gas}$ and $p_{i,t}^{coal}$ respectively denote the forward prices of oil, electricity, gas and coal. $p_{i,t}^{Stoxx}$ stands for the equity futures price index.

Before estimating Equation (1.1), panel unit root and cointegration tests have to be applied. To overcome the cross-sectional independence hypothesis among the panel members (i.e. among the various maturities), we apply second-generation panel unit root tests[8] that relax this restrictive assumption required by first-generation tests.[9]

[6] As an example, Figure 1-1 in Appendix depicts the one-month forward energy prices (in logs).

[7] See Joëts (2010).

[8] See Hurlin and Mignon (2006) and Hurlin (2010) for a detailed presentation of panel unit root tests.

[9] Cross-section dependence can arise for several reasons, such as spatial spillovers, financial contagion, socioeconomic interactions, and common factors (Pesaran, 2004). In the presence of cross-section correlations in the panel, first-generation tests suffer from size distortions. Regarding our panel, the application of the CD test developed by Pesaran (2004)—based on the average of pair-wise correlation coefficients of OLS residuals from the individual regressions—shows that such correlations exist in our sample (results available upon request to the authors).

Results are reported in Table 1.1, all tests considering the unit root as the null hypothesis.[10] The Pesaran (2007) CIPS test is based on Dickey-Fuller-type regressions augmented with the cross-section averages of lagged levels and first differences of the individual series. Regarding the Moon and Perron (2004) test, it is constructed on de-factored observations—deviations from the common components—and the factor loadings are estimated by principal component analysis. The Choi (2002) test relies on an error-components panel model and removes the cross-section dependence by eliminating (i) individual effects using the Elliott, Rothenberg and Stock (1996) methodology (ERS), and (ii) the time trend effect by centering on the individual mean. As shown in Table 1.1, all tests conclude in favor of the unit root hypothesis meaning that all forward energy price series entering in Equation (1.1) are I(1).

Table 1.1: **Second-generation panel unit root tests**

	CIPS	Moon-Perron		Choi		
		t^*_α	t^*_β	P_m	Z	L^*
$p^{oil}_{i,t}$	-2.480 (0.25)	-1.805 (0.03)	-0.700 (0.24)	-3.829 (0.99)	3.393 (0.99)	3.059 (0.99)
$p^{coal}_{i,t}$	-2.078 (0.95)	0.047 (0.51)	0.016 (0.50)	-3.358 (0.99)	2.299 (0.98)	2.041 (0.97)
$p^{elec}_{i,t}$	-3.162 (0.01)	-1.287 (0.09)	-0.783 (0.21)	-5.308 (1.00)	7.894 (1.00)	7.557 (1.00)
$p^{gas}_{i,t}$	-2.707 (0.02)	1.355(0.91)	0.543 (0.70)	-2.152 (0.98)	1.090 (0.98)	0.993 (0.83)

Notes: Between parentheses: p-values. (a) For the CIPS test, all statistics are based on univariate $AR(p)$ specifications with $p \leq 8$ including individual effects and time trends; the critical values tabulated in Pesaran (2007) are -2.769, -2.653, and -2.589, at 1%, 5%, and 10% significance levels respectively. (b) For the Moon and Perron's tests, the long-run variance used in the construction of t^*_α and t^*_β is computed using the Andrews and Monahan (1992)'s estimator; the maximum number of common factors selected using AIC is 8 (see Bai and Ng, 2002); all statistics are computed with individual effects and time trends; the Moon-Perron statistics are standard Normal for large T under the unit root hypothesis. (c) For the Choi's test, the optimal lag orders in the individual ERS statistics (Elliott, Rothenberg and Stock, 1996) for each series are determined with $p_{max} = 12$; all tests are computed with individual effects and time trends specifications; under the unit root hypothesis the Choi's statistics are standard Normal when T and N converge jointly to infinity.

[10] We use the Matlab codes (Version 7.00) provided by Christophe Hurlin for implementing second-generation panel unit root tests (*http://www.univ-orleans.fr/deg/masters/ESA/CH/churlin_R.htm*). Westerlund (2007)'s cointegration tests have been implemented using our own Stata codes based on the algorithm developed by Damyan Persyn, and we rely on the Gauss codes provided by Joakim Westerlund for implementing Westerlund and Edgerton's tests.

Turning now to the cointegration case, we also apply second-generation tests accounting for cross-sectional dependence. The four panel error correction-based tests proposed by Westerlund (2007) rely on structural dynamics and are a panel extension of the Banerjee et al. (1998) tests developped in the time series context. Among the four Westerlund's tests, two consider an homogeneous cointegrating relation under the alternative, while the two others allow for an heterogeneous long-term relationship. Results reported in Table 1.2 show that forward oil prices and the four considered variables are cointegrated. Finally, given that our sample covers a quite turbulent period, we implement the Westerlund and Edgerton (2007) second-generation panel cointegration test that is robust to unknown heterogeneous breaks in both the intercept and slope of the cointegrating regression. Our findings reported in Table 1.2 confirm that energy prices are cointegrated.

Table 1.2: **Second-generation panel cointegration tests**

Westerlund				Westerlund & Edgerton		
Group-mean statistics		Panel statistics		Model	τ_N	ϕ_N
G_τ	G_α	P_τ	P_α	No break	-20.85 (0)	-43.54 (0)
32.462	1.7e+03	-192.407	1.7e+03	Level break	-18.59 (0)	-40.82 (0)
(0)	(0)	(0)	(0)	Regime break	-21.28 (0)	-41.60 (0)

Notes: (1) For the Westerlund's test: (a) between parentheses: p-values with cross-section dependence based on bootstrapped distribution (100 bootstrap replications). (b) Tests are computed with individual effects and time trends. (c) The Bartlett kernel is used for the semiparametric corrections. (d) The leads and lags in the error correction test are chosen using Akaike criterion. (e) The number of common factors is determined by IC_1 criterion (see Bai and Ng, 2004) with a maximum factor number of 5. (2) For the Westerlund and Edgerton's test: (a) between parentheses: p-values. (b) All tests statistics are limiting Normal distributions free of nuisance parameters under the null hypothesis. (c) The tests are implemented using the Campbell and Perron (1991) automatic procedure to select the lag length. (d) We use three breaks, which are determined by grid search.

1.3 Estimating the links between energy prices: Methodology and results

1.3.1 Estimation of the cointegrating relationship

Our considered series being I(1) and cointegrated, we first proceed to the estimation of the cointegrating relationship (1.1). Given that the distributions of the OLS estimates corresponding to Equation (1.1) are biased and dependent on nuisance parameters associated with the serial correlation properties of the data, it is necessary to use an efficient estimation procedure. We rely here on the panel Dynamic OLS (DOLS) procedure developed by Kao and Chiang (2000) and Mark and Sul (2003), which consists in augmenting the cointegrating relationship with lead and lagged differences of the regressors to control for the endogenous feedback effect.[11]

The estimated cointegrating relationship is given by:

$$\hat{p}^{oil}_{i,t} = \hat{a}_i - 0.126 p^{elec}_{i,t} + 0.149 p^{gas}_{i,t} + 0.610 p^{coal}_{i,t} + 0.428 p^{Stoxx}_{i,t} \tag{1.2}$$

This estimated relationship between oil, gas and coal forward prices is positive, while the link between oil and electricity forward prices is negative. It should however be mentioned that interpreting separately the estimated coefficients should be done with caution given that our relationship includes simultaneously three energy prices: the coefficients of the prices variables in Equation (1.2) do not thus directly represent structural estimates of the effect of each variable on the oil price.[12] Having this precaution in mind, the relationship between gas and oil prices has the expected sign given that the gas extraction process is very similar to that of oil. As a consequence, there exists a strong link across the two energies. Turning to coal, which is mainly used for electricity production, an increase in its price leads to a rise in oil price on the long run, due to an increasing demand for electricity and heating. Regarding electricity, two facts have to be highlighted. First, there exists an input-output relationship between this energy and oil. Second, electricity is used in various activities, mainly for final consumption. In Europe, specifically, electricity is intensively used for heating purposes and is thus in competition with oil. The negative link between oil and electricity forward prices on the long run may be interpreted in terms of a substitution effect, rather than in terms of an input-output effect. Finally, given that equity prices may be viewed as a proxy for the economic and financial environment, the positive relationship between oil and equity prices may be interpreted as follows: a rise in equity futures prices refers to a period of growing economic activity, leading to an increase in oil consumption and, consequently, in oil price.

[11] As a robustness check, we also estimate Equation (1.1) using the Fully-Modified OLS (FM-OLS) method proposed by Phillips and Hansen (1990). The results were very similar to those obtained with the DOLS procedure and are available upon request to the authors.

[12] As a consequence and for the sake of robustness, we have also estimated bivariate relationships between oil price and each other price variable. With the exception of electricity, the same positive signs are obtained for the three other estimated coefficients, showing that positive relationships exist between oil price and coal, gas, and stock prices. Regarding electricity, the negative sign may thus come from an indirect impact of the other energy prices, reflecting a possible substitution effect (see below).

1.3.2 The linear error-correction model

The existence of a cointegrating relationship between our variables allows us to estimate an error-correction model (ECM). The estimation of Equation (1.1) gives the forward oil price equilibrium value, denoted as $\hat{p}^{oil}_{i,t}$. The difference between the observed and the equilibrium value of the oil price defines the misalignment for each maturity i:

$$z_{i,t} = p^{oil}_{i,t} - \hat{p}^{oil}_{i,t} \tag{1.3}$$

Considering the standard linear case, the estimation of the corresponding ECM leads to the following results:

$$\widehat{\Delta p^{oil}_{i,t}} = \underset{(-6.01)}{-0.0304} z_{i,t-1} + \underset{(1.77)}{0.2400} \Delta p^{oil}_{i,t-1} \underset{(-7.12)}{-1.1496} \Delta p^{elec}_{i,t-1} + \underset{(8.21)}{0.8674} \Delta p^{gas}_{i,t-1} + \underset{(2.90)}{0.7583} \Delta p^{coal}_{i,t-1} + \underset{(4.19)}{0.6582} \Delta p^{Stoxx}_{i,t-1} \tag{1.4}$$

Given that Equation (1.4) is a dynamic panel data model, we estimate it by the Generalized Method of Moments (GMM), which provides a convenient framework for obtaining efficient estimators in this context.[13] As expected, we find a negative and statistically significant error-correction term, implying that if the "fundamentals" in the last period dictate a lower (resp. upper) oil price than that observed, then the price will decrease (resp. increase) in the current period. The linear ECM implicitly assumes that the adjustment speed towards equilibrium is both continuous and constant, regardless of the extend of the misalignment. However, as mentioned before, given the various factors that may influence energy markets, the adjustment process is likely to be characterized by nonlinearities. As an example, the convergence speed may depend on the size and/or the sign of the deviation from equilibrium, a feature that the previous linear model would not be able to capture. To investigate this possibility, linearity tests should be applied, which is done in the next subsection.

1.3.3 Estimation of the nonlinear oil price dynamics

1.3.3.1 Methodology

To account for the potential nonlinear adjustment of the forward oil price toward its equilibrium value, the corresponding error-correction model has to be specified in a nonlinear form. To this end, we rely on the PSTR model introduced by González et al. (2005):

$$y_{i,t} = \mu_i + \beta_1' x_{i,t} + \beta_2' x_{i,t} g\left(s_{i,t}; \gamma, c\right) + \varepsilon_{i,t} \tag{1.5}$$

[13] See Arellano and Bond (1991) among others.

where $g(s_{i,t};\gamma,c)$ is the transition function, normalized and bounded between 0 and 1. $s_{i,t}$ denotes the transition variable—which may be an exogenous variable or a combination of the lagged endogenous one—, γ the speed of transition from one regime to the other and c the threshold parameter. As it is clear from Equation (1.5), the observations in the panel are divided into two regimes depending on whether the transition variable is lower or larger than c. The logistic specification can be used for the transition function to account for a smooth and gradual change from one regime to the other:

$$g(s_{i,t};\gamma,c)=\left[1+\exp\left(-\gamma\prod_{l=1}^{m}(s_{i,t}-c_l)\right)\right]^{-1} \tag{1.6}$$

with $\gamma>0$ and $c_1\leq c_2\leq ...\leq c_m$. Turning to empirical considerations, it is sufficient to consider only the cases of $m=1$ (logistic PSTR) or $m=2$ (logistic quadratic PSTR) to capture the nonlinearities due to regime switching (see González et al., 2005).

Following the methodology used in the time series context, González et al. (2005) propose a three-step strategy to apply PSTR models: (i) the identification step aiming at testing for homogeneity against the PSTR alternative and selecting both the transition variable and the order m, (ii) the estimation step based on nonlinear least squares,[14] and (iii) the evaluation step that consists in applying misspecification tests to check the validity of the estimated PSTR model.

On the whole, the model that will be estimated is given by:

$$\Delta p_{i,t}^{oil}=\mu_i+(\lambda_1 z_{i,t-1}+B_1X_{i,t})+(\lambda_2 z_{i,t-1}+B_2X_{i,t})g(s_{i,t};\gamma,c)+\varepsilon_{i,t} \tag{1.7}$$

where $X_{i,t}$ represents the vector of contemporaneous and lagged first-differenced forward oil price determinants, namely $\Delta p_{i,t}^{elec}$, $\Delta p_{i,t}^{gas}$, $\Delta p_{i,t}^{coal}$, and $\Delta p_{i,t}^{Stoxx}$. Depending on the value of the transition variable, the link between $\Delta p_{i,t}^{oil}$ and its determinants evolves between B_1 and λ_1 in Regime 1 (corresponding to $g(.)=0$) and B_1+B_2 and $\lambda_1+\lambda_2$ in Regime 2 (corresponding to $g(.)=1$). Three transition variables will be considered: the oil price misalignment, the oil price variation, and the economic and financial environment proxied by the equity futures price returns.

[14] Strictly speaking, the estimation involves two steps. We first remove the fixed effects by centering the variables on their individual means, and then estimate the parameters with nonlinear least squares (NLLS). Using NLLS requires the choice of starting values, which is done by relying on a grid search of initial values for the slope (γ) and threshold (c) parameters. For the slope parameter, we use a list of various possible positive values. Turning to the threshold parameter, the choice of initial values is made such that they have to be comprised between the minimum and the maximum values taken by the transition variable. Given these grids, the estimation of the model is performed for all possible combinations of the initial values. We use the Matlab code (Version 7.01) provided by Christophe Hurlin for the estimation of PSTR models. Note that a similar code is also available for the RATS software on Gilbert Colletaz's web page (*http://www.univ-orleans.fr/deg/masters/ESA/GC/gcolletaz_R.htm*).

1.3.3.2 Results

Following the three-step strategy proposed by González et al. (2005), we start by applying linearity tests. We test the null hypothesis of linearity in Equation (1.7) using three transition variables: equity futures returns, the forward oil price misalignment, and the forward oil price variation. For all three variables, the null of linearity is strongly rejected in favor of the PSTR alternative,[15] meaning that the linear model (1.4) is not appropriate to describe the price adjustment process. Results corresponding to the estimation of the PSTR models are reported in Table 1.3.

Table 1.3: **Estimation of PSTR models**

$s_{i,t}$	$\Delta p^{Stoxx}_{i,t-1}$		$z_{i,t-1}$		$\Delta p^{oil}_{i,t-1}$	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
$z_{i,t-1}$	-0.0040	-0.0479	-0.0111	0.0097	-0.0074	0.0174
	(-4.80)	(-1.64)	(-2.37)	(1.67)	(-6.07)	(3.45)
$\Delta p^{oil}_{i,t-1}$	0.0060	-2.33	-0.1303	0.1639	0.0288	-0.1232
	(1.16)	(-8.63)	(-3.23)	(3.36)	(3.75)	(-6.26)
$\Delta p^{elec}_{i,t-1}$	0.0163	1.9036	0.0484	-0.0288	0.0526	-0.2360
	(5.43)	(14.43)	(1.57)	(-0.78)	(9.71)	(-8.28)
$\Delta p^{gas}_{i,t-1}$	0.0134	0.1585	0.0569	-0.0561	0.0105	0.0068
	(5.27)	(1.11)	(1.82)	(-1.51)	(2.57)	(0.33)
$\Delta p^{coal}_{i,t-1}$	0.0506	0.3725	0.5266	-0.5606	0.0174	0.3197
	(7.28)	(3.44)	(6.63)	(-5.96)	(1.89)	(8.90)
$\Delta p^{Stoxx}_{i,t-1}$	-0.0855	0.0315	-0.7727	0.8407	-0.1254	0.2058
	(-12.40)	(0.44)	(-9.84)	(9.05)	(-11.70)	(4.94)
$\hat{\gamma}$	106.8853		4.7058		60.1668	
$\hat{c}$	0.0736		-0.3623		0.0358	

Between parentheses: t-statistics.

Let us first consider the model with equity futures returns as the transition variable. In this case, forward oil price tends to reverts to its equilibrium value whatever the considered regime. This mean-reverting behavior is slower in the first state corresponding to a stock market which is decreasing or weakly increasing (until a threshold equal to 7%). Assuming that the stock market is a proxy for economic activity, this result is logical in the sense that reversion to the equilibrium is harder and takes a longer time in a depressing period than in an expansion state. Moreover, the other forward energy price returns positively affect oil price returns in both regimes, with a stronger impact in

[15] Detailed results are available upon request to the authors.

Regime 2. This result shows that when financial markets are booming, forward energy prices tend to augment. This may be explained by two reasons: (i) the need for more energy in periods of intense economic activity, and (ii) speculation purposes. Speculation on energy products goes along with speculation on financial assets. Expecting that the growing trend will continue, traders tend to take long positions on long-term contracts, selling them at higher prices before the expiry date and re-investing in new ones; a behavior that produces self-sustaining dynamics (Cifarelli and Paladino, 2010).

When the oil price misalignment acts as the transition variable, the estimated threshold is equal to -36%, corresponding to a 36% undervaluation of the forward oil price compared to its equilibrium value given by the cointegrating relationship. When oil price is strongly undervalued, a mean-reversion dynamics takes place (Regime 1). The more the reduction of the misalignment, the weaker the mean-reverting speed. In other words, corrections of disequilibria appear when oil price tends to strongly decrease, while it is not the case when oil price strongly augments compared to its fundamentals. This illustrates an asymmetric phenomenon: the adjustment process is at play only for high undervaluations, not for overvaluations. Regarding forward energy price returns, they vary in the same way as oil in case of strong undervaluations, with a decreasing influence when the magnitude of undervaluation tends to diminish. In the later case, the variable which has the strongest impact is the equity returns, again putting forward the importance of the speculation phenomenon: when oil price rises, the links across markets tend to be stronger, encouraging speculation. From a speculative viewpoint, it is reasonable to think that when oil prices are highly undervalued, the market is dominated by irrational speculators (chartists), who base their expectations on past prices fluctuations and believe trends to continue in the same direction. These speculators have a destabilizing effect, making prices deviate from their long-run fundamental equilibrium. However, when the threshold of -36% is reached, chartists no longer believe on the undervaluation and rational speculators (fundamentalists)—who base their expectations on economic fundamentals—become more prevalent. Fundamentalists believe that energy prices will revert to the intrinsic long-run equilibrium and therefore have a stabilizing effect. Consequently, chartists change their expectations and become followers of the fundamentalists. When prices tend to be overvalued, an asymmetric phenomenon occurs, that may be explained by the loss aversion behavior. Indeed, investors react differently when they are facing potential losses and profits. According to the prospect theory, agents are more hesitant to sell during overvaluation than to buy during undervaluation (Kahneman and Tversky, 1979).

Consider now the third case, with the forward oil price variations as the transition variable. The mean-reverting behavior is observed only in Regime 1, characterized by an oil price growth rate lower than 3%. This means that there exists a floor price under which oil producers decide to not produce due to profitability considerations. On the contrary, in periods of oil price boom, there is no mean-reverting behavior: the growing price tends to go away from its fundamental value, leading to self-sustaining behaviors.

The other forward energy price returns are positively linked to oil price returns, except in Regime 2 for electricity. Again, this can be interpreted in terms of a substitution effect between electricity and oil when the later reaches very high values. Finally, note the positive relationship between oil and stock returns, a fact that is consistent with speculating dynamics.

1.4 Conclusion

This chapter investigates the relationship between daily forward prices of oil, gas, coal and electricity. Relying on a panel of 35 maturities and controlling for the economic and financial environment using equity futures prices, we test whether energy prices evolve toward a common long-run relationship. Using panel cointegration techniques, we show that all forward price series are cointegrated. More specifically, while oil, gas and coal forward prices are positively linked, oil and electricity display a negative relationship, consistent with a substitution effect between the two energy sources on long horizons. Paying a particular attention to the financial dimension of energy markets, we account for potential nonlinearities notably induced by market participants' behavior. To this end, we estimate panel smooth transition regression models, and show that the forward oil price adjustment process toward its equilibrium value is nonlinear and asymmetric. More precisely, our findings put forward the key role played by speculative factors and self-sustaining dynamics in phases of booming oil prices and growing economic activity.

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Appendix of Chapter 1

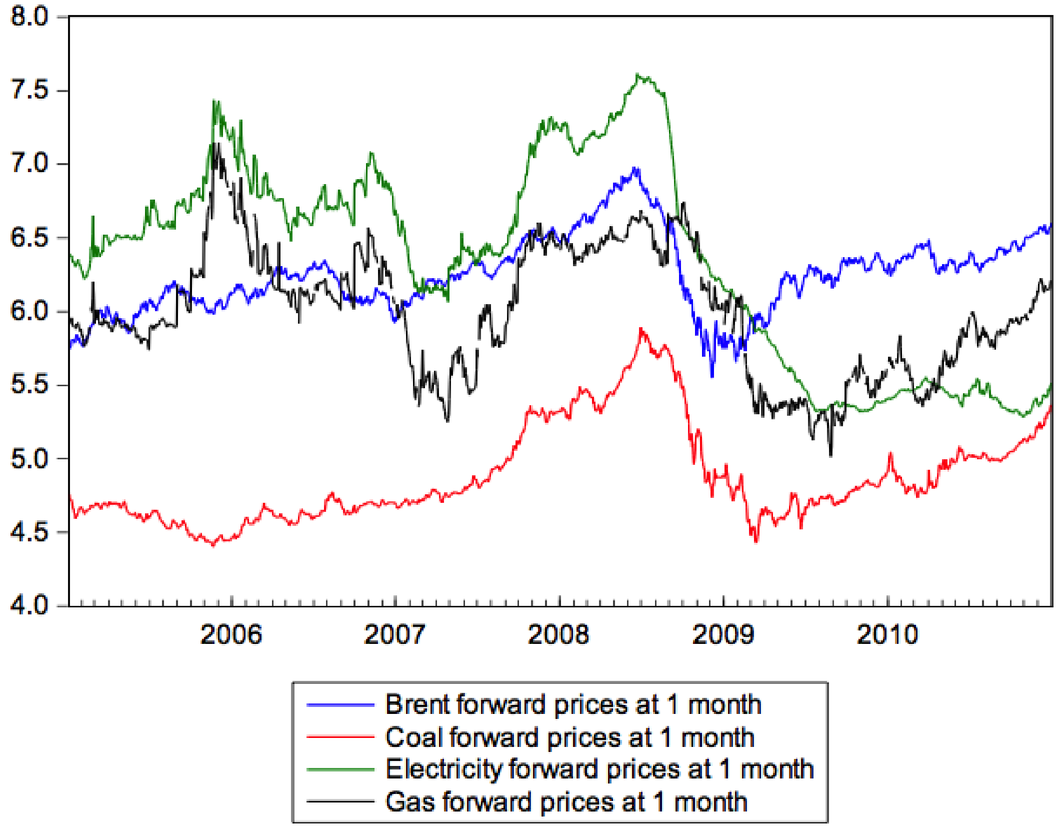

Figure 1-1: One-month forward energy prices (in logarithms)

Chapter 2

Testing for Granger causality in distribution tails: An application to energy markets

Introduction [1]

Since the seminal paper of Granger (1969), many studies have proposed to extend the concept of Granger-Causality. A first stream of literature deals with extensions of Granger-causality in mean.[2] An alternative route has been taken more recently in finance at the light of the recent financial crisis. It proposes to investigate Granger-causality in higher moments (e.g. tail risk) in order to evaluate the transmission of extreme financial markets movements. In this vein, Hong et al. (2009) recently put forward the concept of Granger-causality in risk to test for downside risk spillovers across financial markets. More precisely, they use a kernel-based test to check whether a large downside risk in one market will Granger-cause a large downside risk in another market. Hong et al. (2009) characterize as downside risk a situation where asset returns are lower than the Value-at-Risk (VaR) at a prespecified level (α).

Hong et al. (2009) consider thus the concept of Granger-causality in downside risk between two markets only at a particular risk level. This assumption appears to be restrictive. In particular, as noticed by Engle and Manganelli (2004), dynamics of downside risk can vary considerably across the different risk levels, so a Granger-causality test which does not consider the whole distribution tails, would be much too restrictive. Besides, our multivariate extension has the merit to consider cross-causality: for e.g., causality from one market at risk level $\alpha = 10\%$ to another market at risk level $\alpha = 1\%$. The rejection of the null hypothesis of causality in distribution tails can be due to this particular cross-causality which has a major importance in risk management, as it suggests that moderate extreme downside movements from the first market

[1] This chapter is based on two papers: Candelon, B., Joëts, M., and Tokpavi, S., 2013, Testing for Granger causality in distribution tails: An application to Oil Market Integration, Economic Modelling, 33, 276-285; and Joëts, M., 2012, Energy price transmissions during extreme movements, USAEE/IAEE Working Paper series, nř12-133.

[2] They discriminate in particular for long vs short-run causality (Granger and Lin, 1995), test for frequency domain causality (Breitung and Candelon, 2006) or panel Granger-causality (Dumitrescu and Hurlin, 2012).

can Granger-cause large extreme downside movements in the second market.

This chapter proposes thus an original procedure which allows for testing for Granger-causality in down- and upside risk for multiple risk levels across tail distributions. The procedure can be also extended to test for causality in risk for n markets, with $n > 2$. Following Hong at al. (2009) the estimation of extreme down- and upside risks relies on the Conditional Autoregressive Value-at-Risk (CAViaR) model introduced by Engle and Manganelli (2004) in which the VaRs are estimated directly using an autoregressive specification for the quantiles rather than inverting a conditional distribution as usual in a purely parametric framework (for e.g., a GARCH model under a Student-t distribution). We then consider the multivariate extension of the classical Granger-causality test in mean proposed by Gelper and Croux (2007) and Barret et al. (2010) to build a Granger-causality test for a set of hit functions[3] at different risk levels α_i, $i = 1, .., n$.

A potential uncertainty problem may arise from our two step procedure, where VaRs are estimated beforehand the causality test in risk. Such an issue should not affect the asymptotic properties of the test but its finite sample ones. This issue is investigated via simulation experiments and to minimize this potential bias, critical regions are obtained using the Monte-Carlo approach proposed by Dufour (2006).

This new Granger-causality framework is applied to investigate two relevant issues in energy markets: (i) the oil market integration process; and (ii) the energy price co-movements. Considering the oil market integration hypothesis, the question is of primary importance since even if oil market is often considered as a global market, it is characterized by regional disparities. For example the crude oil price quoted in Texas (WTI) is not the same as the one quoted in London. Besides, these dissimilarities vary when oil prices are on average extremely high or low and for different qualities of crude

[3] A hit function is an indicator function with value 1 (resp. 0) when the market return at a given time is lower (resp. higher) than the prediction of VaR.

oil. The new causality test in risk can then be implemented to check if causal linkages are more or less important during such periods, i.e. whether the markets are more or less integrated during periods of extreme energy prices movements. Furthermore, it is well known that some regional markets are leaders (price-setters) whereas other ones are followers (price-takers). This feature has important implications for the energy policy in many countries to design an optimal set of providers (it should not be exclusively composed by a single category of market) and/or to evaluate any political implication (embargo, war,..) on the global oil market (if the regional oil market is a price-setter, global oil market will be affected whereas it would not be the case if it is price-taker). The implementation of the causality test in risk can put some light on this question and indicate whether price-setter markets change during such periods. Turning to the gereral question of energy price co-movements during extreme movements, we propose to investigate whether potential transmissions between European forward prices of oil, gas, coal and electricity markets exist and can be different depending on both intensity and maturity of the markets.

The rest of the chapter is organized as follows. Section 2.1 describes the concept of Granger-causality in distribution tails, and present the finite sample properties of our tests. Section 2.2 studies the international crude oil markets globalization. Section 2.3 investigates energy price co-movements. Section 2.4 concludes the chapter.

2.1 Granger causality in distribution tails

In this section we develop a framework to test for Granger-causality in distribution tails, that is, whether the occurrence of any tail event for a given time series can help predict the occurrence of any tail event for another time series. The section is divided into two parts. In the first part we describe the econometric environment, give an overview of our testing approach and present the test statistics, while in the second part we simulate its finite sample properties via Monte Carlo studies.

2.1.1 Econometric environment and testable hypotheses

We consider a stochastic process $X \equiv \{X_t : \Omega \to \mathbb{R}^2, t = 1, ..., T\}$ defined on a probability space $(\Omega, \mathcal{F}, P)$ where $\mathcal{F} \equiv \{\mathcal{F}_t, t = 1, ..., T\}$ and $\mathcal{F}_t$ is the σ-field $\mathcal{F}_t = \{X_s, s \leq t\}$. We partition the observed vector X_t as $X_t = (X_{1,t}, X_{2,t})$ where both $X_{1,t}$ and $X_{2,t}$ are continuous random variables of interest. The information set available at time t has the following structure $\mathcal{F}_t \equiv \{\mathcal{F}_{1,t}\} \cup \{\mathcal{F}_{2,t}\}$ with $\mathcal{F}_{1,t} = \{X_{1,s}, s \leq t\}$ and $\mathcal{F}_{2,t} = \{X_{2,s}, s \leq t\}$. Our test is related to the concept of Granger-causality defined in terms of the entire conditional distribution (Granger, 1980; Granger and Newbold, 1986). Using our notations, $X_{2,t}$ does not Granger-cause $X_{1,t}$ in distribution if and only if

$$\Pr\left[X_{1,t} < x \,|\mathcal{F}_{t-1}\right] = \Pr\left[X_{1,t} < x \,|\mathcal{F}_{1,t-1}\right] \text{ a.s. for all } x. \tag{2.1}$$

In this case, past values of $X_{2,t}$ in the information set $\mathcal{F}_{t-1}$ do not carry any useful information that helps predict the conditional distribution of $X_{1,t}$. This definition is rather broad since in many practical situations, a user with a specific objective may be concerned with whether causality occurs or not in particular regions of the distributions of both variables. For example, in the context of downside risk monitoring and diversification, risk managers are usually aware of whether a loss for a business line in their managed portfolio will exceed a fixed large value given that a large loss for another business line has occurred. In the international crude oil markets, prices have experienced strong fluctuations affecting the profile of risk. For investors with long (resp. short) positions in these energy assets, measuring the associated downside (resp. upside) risks and their spillover effect is primordial. From a macroprudential point of view, the recent episode of market turmoil gives many evidence that regulators should also take care about downside risk spillover between financial institutions.

Hong et al. (2009) introduced a formal statistical procedure to test for Granger-causality in downside risk quantified by Value-at-Risk (VaR), the most popular metric of risk in the banking and financial industry. The VaR of a time series at the risk level $\alpha \in (0,1)$ is defined as the α-quantile of the conditional distribution of the given time series. For the two time series we thus have

$$\Pr\left[X_{1,t} < Q_{1,t}\left(\theta_{1,\alpha}\right)|\mathcal{F}_{1,t-1}\right] = \alpha, \tag{2.2}$$

$$\Pr\left[X_{2,t} < Q_{2,t}\left(\theta_{2,\alpha}\right)|\mathcal{F}_{2,t-1}\right] = \alpha, \tag{2.3}$$

with $Q_{1,t}\left(\theta_{1,\alpha}\right)$ and $Q_{2,t}\left(\theta_{2,\alpha}\right)$ the anticipated VaR of $X_{1,t}$ and $X_{2,t}$ respectively at time $t-1$, $\theta_{1,\alpha}$ and $\theta_{2,\alpha}$ two finite-dimensional parameters from the specification of the dynamics of both variables. Consider the following two tail-events time series

$$Z_{1,t}\left(\theta_{1,\alpha}\right) = \begin{cases} 1 & \text{if} \qquad X_{1,t} < Q_{1,t}\left(\theta_{1,\alpha}\right) \\ 0 & \text{else,} \end{cases} \tag{2.4}$$

$$Z_{2,t}\left(\theta_{2,\alpha}\right) = \begin{cases} 1 & \text{if} \qquad X_{2,t} < Q_{2,t}\left(\theta_{2,\alpha}\right) \\ 0 & \text{else.} \end{cases} \tag{2.5}$$

In Hong et al. (2009), the time series $\{X_{2,t}\}$ does not Granger-cause the time series $\{X_{1,t}\}$ in downside risk at level α if the following hypothesis holds[4]

$$\mathbb{H}_0 : \mathbb{E}\left[Z_{1,t}\left(\theta_{1,\alpha}\right)|\mathcal{G}_{t-1}\right] = \mathbb{E}\left[Z_{1,t}\left(\theta_{1,\alpha}\right)|\mathcal{G}_{1t-1}\right], \tag{2.6}$$

where the two information sets are defined as

$$\mathcal{G}_t = \left\{\left(Z_{1,s}\left(\theta_{1,\alpha}\right), Z_{2,s}\left(\theta_{2,\alpha}\right)\right), s \leq t\right\}, \tag{2.7}$$

$$\mathcal{G}_{1t} = \left\{Z_{1,s}\left(\theta_{1,\alpha}\right), s \leq t\right\}. \tag{2.8}$$

Hence, Granger-causality in downside risk for the two-time series $\{X_{1t}\}$ and $\{X_{2t}\}$ is equivalent to Granger-causality in mean for the two tail-events time series $\{Z_{1,t}\left(\theta_{1,\alpha}\right)\}$ and $\{Z_{2,t}\left(\theta_{2,\alpha}\right)\}$. It is worth noting that (2.6) is not a testable hypothesis since the two tail-events time series which depend on the unknown VaRs, $Q_{i,t}\left(\theta_{i,\alpha}\right)$, $i = 1, 2$, are not observable. Hence a model is required for both series, to generate the in-sample VaRs and the corresponding tail-events time series. Hong et al. (2009) rely on the Conditional Autoregressive Value-at-Risk (CAViaR) model introduced by Engle and Manganelli (2004) in which the VaRs are estimated directly using an autoregressive specification for the quantiles rather than inverting a conditional distribution as usual in a purely parametric framework (for e.g., a GARCH model under a Student-t distribution). More precisely, the following specifications are retained to estimate the

[4] Note that both causality in downside and upside risk can be handled in the framework of Hong et al. (2009). In the former case the risk level or coverage rate is set to a small value (for e.g., $\alpha = 1\%$, 5% or 10%). In the latter case, a high value is retained (for e.g., 90%, 95% or 99%) and the tail-events time series are properly defined as follows

$$Z_{i,t}\left(\theta_{i,\alpha}\right) = \begin{cases} 1 & \text{if} \quad X_{i,t} > Q_{i,t}\left(\theta_{1,\alpha}\right), \; i = 1, 2, \\ 0 & \text{else.} \end{cases}$$

VaRs

$$Q_{i,t}\left(\theta_{i,\alpha}\right)=\theta_{i,\alpha}^{(0)}+\theta_{i,\alpha}^{(1)}Q_{i,t-1}\left(\theta_{i,\alpha}\right)+\theta_{i,\alpha}^{(2)}\left(X_{i,t-1}\right)^{+}+\theta_{i,\alpha}^{(3)}\left(X_{i,t-1}\right)^{-}, \tag{2.9}$$

where $(X_{i,t})^{+} = \max(X_{i,t},0)$, $(X_{i,t})^{-} = \min(X_{i,t},0)$, $\theta_{i,\alpha} = \left(\theta_{i,\alpha}^{(0)},\theta_{i,\alpha}^{(1)},\theta_{i,\alpha}^{(2)},\theta_{i,\alpha}^{(3)}\right)$, $i = 1,2$. Note that the autoregressive nature of the CAViaR model captures (directly) in the tails of the distributions some stylized facts in empirical finance with many compelling evidence, such as autocorrelation in daily returns arising from market microstructure biases and partial price adjustment (Boudoukh et al., 1994; Ahn et al., 2002; Eom et al., 2004), volatility clustering (Engle, 1982; Bollerslev, 1986), and time-varying skewness and kurtosis (Hansen, 1994; Harvey and Siddique, 1999, 2000; Jondeau and Rockinger, 2003). Moreover the asymmetric specification in (2.9) adresses the asymmetric response of volatility to news (Black, 1976; Christie, 1982). The parameters of the CAViaR model are estimated by minimizing with respect to the unknown parameters the "check" loss function of Koenker and Bassett (1978), i.e.,

$$\widehat{\theta}_{i,\alpha} = \underset{\theta_{i,\alpha}}{\arg\min}\ \frac{1}{T}\sum\nolimits_{t=2}^{T}\left[\alpha-\mathbb{I}\left(u_{i,t}<0\right)\right]u_{i,t}, \quad i=1,2, \tag{2.10}$$

$$u_{i,t}=X_{i,t}-Q_{i,t}\left(\theta_{i,\alpha}\right), \tag{2.11}$$

with $\mathbb{I}(.)$ the usual indicator function and T the estimation sample length. The testable hypothesis of non-Granger causality in downside risk can thus be written as

$$\mathbb{H}_0:\mathbb{E}\left[Z_{1,t}\left(\widehat{\theta}_{1,\alpha}\right)|\mathcal{H}_{t-1}\right]=\mathbb{E}\left[Z_{1,t}\left(\widehat{\theta}_{1,\alpha}\right)|\mathcal{H}_{1t-1}\right], \tag{2.12}$$

with the observable information sets

$$\mathcal{H}_{1t}=\left\{Z_{1,s}\left(\widehat{\theta}_{1,\alpha}\right), s\leq t\right\}, \tag{2.13}$$

$$\mathcal{H}_t = \left\{ \left(Z_{1,s}\left(\widehat{\theta}_{1,\alpha}\right), Z_{2,s}\left(\widehat{\theta}_{2,\alpha}\right) \right), s \leq t \right\}. \tag{2.14}$$

Hong et al. (2009) adopted a kernel-based nonparametric test which checks for the nullity of the standardized sample cross covariances between the two processes $\left\{ Z_{1,t}\left(\widehat{\theta}_{1,\alpha}\right) \right\}$ and $\left\{ Z_{2,t}\left(\widehat{\theta}_{2,\alpha}\right) \right\}$, under the hypothesis of non-Granger causality in downside risk.[5] The test statistic has a standard asymptotic distribution under the null hypothesis which is not affected by parameter uncertainty in the estimated CAViaR models.

The test developed by Hong et al. (2009) is suitable to check for the existence of Granger-causality in extreme movements of two time series, but at a given risk level α. Our objective in the sequel is to extend this setup, by testing simultaneously Granger-causality in downside risk for multiple risk levels across the distribution tails. Two main reasons motivate our extension. First, it is apparent that when focusing on downside risk spillover effect, what really counts is to check whether causality exists between the left tail distributions of the two time series, and not between quantiles for a single risk level α. Second, estimation results of CAViaR models in Engle and Manganelli (2004) show that the process governing the dynamics of VaRs can vary remarquably across risk levels. Hence, application of the Hong et al. (2009) test can lead to contradictory results with respect to the risk levels, for example at 1%, 5% or 10%. In such a case, it is more suitable to make inference jointly for the three risk levels. From a statistical point of view, this strategy will improve the power properties of the Granger-causality test as more information is exploited. Moreover, our multivariate extension has the merit to consider cross-causality: for e.g., causality from $X_{2,t}$ at risk level $\alpha = 10\%$ to $X_{1,t}$ at risk level $\alpha = 1\%$. The rejection of the null hypothesis of causality in distribution tails can be due to this particular cross-causality which has a major importance in risk management, as it suggests that moderate extreme downside movements of $X_{2,t}$

[5] Note that Hong et al. (2009) also consider in their paper a regression-based approach to test for Granger-causality in downside risk. As we will see in the sequel, our Granger-causality test in distribution tails is a multivariate extension of the latter approach.

can Granger-cause large extreme movements of $X_{1,t}$.

Our testing procedure is based on the multivariate extension of the classical Granger-causality test in mean, where the purpose is to make inference on interactions that take place among groups of variables (Gelper and Croux, 2007; Barret et al., 2010). To present the methodology, let $A = \{\alpha_1, ..., \alpha_m\}$ be a discrete set of m risk levels, strictly between 0 and 1 and considered as relevant for downside risk analysis. For $i = 1, 2$, let $W_{i,t}(\theta_{i,A}) = [Z_{i,t}(\theta_{i,\alpha_1}), ..., Z_{i,t}(\theta_{i,\alpha_m})]$ be the vector of dimension $(m, 1)$ collection of the tail-events variables $Z_{i,t}(\theta_{i,\alpha_k})$ associated to these m risk levels at time t, where $\theta_{i,A} = \left(\theta'_{i,\alpha_1}, ..., \theta'_{i,\alpha_m}\right)'$ is the vector of dimension $(4m, 1)$ with elements the parameters of the m CAViaR models, each at the risk level α_k, $k = 1, ..., m$. The null hypothesis of our non-Granger causality test in distribution tails can be stated as follows

$$\mathbb{H}_0 : \mathbb{E}\left[W_{1,t}(\theta_{1,A}) \,|\mathcal{I}_{t-1}\right] = \mathbb{E}\left[W_{1,t}(\theta_{1,A}) \,|\mathcal{I}_{1,t-1}\right], \tag{2.15}$$

where the sets $\mathcal{I}_{1,t}$ and $\mathcal{I}_t$ correspond respectively to

$$\mathcal{I}_{1,t} = \left\{W_{1,s}(\theta_{1,A}), s \leq t\right\}, \tag{2.16}$$

$$\mathcal{I}_t = \left\{\left(W'_{1,s}(\theta_{1,A}), W'_{2,s}(\theta_{2,A})\right)', s \leq t\right\}. \tag{2.17}$$

If the null hypothesis holds, this means that whatever the risk levels α_k, $k = 1, ..., m$, spillover of extreme downside movements (from X_{2t} to X_{1t}) does not exist. Hence in our setup, Granger-causality in distribution tails is nothing but Granger-causality in mean for the two multivariate processes $W_{i,t}(\theta_{i,A})$, $i = 1, 2$. Following Gelper and Croux (2007) and Barret et al. (2010), the test statistic is easily built by considering the following multivariate linear regression model[6]

$$W_{1,t}\left(\theta_{1,A}\right)=\psi_0+\psi_1 W_{2,t-1}\left(\theta_{2,A}\right)+...+\psi_p W_{2,t-p}\left(\theta_{2,A}\right)+\varepsilon_{1t}, \tag{2.18}$$

where ψ_0 is a vector $(m,1)$ of constants, ψ_s, $s=1,...,p$, are (m,m) matrices of parameters, and ε_{1t} the $(m,1)$ residuals vector with covariance matrix Σ_1. The null hypothesis of non-Granger causality in distribution tails corresponds to

$$\mathbb{H}_0:\psi_1=\psi_2=....=\psi_p=0. \tag{2.19}$$

When this null hypothesis holds, the multivariate regression in (2.18) reduces to

$$W_{1,t}\left(\theta_{1,A}\right)=\psi_0+\varepsilon_{2t}, \tag{2.20}$$

with ε_{2t} the $(m,1)$ residuals vector with covariance matrix Σ_2. As a consequence, the multivariate likelihood ratio test statistic defined as follows[7]

$$\mathrm{LR}=\left[\mathrm{T}-(mp+1)\right]\left[\log\left(\left|\varepsilon_2'\varepsilon_2\right|\right)-\log\left(\left|\varepsilon_1'\varepsilon_1\right|\right)\right], \tag{2.21}$$

can be used to test for the null hypothesis of non-Granger causality in distribution tails as stated in (2.15) or equivalently in (2.19). This test statistic follows under the null hypothesis a chi-squared distribution with degree of freedom equal to pm^2.

[6]It is worth noting that we do not include lagged values of $W_{1,t}\left(\theta_{1,A}\right)$ in the regression equation (2.18), because under the null hypothesis, the m components of $W_{1,t}\left(\theta_{1,A}\right)$ are independent, each following an i.i.d. Bernoulli distribution. This latter property is usually used to backtest Value-at-Risk models (see, Christoffersen, 1998; Engle and Manganelli, 2004; Berkowitz et al., 2011; Candelon et al., 2011; etc.).

[7]Remark that a Fisher version of the LR test can be instead used, when data are scarce.

Let us remark that the above testing approach is not computationally feasible, because the two multivariate processes $W_{1,t}(\theta_{1,A})$ and $W_{2,t}(\theta_{2,A})$ depend respectively on the unknown vector of the CaViaR models parameters $\theta_{1,A}$ and $\theta_{2,A}$. An operational test can be conducted by considering the following null hypothesis

$$\mathbb{H}_0 : \xi_1 = \xi_2 = ... = \xi_p = 0, \tag{2.22}$$

in the multivariate regression:

$$W_{1,t}\left(\widehat{\theta}_{1,A}\right) = \xi_0 + \xi_1 W_{2,t-1}\left(\widehat{\theta}_{2,A}\right) + ... + \xi_p W_{2,t-p}\left(\widehat{\theta}_{2,A}\right) + \varepsilon_{1t}, \tag{2.23}$$

where the true vector of parameters $\theta_{i,A}$, $i = 1, 2$, are replaced by their respective consistent estimators $\widehat{\theta}_{i,A}$. However, uncertainty about the values of $\widehat{\theta}_{i,A}$, $i = 1, 2$, could affect the distribution of the test statistic. This problem is referred to as parameter uncertainty in the framework of hypothesis testing, and can be mitigated relying on robust methods such as Monte Carlo tests. The latters are exact tests, in the sense that the actual probability of Type I error is equal to the nominal significance level. Formally, Monte Carlo tests are performed by generating M independent realizations of the test statistic - say S_i, $i = 1, ...M$ - under the null hypothesis. If we denote S_0 the value of the test statistic obtained for the original sample, as shown by Dufour (2006) in a general case, the Monte Carlo critical region is obtained as $\widehat{p}_M(S_0) \leq \eta$ with $1 - \eta$ the confidence level and $\widehat{p}_M(S_0)$ defined as

$$\widehat{p}_M(S_0) = \frac{M\widehat{G}_M(S_0) + 1}{M + 1}, \tag{2.24}$$

where

$$\widehat{G}_M(S_0) = \frac{1}{M}\sum_{i=1}^{M}\mathbb{I}(S_i \geq S_0), \tag{2.25}$$

when $\Pr(S_i = S_j) \neq 0$, and otherwise

$$\widehat{G}_M(S_0) = 1 - \frac{1}{M}\sum_{i=1}^{M} \mathbb{I}(S_i \leq S_0) + \frac{1}{M}\sum_{i=1}^{M} \mathbb{I}(S_i = S_0) \times \mathbb{I}(U_i \geq U_0). \tag{2.26}$$

Variables U_0 and U_1 are uniform draws from the interval $[0, 1]$. In our framework, application of the Monte Carlo test procedure of Dufour (2006) requires simulating the two multivariate processes $W_{i,t}(\theta_{i,A})$ $i = 1, 2$, under the null hypothesis of non-Granger causality in distribution tails, in order to compute the M independent realizations of the test statistic LM_i, $i = 1, ..., M$, under $\mathbb{H}_0$. This task can be achieved very easily noting that for well-specified CAViaR models, each element of $W_{i,t}(\theta_{i,A})$, $i = 1, 2$, i.e., the tail-event variables $Z_{i,t}(\theta_{i,\alpha_k})$, $k = 1, ..., m$, follows an *i.i.d.* Bernoulli distribution with a success probability equal to α_k. We will show in the sequel that inference based on the Monte Carlo framework is more relevant than the one that relies on the asymptotic chi-square distribution.

2.1.2 Analysis of finite sample properties

This section is devoted to Monte Carlo simulations studies with the objective of evaluating the small sample properties of our Granger-causality test in distribution tails. We evaluate inference both with the asymptotic chi-squared critical region and the Monte Carlo critical region of Dufour (2006).

2.1.2.1 Finite sample size analysis

To illustrate the size performance of our test, we follow Hong et al. (2009) simulating the two time series $X_{1,t}$ and $X_{2,t}$ using the following data generating process (DGP):

$$\begin{cases} X_{i,t} = 0.5X_{i,t-1} + u_{i,t}, \;\; i = 1,2, \\ u_{i,t} = \sigma_{i,t} v_{i,t}, \\ \sigma^2_{i,t} = 0.1 + 0.6\sigma^2_{i,t-1} + 0.2u^2_{i,t-1}, \\ v_{i,t} \sim m.d.s.\ (0,1)\,. \end{cases}$$

Hence, each time series $X_{i,t}$, $i = 1,2$, follows an AR(1)-GARCH model. The two processes are independent and there is no-Granger causality in distribution tails between them. We simulate the size of the test considering three different sample sizes ($T = 500$, 1000, 1500 which correspond roughly to two, four and six years of daily data. For a given value of T, and for each simulation, CAViaR models are estimated to compute the two multivariate tail-events variables $W_{i,t}\left(\widehat{\theta}_{i,A}\right)$, $i = 1,2$, with A the discrete set of the m VaRs risk levels, $A = \{\alpha_1, ..., \alpha_m\}$. With the two multivariate processes $W_{i,t}\left(\widehat{\theta}_{i,A}\right)$, $i = 1,2$, we test the null hypothesis of non-Granger causality in distribution tails checking via the LM statistic the restriction (2.22) in the multivariate regression (2.23).

Table 2.2 in Appendix A reports the empirical sizes of our multivariate LM test statistic (over 500 simulations) for different values of $p \in \{5, 10, 15\}$ the lag order in the regression equation (2.23). The set A of the m VaRs risk levels is set to $A = \{1\%, 5\%, 10\%\}$. These values correspond to the usual risk levels considered when focusing on downside risk analysis.[8] For each simulation, the null hypothesis of non-Granger causality in distribution tails is rejected relying on the asymptotic chi-squared critical region, with two different nominal risk levels $\eta = 5\%$, 10%. Results in Table 2.2 indicate that our Granger-causality test in distribution tails is oversized whatever the sample size T and the value of the lag-order parameter p. For example, with a nominal risk level $\eta = 5\%$

[8]Of course, one can extend the set A by considering more risk levels, for example $A = \{1\%, 2.5\%, 5\%, 7.5\%, 10\%\}$. The advantage of this extension is to consider more information in the inferential procedure. However, when the size of the set A increases, the considered risk levels are more closer, and there is a non zero probability to face a problem of multicollinearity in the multivariate regression (2.23). This reason also motivates our choice of the set A.

and two years of daily data ($T = 500$), the rejection frequency of the null hypothesis is around 15% when $p = 5$ and 17% with $p = 10$. These results show that our regression testing procedure is affected by parameter uncertainty. The problem seems to be more prominent in small samples where the estimated parameters in the CAViaR models fail to converge to the correct model parameters because of data scarcity. The failure of convergence should be more acute at the 1% VaRs risk level compared to the other two VaRs risk levels $(5\%, 10\%)$. Therefore, the parameter uncertainty problem which affects the empirical sizes of our test should come mainly from the estimation errors of the CAViaR models at the 1% VaRs risk level. To confirm this analysis, we report in Table 2.3 (see Appendix A) the empirical sizes of the LM test statistic with $A = \{5\%, 10\%\}$. The presentation is similar to Table 2.2. We observe that the reported rejection frequencies of the null hypothesis are much closer to the nominal risk levels $\eta = 5\%$, 10%.

The above results suggest that for our testing procedure, inference using the asymptotic chi-squared distribution should be conducted only for moderate VaRs risk levels in the left-tail distribution. More precisely, one should not include the 1% VaRs risk level in the set A. Nevertheless, in the analysis of spillover effect in downside movements, considering the extreme case of 1% risk level is crucial, because in financial markets, market prices movements at this risk level have major consequences on the values of assets and the solvability of assets owners. Hence, we propose to make inference with the three VaRs risk levels, i.e., $A = \{1\%, 5\%, 10\%\}$, simulating the critical region through the Monte Carlo approach of Dufour (2006). As already stressed, this testing procedure helps to alleviate the problem of parameter uncertainty by simulating via Monte Carlo experiments, the exact distribution of the test statistic under the null hypothesis. Table 2.4 in Appendix A displays the empirical sizes with the Monte Carlo critical region, where the parameter M (see equations 2.24-2.26) is set to $9,999$. The overall picture from Table 2.4 is that our LM test statistic, used in conjonction with the Monte Carlo procedure of Dufour (2006), is correctly sized. For each sample size T, the choice of the lag-order parameter p has little impact on the sizes of the test.

2.1.2.2 Finite sample power analysis

We now investigate the power of the test. Since causality in distribution tails or in extreme movements is mainly due to causality in mean, variance or higher order moments such as kurtosis and skewness, we assume the following DGPs for the two time series $X_{1,t}$ and $X_{2,t}$, in order to generate data under the alternative hypothesis:

$$\begin{cases} X_{2,t} = 0.5X_{2,t-1} + u_{2,t}, \\ u_{2,t} = \sigma_{2,t} v_{2,t}, \\ \sigma^2_{2,t} = 0.1 + 0.6\sigma^2_{2,t-1} + 0.2u^2_{2,t-1}, \end{cases} \tag{2.27}$$

$$\begin{cases} X_{1,t} = 0.5X_{1,t-1} + 0.2X_{2,t-1} + u_{1,t}, \\ u_{1,t} = \sigma_{1,t} v_{1,t}, \\ \sigma^2_{1,t} = 0.1 + 0.6\sigma^2_{1,t-1} + 0.2u^2_{1,t-1} + 0.7u^2_{2,t-1}, \end{cases} \tag{2.28}$$

where both $v_{1,t}$ and $v_{2,t}$ are martingale difference sequences with mean 0 and variance 1. Under this setting, the time series $X_{2,t}$ Granger causes the time series $X_{1,t}$ in distribution tails via causality in both mean and variance. The empirical powers of our multivariate LM test statistic are computed over 500 simulations, for different values of p the lag-order parameter, and for two nominal risk levels $\eta = 5\%$, 10%. The results are reported in Tables 2.5 and 2.6 for $A = \{1\%, 5\%, 10\%\}$. To stress the relevance of our multivariate approach, we also display in these tables the power of the univariate testing approach of Hong et al. (2009), where A is reduced to the sets $\{1\%\}$, $\{5\%\}$ and $\{10\%\}$ respectively. The rejection frequencies are computed using the Monte Carlo critical region of Dufour (2006), with the parameter M set to $9,999$. Our multivariate test displays fairly good power properties. For example, with $T = 1000$ and $p = 5$, the test rejects the null of non-Granger causality in distribution tails 82%

(resp. 89%) of time when $\eta = 5\%$ (resp. $\eta = 10\%$). As expected, the power increases as the sample size T increases. As usual in the setting of parametric Granger-causality test, increasing the lag-order parameter p lowers the power of the test. Finally and importantly, the advantage of the multivariate approach over the univariate testing procedure of Hong et al. (2009) is clear-cut. Indeed, for a given value of the sample T and the lag-order parameter p, the multivariate test rejects more strongly the null hypothesis of non-Granger causality in distribution tails. For instance, with $\eta = 5\%$, and $(T, p) = (500, 10)$, the rejection frequency is equal to 51% for $A = \{1\%, 5\%, 10\%\}$, whereas it is only equal to 15%, 41%, and 41% for A equal to $\{1\%\}$, $\{5\%\}$, and $\{10\%\}$ respectively.

2.2 Crude oil markets globalization

The oil market constitutes without any doubt the most strategic row commodity market. Periods of extreme high energetic price (often label as oil shock) are usually associated with recession and/or inflationnary pressure (Sadorsky, 1999; Hamilton, 2003; Kilian, 2008; among others). Hence, understanding how oil price is fixed and evolved is a key issue for policy makers in order to implement adequate economic stabilization policies.

Unfortunately this issue is not simple as the oil market is not homogenous and is composed by numerous local markets, sometimes organized into cartels (the most famous being the OPEC[9]) and trading different oil qualities (depending on the API (American Petroleum Institute)[10] and the sulfur content[11]). Different types of crude oils fetch

[9] See Brémond et al. (2011).

[10] The higher the API degree, the lighter (and the better) the crude. Crudes with API higher than 35° are considered light, API between 26° and 35° are medium, whereas all API smaller than 26° are considered heavy.

[11] Crudes with high content in sulphur are said to be sour and are generally avoided, as they produce more pollution and are more harmful for the environment. Crudes are considered to be sweet when the sulphur content does not exceed 0.5% and sour when they do.

distinct prices, and these prices are usually set as a discount or premium to a marker or reference crude oil according to their characteristics (Mabro, 2005; Fattouh, 2006, 2010, 2011; among others).[12] Many observers consider the world oil market as 'one great pool' (Adelman, 1984) in the sense that supply and demand shocks that affect prices in one region are transmitted into other regional markets. Several papers have therefore tested the integration hypothesis of the different crude oil markets (see inter alii Weiner, 1991; Gülen, 1997, 1999; Kleit, 2001; Milonas and Henker, 2001; Lanza et al., 2003; Hammoudeh et al., 2008; Fattouh, 2010) which assumes that same quality crude oil prices should be nearly identical or at least co-move in different regions such as their price differentials would be more or less constant. This perspective has strong implications in terms of energy policy and market efficiency.

Nevertheless, as a consensus is not reached since marker crudes suffer from serious doubts about their ability to generate a marker price,[13] Wlazlowski, Hagstromer, and Giulietti (2011), hereafter WHM, prefer to analyze global market dependencies, finding out if a particular crude oil market can be regarded as benchmark or follower. It is then possible to draw a distinction between price taker markets, which are affected by the variation on other local markets, and price setter markets, which give the pace for price changes. This distinction is therefore essential for policy makers, to evaluate for example the price consequences of an embargo on an oil producer. If this market is price setter (resp. taker) it should (resp. should not) impact the prices on the other local markets. Besides, WHM distinguish 4 qualities and 32 crude oil markets, concluding that widely used benchmarks such as WTI and Brent are indeed in fact global price setters joined by a third crude, the Mediterranean Russian Urals. The Asia Dubai Fateh and the Oman Blend finally act as benchmarks for their segment.

[12] The expansion of the crude oil market allowed the development of market-referencing pricing off spot crude oil markers such as WTI (West Texas Intermediate), Brent and Dubai, which are theoretically considered as benchmarks due to their ownership diversification properties (see, Horsnell and Mabro, 1993).

[13] See Fattouh (2006).

Cook (1998)[14] stresses that integration hypothesis is especially and almost uniquely important when crude oil price movements (upward or downward) are extreme indicating tension either on the demand or supply side. The general feeling is that price differentials would tend to widen across the markets during extreme movements, and decrease otherwise. Thus, the diversification strategy aiming at limiting the impact of an oil shock would be more efficient during extreme prices periods, whereas it would be more difficult and less beneficial in "regular" times. Indeed, the empirical justification of such a theory separating regular and extreme times would have strong policy implications.

This section proposes to investigate this issue by analyzing the global market dependence during extreme crude oil price movements using our new Granger-causality test in distribution tails. To this aim and following WHM, we consider the weekly prices of 32 crude oils extracted from the Energy Information Agency for the period April 21, 2000 to October 20, 2011.[15] Out of the total of 32 crude oils in our sample, 15 fall into the jurisdiction of the OPEC bloc, whereas 17 are not part of it (non-OPEC countries). Each crude oil is also characterized by its quality defined both by its density and its sulphur content.

2.2.1 Results

We implement our Granger-causality test in distribution tails to understand the global architecture of the international crude oil market during extreme movements. Statistically, our goal is to identify for each couple of crude oils, which market (Granger) causes in the distribution tails the others. Economically, our approach investigates the behavior of oil markets during extreme downward and upward (left and right tails)

[14] Confirmed by several reports of the BMO Commodity Derivatives Group. In particular the one published in 2004 entitled "Managing Heavy Oil Price Risk" and available at corporate.bmo.com/cm/market/cdcom/images/Managing_Heavy_Oil_Price_Risk.pdf.

[15] Crude oils included in our data are reported in Table 2.7.

price variations. More precisely, the distinct roles (i.e. leader and follower) for the different varieties of crude oils as well as the global market integration are examined. Results are displayed in Table 2.8 for both left and right tails, corresponding respectively to extreme downside and upside movements. For each side (downside or upside), the first column presents the proportion of time a market Granger-causes other markets.[16] Symmetrically, the second column presents the proportion of time a market is Granger-caused by other ones. The last column displayed the difference between the values reported in the first and the second columns. The results can be analyzed as follows: a crude oil is identified as benchmark or exhibits price setter characteristics in extreme movements, if it causes other crude oils without being caused (or weakly caused) reciprocally. These crude oils are thus highly sensitive to oil market shocks (i.e. they respond to oil market news). On the contrary, crude oils with high price taker and low price setter characteristics follow the trend of the global market, and are less sensitive to oil market shocks. Lastly, crude oils with both high setter and taker dynamics are intermediate between leaders and followers, and can be considered as perfectly integrated. It is worth noting that these three categories can be easily identified focusing on the difference between the proportions displayed in the third column: markets with a large positive (resp. negative) difference in proportions are benchmarks (resp. followers), whereas small absolute values indicate that markets are well integrated in the general market.

Results in Table 2.8 indicate that different varieties of crude oil can have distinct behaviors depending on the direction of the prices changes. Indeed, it appears that both WTI and Europe Brent behave as benchmarks (they cause other crude oils and are weakly affected reciprocally) for the international crude oil market. However, WTI seems to be price setter mainly in downside movements indicating the well known

[16] Inferences are conducted at the 5% nominal risk level. Following WHM, we set the value of the lag-order parameter p to 16 (4 months). Results available from the authors upon request show that our findings are robust with respect to p.

predominant role of this market. Furthermore, unlike WHM's analysis, we find that Mediterranean Russian Urals is a benchmark only in extreme downside movements. Europe Forcados also appears as benchmark in downside movements. Ecuador Oriente, and to a lesser extent, Mexico Isthmus and Mexico Maya, turn out to be benchmarks in extreme upside movements. Colombia Cano Limon, Malaysia Tapis, Saudi Arabia Saudi Light, Saudi Arabia Arab Medium, and Ecuador Oriente are followers in periods of large price decrease, whereas Mediterranean Russian Urals and Kuwait Blend show the same characteristic in periods of large price increase. Besides, and importantly, Asia Dubai Fateh and Oman Blend which are considered in practice as benchmarks for their segment, do not exhibit price setter characteristics in the universe of the 32 crude oils considered. To summarize, our results in Table 2.8 suggest that crude oils that yield a higher proportion of the more valuable final petroleum products and require a simple refining process (i.e. WTI, Brent, Europe Forcados,...) usually drive prices over those that yield lower fraction of petroleum products and require more refining process (i.e. heavy/sour crude markets). Moreover, oil price differentials and leadership characteristics vary according to price directions. As documented by Fattouh (2010), these phenomena can result from non-parallel movements coming from the local condition of each market. The relative demand for various final petroleum products is driven by seasonal component which is likely to affect crude oil markets in disctinct way.

Is the crude oil markets less or more integrated in periods of extreme movements? The question whether the international oil market is one great pool or is regionalized during extreme movements has important implications for policy makers and portfolio managers. For instance, Weiner (1991) argues that the effectiveness of energy policies depends to the fact that the impact of such policy can be extend to other regions or not. From an energy portfolio managers viewpoint, the issue of the diversification in the international crude oil markets during extreme fluctuations is of primary importance to manage their intrinsic risks. In the literature, the intuition is that crude oil markets are less integrated in extreme situations. The rationale of this claim (see, Cook, 1998; BMO, 2004; Bacon and Tordo, 2005) is that if the demands for all petroleum products increased proportionately, and all product prices and the general crude price also increased proportionately, then crudes with the largest proportion of high value products would increase in price relative to crudes with a lower proportion of high value products, with the result that price differential would tend to widen across the crude oil markets. The symmetric reasoning holds in the case of general fall in demands and prices. To confirm this analysis, we report in Table 2.9 the same statistics as in Table 2.8, with the difference that we consider Granger-causality test in mean rather than in distribution tails. In both tables, we measure the level of markets integration by the mean of the absolute value of the differences between the two percentages (setter and taker). The lower the value of this statistic, the more integrated are crude oil markets. Our results confirm the intuition that crude oil markets are less integrated in extreme situations. Indeed, the price differentials between various pairs of crude follow very different patterns depending on the type of crude oil as well as if the crude is linked to an liquid futures market. Theoretically, the presence of liquid futures market strengthening the cost-of-carry relationship between crude oils helps make more distant markets more unified. Nevertheless, long-run arbitrage across international oil markets, during extreme movements periods, is not costless and shifts in the standard benchmarks can cause temporary decoupling prices, and so improve the possibility of diversification. Hence, the possibility of diversification turns out to be enhanced during the periods of extreme movements in crude oil prices.

To go deeper beyond these results, we implement our analysis conditional to the quality segment of crude oils. Following WHM, we consider three quality segments: light & sweet, medium & sweet, and medium & sour. From table 2.7, it is easy to see that the light & sweet group has 9 crude oils, the medium & sour group contains 13 crude oils, while the medium & sweet group has 6 crude oils. Further potential groups, in particular those involving sour crudes, were discarded given limitations of the sample size. Results are displayed in Tables 2.10, 2.11 and 2.12. Regarding to the light density and sweet crude oils (Table 2.10), WTI and Europe Brent are leaders in extreme price falls, WTI being the dominant crude oil, while in extreme price rises, only WTI behaves as benchmark. All other crude oils in this quality segment can be considered as followers (low setter and high taker proportions) or integrated to different extent (high setter and taker proportions), in periods of extreme downside movements. Malaysia Tapis appears clearly as a follower in extreme upside movements. Concerning the medium density and sweet crude oils (Table 2.11), Europe Forcados (resp. Colombia Cano Limon) can be considered as benchmark in extreme downside (resp. upside) movements. Finally, for the medium density and sour crude oils (Table 2.12), two markets, that is, Mediterranean Russian Urals and Mediterranean Seri K Iran Light appear to be preponderant in extreme downside movements, whereas Ecuador Oriente and Mexico Isthmus are the leaders in extreme upside movements. These findings are different from those reported by Montepeque (2005) and WHM about the lack of leading benchmarks and a high degree of integration in this group.

Our analysis goes on, distinguishing OPEC from non-OPEC members. Table 2.13 gathers the outcomes of the Granger-causality test and indicates a very high degree of integration in periods of positive extreme movements, with a lack of leading benchmark in the group of OPEC countries. For negative extreme movements, Europe Forcados, Algeria Saharan Blend, and Europe Libyan Es Sider are the dominant markets, whereas Asia Dubai Fateh and Saudi Arabia Arab Medium are clearly followers. When considering the non-OPEC members, WTI and Europe Brent are dominant in extreme downside movements, with WTI being the leader. Both markets dominate other crude oils equally in extreme upside movements. These distinct results depending on the side of the distribution (upside or downside), would be the consequence of fundamental and speculative specificities of each market. Indeed, unlike WTI crude oil, which prices are largely reflected by market fundamentals, Europe Brent oil market is relatively opaque (Miller et al., 2010), with inherent lack of transparency and illiquidity in price determination processes. Consequently, the market could become unhinged from physical factors by action of market participants. Moreover, since several years, Brent and more generally North Sea crude oils have known a sharp decline in production, and more of the supply is now mainly absorbed locally in Europe. Therefore, Brent has become disconnected from US and Asian markets (Miller et al., 2010). In this context, two types of extreme risk could exist in international oil market depending on downside and upside circumstances: "speculative risk" and "fundamental risk". First, in periods of price decreases, fundamental mechanisms would dominate speculative ones. The fundamental mechanisms would be based on the international oil demand from North American and Asian emerging countries on NYMEX rather than IPE markets leading to the dominance of WTI crude oil. Second, in periods of price increases, fundamental and speculative mechanisms would operate equally in oil markets, where financial investors without any physical interests could influence benchmarks through speculative purpose. This makes both crude oil markets to be dominant to the same extent. Note that in the group of non-OPEC countries, Mediterranean Russian Urals (resp. Ecuador Oriente) appears as a third benchmark in extreme price falls (resp. rises). These results are consistent with those reported in Table 2.8 where all the 32 crude oils are considered. It is worth noting that these benchmarks once established, attract liquidity; and liquidity attracts further liquidity. Such circularity creates an exceptional inertia making extremely difficult for alternative benchmarks to arise, even if the latter becomes unreliable. However, permanent dominance cannot exist and natural market equilibrium and realities will impose alternative setter.

To sum up, several interesting conclusions can be drawn from our analysis: extreme crude oil prices are governed by non-OPEC markets rather than OPEC ones. More precisely, WTI and Brent crude oils are price setters both in downside and upside price movements, due to the fundamental and speculative components of each market. Surprisingly, Mediterranean Russian Urals and Europe Forcados (resp. Ecuador Oriente) also act as benchmarks in periods of extreme downside (resp. upside) price movements. Asia Dubai Fateh and Oman Blend, the acclaimed crude oil benchmarks act as followers rather than leaders. Besides, we observe that the integration level between crude oil markets tends to decrease during extreme periods.

2.3 Energy price transmissions during extreme movements

Energy price dynamics are known to be frequently volatile with extensive amplitude affecting the whole economy (Sadorsky (1999), Hamilton (2003), Edelstein and Kilian (2007), Kilian (2008), among others). In the literature, these fluctuations are attributed to both real and financial factors, such as international energy demand/supply conditions and market manipulation (Kilian (2008), Hamilton (2009), Kaufmann and Ullman (2009), Kilian (2009), Cifarelli and Paladino (2010), Ellen and Zwinkels (2010), Lombardi and Van Robays (2011), Kilian and Murphy (2012) among others), leading to extreme market risks for energy participants and governments. Moreover, energy markets have recently experienced significant developments likely to influence price dynamics. European gas and electricity markets, initially monopolistic, have become competitive due to the recent deregulation process, allowing the emergence of new contracts making prices more influenced by participants than regulators (Mjelde and Bessler (2009)). In this light, market volatility may increase and the quantification of the maximum prices appears to be primordial in risk management for one's ability to make proper investment, operational, and contractual decisions.

Due to the globalization process, economies are related to each other notably through trade and investment, so any news about economic fundamentals in one country most likely have implications in other countries (Lin et al. (1994), Ding et al. (2011), among others). From a general viewpoint, this perspective may obviously be extended to energy market behaviors which are known to be interrelated through production, substitution and competitive processes. Indeed, several studies have validated the fact that oil, gas, coal and electricity prices may be interconnected in the long run (Bachmeier and Griffin (2006), Mjelde and Bessler (2009), Mohammadi (2009), Ma and Oxley (2010), and Joëts and Mignon (2011), among others). However, previous analyses mainly focus on "regular" time[17] fluctuations without considering periods of extreme price movements (upward and downard) whereas energy prices are often characterized by intense dynamics. The general feeling along this way is that correlations between assets tend to be stronger during excessive fluctuations periods. This phenomenon, which has been largely studied in the financial literature[18] suggests that comovements are larger when we focus on large absolute-value returns, and seem more important in bear markets. Under this market-comovement scenario, price movements are driven by fads and a herd behavior may be transmittable across markets (in the sense of Black (1986) and Delong et al. (1990)). High volatility is therefore coupled with highly interrelated markets making diversification almost impossible under uncertain movements. These comovements in absolute price changes are often associated with belief dispersion (Shalen (1993)) resulting in a lack of confidence in market fundamentals. When new information occurs, distinct prior beliefs give incitation to trade leading to price changes. When traders revise their prior beliefs according to new information, it takes time for the market to "resolve" these heterogeneous behaviors which contribute to volatility clustering (Shalen (1993) and Lin, Engle and Ito (1994) among others). Thus, the diversification strategy aiming at limiting the impact of excessive movements would be almost impossible because of the markets integration, whereas it has more sense in "regular" times. As periods of extreme high energy prices have been proved to be economically detrimental (Sadorsky (1999), Oberndorfer (2009), among others), this section proposes to extend this issue by analysing energy price comovements during periods of erratic fluctuations. This phenomenon would have important macroeconomic and microeconomic implications since absence of diversification can

[17] Regular periods are subjectively defined by times of low fluctuations.

[18] See King and Wadhwani (1990), Lin, Engle and Ito (1994), Longin and Solnik (1995), Karolyi and Stulz (1996), Longin and Solnik (2001), Ramchand and Susmel (1998), Ang and Bekaert (2002), Hong et al. (2007), Amira et al. (2009), and Ding et al. (2011) to name few.

lead to heavy potential losses for market participants and governements. For instance, from a macroeconomic viewpoint, a perfect perception of price movements and market risk are of primary importance for policy targeting of energy-importing or exporting countries. At a microeconomic level, the price behavior, market risk and their potential transmission mechanisms are relevant to evaluating real investment decisions using the well-known asset pricing model.

In order to apprehend extreme movements, the Value-at-Risk (VaR) approach is an important tool and is widely used in financial markets.[19] VaR is often used to measure market risk with a single numeric value by means of the probability distribution of a random variable. It is defined as the expected maximum loss over a target horizon for a given confidence interval (see Jorion (2007)). Due to the strong volatility of commodity markets, this methodology has been recently extended to oil markets—see, Cadebo and Moya (2003), Giot and Laurent (2003), Feng et al. (2004), Sadeghi and Shavvalpour (2006), and Fan et al. (2008)—and to the oil and gas markets—see, Aloui and Mabrouk (2006)— which evaluate the risk losses in WTI, Brent crude oil and gas markets using different techniques (Historical simulation standard approach, RiskMetrics (RM), variance-covariance method based on various GARCH models, among others). However, these methodologies are quite restrictive because they are based on several strong assumptions. For instance, the nonparametric Historical simulation approach is based on a time-constant returns unconditional distribution and fractile. The parametric RM approach is based on the linear risk and the normality of price changes, which is not consistent with the market reality. Finally, GARCH methodologies suffer from the positivity and/or symmetry constraints often imposed on the coefficient parameters.[20] We improve this literature by considering extreme movements (upward and downward) of European oil, gas, coal and electricity markets using the semiparametric Conditional

[19]One of the main advantage of VaR cited in literature is its user friendly way to concisely presents risk supported by the regulatory authorities.

[20]Recent GARCH approaches have been developed to remove these assumptions, such as E-GARCH, GJR-GARCH, and GARCH models under a Student-t distribution to name few.

Autoregressive VaR (CAViaR) approach developed by Engle and Manganelli (2004), which is considered to be less restrictive than other methodologies.

Despite the apparent market globalization, transmission effects among energy markets during extensive periods have been scarcely studied. Lin and Tamvakis (2001) first studied spillover effects among NYMEX and IPE crude oil contracts in both non-overlapping and simultaneous trading hours, and found significant transmission effects. However, they do not use the crucial information about the quantile of the distribution, which is of primary importance to apprehend tremendous variations.[21] More recently, Fan et al. (2008) evaluate the market risk of daily Brent and WTI crude oil returns from May 20th, 1987 to August 1st, 2006 using a GED-GARCH model. They examine the downside and upside extreme risk spillover between both markets using the Granger causality test developed by Hong et al. (2009). Results show that the VaR model based on GED method performs relatively well, and that the WTI and Brent returns have significant two-way causality effect in both downside and upside risks at 95% or 99% confidence levels. Further analysis reveals that at the confidence level of 99%, the WTI market risk information can help to forecast extreme Brent market risk when negative news occur, but the reverse effect does not exist. However, their results are based on a restrictive parametric GARCH approach which is again not consistent with market reality, and authors investigate risk spillover at specific confidence level (95% and 99%) while the information in tails distribution is of primary importance.[22] Our test that we develop in Section 2.1 (hereafter CJT test) allows to overcome this problem by considering a multivariate extension of the Granger causality approach.

In this chapter, our aim is to investigate energy price return transmissions during both "normal" and extreme fluctuations periods by using the traditional Granger causality

[21] According to Gouriéroux and Jasiak (2001), volatility cannot be considered as a statisfactory measure of risk when extreme market movements occur.

[22] According to Engle and Manganelli (2004), dynamics of VaRs can vary considerably across risk levels.

test (in mean) and its multivariate CJT extension – the later focusing on causality in distribution tails rather than quantile at specific level. Relying on European forward energy prices rather than spot data, we purge short-run demand and supply from noise that affects market fluctuations and account for both fundamental and speculative pressures (Joëts and Mignon (2011)).[23] Because comovements between markets can vary considerably over time and in order to see if diversification can be more profitable as maturity increases, we propose to investigate forward price transmission mechanims at 1, 10, 20, and 30 months.

2.3.1 Risk measurement

We consider daily data over the January 3, 2005 to December 31, 2010 period. In order to allow for both fundamental and speculative pressures, we rely on European forward price returns at 1, 10, 20, 30 months for oil, gas, coal and electricity markets.[24] Energy prices are quoted in US dollars per tonne of oil equivalent ($/toe) and are extracted from the Platt's Information Energy Agency. Figure 1 in Appendix B depicts the one month forward returns (defined as prices in first log difference) in the whole sample and reveals the volatility clustering of energy markets.[25],[26] Basic descriptive statistics for prices at 1 month are computed and reported in Table 2.1. They reveal that each return series, compared to the standard normal distribution, are asymmetric (oil, gas and electricity returns are right skewed while coal returns are left skewed) and leptokurtic, revealing fat tail distributions. Due to the specific nature of its market (i.e. non-storablility, inelasticity of the supply,...) electricity returns are frequently affected

[23]Indeed, the forward energy markets can result in both physical delivery and speculative purposes.

[24]Due to space constraints, we only report results corresponding to 1 month. The results for the other maturities are similar and are available upon request to the author.

[25]The volatility clustering is effective when strong fluctuations (resp. low) are followed by strong (resp. low) perturbations.

[26]Energy forward prices at 10, 20, and 30 month (not reported here) are characterized by the same clustering property.

by regime switching causing tail behavior higher than fossil energies (1.7 and 25 for skewness and kurtosis respectively).

The energy returns seem to behave as strongly volatile financial assets. The financial properties of forward energy markets lead us to use an asymmetric CAViaR specification to model energy VaRs. From Table 2.15 to Table 2.18 in Appendix B, estimations and backtesting for each return series (at 1 month) are reported at 1%, 5% and 10% quantile levels for both downside and upside risks. Results confirm the asymmetric behavior of each market for both downside and upside risks ($\theta^{(2)}$ and $\theta^{(3)}$ are significant for all series). This asymmetric component appears between bullish and bearish markets and between left and right tails, which reveals that energy price behaviors are different depending on the mood of the market. Generally, for fossil energies, negative returns are predominant in downside risk while positive returns are higher in upside one. Moreover, left tail behavior (downside risk) seems to be higher than right tail dynamic (upside risk). For electricity returns, relying to CAViaR estimation, asymmetric dynamic seems to be less pronounced. It may come from a misspecified risk model. Indeed, the dynamic quantile (DQ) test is applied to check the adequacy of the VaRs estimation, and results show that our models are well specified for energy fossil only. The misspecification of electricity VaR model may be due to the high occurrence of extreme values and potential regime switching. In our analysis, the misspecified problem is not a constraint because risk apprehension is more widely affected by parameter incertainty. Risk estimation is therefore strongly influenced by model assumptions and parameterizations. In our Granger causality context, CJT approach deals with this issue by using Monte Carlo procedure to compute p-values of test. In this way, p-values are simulated and the misspecified parameters of electricity VaR model are corrected.

Table 2.1: **Summary statistics for the daily forward energy returns at 1 month**

	Brent	Gas	Coal	Electricity
Mean	0.00053	0.00017	0.00038	−0.00062
Variance	0.00053	0.00035	0.00033	0.00088
Skewness	0.13679	0.00327	−0.57407	1.76840
Kurtosis	8.97939	6.47279	9.93896	25.31240
Jarque-Bera test	2333.29 (0.00)	785.431 (0.00)	3221.56 (0.00)	33236.7 (0.00)

Notes: p-values for corresponding null hypotheses are reported in parentheses. The statistics are computed over the period 2005-01-04 : 2010-12-30.

2.3.2 Energy price transmission

Using Granger causality approach, we propose to investigate transmission mechanisms between energy price returns during both regular times and extreme volatility periods. Table 2.19 in Appendix B reports results of Granger causality in mean, to investigate energy price interactions at 1 month during normal times. It reveals that, except for oil and coal prices, no short-run causalities exist across energy markets confirming the results in favor of long-run interactions rather than short-term comovements. The same result (not reported here) is also observable for prices at 10, 20, and 30 months. Considering extreme occurrences, Table 2.20 gathers Granger causality test in tails distribution for prices at 1 month through CJT approach. It shows that comovements are higher between markets during periods of price decrease, while during situations of price increase no significant causalities exist. These relations appear to be relevant mainly across fossil energies. Energy prices at 1 month behave as stock returns which are characterized by asymmetric causalities between downturn and upturn situations making diversification almost impossible during extreme volatility periods.

According to Ding et al. (2011) for financial markets, this asymmetric phenomenon could be attributed to several fundamental and speculative factors. For instance, a popular incidence documented by many studies (Kim et al., 2008; Campbell and Diebold,

2009, among others) is that when economy experiences negative shock, the volatility of fundamental variables is usually higher and accompanied by an increase of fundamental risk. Moreover, Campbell and Hentschel (1992) find that during extreme price movements, market downturn is more likely associated with high market risk. This finding is consistent with our results on energy market behaviors.
Furthermore, Demirer and Lien (2004) find that during periods of extreme prices decrease, individual firm returns tend to comove more closely causing stronger transmission mechanism between companies. It is therefore reasonable to think that such behaviors also exist across energy industries.

The energy market causality dynamics could also be explained by various behavioral considerations. Indeed, there is evidence that investors react more sensitively to bad news than good news. According to Barberis et al. (1998), following a string of positive shocks, the investors expect that the trend will continue in the same way (i.e. they expect another positive shock). If good news is announced, the positive shock is largely anticipated and the market response appears to be relatively small. However, negative shocks impact returns significanlty since bad news appears more as a surprise. In the same context, the popular prospect theory of Kahneman and Tversky (1979) shows that investors react differently to market circumstances due to the notion of loss aversion. They are more hesitant to sell in overvaluation than to buy in undervaluation (they are more sensitive to undervaluation) causing asymmetric dynamics between bearish and bullish markets. Another possible explanation could be relative to the emotion component of energy markets. Recent researches have found that feelings can have significant impact on equity returns under uncertain and risky environment even if emotions are unrelated to the decision context.[27] According to Forgas (1995), feelings will become predominant as risk and uncertainty increase. Considering that market risk increases during downturn periods, investors should be more influenced by their

[27] See Saunders (1993), Hirshleifer and Shumway (2003), Cao and Wei (2002), Kamstra et al. (2000), Kamstra et al. (2003), and Dowling and Lucey (2005, 2008), among others.

emotions during extreme prices decrease. In this context, Joëts (2012) confirms that energy market dynamics tend to be more influenced by emotions when extreme bearish market movements occur. This phenomenon is likely to cause asymmetric causality behaviors making diversification almost impossible.

2.3.3 Maturity effect

While energy forward prices at 1 month appear to be characterized by an asymmetric comovement with a downturn predominence, energy markets dynamic seems to be different as maturities increase. Considering comovements during extreme fluctuations, Table 2.21 to Table 2.23 gather CJT Granger causality tests for energy forward prices at 10, 20, 30 months respectively.[28] They show that causality between markets varies strongly over time. Indeed, compared to the 1 month prices maturity, energy market interactions seem to be less pronounced as maturity increases. For instance, asymmetric downturn causality remains significant for energy prices at 10 months, while this dynamic fades strongly at 20 and 30 months making diversification more profitable at longer maturities. This phenomenon could be attributable to the well known Samuelson effect which reveals an eventual prices maturity segmentation across energy markets. This effect would tend to influence the volatility of the series across maturity leading to a decrease of comovements between energy markets.

On the whole, our analysis shows that energy price return relationships increase during periods of extreme movements, especially in bear markets circumstances. Indeed, while almost no causality exists during "normal" times, price comovements are higher during market downturns as compared to upturns. This phenomenon leads to asymmetric interactions in energy price returns, showing that energy markets behave as stock markets making diversification almost impossible during high volatility periods.

[28] Granger causality tests in mean (normal times) are also computed showing no significant energy price relationship (results available upon request to the author).

However, this phenomenon tends to disappear as maturity increases, indicating that diversification could be more profitable at longer horizons (such as 20 and 30 months).

2.4 Conclusion

This chapter develops a novel Granger-causality test in risk. Elaborating on Hong et al. (2009) who consider the concept of Granger-causality in risk between two markets only at a particular risk level, we elaborate an original procedure which allows for testing for Granger-causality in down- and upside risk for multiple risk levels across tail distributions. After presenting the asymptotic distribution, a simulation exercise shows that applying the Dufour (2006) Monte-Carlo technique to calculate critical regions, tackles the potential uncertainty problem which may arise from our two-step procedure. This new test is illustrated by two applications. The first one deals with the oil markets. We implement our test to check if causal linkages are more or less important during extreme price movements periods and to determine if local markets are price-setters or price-takers. This last issue has important implications for the energy policy in many countries to design an optimal set of providers and/or to evaluate any political implication (embargo, war,..) on the global oil market.

Several interesting results can be drawn: extreme crude oil prices are governed by non-OPEC markets rather than OPEC ones. More precisely, WTI and Brent crude oils are price setters both in downside and upside price movements, due to the fundamental and speculative components of each market. Surprisingly, Mediterranean Russian Urals and Europe Forcados (resp. Ecuador Oriente) also act as benchmarks in periods of extreme downside (resp. upside) price movements. Asia Dubai Fateh and Oman Blend, the acclaimed crude oil benchmarks act as followers rather than leaders. Besides, we observe that the integration level between crude oil markets tends to decrease during extreme periods.

These results highlight the leading role played by the US and UK markets in the determination of crude oil prices. Understanding and forecasting crude oil price evolutions in periods of extreme price occurences would require a precise analysis of these two high quality markets. Nevertheless, attention should be payed to additional leading markets which have lower quality: Mediterranean Russian Urals, Europe Forcados, and Ecuador Oriente. This chapter also paves the way to important advices for energy policy as it indicates that diversification strategies are the more relevant in periods of sharp variations in crude oil prices.

Our second applications is devoted to the investigation of energy transmission mechanisms across forward price returns of oil, gas, coal, and electricity during both normal and extreme volatility periods. Using Granger causality approach in mean as well as in tails distribution, we show that energy price comovements increase during extreme fluctuations, while they are almost nonexistent in regular times. More precisely, energy market causalities appear to be stronger during bear markets, indicating a possible relation between volatility and comovements at shorter maturities. The phenomenon could be attributed to several fundamental and speculative factors, showing that energy markets behave as financial assets. Regarding portfolio diversification, unstable asset relationships might lead energy risk managers to exaggerate the benefits of diversification during extreme downturn variations making suboptimal portfolio allocations. However, probably due to a Samuelson effect, energy markets comovements vary from shorter to longer maturity and seem to be fading as maturity increases. This maturity effect shows that, contrary to short maturity, diversification could be more profitable at longer ones.

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Appendix of Chapter 2

A Sample properties

Table 2.2: Empirical sizes with the asymptotic critical region: $A = \{1\%, 5\%, 10\%\}$

	$p = 5$	$p = 10$	$p = 15$
	Nominal risk level $\eta = 5\%$		
$T = 500$	0.1503	0.1703	0.1523
$T = 1000$	0.1122	0.1222	0.1022
$T = 1500$	0.1142	0.1002	0.1122
	Nominal risk level $\eta = 10\%$		
$T = 500$	0.2144	0.2044	0.2064
$T = 1000$	0.1523	0.1743	0.1583
$T = 1500$	0.1743	0.1663	0.1764

Notes: The table displays the empirical rejection frequencies of the multivariate LM statistic under the null of non-Granger causality in distribution tails. The statistics are reported for different sample sizes, values of the lag order p in the multivariate regression (23), and nominal risk level η. The rejection frequencies are computed using the chi-squared asymptotic distribution.

Table 2.3: Empirical sizes with the asymptotic critical region: $A = \{5\%, 10\%\}$

	$p = 5$	$p = 10$	$p = 15$
	Nominal risk level $\eta = 5\%$		
$T = 500$	0.0802	0.0701	0.0782
$T = 1000$	0.0782	0.0661	0.0621
$T = 1500$	0.0441	0.0621	0.0701
	Nominal risk level $\eta = 10\%$		
$T = 500$	0.1343	0.1303	0.1343
$T = 1000$	0.1222	0.1162	0.1222
$T = 1500$	0.0922	0.1162	0.1263

Notes: The table displays the empirical rejection frequencies of the multivariate LM statistic under the null of non-Granger causality in distribution tails. The statistics are reported for different sample sizes, values of the lag order p in the multivariate regression (23), and nominal risk level η. The rejection frequencies are computed using the chi-squared asymptotic distribution.

Table 2.4: Empirical sizes with the Monte Carlo critical region: $A = \{1\%, 5\%, 10\%\}$

	$p = 5$	$p = 10$	$p = 15$
	Nominal risk level $\eta = 5\%$		
$T = 500$	0.0441	0.0401	0.0501
$T = 1000$	0.0461	0.0501	0.0641
$T = 1500$	0.0721	0.0661	0.0721
	Nominal risk level $\eta = 10\%$		
$T = 500$	0.1022	0.1102	0.1182
$T = 1000$	0.1082	0.1242	0.1222
$T = 1500$	0.1242	0.0962	0.1303

Notes: The table displays the empirical rejection frequencies of the multivariate LM statistic under the null of non-Granger causality in distribution tails. The statistics are reported for different sample sizes, values of the lag order p in the multivariate regression (23), and nominal risk level η. The rejection frequencies are computed relying on the Monte Carlo critical region.

Table 2.5: Empirical powers with the Monte Carlo critical region: nominal risk level = 5%

	$p = 5$	$p = 10$	$p = 15$
	$A = \{1\%, 5\%, 10\%\}$		
$T = 500$	0.5331	0.5150	0.5030
$T = 1000$	0.8216	0.7355	0.7094
$T = 1500$	0.9319	0.9238	0.8617
	$A = \{1\%\}$		
$T = 500$	0.2164	0.1543	0.1182
$T = 1000$	0.3166	0.2946	0.2565
$T = 1500$	0.4790	0.5190	0.4569
	$A = \{5\%\}$		
$T = 500$	0.4910	0.4148	0.3607
$T = 1000$	0.6774	0.6814	0.6232
$T = 1500$	0.8737	0.8297	0.7996
	$A = \{10\%\}$		
$T = 500$	0.5230	0.4128	0.3928
$T = 1000$	0.7255	0.7054	0.6112
$T = 1500$	0.8978	0.8657	0.8176

Notes: The first panel of the Table displays the empirical rejection frequencies of the multivaraite LM statistic under the alternative of Granger-causality in distribution tails. The statistics are reported for different sample sizes, values of the lag order p in the multivariate regression (23), and nominal risk level η. For comparison, the following panels present the same statistics for the univariate test of Hong et al. (2009). The rejection frequencies are computed relying on the Monte Carlo critical region.

Table 2.6: Empirical powers with the Monte Carlo critical region: nominal risk level = 10%

	$p = 5$	$p = 10$	$p = 15$
	$A = \{1\%, 5\%, 10\%\}$		
$T = 500$	0.6874	0.6754	0.6072
$T = 1000$	0.8938	0.8637	0.8196
$T = 1500$	0.9739	0.9519	0.9259
	$A = \{1\%\}$		
$T = 500$	0.3868	0.2525	0.2585
$T = 1000$	0.5311	0.4890	0.3868
$T = 1500$	0.6032	0.6052	0.5792
	$A = \{5\%\}$		
$T = 500$	0.6393	0.5772	0.4890
$T = 1000$	0.7896	0.7756	0.7315
$T = 1500$	0.9158	0.9038	0.8517
	$A = \{10\%\}$		
$T = 500$	0.6553	0.5731	0.5210
$T = 1000$	0.8056	0.8036	0.7255
$T = 1500$	0.9399	0.9178	0.8818

Notes: The first panel of the Table displays the empirical rejection frequencies of the multivariate LM statistic under the alternative of Granger-causality in distribution tails. The statistics are reported for different sample sizes, values of the lag order p in the multivariate regression (23), and nominal risk level η. For comparison, the following panels present the same statistics for the univariate test of Hong et al. (2009). The rejection frequencies are computed relying on the Monte Carlo critical region.

B Oil markets globalization

Table 2.7: Details of Crudes analyzed

Crude	API	Sulphur (%)
Non-OPEC		
WTI Cushing	40°-light	0.2-sweet
Europe Brent	38°-light	0.4-sweet
Europe Norwegian Ekofisk	43°-light	0.1-sweet
Canadian Par	40°-light	0.3-sweet
Canada Lloyd Blend	22°-heavy	3.1-sour
Mexico Isthmus	35°-medium	1.5-sour
Mexico Maya	22°-heavy	3.3-sour
Colombia Cano Limon	30°-medium	0.5-sweet
Ecuator Oriente	29°-medium	1.0-sour
Angola Cabinda	32°-medium	0.2-sweet
Cameroon Kole	35°-medium	0.3-sweet
Egypt Suez Blend	32°-medium	1.5-sour
Oman Blend	34°-medium	0.8-sour
Australia Gippsland	45°-light	0.1-sweet
Malaysia Tapis	44°-light	0.1-sweet
Mediterranean Russian Urals	32°-medium	1.3-sour
China Daqing	33°-medium	0.1-sweet
OPEC		
Saudi Arabia Saudi Light	34°-medium	1.7-sour
Saudi Arabia Arab Medium	31°-medium	2.3-sour
Saudi Arabia Saudi Heavy	28°-medium	2.8-sour
Asia Murban	40°-light	0.8-sour
Asia Dubai Fateh	32°-medium	1.9-sour
Qatar Dukhan	40°-light	1.2-sour
Mediterranean Seri Kerir Iran Light	34°-medium	1.4-sour
Mediterranean Seri Kerir Iran Heavy	31°-medium	1.6-sour
Kuwait Blend	31°-medium	2.5-sour
Algeria Saharan Blend	44°-light	0.1-sweet
Europe Nigerian Bonny Light	37°-light	0.1-sweet
Europe Forcados	30°-medium	0.3-sweet
Europe Libyan Es Sider	37°-light	0.4-sweet
Indonesia Minas	34°-medium	0.1-sweet
Venezuela Tia Juana	31°-medium	1.1-sour

Table 2.8: Results of Granger-causality test in distribution tails

Crude	Left Tail			Right Tail		
	Setter (1)	Taker (2)	(1)-(2)	Setter (1)	Taker (2)	(1)-(2)
WTI	0.9677	0.0000	0.9677	0.9677	0.3226	0.6452
Europe Brent	0.9677	0.0968	0.8710	0.9677	0.3548	0.6129
Europe Norwegian Ekofisk	0.8387	0.7097	0.1290	0.0968	0.1290	−0.0323
Canadian Par	0.6452	0.8710	−0.2258	0.1935	0.0645	0.1290
Canada Lloyd Blend	0.0323	0.1613	−0.1290	0.0323	0.0645	−0.0323
Mexico Isthmus	0.5484	0.8710	−0.3226	0.5484	0.1613	0.3871
Mexico Maya	0.5806	0.8387	−0.2581	0.4839	0.1290	0.3548
Colombia Cano Limon	0.2581	0.9355	−0.6774	0.3871	0.1290	0.2581
Ecuador Oriente	0.5484	0.9355	−0.3871	0.7419	0.0645	0.6774
Angola Cabinda	0.8065	0.6774	0.1290	0.1613	0.0968	0.0645
Cameroon Kole	0.9355	0.7419	0.1935	0.0323	0.1935	−0.1613
Egypt Suez Blend	0.8710	0.9032	−0.0323	0.0968	0.0968	0.0000
Oman Blend	0.9032	0.8065	0.0968	0.0645	0.3871	−0.3226
Australia Gippsland	0.7097	0.6452	0.0645	0.1935	0.2903	−0.0968
Malaysia Tapis	0.4516	0.9677	−0.5161	0.5484	0.8065	−0.2581
Mediter. Russian Urals	0.9355	0.4516	0.4839	0.2581	0.6774	−0.4194
China Daqing	0.7742	0.9032	−0.1290	0.0323	0.3226	−0.2903
Saudi Arabia Saudi Light	0.3548	0.7742	−0.4194	0.0968	0.1290	−0.0323
Saudi Arabia Arab Medium	0.4194	0.8065	−0.3871	0.0968	0.2258	−0.1290
Saudi Arabia Saudi Heavy	0.6452	0.6774	−0.0323	0.0968	0.1290	−0.0323
Asia Murban	0.6774	0.8065	−0.1290	0.0968	0.2903	−0.1935
Asia Dubai Fateh	0.6129	0.9355	−0.3226	0.0645	0.3548	−0.2903
Qatar Dukhan	0.8065	0.7419	0.0645	0.1290	0.4516	−0.3226
Mediter. Seri K Iran Light	0.6129	0.4194	0.1935	0.0968	0.0968	0.0000
Mediter. Seri K Iran Heavy	0.4194	0.6129	−0.1935	0.1935	0.2903	−0.0968
Kuwait Blend	0.8387	0.8710	−0.0323	0.1290	0.5806	−0.4516
Algeria Saharan Blend	0.8065	0.5806	0.2258	0.0968	0.1613	−0.0645
Europe Nigerian Bonny Light	0.8387	0.7742	0.0645	0.1613	0.0968	0.0645
Europe Forcados	0.8387	0.3548	0.4839	0.1290	0.0968	0.0323
Europe Libyan Es Sider	0.9032	0.6452	0.2581	0.1290	0.0645	0.0645
Indonesia Minas	0.8065	0.5806	0.2258	0.0968	0.2903	−0.1935
Venezuela Tia Juana	0.6452	0.9032	−0.2581	0.3226	0.1935	0.1290
Mean absolute value			0.2782			0.2137

Note: For each crude oil, the table displays the proportion of time the Granger-causality test in distribution tails rejects the null of no-causality for the system of pair markets. Nominal size is set to 5 percent.

Table 2.9: Results of Granger-causality test in mean

Crude	Setter (1)	Taker (2)	(1)-(2)
WTI	1.0000	0.8065	0.1935
Europe Brent	1.0000	0.0323	0.9677
Europe Norwegian Ekofisk	0.8065	0.7742	0.0323
Canadian Par	0.9355	0.9677	−0.0323
Canada Lloyd Blend	0.8387	0.6129	0.2258
Mexico Isthmus	0.9032	0.9355	−0.0323
Mexico Maya	0.9355	0.9677	−0.0323
Colombia Cano Limon	0.9032	0.9355	−0.0323
Ecuador Oriente	0.8387	0.8710	−0.0323
Angola Cabinda	0.7742	0.8065	−0.0323
Cameroon Kole	0.7097	0.6774	0.0323
Egypt Suez Blend	0.7097	0.7742	−0.0645
Oman Blend	0.8387	0.9355	−0.0968
Australia Gippsland	0.9355	0.9677	−0.0323
Malaysia Tapis	0.4839	0.9677	−0.4839
Mediter. Russian Urals	0.9677	0.9677	0.0000
China Daqing	0.9355	0.9677	−0.0323
Saudi Arabia Saudi Light	0.9355	0.9677	−0.0323
Saudi Arabia Arab Medium	0.9355	0.9355	0.0000
Saudi Arabia Saudi Heavy	0.9355	0.8710	0.0645
Asia Murban	0.8710	0.8387	0.0323
Asia Dubai Fateh	0.8387	0.8387	0.0000
Qatar Dukhan	0.8387	0.9032	−0.0645
Mediter. Seri K Iran Light	0.9355	0.8710	0.0645
Mediter. Seri K Iran Heavy	0.9355	0.8065	0.1290
Kuwait Blend	0.8065	0.8387	−0.0323
Algeria Saharan Blend	0.7097	0.8065	−0.0968
Europe Nigerian Bonny Light	0.8065	0.9032	−0.0968
Europe Forcados	0.9032	0.8710	0.0323
Europe Libyan Es Sider	0.7097	0.8710	−0.1613
Indonesia Minas	0.9355	0.9677	−0.0323
Venezuela Tia Juana	0.6452	1.0000	−0.3548
Mean absolute value			0.1109

Note: For each crude oil, the table displays the proportion of time the Granger-causality test in mean rejects the null of no-causality for the system of pair markets. Nominal size is set to 5 percent.

Table 2.10: Results of Granger-causality test in distribution tails: Light density and sweet

Crude	Left Tail			Right Tail		
	Setter (1)	Taker (2)	(1)-(2)	Setter (1)	Taker (2)	(1)-(2)
WTI	0.8750	0.0000	0.8750	0.8750	0.1250	0.7500
Europe Brent	0.8750	0.1250	0.7500	0.8750	0.5000	0.3750
Europe Norwegian Ekofisk	0.7500	0.8750	−0.1250	0.1250	0.3750	−0.2500
Canadian Par	0.7500	1.0000	−0.2500	0.2500	0.2500	0.0000
Australia Gippsland	0.7500	0.8750	−0.1250	0.2500	0.2500	0.0000
Malaysia Tapis	0.7500	1.0000	−0.2500	0.2500	0.8750	−0.6250
Algeria Saharan Blend	0.6250	1.0000	−0.3750	0.2500	0.3750	−0.1250
Europe Nigerian Bonny Light	0.7500	1.0000	−0.2500	0.1250	0.3750	−0.2500
Europe Libyan Es Sider	0.7500	1.0000	−0.2500	0.3750	0.2500	0.1250
Mean absolute value			0.3611			0.2778

Note: For each crude oil, the table displays the proportion of time the Granger-causality test in distribution tails rejects the null of no-causality for the system of pair markets. Nominal size is set to 5 percent.

Table 2.11: Results of Granger-causality test in distribution tails: Medium density and sweet

Crude	Left Tail			Right Tail		
	Setter (1)	Taker (2)	(1)-(2)	Setter (1)	Taker (2)	(1)-(2)
Colombia Cano Limon	0.2000	1.0000	−0.8000	0.4000	0.0000	0.4000
Angola Cabinda	0.8000	0.8000	0.0000	0.2000	0.0000	0.2000
Cameroon Kole	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000
China Daqing	0.8000	0.8000	0.0000	0.0000	0.4000	−0.4000
Europe Forcados	1.0000	0.4000	0.6000	0.0000	0.0000	0.0000
Indonesia Minas	1.0000	0.8000	0.2000	0.0000	0.2000	−0.2000
Mean absolute value			0.2667			0.2000

Note: For each crude oil, the table displays the proportion of time the Granger-causality test in distribution tails rejects the null of no-causality for the system of pair markets. Nominal size is set to 5 percent.

Table 2.12: Results of Granger-causality test in distribution tails: Medium density and sour

Crude	Left Tail			Right Tail		
	Setter (1)	Taker (2)	(1)-(2)	Setter (1)	Taker (2)	(1)-(2)
Mexico Isthmus	0.8333	0.9167	−0.0833	0.5833	0.0833	0.5000
Ecuador Oriente	0.5000	1.0000	−0.5000	0.8333	0.0000	0.8333
Egypt Suez Blend	1.0000	1.0000	0.0000	0.1667	0.0000	0.1667
Oman Blend	1.0000	1.0000	0.0000	0.0000	0.4167	−0.4167
Mediter. Russian Urals	1.0000	0.2500	0.7500	0.2500	0.6667	−0.4167
Saudi Arabia Saudi Light	0.5000	0.7500	−0.2500	0.1667	0.0833	0.0833
Saudi Arabia Arab Medium	0.5000	0.6667	−0.1667	0.1667	0.2500	−0.0833
Saudi Arabia Saudi Heavy	0.8333	0.5833	0.2500	0.0833	0.0833	0.0000
Asia Dubai Fateh	0.5000	1.0000	−0.5000	0.0000	0.4167	−0.4167
Mediter. Seri K Iran Light	0.8333	0.3333	0.5000	0.1667	0.0000	0.1667
Mediter. Seri K Iran Heavy	0.5833	0.4167	0.1667	0.3333	0.2500	0.0833
Kuwait Blend	0.8333	0.9167	−0.0833	0.0833	0.7500	−0.6667
Venezuela Tia Juana	0.7500	0.8333	−0.0833	0.3333	0.1667	0.1667
Mean absolute value			0.2564			0.3077

Note: For each crude oil, the table displays the proportion of time the Granger-causality test in distribution tails rejects the null of no-causality for the system of pair markets. Nominal size is set to 5 percent.

Table 2.13: Results of Granger-causality test in distribution tails: OPEC

Crude	Left Tail			Right Tail		
	Setter (1)	Taker (2)	(1)-(2)	Setter (1)	Taker (2)	(1)-(2)
Saudi Arabia Saudi Light	0.2857	0.8571	−0.5714	0.0714	0.0000	0.0714
Saudi Arabia Arab Medium	0.2857	0.7857	−0.5000	0.0714	0.1429	−0.0714
Saudi Arabia Saudi Heavy	0.5714	0.5000	0.0714	0.0714	0.0000	0.0714
Asia Murban	0.7143	0.8571	−0.1429	0.0000	0.0714	−0.0714
Asia Dubai Fateh	0.5000	1.0000	−0.5000	0.0000	0.1429	−0.1429
Qatar Dukhan	0.8571	0.7857	0.0714	0.0714	0.2857	−0.2143
Mediterranean Seri K Iran Light	0.5714	0.2857	0.2857	0.0714	0.0000	0.0714
Mediterranean Seri K Iran Heavy	0.4286	0.5714	−0.1429	0.2143	0.0000	0.2143
Kuwait Blend	0.9286	0.9286	0.0000	0.0714	0.6429	−0.5714
Algeria Saharan Blend	0.9286	0.5000	0.4286	0.0714	0.0000	0.0714
Europe Nigerian Bonny Light	0.8571	0.7143	0.1429	0.2143	0.0714	0.1429
Europe Forcados	0.8571	0.2857	0.5714	0.0714	0.0000	0.0714
Europe Libyan Es Sider	1.0000	0.5714	0.4286	0.0714	0.0000	0.0714
Indonesia Minas	0.7143	0.5000	0.2143	0.0000	0.0714	−0.0714
Venezuela Tia Juana	0.5714	0.9286	−0.3571	0.3571	0.0000	0.3571
Mean absolute value			0.2952			0.1524

Notes: For each crude oil, the table displays the proportion of time the Granger-causality test in distribution tails rejects the null of no-causality for the system of pair markets. Nominal size is set to 5 percent.

Table 2.14: Results of Granger-causality test in distribution tails: Non-OPEC

Crude	Left Tail			Right Tail		
	Setter (1)	Taker (2)	(1)-(2)	Setter (1)	Taker (2)	(1)-(2)
WTI	0.9375	0.0000	0.9375	0.9375	0.4375	0.5000
Europe Brent	0.9375	0.1250	0.8125	0.9375	0.4375	0.5000
Europe Norwegian Ekofisk	0.8125	0.7500	0.0625	0.1250	0.1875	−0.0625
Canadian Par	0.6250	0.8750	−0.2500	0.1875	0.1250	0.0625
Canada Lloyd Blend	0.0000	0.2500	−0.2500	0.0625	0.1250	−0.0625
Mexico Isthmus	0.5625	0.8125	−0.2500	0.5625	0.3125	0.2500
Mexico Maya	0.5625	0.8750	−0.3125	0.3750	0.2500	0.1250
Colombia Cano Limon	0.3125	0.8750	−0.5625	0.3750	0.2500	0.1250
Ecuador Oriente	0.6250	0.8750	−0.2500	0.7500	0.1250	0.6250
Angola Cabinda	0.7500	0.6875	0.0625	0.2500	0.1875	0.0625
Cameroon Kole	0.8750	0.7500	0.1250	0.0625	0.3750	−0.3125
Egypt Suez Blend	0.8125	0.8125	0.0000	0.1250	0.1875	−0.0625
Oman Blend	0.8125	0.6875	0.1250	0.1250	0.5000	−0.3750
Australia Gippsland	0.6875	0.6875	0.0000	0.1875	0.3750	−0.1875
Malaysia Tapis	0.3750	0.9375	−0.5625	0.5000	0.6875	−0.1875
Mediterranean Russian Urals	0.8750	0.5000	0.3750	0.1875	0.6875	−0.5000
China Daqing	0.7500	0.8125	−0.0625	0.0625	0.5625	−0.5000
Mean absolute value			0.2941			0.2647

Notes: For each crude oil, the table displays the proportion of time the Granger-causality test in distribution tails rejects the null of no-causality for the system of pair markets. Nominal size is set to 5 percent.

C Energy price transmissions

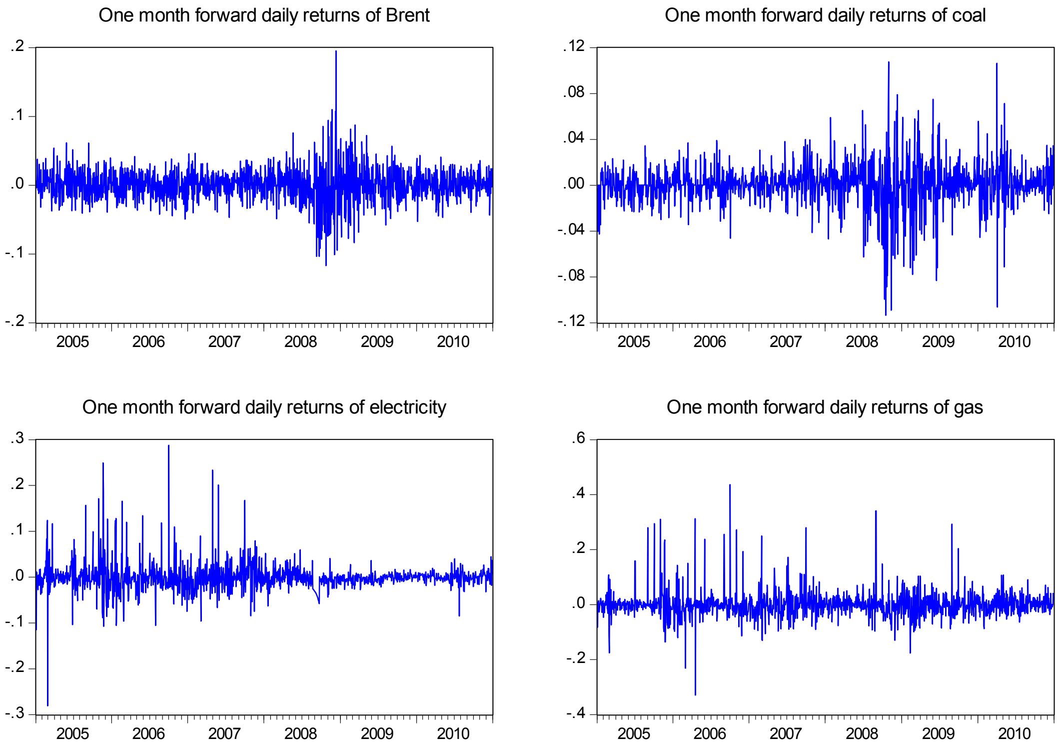

Figure 2-1: One month forward energy returns (prices in first log difference)

Table 2.15: CAViaR estimation results for daily oil returns at 1 month

	Downside Risk			Upside Risk		
	$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 10\%$	$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$
$\theta^{(0)}$	0.0012	0.0013	0.0009	0.0004	0.0005	0.0008
	[0.0002]	[0.0002]	[0.0002]	[0.0001]	[0.0002]	[0.0005]
	(0.0154)	[0.0000]	(0.0001)	(0.0000)	(0.0007)	(0.0715)
$\theta^{(1)}$	0.9653	0.9411	0.9439	0.9771	0.9793	0.9730
	[0.0104]	[0.0199]	[0.0120]	[0.0081]	[0.0082]	[0.0114]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\theta^{(2)}$	-0.4880	0.4635	0.4443	1.2285	1.2759	2.1296
	[0.0359]	[0.0478]	[0.0476]	[0.0186]	[0.0150]	[0.0387]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\theta^{(3)}$	-2.4313	-2.2109	-1.7239	0.4087	0.3987	0.0140
	[0.00314]	[0.0524]	[0.0196]	[0.0177]	[0.0196]	[0.0435]
	(0.0000)	(0.0000)	(0/0000)	(0.0000)	(0.0000)	(0.3735)
% Hit	0.0102	0.0505	0.0997	0.1004	0.0505	0.0090
DQ test Stat	4.8256	1.3346	2.2793	5.5953	4.5916	0.3617
DQ test P-value	0.3057	0.8555	0.6845	0.2315	0.3318	0.9855

Notes: The values in brackets (resp. parentheses) are the standard errors (resp. p-values) of the estimated parameters. Engle and Manganelli's DQ test is applied to check the adequacy of the specified VaR model, where the first four lagged hits are used as instruments.

Table 2.16: CAViaR estimation results for daily gas returns at 1 month

	Downside Risk			Upside Risk		
	$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 10\%$	$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$
$\theta^{(0)}$	0.0739	−0.0461	0.0349	0.0399	0.0667	−0.0013
	[0.0297]	[0.0461]	[0.0044]	[0.0034]	[0.0060]	[0.0011]
	(0.0064)	[0.2813]	(0.0000)	(0.0000)	(0.0000)	(0.1105)
$\theta^{(1)}$	0.0974	0.0429	0.0146	−0.0579	−0.0725	1.0081
	[0.3091]	[1.5356]	[0.1087]	[0.0174]	[0.0210]	[0.0036]
	(0.3763)	(0.4889)	(0.4468)	(0.0004)	(0.0003)	(0.0000)
$\theta^{(2)}$	2.5281	2.8731	1.7770	−0.1407	−0.2504	0.4449
	[0.0443]	[0.0439]	[0.0482]	[0.0282]	[0.0549]	[0.0453]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\theta^{(3)}$	−7.8342	−7.2216	−6.4634	−2.1672	−3.4997	0.5623
	[0.1187]	[0.1727]	[0.1164]	[0.1241]	[0.1301]	[0.0581]
	(0.0000)	(0.0505)	(0/0000)	(0.0000)	(0.0000)	(0.0000)
% Hit	0.0096	0.0505	0.1010	0.1004	0.0499	0.0077
DQ test Stat	0.7554	2.2095	3.4373	15.8352	16.4263	7.2900
DQ test P-value	0.9443	0.6973	0.4875	0.0032	0.0025	0.1213

Notes: The values in brackets (resp. parentheses) are the standard errors (resp. p-values) of the estimated parameters. Engle and Manganelli's DQ test is applied to check the adequacy of the specified VaR model, where the first four lagged hits are used as instruments.

Table 2.17: CAViaR estimation results for daily coal returns at 1 month

	Downside Risk			Upside Risk		
	$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 10\%$	$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$
$\theta^{(0)}$	0.0015	0.0018	0.0012	0.0008	0.0015	0.0024
	[0.0007]	[0.0005]	[0.0002]	[0.0002]	[0.0003]	[0.0008]
	(0.0166)	[0.0001]	(0.0000)	(0.0002)	(0.0000)	(0.0018)
$\theta^{(1)}$	0.9205	0.8737	0.8685	0.9339	0.9043	0.9154
	[0.0422]	[0.0339]	[0.0255]	[0.0212]	[0.0187]	[0.0275]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\theta^{(2)}$	6.5207	4.8475	3.0796	1.2313	1.8592	1.6271
	[0.0729]	[0.0733]	[0.0433]	[0.0213]	[0.0593]	[0.0367]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\theta^{(3)}$	-5.1929	-5.7090	-4.5016	-1.6186	-4.8571	-5.6179
	[0.0897]	[0.1048]	[0.0405]	[0.0317]	[0.0491]	[0.0801]
	(0.0000)	(0.0000)	(0/0000)	(0.0000)	(0.0000)	(0.0000)
% Hit	0.0096	0.0518	0.1010	0.0991	0.0492	0.0102
DQ test Stat	6.2437	1.0565	5.0378	8.5870	2.1926	4.8216
DQ test P-value	0.1817	0.9011	0.2834	0.0723	0.7004	0.3061

Notes: The values in brackets (resp. parentheses) are the standard errors (resp. p-values) of the estimated parameters. Engle and Manganelli's DQ test is applied to check the adequacy of the specified VaR model, where the first four lagged hits are used as instruments.

Table 2.18: CAViaR estimation results for daily electricity returns at 1 month

	Downside Risk			Upside Risk		
	$\alpha = 1\%$	$\alpha = 5\%$	$\alpha = 10\%$	$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$
$\theta^{(0)}$	0.0216	0.0010	0.0023	0.0001	0.0002	-0.0003
	[0.0162]	[0.0003]	[0.0003]	[0.0000]	[0.0001]	[0.0001]
	(0.0911)	[0.0003]	(0.0000)	(0.0000)	(0.0001)	(0.0150)
$\theta^{(1)}$	0.5554	0.9450	0.8440	0.9888	0.9811	1.0070
	[0.3317]	[0.0150]	[0.0204]	[0.0036]	[0.0055]	[0.0012]
	(0.0470)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\theta^{(2)}$	10.1970	0.5385	0.6816	-0.1351	0.0713	0.4042
	[0.3303]	[0.0142]	[0.0110]	[0.0050]	[0.0229]	[0.0172]
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0009)	(0.0000)
$\theta^{(3)}$	-6.2203	-1.8982	-3.7098	-0.3443	-0.8840	0.9902
	[0.3773]	[0.0099]	[0.0151]	[0.0068]	[0.0159]	[0.0197]
	(0.0000)	(0.0000)	(0/0000)	(0.0000)	(0.0000)	(0.0000)
% Hit	0.0102	0.0505	0.1004	0.1017	0.0512	0.0090
DQ test Stat	6.5967	46.4104	80.6409	45.1708	19.3953	7.1560
DQ test P-value	0.1588	0.0000	0.0000	0.0000	0.0007	0.1279

Notes: The values in brackets (resp. parentheses) are the standard errors (resp. p-values) of the estimated parameters. Engle and Manganelli's DQ test is applied to check the adequacy of the specified VaR model, where the first four lagged hits are used as instruments.

Table 2.19: Results of Granger causality test in mean at 1 month ("normal" times)

$X \Rightarrow Y$	Oil	Gas	Coal	Electricity
Oil	X	1.10 (0.31)	4.05 (0.00***)	0.77 (0.80)
Gas	1.32 (0.11)	X	0.67 (0.90)	0.94 (0.35)
Coal	1.07 (0.35)	1.29 (0.12)	X	0.54 (0.98)
Electricity	0.79 (0.77)	1.22 (0.19)	0.87 (0.66)	X

Notes: Between parentheses p-values. *** denotes rejection of the null hypothesis at 1% significance level. Granger causality tests are computed using p=30 lags. Causality run from the left series to the top series.

Table 2.20: Results of Granger causality test in distribution tails at 1 month (extreme movements)

	$X \Rightarrow Y$	Oil	Gas	Coal	Electricity
		DR			
DR	Oil	X	301.6 (0.09*)	347.6 (0.00***)	325.7 (0.05*)
	Gas	360.49 (0.00***)	X	372.5 (0.00**)	340.02 (0.05*)
	Coal	2.03 (0.99)	6.05 (0.68)	X	328.27 (0.03**)
	Electricity	11.10 (0.25)	4.29 (0.70)	9.08 (0.38)	X
		UR			
UR	Oil	X	7.83 (0.38)	4.25 (0.86)	4.85 (0.81)
	Gas	4.28 (0.86)	X	6.83 (0.15)	15.25 (0.10)
	Coal	4.26 (0.83)	4.96 (0.79)	X	2.44 (0.98)
	Electricity	3.92 (0.89)	12.92 (0.17)	13.67 (0.14)	X

Notes: Between parentheses p-values. *** (resp. **,*) denotes rejection of the null hypothesis at 1% significance level (resp. 5%, 10%). Granger causality tests are computed using p=30 lags. DR and UR denote Downside and Upside Risks respectively. Causality run from the left series to the top series.

Table 2.21: Results of Granger causality test in distribution tails at 10 month (extreme movements)

	$X \Rightarrow Y$	Oil	Gas	Coal	Electricity
		DR			
DR	Oil	X	317.23 (0.02**)	376.4 (0.00***)	387.7 (0.00***)
	Gas	230.40 (0.96)	X	246.9 (0.83)	245.47 (0.85)
	Coal	225.81 (0.97)	305.27 (0.06*)	X	245.30 (0.85)
	Electricity	462.14 (0.33)	482.04 (0.10)	439.55 (0.62)	X
		UR			
UR	Oil	X	256.08 (0.71)	464.70 (0.30)	286.80 (0.23)
	Gas	271.20 (0.46)	X	266.16 (0.55)	299.62 (0.10)
	Coal	288.93 (0.20)	259.11 (0.67)	X	260.18 (0.65)
	Electricity	390.62 (0.12)	497.56 (0.17)	225.10 (0.97)	X

Notes: Between parentheses p-values. *** (resp. **,*) denotes rejection of the null hypothesis at 1% significance level (resp. 5%, 10%). Granger causality tests are computed using p=30 lags. DR and UR denote Downside and Upside Risks respectively. Causality run from the left series to the top series.

Table 2.22: Results of Granger causality test in distribution tails at 20 month (extreme movements)

	$X \Rightarrow Y$	Oil	Gas	Coal	Electricity
		DR			
DR	Oil	X	324.79 (0.01**)	385.15 (0.00***)	461.91 (0.18)
	Gas	278.93 (0.34)	X	276.11 (0.38)	570.51 (0.17)
	Coal	238.69 (0.91)	306.85 (0.06*)	X	247.59 (0.83)
	Electricity	463.15 (0.32)	575.02 (0.14)	581.14 (0.10)	X
		UR			
UR	Oil	X	280.16 (0.32)	466.49 (0.28)	324.26 (0.01**)
	Gas	243.67 (0.87)	X	496.49 (0.06*)	323.88 (0.01**)
	Coal	249.15 (0.81)	295.93 (0.13)	X	552.77 (0.34)
	Electricity	451.93 (0.46)	481.14 (0.14)	252.99 (0.76)	X

Notes: Between parentheses p-values. *** (resp. **,*) denotes rejection of the null hypothesis at 1% significance level (resp. 5%, 10%). Granger causality tests are computed using p=30 lags. DR and UR denote Downside and Upside Risks respectively. Causality run from the left series to the top series.

Table 2.23: Results of Granger causality test in distribution tails at 30 month (extreme movements)

	$X \Rightarrow Y$	Oil	Gas	Coal	Electricity
		DR			
DR	Oil	X	357.99 (0.00***)	468.71 (0.26)	291.42 (0.17)
	Gas	226.62 (0.97)	X	568.08 (0.19)	398.27 (0.96)
	Coal	236.01 (0.93)	275.22 (0.40)	X	243.78 (0.87)
	Electricity	280.55 (0.31)	311.31 (0.04**)	537.86 (0.51)	X
		UR			
UR	Oil	X	572.70 (0.15)	327.41 (0.00***)	668.19 (0.14)
	Gas	275.01 (0.40)	X	455.79 (0.41)	268.84 (0.50)
	Coal	267.81 (0.52)	381.29 (0.13)	X	272.98 (0.43)
	Electricity	446.29 (0.54)	562.14 (0.00***)	476.28 (0.28)	X

Notes: Between parentheses p-values. *** (resp. **,*) denotes rejection of the null hypothesis at 1% significance level (resp. 5%, 10%). Granger causality tests are computed using p=30 lags. DR and UR denote Downside and Upside Risks respectively. Causality run from the left series to the top series.

Chapter 3

Mood-misattribution effect on energy markets: A biorhythm approach

Introduction [1]

Energy price dynamics are known to be frequently volatile with extensive amplitude affecting the whole economy (Sadorsky, 1999; Hamilton, 2003; Kilian, 2008, among others). However, understanding strong energy market fluctuations is a rather difficult task given its apparent erratic behavior and the various potential factors that may be at play. In the literature, these fluctuations are often attributed to both real and financial factors, such as international energy demand/supply conditions and market manipulation (Hamilton, 2009; Kaufmann and Ullman, 2009; Kilian, 2009; Cifarelli and Paladino, 2010; Ellen and Zwinkels, 2010; Lombardi and Van Robays, 2011, among others), leading to extreme market risks for energy participants and governments. This phenomenon would have macroeconomic and microeconomic implications since the increasing market risks may lead in turn to distinct market apprehension and perception affecting the decision-making of participants. This question can be investigate in different ways depending the underlying assumption about the behavior of economic agents. Regarding the traditional economic and financial approaches, a rational agent is defined as someone who used all available information to anticipate future evolutions and allocate his portfolio, so that anticipations are well established on average. Under this hypothesis, rational investors will always choose equities with the best benefit-risk trade off in the Efficient Market Hypothesis (EMH) sense.

However, with regard to the development of behavioral finance (Shleifer, 2000; Thaler, 2005, among others), this traditional approach seems to be too restrictive in the sense that individual rationality appears to be bounded (Simon, 1982, 1987a and 1987b). In this context, the economic agent is not a simple calculator but a human with biaises whose decision-making process is influenced by cognitive and emotional resentments.

[1] A first version of this chapter has been published as Joëts, M., 2012, Mood-misattribution effect on energy finance: A biorhythm approach, in International Symposia in Economic Theory and Econometrics, ed. William Barnett et Fredj Jawadi, Emerald Publishing, Bingley, Vol. 22.

This characteristic leads to distinct asset valuations among investors which can create excess volatility in financial markets (Black, 1986). The seminal work of Damasio (1994) shows that emotions can affect behavior and play a crucial role in the decision process where lack of feelings leads to suboptimal choices. In this way, recent researches in behavioral finance have studied the influence of emotions through the mood misattribution impact on decision-making. According to Loewentein et al. (2001), the mood misattribution perspective relies on the hypothesis that individuals who take their decision under risk and uncertainty are unconsciously influenced by their relative emotional states even if moods are unrelated to their choices (Schwarz and Clore, 1983). Therefore, emotions could provide some explanations to irrational financial markets fluctuations.

In finance, recent studies have shown significant mood impact on equity pricing.[2] However, they focus on specific classes of assets. In order to bring new elements to the recent energy prices increase and assuming that excess volatility could be due partly to some investors influenced by their emotional states, we investigate the impact of mood misattribution on energy finance[3] by considering forward energy market dynamics such as oil, gas, coal and electricity during both "normal times" and periods of extreme (upward and downward) price movements. By relying on forward energy prices, we are able to account for both fundamental and speculative pressures (Joëts and Mignon, 2011).[4]

In order to investigate mood effect, a biorhythm approach is adopted considering the Seasonal Affective Disorder (SAD) framework developed by Kamstra et al. (2003). This approach known as 'winter blues' considers that seasonal variation in the number of hours of sunlight per day can lead to anxious state which in turn can affect risk

[2]See references in Section 3.2.

[3]This approach is relatively new since it combines both energy market phenomena and theory of financial markets.

[4]Indeed, the forward energy market can result in both physical delivery and speculative purposes.

apprehension and decision-making of investors. Therefore, the SAD variable can be seen as an approximation of emotion which can affect the energy market fluctuations through the psychology of participants. Assuming that feelings influence behavior and risk perception of investors, we analyze mood effect on energy market variations in in-sample and out-of-sample contexts. Both normal and extreme volatility periods are considered using OLS and quantile regression approaches.

Our contribution is fourfold. First, the relationship between emotion and energy markets is studied using biorhythm approach through the SAD proxy variable. Second, by relying on European forward prices of oil, coal, gas and electricity, we purge short-run demand and supply from noise that affects market fluctuations, and account for both fundamental and speculative pressures. Third, we investigate the emotional phenomenon of energy market dynamics considering normal and extreme market circumstances. Finally, we compare the out-of-sample properties of our *SAD model* against a pure *macroeconomic model* in terms of predictive ability to see which strategy is the more fitted and can be used to improve energy porfolio allocation.

The rest of the chapter is organized as follows. Section 3.1 presents the theoretical research background on which the investigation of investors' feelings is based. Section 3.2 reviews the existing literature on mood misattribution and equity pricing. Empirical application on energy markets is displayed in Section 3.3, and Section 3.4 concludes the article.

3.1 Mood influences on investor decision-making under uncertainty

In the traditional portfolio choice theories, the process of investors' decision is assumed to be quantitatively characterized by the weight of costs and benefits of all possible outcomes. In this perspective, rational investors choose the outcome with the best risk-benefit trade off (see Markowitz, 1952; Sharpe, 1964, among others). This type of behavior is what Loewenstein et al. (2001) describe as a *'consequentialist perspective'* which does not account for the emotional impact on the decision-making process. However, in practice these traditional approaches may be viewed as unrealistic since feelings play a crucial role in the perception of the environment, especially under risky and uncertain context (see, Zajonc, 1980; Schwarz, 1990; Forgas, 1995; Isen, 2000; Loewenstein et al., 2001, among others).

Behavioral finance coupled with the reconsideration of the rational investor concept bring to the light the recent interest in feelings impact on economic behavior leading to the development of a new class of models. The latters introduce expected emotions which are defined as emotions that are expected to be experienced by investors given a certain outcome level. This concept has been developed through the Loomes and Sugden (1982)'s regret model and applied in finance in the myopic loss aversion theory of Benartzi and Thaler (1995). Despite the fact that expected emotions constitute an advance over the traditional consequentialism approach, this concept appears to be relatively restrictive in the sense that it considers expected feelings rather than feelings experienced at the time of decision-making. According to Schwarz (1990), it seems coherent that people make different investment decisions depending on their positive and negative moods even if mood is unrelated to the decision context (Schwarz and Clore, 1983).

To overcome this limit, Loewenstein et al. (2001) develop the risk-as-feelings model which incorporates emotions influence at the time of making decision by allowing expected emotions, subjective probabilities and extra factors (i.e. mood, ...) that affect decision-making.[5] In their modeling framework, Loewenstein et al. (2001) suppose

[5] For more details, see the excellent survey of Dowling and Lucey (2005).

that investors' decisions under risky and uncertain environment are strongly affected by feeling perception. The authors use the three following premises derived from psychology : i) Cognitive evaluations include emotional reactions[6], ii) Emotions inform cognitive evaluations[7], and iii) Feelings can affect behavior.[8] According to Loewenstein et al. (2001)'s risk-as-feeling model, decision-making is the consequence of the inter-connected processes of cognition evaluation and emotions which in turn affect behavior.

In a complementary way of Loewenstein et al. (2001), Forgas (1995) develops an Affect Infusion Model (AIM) which covers the extent to which people rely to their respective feelings. Forgas argues that emotions influence the decision process depending on the risky and uncertain choice environment context. In this framework, he defines two kinds of strategies depending on the situation. The first one is the Low Affect Infusion Strategies (LAIS), used under familiar situations which involve less riskier and low complexity circumstances. The second one is the High Affect Infusion Strategies (HAIS) which are employed for more complex decision processes, under highly risky context. According to the AIM of Forgas (1995), feeling becomes predominant as risk and uncertainty increase. For instance, under optimal porfolio choice, investor should be characterized by HAIS framework where decision-making would be strongly dependent to her mood states.

According to this literature, feelings appear to have an influence on economic and financial behaviors. In a risky context, many factors can influence decision-making even if they are not related to decision. Mood is therefore seen as information as well as human misattribution emotions.

[6]According to Zajonc (1980), emotions are considered to be postcognitive.

[7]Researches in psychology show that optimistic and pessimistic behaviors tend to be linked to good and negative moods (see, Isen et al., 1978; Bower, 1981; Johnson and Tversky, 1983; Bower, 1991, among others).

[8]According to pioneer works of Damasio (1994), people with impaired ability to feeling emotions tend to make suboptimal decisions under risky and uncertain environment.

3.2 Mood-as-information and misattribution: literature review

In the literature, two types of feeling determinants are considered: the mood misattribution and the affect heuristic. While the later argues that people's decision-making is governed by images and associated feelings that are induced by decision process, the former maintains that mood can be induced by the environmental context such as weather, biorhythms and social events. These determinants leading to mood fluctuations are likely to affect investors' decision process and therefore financial stock markets.

Recent researches on behavioral and emotional finance mainly focus on mood misattribution by studying empirical evidence of mood fluctuations on equity returns. These factors influencing the positive and negative mood states are likely to modify the risk assessments. Saunders (1993), focusing on weather-based influences[9] on mood and behaviour, examines the potential impact of weather on both Dow Jones Industrial index from 1927 to 1989 and NYSE/AMEX indices from 1962 to 1989. Under the hypothesis that bad and good weathers lead to pessimistic and optimistic moods respectively and, in turn, to lower and higher returns, Saunders investigates the relationship between New York equity prices and the level of cloud cover in New York. He finds a significant relationship between both variables showing that mood misattribution effect can exist and be exploited in portfolio consideration. Hirshleifer and Shumway (2003) extended Saunders' analysis by considering the relationship between the de-seasonalized cloud cover and daily equity returns in 26 international markets from 1982 to 1997. Their results confirm a significant negative relationship between cloud cover and equity re-

[9] Psychological studies have seen that fluctuations of hours of sunshine can induce fluctuations in mood (see, Persinger, 1975; Howarth and Hoffman, 1984; Eagles, 1994).

turns and the fact that weather affects stock returns variabilities.[10] Cao and Wei (2002) based on psychological evidences, find significant impact of temperature on equity returns of eight financial markets from July 3, 1962 to July 3, 2001. Lower temperatures lead to higher returns while higher temperatures lead either to higher or lower stocks.

In the mood misattribution research, other studies have extended reflexion to broader proxies related to human biorhythms, and investigated misattribute impact of biological cycles on equity returns. Kamstra et al. (2000), assuming that an interruption of body's circadian cycle can cause anxiety and depression (Coren, 1996), investigate the influence of interruptions to sleep patterns induced, twice a year, by Daylight Savings Time Changes (DSTCs) on equity returns of US, Canadian, German and UK markets. They find a significant negative relationship between returns and DSTCs reflecting a negative impact of such biological effect. Kamstra et al. (2003) further investigate the potential impact of biorhythms and emotions on investment decisions by considering a depressive phenomenon known as Seasonal Affective Disorder (SAD) or 'winter blues'. This phenomenon is characterized by the fact that seasonal variation in hours of sunlight in the day can lead to anxious states (Cohen et al., 1992; Rosenthal, 1998) which in turn can affect risk apprehension. Due to different SAD effects depending on latitude locations, the authors investigate SAD/returns relationship including major equity indexes in both Northern and Southern Hemisphere countries. They find a significant SAD effect leading to seasonal pattern in returns. Then, due to SAD effect, equity returns are predicted to be lower between Autumn Equinox and Winter Solstice. Moreover, an asymmetric component appears between fall and winter. Investors are considered to be risk averse and shun risky assets during fall while they seem to resume their risky holding during winter. Recently, to check the robustess of global mood influences, Dowling and Lucey (2005, 2008) investigate the impact of seven mood proxies variables (i.e. weather data (precipitation, temperature, wind, geomagnetic storms)

[10] High and low cloud covers are associated to low and high stock returns respectively.

and biorhythm data (SAD, DSTCs, lunar phases)) on returns and variance of 37 global equity markets from 12th December 1994 to 10th November 2004 using various robust econometric methods (GARCH specifications). They find that SAD effect is the most predominant one on equity pricing which means that winter blues is significant in both returns and variance of stocks.

These studies put forward that mood misattribution effect exists and tends to influence equity prices fluctuations. However, beyond this scope of research, it appears to be primordial to assess feeling effects on a most widely class of assets. In this way, we investigate the relationship between mood and energy market dynamics to see whether recent price fluctuations can be attributed to emotional considerations. Specifically, we distinguish between usual and extreme phases, and focus on the relation between mood misattribution and market variations by considering SAD approach: mood is proxied by SAD variable, while regular and extreme variations by both OLS and quantile regressions.

3.3 Empirical investigation

3.3.1 Data and preliminary results

We consider daily data over the January 3, 2005 to December 31, 2010 period.[11] We rely on European forward prices at 1 month of oil, gas, coal, and electricity. Energy prices data are extracted from the Platt's Information Energy Agency. To control for the economic and financial environment that may impact all energy price series (such as increasing demand from Asian emerging countries or speculation), we rely on a European equity futures price index—which has the advantage of being available at

[11] This period is particularly relevant since it accounts the recent financial perturbations where energy prices appeared strongly volatile.

a daily frequency. This variable also allows considering energy markets as financial assets and controls for the recent financial turmoil. Our retained equity variable is the Dow Jones Euro Stoxx 50, the European leading stock index for futures contracts, extracted from Datastream. In order to account for the energy prices risk premium, the euro/dollar US exchange rate is considered as a control variable. Basic statistical characteristics are reported in Table 3.1. They reveal that all energy return series are asymmetric (oil, gas and electricity returns are right skewed while coal returns are left skewed) and leptokurtic, indicating fat tail distributions. Due to the specific nature of electricity market (i.e. non-storability, inelasticity of the supply,...), returns are frequently affected by regime switching causing tails behavior higher than fossil energies (1.7 and 25 for the skewness and kurtosis respectively).

The mood proxy data defined as SAD variable, is calculated following Kamstra et al. (2003)'s formula. It gives an approximation of both the reduction of hours of daylight from Autumn Equinox to Winter Solstice, and the lengthening of the day from Winter Solstice to Spring Equinox.[12]

SAD variable is defined as follows:

$$SAD_t = \begin{cases} H_t - 12 & \text{for trading days in the fall and winter} \\ \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

where H_t is the time from sunset to sunrise at a particular location. Value 12 denotes roughly average number of hours of night over the entire year at any location. Therefore, SAD_t is constructed to reflect the relative length of night in fall and winter compared to the mean annual length of 12 hours. According to psychological consid-

[12] In Northern Hemisphere countries, Autumn Equinox, Winter Solstice, and Spring Equinox start respectively at September 21st, December 21st, and March 20th. In Southern Hemisphere countries they begin at March 21st, June 21st, and September 20th. For more details, see Kamstra et al. (2003).

erations, SAD is characterized as a binary variable which varies only over the fall and winter.

Following Kamstra et al. (2003), H_t, the number of hours of night is different depending on the country location and can be calculated using standard approximation from spherical trigonometry.

$$H_t = \begin{cases} 24 - 7.72 \times \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan\left(\lambda_t\right)\right] & \text{in the Northern Hemisphere} \\ \\ 7.72 \times \arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan\left(\lambda_t\right)\right] & \text{in the Southern Hemisphere} \end{cases} \tag{3.2}$$

where "arccos" is the *arc cosine*, δ the latitude which depends on countries location[13], and λ_t the sun's declination angle defined as follows:

$$\lambda_t = 0.4102 \times \sin\left[\left(\frac{2\pi\delta}{365}\right)\left(julian_t - 80.25\right)\right] \tag{3.3}$$

where "$julian_t$" sets for the number position of the day in the year numbered from 1 to 365.[14]

According to Kamstra et al. (2003), SAD variable is defined by $(H_t - 12)$ from Autumn Equinox to Spring Equinox and 0 otherwise. In this framework, during SAD period, investors are considered to be risk averse and to allocate their portfolios to safer assets affecting negatively energy market dynamics. On the contrary, from Spring Equinox to

[13] Following Kamstra et al. (2003), we distinguished Northern Hemisphere and Southern Hemisphere countries by averaging larger markets in North and South latitudes respectively (for more details, see Appendix).

[14] $julian_t$ is equal to 1 for January 1, 2 for January 2, and so on.

Autumn one, no SAD effect exists. Beside, SAD phenomenon is deeply influenced by geographical location. Therefore, we expect to have stronger impact in Northern Hemisphere countries rather than Southern Hemisphere countries, the later being closest to the equator where seasonal variations in daylight are small.

3.3.2 Results and analysis

In order to investigate mood-misattribution effect on energy markets during regular and extreme price movements, we adopt the traditional OLS framework as well as the quantile regression approach introduced by Koenker and Basset (1978).

Consider the following linear model:

$$Y_t = X_t'\beta + \nu_t \tag{4}$$

where Y and X are the endogeneous and exogeneous variables respectively, ν being the error term. In the traditional OLS framework, the dependent variable is supposed to fluctuate randomly around the conditional mean of the conditional distribution of Y $(E[Y/X, \beta])$, allowing to study the influence of exogeneous variables under regular time perspective. On the contrary, quantile analysis allows to examine the manner in which a set of explanatory variables can affect the conditional distribution of the dependent variable. By this approach, we focus on extreme occurrences considering different quantiles of the conditional distribution. In order to account for both upward and downward price movements, two quantiles are considered ($\theta = 0.05$ and 0.95).

The following regressions are estimated

$$r_t^{(i)} = \alpha + \beta SAD_t^{(j)} + \gamma Stoxx_t + \delta Rate_t + \varepsilon_t^{(i)} \tag{5}$$

where $r_t^{(i)}$ is the returns series for energy i (oil, gas, coal and electricity respectively). $SAD_t^{(j)}$ is the emotional proxy variable at j hemisphere (Northern and Southern Hemispheres respectively). $Stoxx_t$ and $Rate_t$ are the control variables for the economic and financial environment.

Table 3.2 reports the results of the OLS estimation of Equation (5) considering SAD effect on forward energy markets at 1 month during normal times. Distinguishing Northern and Southern Hemisphere countries, estimations reveal that SAD component has no any significant impact on energy market fluctuations in regular circumstances. More precisely, emotions do not affect energy markets when price movements are "usual" which corroborates the fact that during normal times, energy price dynamics are mainly governed by fundamentals. Regarding to the extreme market perspectives, Table 3.3 reports SAD effect on energy returns using quantile regression approach. A geographic differentiation is considered as well as downward and upward price movements. We see that SAD has different impacts depending on the hemisphere location. Considering Northern Hemisphere, results show that during periods of prices decrease, energy markets are influenced by emotional effects. Indeed, regarding the left-tail behavior, SAD variables are significant and have negative impact for each market. This phenomenon reflects a mood-misattribution bias where environment leads to depressive states which in turn affects risk perception of investors. Moods are unrelated to energy portfolio choices, however investors are negatively affected by their emotions which self-sustain risk aversion behavior. Under SAD framework, energy prices decreases may be partly explained by emotional considerations which tend to affect investors' risk apprehension. Extreme movements are inherently associated with higher risk situation. From the upward point of view, SAD variable doesn't have any effect on energy markets. Considering Southern Hemisphere, we observe the opposite phenomenon regarding SAD effect on energy markets. As before, SAD is significant for each market during periods of price decrease, however, this impact appears to be positive on risk perception. It is not surprising to find lack of negative seasonal patterns in Southern

Hemisphere countries because they are located closest to the equator where seasonal variations in daylight are quite small. Therefore, investors from Southern Hemisphere countries are less influenced by SAD components.

Investors who suffer from SAD effect are supposed to be risk averse and shun risky assets during fall and to resume their risky holding during winter. Therefore, SAD should have negative impact during fall and positive effect during winter.[15] To further investigate the asymmetric seasonal phenomenon between fall and winter during extreme volatility situations, we estimate the following quantile regression allowing both SAD fall and winter variables:

$$r_t^{(i)} = \alpha + \beta_1 SAD_t^{fall(j)} + \beta_2 SAD_t^{win(j)} + \gamma Stoxx_t + \delta Rate_t + \varepsilon_t^{(i)} \tag{3.4}$$

where $SAD_t^{fall(j)}$ is conducted from September 21 to December 20 for Northern Hemisphere countries, and from March 21 to June 20 for Southern Hemisphere countries. $SAD_t^{win(j)}$ runs from December 21 to March 20 for North, and from June 21 to September 20 for South.

Table 3.4 reports the asymmetric effect of SAD variables on energy markets at 1 month during extreme variations. Regarding Northern Hemisphere countries, SAD variable during fall has the expected effect (significant and negative) in downside risk context for each market. Investors are risk averse during fall and allocate their portfolios to safest assets which tend to impact energy downside risk. From upside point of view, SAD variable is significant and positive during winter for oil, gas and electricity markets only. Regarding the asymmetric component, from Winter Solstice to Spring Equinox, investors' moods are heightened leading them to become more willing to resume the

[15] According to SAD principle, the predicted negative effect during fall is the result of decrease in hours of sunlight. During winter, the predicted positive effect is due to an increase in hours of sunlight.

risk of their respective investments. From Southern Hemisphere perspective, both SAD fall and winter appear to have significant and positive effect in downside risk. Mood and energy prices are positively related which indicate the relative lower impact of emotion, in terms of seasonal variations, for countries closest to equator.

Our results are consistent with Forgas (1995)'s analysis which considers that agents are more influenced by moods under extreme situations rather than during normal ones. Extreme movements being inherently associated with high risk situation, recent energy prices fluctuations may be due in part to a misattribute emotional phenomenon which appears to be significant and negative during periods of price decrease only for Northern Hemisphere countries. Surprisingly, this phenomenon is no longer valid during periods of price increase reflecting that other factors should be considered.

3.3.3 Out-of-sample predictive ability of SAD approach

The previous section shows that SAD variable, as a proxy for emotion, impacts significantly energy prices dynamics during extreme downward fluctuation periods. This phenomenon appears to be preponderant in Northern Hemisphere countries which are considered to be more influenced by variations in daylight hours. Considering that forecasting is central to apprehend energy prices dynamics in economic and financial decision-making for government institutions, regulatory authorities, and investors, we investigate the out-of-sample properties of our *SAD model* against a pure *macroeconomic model* in terms of predictive ability. The former is of the form of Equation (5), while the latter removes the effect of the SAD variable. In this way, we use the conditional Giacomini-White (2006)'s approach to evaluate the relative merit of the two forecast alternatives. Giacomini and White (2006) propose a test of Conditional Predictive Ability which allows to compare the forecasting properties of two models, given a general loss function.[16] Their test allows to directly apprehend the effect of estimation uncertainty on relative forecasting performance. Moreover, it considers a less restrictive framework than previous methodologies since it permits a unified treatment of nested and nonnested models and also can accommodate more general estimation procedures in the derivation of the forecast.

Suppose one wants to compare the accuracy of the two competing forecasts for the τ-steps-ahead of the variable $Y_{t+\tau}$, using a loss function $L_{t+\tau}(.)$ and the information set $\mathcal{F}_t$. Giacomini and White (2006) propose to test the following null hypothesis:

$$H_0 : E\left[L_{t+\tau}(Y_{t+\tau}, \widehat{f}_{t,m_f}) - L_{t+\tau}(Y_{t+\tau}, \widehat{g}_{t,m_g})|\mathcal{F}_t\right] = 0 \tag{3.5}$$

$$\equiv E\left[\Delta L_{m,t+\tau}|\mathcal{F}_t\right] = 0$$

where $\widehat{f}_{t,m_f} \equiv f\left(W_t, ..., W_{t-m_{f+1};}\widehat{\beta}_{t,m}\right)$ and $\widehat{g}_{t,m_g} \equiv f\left(W_t, ..., W_{t-m_{g+1};}\widehat{\beta}_{t,m}\right)$ are measurable functions of a stochastic process W defined on a complete probability space $(\Omega, \mathcal{F}, P)$. The expectations are conditional to the set of information $\mathcal{F}_t$. The null hypothesis states that one cannot predict which forecasting methods will be accurate at the $t + \tau$ target horizon. Following Giacomini and White (2006), the test statistic is of the form:

$$T^h_{m,n} = n\left(n^{-1}\sum_{t=m}^{T-1} h_t \Delta L_{m,t+1}\right)' \widehat{\Omega}_n^{-1}\left(n^{-1}\sum_{t=m}^{T-1} h_t \Delta L_{m,t+1}\right) \tag{3.6}$$

$$= n\overline{Z}'_{m,n}\widehat{\Omega}_n^{-1}\overline{Z}_{m,n} \sim \chi^2_{q,1-q}$$

[16] This literature was initiated by Diebold and Mariano (1995), West (1996), McCracken (2000), Clark and McCracken (2001), Corradi et al. (2001), and Chao et al. (2001), to name few.

where $\overline{Z}_{m,n} \equiv n^{-1}\sum_{t=m}^{T-1} Z_{m,t+1}$, $Z_{m,t+1} \equiv h_t \Delta L_{m,t+1}$, and $\widehat{\Omega}_n \equiv n^{-1}n^{-1}\sum_{t=m}^{T-1} Z_{m,t+1} \times Z'_{m,t+1}$ is a $q \times q$ matrix that consistently estimates the variance of $Z_{m,t+1}$. h_t is the test function which can be chosen by researchers to include variables that are relevant to help distinguish between the two models.[17]

As suggested by the authors, in order to compare the accuracy of the two competing approaches (*SAD model* vs *macroeconomic model*) we consider rolling window estimators.[18] Due to the relevance of SAD effect, we focus on Northern Hemisphere countries and downturn movements only. Our in-sample estimation goes from January 3, 2005 to February 7, 2009 and produces sequences of τ-step-ahead forecasts for $\tau = 1$ using a rolling window estimation procedure with $m = m_f = m_g = 1174 + \tau$. Then, in order to choose the best forecasting model, we use the two-step decision rule procedure proposed by Giacomini and White (2006):

1. Step 1: Regress $\Delta L_{m,t+1} = L_{t+\tau}\left(Y_{t+\tau}, \widehat{f}_{t,m_f}\right) - L_{t+\tau}\left(Y_{t+\tau}, \widehat{g}_{t,mg}\right)$ on h_t over the out-of-sample period and let $\widehat{\delta}_n$ be the regression coefficient. Apply the test and, in case of rejection of the null, proceed to step 2.

2. Step 2: $\widehat{\delta}'_n h_T \approx E\left[\Delta L_{m,t+1} | \mathcal{F}_t\right]$ indicates the decision rule: if $\widehat{\delta}'_n h_T > c$, the performance of g is better, whereas if $\widehat{\delta}'_n h_T < c$, f is the best choice ($c = 0$, is a user-specified threshold value). In our case, g and f respectively denote the *SAD model* and the *macroeconomic model.*

Table 3.5 gathers results of the two-step test procedure for each energy market. The first step indicates that for each energy price the null hypothesis is rejected. Therefore, the two competing models (*SAD model* and *macroeconomic model*) are not equally

[17]We use the moving average of past loss differences.

[18]As clearly mentioned by the authors, this limited memory approach is privileged for two reasons: (i) it imposes no restrictions on the estimators other than finite memory, and (ii) the analysis required is straightforward (see Giacomini and White, 2006).

accurate on average. It means that whatever the forecast target date $t + \tau$, one model outperforms the other one in terms of forecasting performance. The second step allows to choose the suitable model strategy by indicating the proportion of time one model outperforms the other. Results in Table 3.5 reveal that for each energy price series, the *SAD model* outperforms the *macroeconomic model* in terms of forecasting performance. Our *SAD model* is therefore more adequate to apprehend the energy prices dynamic reinforcing our finding in favor of the emotional component of the markets. This finding appears to be particulary relevant in the sense that it shows that extreme energy prices fluctuations could be dictated by irrational movements without any economic foundation. In this perspective, the *SAD model* could be useful for energy investors to improve portfolio performance and manage risk exposure.

3.4 Conclusion

This chapter investigates the relationship between emotion and European forward energy prices during normal times and periods of extreme price movements. Relying on mood-misattribution hypothesis, we use Seasonal Affective Disorder (SAD) variable as a proxy to analyze the seasonal patterns effect on energy risk apprehension. Using both OLS and quantile biorhytm approach, we show that SAD phenomenon appears to be significant during extreme fluctuation periods only. More precisely, emotions affect energy market dynamics during periods of price decrease. This phenomenon is directly linked to the psychology of investors considered to be negatively influenced by seasonal variations of daylight affecting their risk perception. This effect appears to be different depending on the geographical location. Indeed, while Northern Hemisphere countries are primarily affected by negative seasonal relationships, SAD affects positively Southern Hemisphere countries which is consistent with the fact that seasonal variations of daylight are smaller for this group. Paying a particular attention to the asymmetric effect between fall and winter, we show a negative impact of SAD during fall and a positive one during winter for Northern countries, consistent with the seasonal hypothesis. Our findings put foward the key role played by feelings in phase of price falling. The significant role played by emotion in markets dynamic is confirmed in terms of forecasting performance. The out-of-sample investigation comparing the predictive ability of *SAD model* against pure *macroeconomic model* indicates that the emotional model outperforms significantly the economic model. Therefore, feelings appear to be preponderant in explaining price dynamics and and could be relevant to improve resource allocation and portfolio performance.

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Appendix of Chapter 3

A Latitude data description

To construct simplest latitude values, we select larger markets in North and South Hemispheres respectively, then average each latitude in order to obtain two representatives values for North and South geographical locations. For North latitude, we obtain 48.89° by selecting and averaging: Turkey (Ankara), US (Washington), Canada (Ottawa), Italy (Roma), Switzerland (Bern), Austria (Vienna), France (Paris), Luxembourd, Belgium (Brussels), Germany (Berlin), UK (London), Netherlands (Amsterdam), Ireland (Dublin), Denmark (Copenhagen), Norway (Olso), Sweden (Stockholm), Finland (Helsinki), China (Beijing), and Japan (Tokyo). For South latitude, we obtain 30.33° by choosing: New-Zealand (Wellington), Indonesia (Jakarta), South Africa (Johannesburg), Chile (Santiago), Australia (Camberra), and Argentina (Buenos Aires).

Table 3.1: Summary statistics for the daily energy forward returns at 1 month

	Brent	Gas	Coal	Electricity
Mean	0.00053	0.00017	0.00038	−0.00062
Variance	0.00053	0.00035	0.00033	0.00088
Skewness	0.13679	0.00327	−0.57407	1.76840
Kurtosis	8.97939	6.47279	9.93896	25.31240
Jarque-Bera test	2333.29 (0.00)	785.431 (0.00)	3221.56 (0.00)	33236.7 (0.00)

Notes: p-values for corresponding null hypotheses are reported in parentheses.

Table 3.2: SAD effect on energy forward markets under normal times

	Oil	Gas	Coal	Electricity
		Northern Hemisphere		
α	0.0006	0.002	0.0003	-0.0004
	(0.89)	(1.38)	(0.64)	(-0.45)
βSAD_t	$-9.27E-05$	-0.001	$9.72E-05$	-0.0001
	(-0.23)	(-1.52)	(0.33)	(-0.26)
$\gamma Stoxx_t$	0.017	0.054	0.322	-0.018
	(0.43)	(0.64)	(10.69^a)	(-0.34)
$\delta Rate_t$	-0.047	1.224	0.518	0.276
	(-0.51)	(6.36^a)	(7.59^a)	(2.32^a)
		Southern Hemisphere		
α	0.0005	-0.001	-0.0001	-0.0008
	(0.77)	(-0.34)	(-0.01)	(-0.89)
βSAD_t	$1.57E-05$	0.001	0.0006	0.0005
	(0.02)	(1.07)	(1.48)	(0.55)
$\gamma Stoxx_t$	0.007	0.062	0.324	-0.023
	(0.18)	(0.74)	(10.70^a)	(-0.44)
$\delta Rate_t$	-0.021	1.178	0.514	0.285
	(-0.23)	(6.15^a)	(7.50^a)	(2.38^a)

Notes: Between parentheses t-stats. ^{a} denotes rejection of the null hypothesis at 1%, 5% or 10% significance level.

Table 3.3: SAD effect on energy forward markets under extreme price movements

	Oil		Gas		Coal		Electricity	
	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)
Northern Hemisphere								
α	−0.033	0.031	−0.050	0.060	−0.024	0.026	−0.033	0.034
	(-21.53^a)	(22.24^a)	(-14.74^a)	(9.55^a)	(-13.26^a)	(13.82^a)	(-15.17^a)	(11.84^a)
βSAD_t	−0.001	0.001	−0.007	0.001	−0.002	0.0003	−0.003	0.003
	(-2.31^a)	(1.45)	(-3.65^a)	(0.49)	(-1.69^a)	(0.34)	(-3.08^a)	(1.14)
$\gamma Stoxx_t$	0.159	−0.077	0.082	0.076	0.410	0.305	0.176	−0.332
	(2.24^a)	(-2.30^a)	(0.80)	(0.20)	(6.07^a)	(3.34^a)	(2.10^a)	(−0.48)
$\delta Rate_t$	−0.195	−0.088	1.371	0.624	0.84	0.459	−0.048	1.011
	(−0.93)	(−0.42)	(3.77^a)	(0.61)	(4.82^a)	(2.52^a)	(−0.120)	(1.76^a)
Southern Hemisphere								
α	−0.038	0.035	−0.070	0.064	−0.030	0.025	−0.042	0.037
	(-16.50^a)	(21.40^a)	(-13.84^a)	(11.15^a)	(-13.49^a)	(15.01^a)	(-17.09^a)	(9.55^a)
βSAD_t	0.003	−0.002	0.013	−0.002	0.004	0.002	0.005	−0.001
	(2.26^a)	(−1.39)	(3.85^a)	(−0.45)	(2.54^a)	(1.19)	(2.90^a)	(−0.79)
$\gamma Stoxx_t$	0.216	−0.101	0.146	0.082	0.387	0.282	0.210	−0.160
	(3.19^a)	(-2.26^a)	(1.72^a)	(0.18)	(12.00^a)	(2.83^a)	(3.07^a)	(0.25)
$\delta Rate_t$	−0.242	0.038	1.291	0.572	0.86	0.505	−0.121	0.89
	(−1.18)	(0.259)	(3.25^a)	(0.526)	(7.14^a)	(2.92^a)	(−0.463)	(1.58)

Notes: Between parentheses t-stats. ^{a} denotes rejection of the null hypothesis at 1%, 5% or 10% significance level. UR and DR denote upward and downward price movements respectively.

Table 3.4: Asymmetric SAD effect on energy forward markets under extreme price movements

	Oil		Gas		Coal		Electricity	
	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)	DR (θ=0.05)	UR (θ=0.95)
Northern Hemisphere								
α	-0.033	0.031	-0.050	0.059	-0.024	0.027	-0.033	0.034
	(-20.86^a)	(22.80^a)	(-14.68^a)	(9.18^a)	(-13.75^a)	(15.25^a)	(-14.61^*)	(12.99^a)
$\beta_1 SAD_t^{fall}$	-0.003	-0.0002	-0.007	0.003	-0.002	-0.009	-0.003	0.005
	(-1.97^a)	(-0.28)	(-3.64^a)	(0.68)	(-2.85^a)	(-0.67)	(-2.37^a)	(1.59)
$\beta_2 SAD_t^{win}$	-0.001	0.002	-0.007	0.001	-0.001	0.003	-0.005	0.001
	(-1.04)	(2.06^a)	(0.23)	(-1.70^a)	(-0.63)	(0.44)	(-0.25)	(-1.98^a)
$\gamma Stoxx_t$	0.159	-0.082	0.082	0.054	0.403	0.278	0.172	-0.117
	(1.89^a)	(-1.87^a)	(0.802^a)	(0.118)	(7.61^a)	(2.71^a)	(2.37^a)	(-0.25)
$\delta Rate_t$	-0.200	0.006	1.371	0.661	0.774	0.554	0.043	0.960
	(-0.89)	(0.046)	(3.75^a)	(0.57)	(4.30^a)	(5.02^a)	(0.12)	(2.78^a)
Southern Hemisphere								
α	-0.038	0.035	-0.070	0.064	-0.029	0.025	-0.042	0.040
	(-16.42^a)	(21.54^a)	(-13.29^a)	(11.10^a)	(-13.47^a)	(15.00^a)	(-17.42^a)	(9.40^a)
$\beta_1 SAD_t^{fall}$	0.004	-0.002	0.015	-0.002	0.004	0.002	0.006	-0.007
	(2.71^a)	(-1.26)	(3.98^a)	(-0.41)	(2.06^a)	(1.17)	(2.59^a)	(-1.62)
$\beta_2 SAD_t^{win}$	0.003	-0.003	0.012	-0.002	0.003	0.002	0.007	-0.001
	(1.65^a)	(-1.15)	(2.95^a)	(-0.37)	(2.44^a)	(0.86)	(3.25^a)	(-0.41)
$\gamma Stoxx_t$	0.219	-0.106	0.117	0.081	0.392	0.283	0.221	0.354
	(3.33^a)	(-2.37^a)	(1.02)	(0.16)	(12.01^a)	(2.69^a)	(3.58^a)	(3.46^a)
$\delta Rate_t$	-0.267	0.066	1.409	0.582	0.865	0.499	-0.149	0.651
	(-1.30)	(0.50)	(3.62^a)	(0.49)	(7.26^a)	(2.71^a)	(-0.61)	(1.25)

Notes: Between parentheses t-stats. ^{a} denotes rejection of the null hypothesis at 1%, 5% or 10% significance level. UR and DR denote upward and downward price movements respectively.

Table 3.5: Conditional Predictive Ability Test

Model strategy	macroeconomic model			
	Brent	Gas	Coal	Electricity
SAD model	196.83 (0.00*) [0.98+]	262.36 (0.00*) [1.00+]	182.94 (0.00*) [1.00+]	165.65 (0.00*) [1.00+]

Notes: Between parentheses p-values. * denotes rejection of the null hypothesis at 1% significance level. Between brackets the proportion of time the method in the column outperforms the method in the row over the out-of-sample period, according to the Giacomini and White (2006)'s decision rule. + indicates that the SAD model outperforms the macroeconomic model more than 50% of the time.

Chapter 4

Heterogeneous beliefs, regret, and uncertainty: The role of speculation in energy price dynamics

Introduction

The recent and unprecedented surge observed in energy prices, and especially in crude oil price, from 2003 to 2008 has given rise to hot public and academic debates about the true nature of these shocks. Due to the potential impact of these huge movements on most economies (Sadorsky, 1999; Hamilton, 2003; Edelstein and Kilian, 2007; Kilian, 2008, among others), the effectiveness of economic policies strongly depends on the identification of the major causes of energy prices movements. Since Greenspan (2004)'s intervention about the existence of speculators in oil market, a popular view about the origins of price surge is that these movements cannot be attributed to economic fundamentals (such as changes in supply and demand conditions), but are caused by the increasing financialization of commodities. This financialization should in turn cause volatility clustering phenomena, extreme movements, higher comovements between oil, financial assets, and commodity prices, as well as increased impact of financial investors decisions (such as hedge funds, swap dealers, ...). The question of the influence of financial investors on energy prices is of primary importance from both economic and political points of view. Economically, the role of speculation in energy markets raises the question of the trade-off between private and public interests, since financialization is often defined as being benefical from private perspective without any benefical considerations from a social planner's point of view. Politically, the debate is even more relevant since it brings credibility about regulation of commodity derivatives markets in the same way that the G20 governments try to regulate financial markets by limiting speculative behaviors.[1]

Therefore, there has been a renewal of interest in the academic literature for this topic, even if no clear cut conclusion has emerged. Indeed, the question about the

[1]In 2010, the U.S government has initiated the Dodd-Frank Wall Street Reform and Consumer Protection Act on commodity markets to limit speculative behaviors by mandatoring centralized clearing of OTC standard contracts and automation of the Securities and Exchange Commission.

role of speculation in commodity markets is not trivial; identifying and quantifying this phenomenon being a difficult task because trader positions are relatively opaque. As we will see in Section 4.1, some studies define the phenomenon as the consequence of increased comovements between markets, while some others consider markets as composed by different shocks which affect price dynamics. However, these approaches mainly focus on the oil market without considering other energy prices, whereas the same movements occur in these markets. More importantly, they assume that the market is efficient in the sense that investors are rational and representative, and the oil price fully reflects all the available information. Oil market efficiency was however rejected by GjØlberg (1985), and Moosa and Al-Loughani (1994). Moreover, according to Kirman (1992), aggregation arguments under rational behaviors are insufficient to reduce markets to a single representative agent. Indeed, following Townsend (1983) and Singleton (1987) it seems reasonable to consider heterogeneous expectations, and it appears optimal for each agent to forecast the forecasts of others. Fundamentals are important but a variety of different models may be relevant to explain behaviors in energy markets. The purpose of this chapter is precisely to bring new theoretical elements to understand who and what drive the markets.

Another important limitation in the existing literature is that it has been based on an analysis of risk as opposed to uncertainty.[2] Therefore, previous studies suppose that agents have no considerations about uncertainty on their models, their priors or the future evolution of prices, although allowing uncertainty could be relevant to account for some "anomalies" and stylised facts of markets.

Previous analyses thus evolve in a constrained world where agents are rational and where uncertainty does not exist. To deal with these limits we propose a new theoretical and empirical framework to investigate what drives energy price fluctuations. Our theoretical model overcomes the restrictive assumption of rationality by considering that heterogeneous expectations could be the cause of recent prices movements. We

[2] By risk we consider that agents know the probability distribution of a random variable, as opposed to uncertainty when agents have no knowledge about it.

propose to extend the traditional heterogeneous agent model (HAM) of Brock and Hommes (1997, 1998) in the same way as Kozhan and Salmon (2009) to account for uncertainty in the markets. We therefore assume that investors are faced with forming energy price expectations and consider the worst outcome within the set of different models in some interval, where the size of interval is a subjective choice of agents allowing to capture different degrees of uncertainty aversion. In traditional HAM, agents are supposed to switch between different strategies characterizing heterogeneous specifications according to a cognitive learning process. We propose to extend this rule to a more realistic one which accounts for both cognitive and emotional dimensions by a regret criterion *à la* Bell (1982) and Loomes and Sugden (1982).[3]

We also estimate our model empirically using nonlinear least squares (NLS) methods to investigate whether heterogeneous expectations and uncertainty exist in the markets and can lead to strong fluctuations of energy prices. Estimations are done during both normal times and extreme movements periods[4] in order to see if the behavior of prices can be different depending on the intensity of the markets.[5] The theoretical model is then compared to a random walk (RW) in terms of predictive ability. To our best knowledge, investigating the relative impact of financialization on energy price fluctuations through behavioral and emotional aspects under uncertainty during normal and extreme situations has never been done before.

The chapter is organised as follows. The next section provides a literature review on the role of speculation on energy markets. Section 4.2 describes our theoretical framework, and Section 4.3 outlines specification and estimation procedure of the model. Section 4.4 contains in-sample and out-of-sample estimation results, and Section 4.5 concludes the chapter.

[3]According to the seminal work of Damasio (1994), emotion can also affect behavior and play a crucial role in the decision process, where lack of feelings leads to suboptimal choices.

[4]Normal times are approximated by price movements in the mean of the distribution, while extreme fluctuations periods are in the quantiles.

[5]By intensity of the markets, we consider price movements during normal times and extreme prices' fluctuation periods.

4.1 The role of speculation on energy markets: what have we learned so far?

This section reviews the literature related to the impact of speculation on energy markets, and more specifically on oil future prices.[6] We discuss the relative conceptualization of "commodity speculation" and how it can impact prices dynamics. We identify four strands in this literature. One strand links the participation of financial investors in oil markets to the evidence of increased comovements between oil, commodity, and stock prices. Another strand looks at the causal relationship between the position taken by index fund managers and oil prices. The third approach considers structural VAR models to investigate the impact of speculation. Finally, the fourth approach assumes that the existence of heterogeneous traders in the markets, namely fundamentalists and chartists, can impact prices fluctuations.[7]

In this hot debate about the financialization of oil market, and more generally of commodity markets, the key question is how to defining what we call "commodity speculation". According to Kilian and Murphy (2013), a general definition of speculation in oil market refers to a situation where "anyone buying crude oil not for current consumption, but for future use". Following this definition, speculative investors can have two options, buying physical oil now and store it to accumulate oil inventories, or buying crude oil futures contracts. Therefore, according to Alquist and Kilian (2010)'s analysis, speculation in one of these markets will be necessarily reflected in speculation in other market. In this sense, speculation would not be economically "irrational" because it seems reasonable that oil producers, considered as physical traders, will stock up on crude oil to smooth production of refined products. Speculation would be essential to

[6] This debate mainly focuses on the oil market due to its potential impact on the real economy (see, Hooker, 1996; Rotember and Woodford, 1996; Hamilton, 2003, Sauter and Awerbuch; 2003,...).

[7] Unlike Fattouh et al. (2012), we do not talk about the relationship between oil future and spot prices, as well as the role of time-varying risk premia in oil futures markets.

oil market to function because it provides liquidity and assists price discovery process. However, speculation in the public debate has a negative connotation because it is often viewed as an excessive phenomenon. This excessive phenomenon would be the consequence of private interests, increasing prices movements and affecting the social welfare. Determining excessive speculative behaviors is a difficult task because they do not necessary come from the position taken by the traders. Commercial traders generally act as hedgers to protect their physical interests, while noncommercials traders are often considered as speculators. However, as documented by Büyüksahin and Harris (2011), we can have situations where commercial investors have speculative position in the sense that they take a stance on the commodity price without hedging it in the futures market.

4.1.1 Comovements between commodity and financial prices

Since 2003, without explicit mention to financialization, there is clear evidence of increased proportion of financial investors in oil futures markets (see, Alquist and Kilian, 2010; Büyüksahin et al., 2009; Tang and Xiong, 2011; Hamilton and Wu, 2011, Hache and Lantz, 2013, among others). The first strand of literature on this topic focuses on comovements between commodity prices, mainly oil prices, and stock markets, as well as volatility spillover effects. Hammoudeh et al. (2004), using cointegration techniques as well as ARCH-type specifications among five daily S&P oil sector stock indices and five daily oil prices for the US oil markets from July 1995 to October 2001 find volatility spillover effects from the oil futures market to the stocks of some oil sectors. Chiou and Lee (2009) focusing on the asymmetric effects of WTI daily oil prices on S&P 500 stock returns from January 1992 to November 2006, investigate the structure changes in this dependency relationship. Using the Autoregressive Conditional Jump Intensity model with expected, unexpected and negative unexpected oil price fluctuations, they find that high fluctuations in oil prices have asymmetric unexpected effects on stock returns. Filis et al. (2011) analyze time-varying correlations between oil prices and stock markets by differentiating oil-importing (USA, Germany, and the Netherlands) and oil-exporting (Canada, Mexico, and Brazil) countries. They find that the conditional variances of oil and stock prices do not differ for each group. Büyüksahin et al. (2010), Silvennoinen and Thorp (2010), Choi and Hammoudeh (2010), and Cretì et al. (2013) show that conditional correlations between commodity returns and stock index have increased recently, especially in periods of high volatility. Büyüksahin and Robe (2011) further document that the increase in prices comovements is related to the entry of hedge funds in both markets. Different general conclusions can emerge from these studies. Indeed, some studies argue that increased comovements between markets lead to decrease potential diversification (Silvennoinen and Thorp, 2010), while some others suggest that these comovements between prices develop transmissions from a wide range of commodity and financial markets (Tang and Xiong, 2011). However, this literature does not imply that recent surge in commodity prices was caused by "commodity speculators". It could be due to many macroeconomic fundamental factors others than financial speculation.

4.1.2 Index funds positions and commodity prices

Some other studies have focused on the question whether index funds positions can create higher commodity returns. Master (2008, 2010), and Singleton (2012), using highly aggregated Commodity Futures Trading Commission (CFTC) data on positions of index funds concluded that financial investments affect crude oil returns. However, Büyüksahin et al. (2009, 2010a,b, 2011a,b) show that to study the impact of speculation, heavily aggregated data are not suitable. Büyüksahin and Harris (2011) and Brunetti et al. (2011) by considering specific categories of traders (such as hedge funds and swap dealers) investigate the impact of positions in oil futures prices and volatility. They find relevant causality from market conditions to speculators, as well as the fact that speculators provide liquidity to the market.

4.1.3 Structural models

A third strand of the literature is concerned with strucural economic models of oil markets. Kilian and Murphy (2013) are among the first to quantify the effect of speculative demand shocks on the real price of oil. In the same verge of Kilian (2009a,b), Kilian and Murphy (2012), and Baumeister and Peersman (2012), they use structural vector autoregressive (VAR) models to disentangle demand and supply shocks in oil markets. They consider four strucural shocks: (i) an unanticipated disruption in the flow of supply of oil, (ii) an unanticipated increase in the flow of the demand of oil associated with an unexpected change in the business cycle, (iii) a positive speculative demand shock, and (iv) residual oil demand shock.[8] Using data back to 1973, the model finds no evidence for speculation causing the price surge, price changes being caused by fundamental characteristics, such as supply and demand conditions. More recently, Juvenal and Petrella (2011), and Lombardi and Van Robays (2011) propose to extend Kilian and Murphy's model by introducting an additional shock (respectively speculation by oil producers for the former, and 'nonfundamental' financial speculation shock for the latter) and find evidence of financial speculation impact on oil markets.

4.1.4 Heterogeneous agents and price fluctuations

All previously mentioned studies are based on the representative agent paradigm and assume intuitively that agents in commodity markets are fully rational. It appears that results about the impact of speculation regarding the recent energy prices surge are not so clear. Some of them attest the existence of "commodity speculation", while some others reject this explanation. Since the work of Simon (1957), the representative agent assumption seems to be too restrictive, in the sense that there is only one way of behaving rationally while there is an infinite number of ways of behaving boundedly

[8] For more details see Kilian and Murphy (2012).

rational. A possible cause of the large price volatility of commodity markets could be therefore the existence of heterogeneous speculators in the markets. Originally focusing on financial and exchange rate markets, this literature turned to commodity markets to investigate potential anomalies in prices fluctuations. He and Westerhoff (2005), Westerhoff and Reitz (2005), Reitz and Westerhoff (2007), and Reitz and Slopek (2009), are among the first to introduce models with heterogeneous agents for commodity markets and find significant evidence of trader heterogeneity and switching behavior in prices fluctuations. More recently, Ellen and Zwinkels (2010) rely on the HAM of Brock and Hommes (1997, 1998) to study the impact of heterogeneous traders in Brent and WTI crude oil prices. They find that oil prices are mainly governed by fundamental factors (such as political and economic issues, ...), but find also that speculators are present in the markets and usually have destabilizing effects on the price of oil. These studies are mainly concerned about spot prices where oil companies are pretty much the same. More importantly, they cannot drive up the price without increasing inventories (unless the elasticity of demand is literally zero).

4.1.5 Extending the previous literature

The literature explaining the potential reasons of the recent commodity prices surge does not go in the same way so that we do not really understand what cause these markets so volatile. It seems clear that the dynamics of commodities, and especially of energy prices has increased significanlty since 2003, and it appears also relevant that the properties of these prices tend to be close to those of traditional financial assets (such as volatility clustering, autocorrelation, to name few (see Joëts, 2012)). What really cause these specific behaviors?

Our chapter proposes to investigate these specific characteristics by considering a less restrictive approach than previous methodologies. Because quantifying the problem of excessive speculation is not trivial, we do not really talk about speculative phenomenon in its economic sense but rather try to understand if "irrational" expectations[9] can cause abnomal fluctuations in the markets. More formally, we propose to relax the rational agent paradigm by considering a model with heterogeneous beliefs (Brock and Hommes, 1997 and 1998) where agents are allowed to switch between "rational and irrational" behaviors according to an emotional regret process. Moreover, we introduce a new circunstance where energy prices can experience strong fluctuations. Indeed as suggested by Knight (1921) and Keynes (1921), the reason why the standard approach, based on expected utility theory, fails to explain "abnomal" behaviors may be because agents in the markets may face to uncertainty as opposed to risk.[10] In our context investors may simply face to uncertainty when they have no prior about their future energy prices expectations. Uncertainty averse agents are therefore supposed to interact with uncertainty neutral ones which can cause energy prices movements even more important. The purpose of this chapter is therefore to investigate theoretically and empirically the proportion of each trader in energy markets (oil, gas, coal and electricity prices) during both normal times and extreme fluctuations periods to see whether the weight of irrational agents can exceed that of rational ones and leads to excessive energy prices movements (*i.e.* which do not reflect fundamentals of each market).

4.2 Theoretical model

In this section, we develop a simple and stylized HAM that will be used to evaluate the effect of heterogeneous speculators on energy prices. The model is based on the model introduced by Brock and Hommes (1997, 1998) and extended by of Kozhan and Salmon (2009). We propose a new specification of the HAM by integrating Bell (1982)

[9] By irrational we think about naïve behaviors or noisy investors.

[10] According to Bewley (2002), the distinction between risk and uncertainty is defined by the fact that a random variable is risky if its probability distribution is known, and uncertain if its distribution is unknown.

and Loomes and Sugden (1982)'s regret approaches where agents are allowed to switch between each strategy through an emotional learning process. More formally, there are different types of agents in the market forming heterogeneous expectations in uncertain universe which interact by a regret learning specification.

The dynamic of prices can be expressed as follows:

$$\Delta p_t^{(i)} = \zeta + \kappa D_t^{(i)} + \varepsilon_t \tag{4.1}$$

where $\Delta p_t^{(i)}$ denotes the dynamic of prices between t and $t-1$ of energy i, with i being respectively oil, gas, coal or electricity prices. $D_t^{(i)}$ is the aggregate demand function at time t for each i, and ε_t is an error term $\varepsilon_t \sim (0; \sigma_\varepsilon^2)$. The aggregate demand function is the consequence of the disaggregate demands of each different type of traders.

In our economy, we assume that each agent can invest in both risk-free and and risky assets. An agent wealth at time t is determined by his trading activity and is equal to[11]

$$W_t = (1 + r_{t-1})W_{t-1} + (P_t + y_t - (1 + r_{t-1})P_{t-1})d_{t-1} \tag{4.2}$$

where W_t and W_{t-1} are the wealths of each agent at time t and $t-1$, P_t is the price (ex-dividend) of the risky asset at time t, y_t is the dividend of the risky asset, d_{t-1} is the demand for risky asset at $t-1$. r_t is the risk-free rate.

As in the traditional Brock and Hommes (1997)'s model, there are two types of investors which interact in the market, namely fundamentalists and chartists. The former group believes that there exists an equilibrium price (the fundamental value) around which the price will always fluctuate. Fundamentalists' expectations of the energy price dynamics

[11] For simplicity, we do not further report the exponent i for each series.

are therefore proportional to the observed difference between the fundamental value and the price at $t-1$ according to the following equation

$$E_t\left(P_{t+1}/F\right) = P_{t-1} + \alpha\left(\overline{P}_t - P_{t-1}\right) \tag{4.3}$$

with $0 \leq \alpha \leq 1$. $\overline{P}_t$ is the fundamental price of the energy market considered. F denotes fundamentalist behavior at time t. E_t denotes the conditional expectation at time t.

In parallel, we assume that to predict future price evolution, chartist investors use a simple long-short moving average rule given by

$$E_t\left(P_{t+1}/C\right) = P_{t-1} + \alpha'\left(\frac{1}{MA^s}\sum_{j=1}^{MA^s} P_{t-j} - \frac{1}{MA^l}\sum_{j=1}^{MA^l} P_{t-j}\right) \tag{4.4}$$

with $\alpha' > 0$, MA^s and MA^l the respective lengths of the short and long moving average windows. C denotes chartist behavior at time t. E_t denotes the conditional expectation at time t.

The fact that the market can be summarized by these two types of beliefs is well established in the financial and exchange rate literatures (see, Taylor and Allen,1992; Cheung et al., 2004; Broswijk et al., 2007; de Jong et al., 2010, to name few). Because energy markets can, depending on the context, behave as traditional financial assets (see, Joëts, 2012), we assume that these two traders' types may also be present in these markets. Reitz and Slopek (2009), Ellen and Zwinkels (2010), and Büyüksahin and Harris (2011), among others, have shown that in oil market, participants act as "trend followers", where retroactive effects influence the positions taken by stakeholders. In our model, the information available to both types of traders at time t is the past level of prices, and past and present values of fundamental variables. Following Brock and Hommes (1998), Boswijk et al. (2007), and Kozhan and Salmon (2009), we assume for analytical tractability that investors have homogeneous expectations about the conditional second moment of price movements.[12]

4.2.1 Demand functions

Following Kozhan and Salmon (2009), we have four distincts individual demand functions depending on the strategy used and the uncertainty context (*i.e.* uncertainty neutral/averse demand from fundamentalist/chartist traders). In the sequel, we denote $d_t^u(B)$ and $d_t^n(B)$ the individual demands from uncertainty averse and neutral traders, with $B = F, C$.

4.2.1.1 Uncertainty neutral agents

In this case, we are in the situation where both fundamentalist and chartist investors are considered to be neutral to uncertainty. In other words, they are indifferent between their ignorance about an uncertain prospect or a situation in which they have no prior experience. Their risk preferences are characterized by a myopic mean-variance utility function, and agents maximize their expected utility functions as follows

$$E_t\left(U\left(W_{t+1}^n\right)/B\right) = E_t\left(W_{t+1}^n/B\right) - \frac{\gamma}{2}V_t\left(W_{t+1}^n/B\right) \underset{d_t^n}{\rightarrow} \max \tag{4.5}$$

where U and V denote respectively utility and the conditional variance, γ is the risk aversion parameter assumed to be the same across individuals. The wealth of uncertainty neutral agent at $t+1$ is given by

$$W_{t+1}^n = (1+r_t)\,W_t^n + (P_{t+1} + y_{t+1} - (1+r_t)\,P_t)\,d_t^n \tag{4.6}$$

[12] $E_t\left(P_t^2/B\right) = E_t\left(P_t^2\right)$, where $B = F, C$.

Maximizing the mean-variance expected utility with respect to d_t^n give us the following expression[13]

$$d_t^n = \frac{E_t\left[\left(P_{t+1} + y_{t+1} - (1 + r_t)\, P_t\right)/B\right]}{\gamma V_t\left[\left(P_{t+1} + y_{t+1} - (1 + r_t)\, P_t\right)/B\right]} \tag{4.7}$$

Beliefs about future dividends are considered to be the same for all traders types and to be equal to the true conditional expectation $(E_t\,(y_{t+1}/B) = E_t\,(y_{t+1}))$. We also assume that in a special case, the dividend follows an i.i.d process, such as $E_t\,(y_{t+1}) = \overline{y}$.[14] For analytical tractability, the conditional variance is assumed to be equal and constant for all types of investors, so $V_t = \sigma^2$. The equation (3.5) can be simplified as follows

$$d_t^n = \frac{E_t\,(P_{t+1}/B) + \overline{y} - (1 + r_t)\, P_t}{\gamma\sigma^2} \tag{4.8}$$

4.2.1.2 Uncertainty averse agents

Because the assumption of neutral uncertainty appears to be too restrictive in our case, we allow the existence of uncertainty averse agents on energy markets. Unlike neutral category, uncertainty averse agents are attentive to the misreading and potential unmeasurability of their models or associated probability distributions. They maximize their maxmin myopic mean-variance utility function of future wealth.[15] As in Kozhan and Salmon (2009), the preferences of uncertainty averse fundamentals/chartists are expressed by the set of possible expectations of future energy prices evolutions. In turn, the set of different possibilities is determined by a symmetric bandwidth ϑ around the base of uncertainty neutral expectations. Therefore, the future energy prices movements expected by the uncertainty averse agents are assumed to fluctuate in the interval $\Lambda = [E_t\,(P_{t+1}/B) - \vartheta; E_t\,(P_{t+1}/B) + \vartheta]$.

[13] See Kozhan and Salmon (2009) for proof.
[14] $\overline{y}$ being a constant term.
[15] For more details see Gilboa and Schmeidler (1989) and Garlappi et al. (2007).

$$E_t\left(U\left(W^u_{t+1}\right)/B\right) = \min_{\theta\in\Lambda} E_t\left(W^u_{t+1}(\theta)/B\right) - \frac{\gamma}{2} V_t\left(W^u_{t+1}(\theta)/B\right) \underset{d^u_t}{\rightarrow} \max \tag{4.9}$$

where θ is the anticiped prices in the interval Λ. The wealth of averse agents at $t+1$ is given by

$$W^u_{t+1}(\theta) = (1+r_t)\, W^u_t(\theta) + (P_{t+1} + y_{t+1} - (1+r_t)\, P_t)\, d^u_t \tag{4.10}$$

When averse agents maximize their maxmin expected utilities with respect to d^u_t, they are able to determine three optimal demand functions according to the interval Λ, namely $S(B)$, $S_{\max}(B)$, and $S_{\min}(B)$

$S(B) = \frac{E_t(P_{t+1}/B)+\overline{y}-(1+r_t)P_t}{\gamma\sigma^2}$

$S_{\max}(B) = \frac{(E_t(P_{t+1}/B)+\vartheta)+\overline{y}-(1+r_t)P_t}{\gamma\sigma^2}$

$S_{\min}(B) = \frac{(E_t(P_{t+1}/B)-\vartheta)+\overline{y}-(1+r_t)P_t}{\gamma\sigma^2}$

According to Kozhan and Salmon (2009), given the level of energy prices P_t, the optimal strategy in Λ for uncertainty averse investors is to keep d^u_t units of energy according to the following rules[16]

$$d^u_t = \begin{cases} S_{\min}(B) \text{ if } P_t < E_t(P_{t+1}/B) - \vartheta \\ 0 \text{ if } E_t(P_{t+1}/B) - \vartheta < P_t < E_t(P_{t+1}/B) + \vartheta \\ S_{\max}(B) \text{ if } E_t(P_{t+1}/B) + \vartheta < P_t \end{cases} \tag{4.11}$$

[16] See Kozhan and Salmon (2009) for more details.

4.2.2 Learning process through emotional regret interaction

In traditional HAMs, agents may change their strategies at every period of time (they choose to become fundamentalists or chartists). The learning process is generally similar to case-based reasoning scenario, where agents evaluate the market and choose their investment strategies based on comparison of the cumulative past performances of each forecasting rule (see Kirman, 1993; De Grauwe and Grimaldi, 2006; Kirman et al., 2007; Boswijk et al., 2007; Kozhan and Salmon, 2009; Ellen and Zwinkels, 2010, among others). However, these learning processes are cognitively oriented while psychologic studies have shown that investors' decision processes are the conjunction of both cognitive and emotional factors (see, Zajonc, 1980; Schwarz, 1990; Damasio, 1994; Forgas, 1995; Isen, 2000; Loewenstein et al., 2001, among others).[17] To account for the potential impact of feelings in the behavior of agents, we propose to introduce a learning emotional switching process based on anticipated emotions, defined as emotions that are expected to be experienced by investors given a certain outcome level. Intuitively, the switching mechanism is based on the regret theory of Loomes and Sugden (1982) and Bell (1982). More formally, at the beginning of period t, agents anticipate the regret they could experienced if they have chosen the fundamental strategy rather than the other one. Agents are allowed to switch between different strategies (fundamental vs chartist), and also between their reaction to uncertainty in the market (averse vs neutral) according to this regret criterion. Regret appears to be a cognitively-based emotion of pain and anger when agents observe that they took a bad decision in the past and could have taken one with better outcome. In our case, agents will experience regret when their investment (based for example on fundamental strategy) yields, ex-

[17]The impact of feelings in decision process has been widely confirmed empirically in stock market fluctuations (Saunders, 1993; Cao and Wei, 2002; Kamstra et al., 2000; Hirshleifer and Shumway, 2003; Kamstra et al., 2003; Dowling and Lucey, 2005 and 2008), and more recently in energy price dynamics (Joëts, 2012).

post a lower performance than an obvious alternative strategy (chartist strategy) they could haven chosen.[18]

Within this framework, suppose that $\pi_{t+1}(F, C)$ denotes the probability of a trader to adopt fundamentalist behavior at time $t+1$ by the following multinomial logistic expression

$$\pi_{t+1}(F, C) = \frac{e^{\beta H_t^n(F,C)}}{e^{\beta H_t^n(F,C)} + e^{\beta H_t^n(C,F)}} \tag{4.12}$$

where $\pi_{t+1}(F, C) \in <0, 1>$ denotes the fraction of fundamentalists in the market (*i.e.* the probability to become fundamentalist rather than chartist at $t+1$), such as $\pi_{t+1}(C, F) = 1 - \pi_{t+1}(F, C)$, the fraction of chartists at time $t+1$. The parameter β is the intensity of choice and represents the matter to which the regret/rejoice feelings relative to a certain strategy at t determine whether it is adopted at $t+1$. More explicitly, β measures the extent to which investors hold their believe even though the other option might be more attractive. $H_t^n(F, C)$ and $H_t^n(C, F)$ are both based on the following regret expression

$$H_t^n(F, C) = V^n(F) + f(V^n(F) - E[V^n(C)])$$

$$H_t^n(C, F) = V^n(C) + f(V^n(C) - E[V^n(F)])$$

with $f(.)$ the regret function. $V^n(F)$ is the utility of being F and not C , and $V^n(C)$ is the utility of being C and not F. Each utility is discounted sums of the one-period utilities of the respective uncertainty neutral fundamentalist and chartist investors in the following general form

[18] Contrary to disappointment, which is experienced when a negative outcome happens relative to prior expectations, regret is strongly associated with a feeling of responsability for the choice that has been made.

$$V^n(B) = \sum_{k=1}^{K} \omega^{k-1} U\left(h_{t-k+1}^n(B)\right) \tag{4.13}$$

ω being the discount factor, $h_t^n(B) = (1+r_{t-1})W_{t-1}^n(B) + (P_t + y_t - (1+r_{t-1})P_{t-1})d_{t-1}^n(B)$. Anticipation of $V^n(B)$, is expressed as $E[V^n(B)] = V^n(B) + \varepsilon_t$, with ε_t an error term $\varepsilon_t \sim (0; \sigma_\varepsilon^2)$.

Our regret function is given by the following rule:

- if $V^n(F) > E[V^n(C)] \Rightarrow \Delta V^{n,F} > 0$, the group of fundamentalists feels rejoice and the probability to become F at time $t+1$ increases (the same analysis holds for chartist group);
- if $V^n(F) < E[V^n(C)] \Rightarrow \Delta V^{n,F} < 0$, the group of fundamentalists feels regret and the probability to become F at time $t+1$ decreases (the same analysis holds for chartist group).

Simultaneously, with the fundamental/chartist switching mechanism an agent can also change his reaction according to the level of uncertainty present in the market. Agent can be neutral to uncertainty if he considers the information available in the market as certain and has no doubt about his model or potential prior. He will be more willing to choose the expected utility strategy. However, neutral agent is allowed to switch to uncertainty averse behavior. As discussed by Kozhan and Salmon (2009), under severe uncertainty about the condition and the future evolution of the market, the agent will use maxmin strategy whereas under weak uncertainty he will earn some positive utility and will be less sensitive to bad outcomes. In the same manner, the probability to become uncertainty neutral is given by

$$\pi_{t+1}(n, B) = \frac{e^{\beta' H_t^n(B)}}{e^{\beta' H_t^n(B)} + e^{\beta' H_t^u(B)}} \tag{4.14}$$

$H_t^u(B)$ is the regret expression of averse uncertainty agent with

$$H_t^u(F,C) = V^u(C) + f\left(V^u(F) - E\left[V^u(C)\right]\right)$$

$$H_t^u(C,F) = V^u(F) + f\left(V^u(C) - E\left[V^u(F)\right]\right)$$

and

$$V^u(B) = \sum_{k=1}^{K} \omega^{k-1} U\left(h_{t-k+1}^u(B)\right) \tag{4.15}$$

where $h_t^u(B) = (1 + r_{t-1})W_{t-1}^u(B) + (P_t + y_t - (1 + r_{t-1}) P_{t-1})d_{t-1}^u(B)$.

4.2.3 The aggregate demand function

The aggregate demand function is characterized by the four disaggregate demands of each trader. z_t denotes the proportion of fundamentalists in the market and $(1 - z_t)$ the proportion of chartists. W_t is the proportion of uncertainty neutral investors while $(1 - W_t)$ represents the proportion of uncertainty averse agents. Finally N is the total of agents. The general form of the aggregate demand function is

$$D_t = N\left[\underbrace{\left(z_t W_t^F d_t^{F,n} + z_t\left(1 - W_t^F\right) d_t^{F,u}\right)}_{fundamentalist\ group} + \underbrace{\left((1 - z_t) W_t^C d_t^{C,n} + (1 - z_t) W_t^C d_t^{C,u}\right)}_{chartist\ group}\right] \tag{4.16}$$

Equation (4.16) is then inserted in the relation (4.1) to investigate the impact of each category of investors on the dynamic of energy prices.

4.3 Specification and estimation

Due to the complex nonlinear specification of the model, HAMs have not often been estimated, but simulated. Boswijk et al. (2007), de Jong et al. (2009), Reitz and Slopek (2009), and more recently Ellen and Zwinkels (2010) are among the first to estimate HAMs with switching mechanism on the S&P500, option market and oil market respectively. In our empirical section, we consider daily data over the January 3, 2005 to December 31, 2010 period. The sample has the particularity to cover the strong dynamics that we observed recently in energy market. In order to allow for both fundamental and speculative pressures, we rely on European forward prices at 1 month for oil, gas, coal and electricity markets. Energy prices are quoted in US dollars per tonne of oil equivalent ($/toe) and are extracted from the Platt's Information Energy Agency.

As mentioned in Section 4.2, our model is characterized by the interaction of fundamentalist and chartist agents. Therefore for the model to function, it is necessary to set a stabilizing group against a destabilizing one. The fundamentalist group bases expectations around the fundamental value $\overline{P}_t$. To compute the fundamental value of each energy market, we use the moving average of each price over a period of 60 days.[19] One might argue that the moving average rule cannot constitute a true theoretical fundamental value. For instance, Reitz and Slopek (2009) generate the fundamental value of oil price based on Chinese oil imports. However, as discussed by Ellen and Zwinkels (2010), this type of fundamental value causes an informational advantage making this method inappropriate in practice. Moreover, our moving average rule allows us to consider fundamentalists as somewhat more broadly. The chartist agents, for their part, use a simple 1-50 moving average rule. Figure 4-6 in Appendix depicts the energy prices and their respective fundamental values (in logarithm) and shows the relevance

[19] Results are robust to the choice of the window length. They are available upon request to the author.

of our fundamental prices.

Table 4.1 in Appendix reports descriptive statistics of energy price returns and misalignment between prices and fundamentals. They reveal that kurtosis of each energy return series is largely above three, which means that the distribution is peaked with fat tails indicating strong uncertainty on the markets. The specific properties of electricity market (i.e. non-storablility, inelasticity of the supply,...) cause thicker tails than other series. Skewness shows that oil, gas, and electricity returns are generally right skewed while coal returns are left skewed. These confirm our view of strong fluctuation in energy prices. Regarding the misalignment between prices and fundamental values, positive mean for oil and gas signifies that prices are generally overvalued, while negative mean for coal and electricity suggests an undervaluation.

Our model, characterized by the general form of equation (4.1), is estimated using NLS. As we mentioned, the proportion of each agent in the markets follows a multinomial logistic rule. The optimal values for K in equations (4.13) and (4.15) are determined by Akaike criterion.[20]

4.4 Empirical results

This section is devoted to test whether the different types of traders we specified are active in energy markets, and to determine their relative weights in explaining price fluctuations. We also propose an out-of-sample analysis to compare the predictive ability of our theoretical model against a simple random walk.

[20] $K = 6$ for oil, $K = 3$ for gas, $K = 3$ for coal, and $K = 2$ for electricity.

4.4.1 In-sample analysis

In order to investigate whether heterogeneous beliefs, and especially uncertainty can dictate energy price dynamics, we propose to estimate different specifications of our model (*i.e.* with and without ambiguity). Moreover, as documented by Joëts (2012), the dynamic of energy prices can be considerably different depending on the intensity of the market.[21] Therefore, we also intend to estimate our model during extreme fluctuations periods to investigate whether investors' behaviors are more severe in this circumstance.

Our model is estimated for each energy market. Tables 4.2, 4.3, 4.4, and 4.5 report in-sample estimation results during normal times, respectively for oil, gas, coal, and electricity markets. First regarding the neutral case (*i.e* without uncertainty), fundamental traders only impact energy markets. Indeed, although there is a significant switching phenomenon[22] between fundamental and chartist expectations, the role of "trend followers" appears to be irrelevant. In neutral restrictive case scenario, fundamental considerations, such as changes in the supply and demand conditions (for example OPEC decisions, refining capacity, humanitarian unrest, increasing energy demand from Asian emerging countries,...), would drive future energy prices evolutions.
Let us now turn to a less restrictive case by considering that uncertainty can exist in the markets and can cause future price fluctuations even more ambiguous for participants. In this context, the influence of uncertainty in decision-making process could create large gaps between prices and fundamental values leading non-commercial investors more motivated to enter into the market. As we can see, neutral and averse fundamentalists coexist with averse chartists for almost all prices, whereas averse fundamentalists

[21] Using a new test of Granger causality in risk Joëts (2012) finds that interactions between energy prices can be more intense during extreme periods.

[22] The intensity of choice β is positive and highly significant for each market.

appear to be rationally bounded and more prone to switch toward chartist strategy. The switching mechanisms between fundamental/chartist and between neutral/averse are significant and positive indicating that a double change of attitude exists. Fundamentalist and chartist traders are not sure about their respective beliefs on the market so they perpetually switch between strategies following "the way of largest number", making price movements even more important, creating in turn more uncertainty. This market phenomenology tends to favor "trend followers" against fundamental traders.
Figure 4-1 reports the trader weights in mean for each market with respect to their significance impact. For each market, chartist agents seem to be dominant. While this dominance is weak for the gas market, it is clearer for other series. Indeed, considering that oil market is mainly composed by fundamentalits and chartists neutral and uncertain traders, the role of chartists' behaviors is largely ascendant. Turning to the coal market, this superiority is even more important, where fundamentalists uncertain agents seem to prefer to switch to "trend followers" attitude than to keep the fundamental strategy. Regarding electricity prices, two types of traders are mainly present in the market (*i.e.* fundamentalists and chartists uncertain). As for the gas market, the preponderance of one group (chartists uncertain) against another (fundamentalists) is not immoderate in this market. This similarity between gas and electricity prices can be the consequence of existing input-output relations between both markets.[23] The specific nature of gas market compared to oil one can be attributed to the recent European liberalization process making long-term gas contracts no longer indexed to oil market, but to spot and futures prices.[24] This fact leads gas prices submit to fundamental and financial pressures in almost the same proportion. Moreover, unlike oil prices which are internationally organized through liquid markets, gas prices are regionally managed and less subjected to the international macroeconomic uncertainty.

[23]Usually, the natural gas is used as an input to the electricity production process.
[24]Unlike futures prices which are most prone to be influenced by financial investors, spot prices usually reflect market fundamentals.

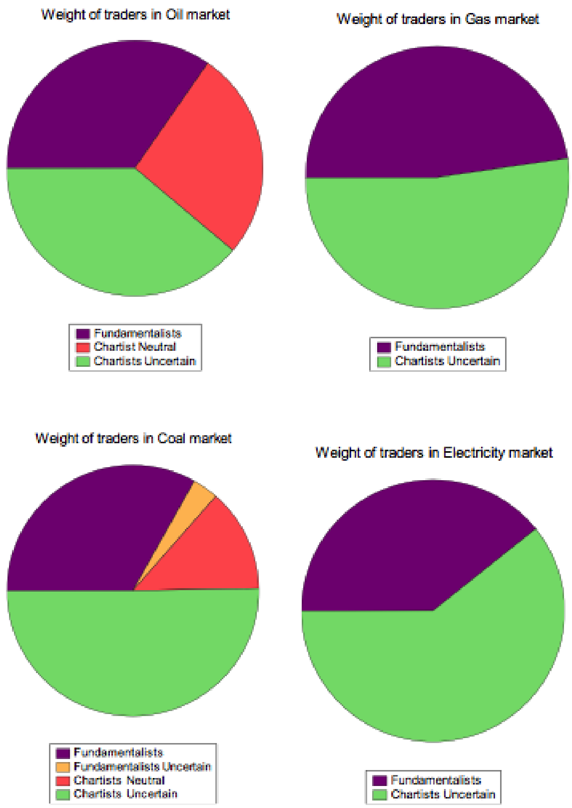


Figure 4-1: Trader weights in energy markets during normal times

As previously mentioned, the dynamic of prices can be considerably different if we look at extreme price movements. We propose to investigate the proportion of each traders during extreme fluctuations periods by using quantile regression approach.[25] This method allows us to distinguish between extreme downward and upward movements. As before, we propose restrictive and unrestrictive forms of our model (*i.e.* neutral and uncertain specifications). Tables 4.6, 4.7, 4.8, and 4.9 report the estimation results of neutral HAM for oil, gas, coal, and electricity markets respectively at both downside and upside circumstances. The proportion of each agent is not constant in the markets depending on the side of the distribution. Indeed, for all series, fundamentalists and chartists interact during downward extreme prices fluctuations, while during upward movements only fundamentalist behaviors are determinant (except for oil where both agents coexist). In other words, if we assume no uncertainty in the decision-making process, fundamental considerations would be the main consequence of prices increase, while both fundamental and speculative pressures would be that of prices decrease. However, because no ambiguity is a restrictive assumption, we propose to extend our analysis to the case of uncertainty to investigate whether averse behaviors are more important during extreme movements rather than normal times.

Tables 4.10, 4.11, 4.12, and 4.13 show estimation results of uncertain HAM of oil, gas, coal, and electricity prices respectively (downside and upside). We can see that compared to normal times, the composition of each market has changed significantly. Energy markets movements are characterized by the interaction of both neutral and averse agents, however the weight of averse traders seems to be higher compared to normal times. As before, the proportion of each trader in markets is different depending on the side of the distribution. Regarding the downside context, uncertainty causes chartists behaviors to be more present in the market making prices decrease extremely rapid through self-fulfilling prophecy. This phenomenon has been recently observed empirically in energy markets. For instance, oil Brent price has increased sharply

[25] For simplicity we suppose that switching parameters are the same as those estimated during normal times.

between mid-2007 and mid-2008 to a level of almost \$140 per barrel, and decreased to less than \$40 per barrel at the end of 2008. With less intensity, same movements have been observed on gas, coal and electricity markets showing potential herd behaviors in prices. Turning to the upside context, unlike during normal periods, extreme upward movements are not only characterized by fundamental expectations, but also by speculators probably not related to physical interests. Generally speaking, the fundamental nature of energy prices seems to fade in benefit to "irrational exuberance" as the fluctuations become more intense.

Figures 4-2, 4-3, 4-4, and 4-5 show the traders weight in each market during extreme downward and upward movements, and confirm this fact. Indeed, during extreme prices decrease, energy markets are clearly dominated by chartists uncertain agents supporting our intuition about the fact that uncertainty increases and in turn leads to "cascading behaviors". During extreme prices increase, oil and electricity markets are dominated by both fundamentalists and chartists uncertain in the same proportion, whereas the latter is more important for coal market and less significant for gas market. However, the difference between each market appears to be less pronounced than during normal times.[26] This phenomenon can be explained by existing interconnections between energy prices which are exacerbated during extreme fluctuation periods by diversified commodity index investors who have large diversified multi-asset investment strategies.

4.4.2 Out-of-sample diagnostic

In this section, we investigate the forecasting ability of our HAM regret model against the RW model. Forecats are created using an expanding window of observa-

[26] This finding goes in the same way of Joëts (2012) about asymmetric behaviors of energy markets during upside and downside movements.

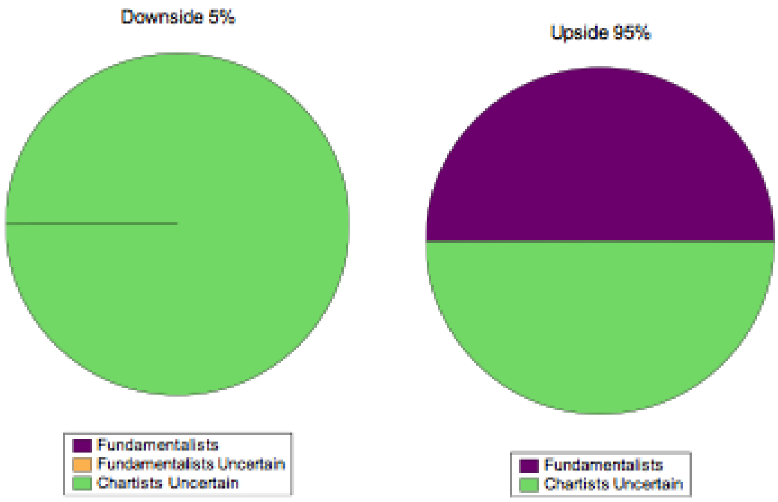


Figure 4-2: Trader weights in Oil market during extreme movements

tions. More precisely, both models are estimated from January 3, 2005 to December 31, 2007, then out-of-sample estimations are computed until December 31, 2010. The relative performance of the two forecast alternatives is evaluated by using the conditional Giacomini-White (2006)'s approach. Giacomini and White (2006) propose a test of Conditional Predictive Ability which allows to compare the forecasting properties of two models, given a general loss function.[27] This test allows to directly apprehend the effect of estimation uncertainty on relative forecasting performance. Moreover, it considers a less restrictive framework than previous methodologies since it permits a unified treatment of nested and nonnested models and also can accommodate more general estimation procedures in the derivation of the forecasts. As discussed by Giacomini and White (2006) in order to choose the best forecasting model, we use a two-step decision rule. The first one allows us to see whether there is a different predicitive ability between the two competing models, then the second step procedure lets

[27]This literature was initiated by Diebold and Mariano (1995), West (1996), McCracken (2000), Corradi et al. (2001), and Chao et al. (2001), to name few.

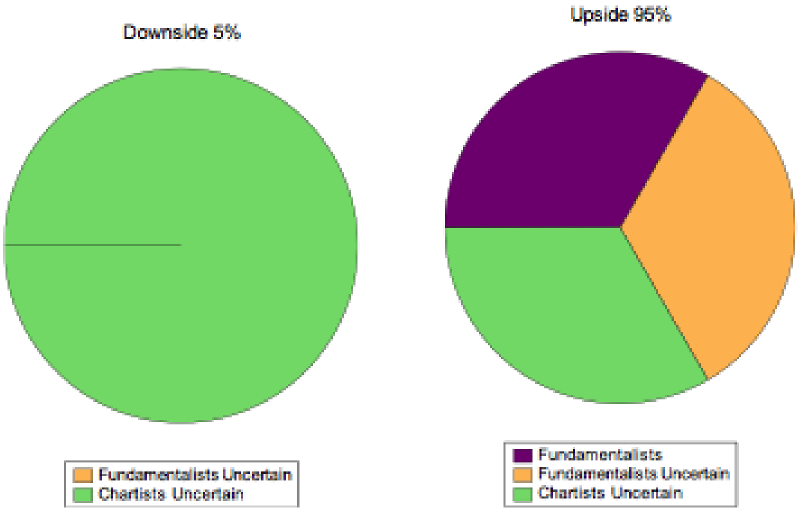


Figure 4-3: Trader weights in Gas market during extreme movements

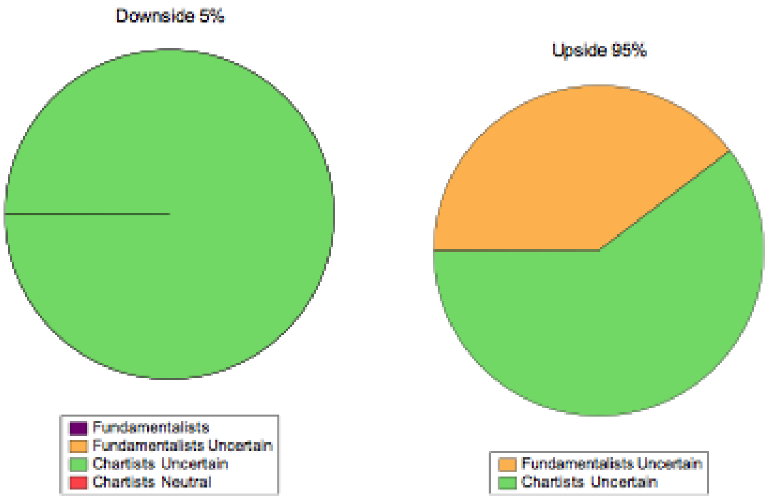
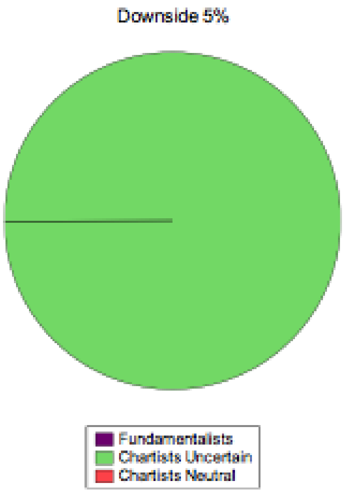


Figure 4-4: Trader weights in Coal market during extreme movements



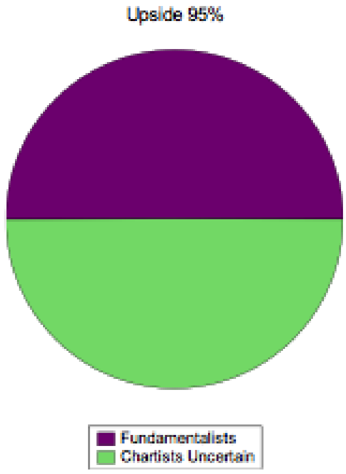


Figure 4-5: Trader weights in Electricity market during extreme movements

us to decide which model is the best.[28] This methodology is applied to each energy market to see whether HAM is the best model.

Table 4.14 reports results of the two-step test procedure for each energy market. The first step is characterized by the rejection of the null hypothesis of equal performance meaning that both HAM and RW models are not equally accurate on average. In other words, it means that one model necessary outperforms the other one in terms of predictive ability. The second step of the Giacomini-White procedure reveals that for each energy prices, the HAM outperforms the RW in terms of forecasting performance. Our HAM is therefore more adequate to apprehend the energy prices dynamics, renforcing the fact that heterogeneous beliefs, regret, and uncertainty could be the causes of high volatility of energy prices.

[28]For more details see Giacomini and White (2006).

4.5 Conclusion

In this chapter we provide an original behavioral and emotional analysis of the impact of financialization on energy markets under uncertainty. For this purpose we suppose that energy price fluctuations can be caused by heterogeneous expectations, as well as uncertainty in decision-making process. Our stylized heterogeneous agent model allows investors to switch between different strategies according to market circumstances.
Turning to the empirical analysis of oil, gas, coal and electricity markets over the January 2005 to December 2010 period, our results indicate that the proportion of each trader in the markets is different depending on the degree of uncertainty considered, as well as the intensity of fluctuations. Energy prices fluctuations are mainly governed by fundamentalist expectations when agents in the markets evolve under certain context, while both fundamental and speculative behaviors are the source of prices movements under uncertain world. We have also shown that trader weights could be different if we look at extreme situations. The proportion of uncertainty averse agents increases during extreme downward movements leading to situations where the fundamental nature of the markets fades in benefit to irrational fluctuations as "cascading behaviors". The conclusion is more parsimonious regarding extreme upward movements since price increases are the consequence of both fundamental and chartist traders. All in all, our chapter shows the limit of previous literature considering a too restrictive framework. We see that if we extend the analytical framework, we could have better perception and understanding of what drive energy markets.

Our model has obviously some limitations. Chartists have usually more complex behavior than a simple trend follower specification, and fundamentalist behavior could be also more sophisticated to account for the specific nature of each energy market. Despite these limitations the model outperforms standard benchmarks, and provides a first step toward the analysis of behavioral and emotional attitudes of energy investors facing uncertainty. Further work should be done to give a concise definition of what we call excessive "commodity speculation", as well as to explore more precisely if it can be costly in terms of social welfare.

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Appendix of Chapter 4

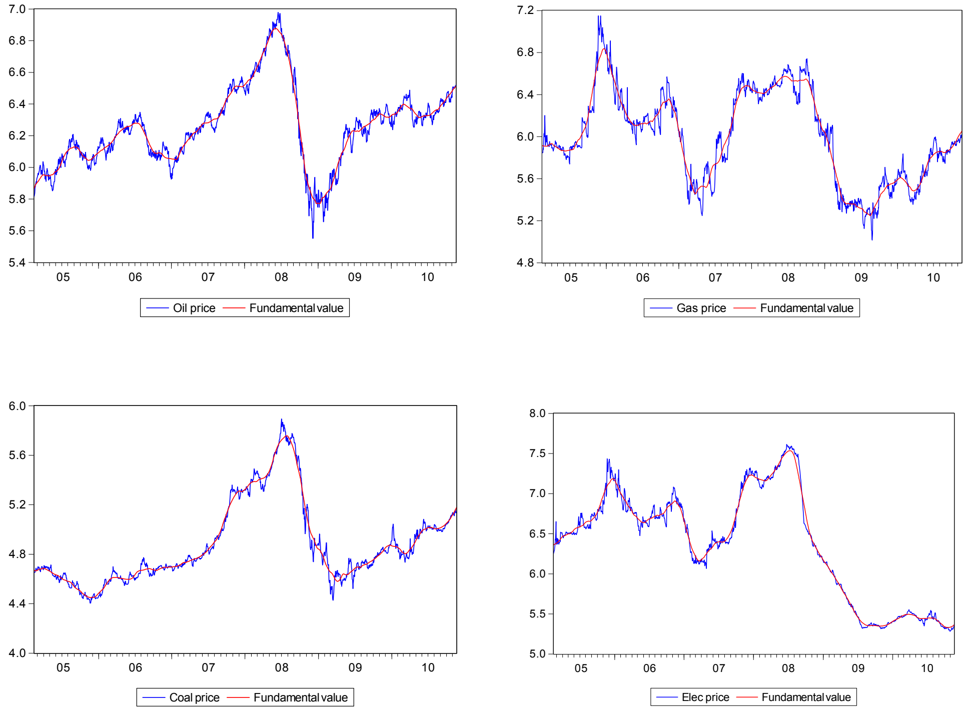

Figure 4-6: Energy prices and fundamental values at 1 month (in logarithm)

Table 4.1: Descriptive statistics

	Oil		Gas		Coal		Electricity	
	Δp	$p-\overline{p}$	Δp	$p-\overline{p}$	Δp	$p-\overline{p}$	Δp	$p-\overline{p}$
Mean	0.0004	0.003	0.0001	−0.0001	0.0003	−0.0002	−0.0006	0.0002
Std. Dev	0.023	0.047	0.047	0.099	0.018	0.045	0.030	0.063
Skewness	0.144	−0.455	2.029	0.127	−0.573	−0.099	1.81	0.419
Kurtosis	8.92	4.80	19.31	3.94	10.08	5.62	25.17	5.98

Notes: Δp denote price returns, and $p-\overline{p}$ the price deviation from the fundamental value of the energy considered.

Table 4.2: In-sample estimation results for oil market during normal times

	Oil	
	neutral	uncertainty
ζ	0.0007 (0.99)	0.0006 (0.85)
κ_1	$6.30E-06^{**}$ (2.34)	$-5.42E-06^{**}$ (-2.27)
κ_2	NA	$9.49E-05^{***}$ (1.76)
κ_4	$2.40E-05$ (1.27)	$-2.90E-05$ (-1.01)
κ_5	NA	$8.07E-05^{*}$ (2.80)
Switching		
β_1	0.139^{*} (6.89)	0.140^{*} (12.32)
β_2	NA	0.043^{*} (13.29)

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists, β is the parameter for intenstity of choice. *,**,*** denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.3: In-sample estimation results for gas market during normal times

	Gas	
	neutral	uncertainty
ζ	-0.0007 (-0.58)	-0.0003 (-0.25)
κ_1	-0.0001^{**} (-2.07)	$4.47E-05^{**}$ (2.29)
κ_2	NA	-0.0004 (-1.49)
κ_4	$-2.85E-05$ (-0.26)	-0.0001 (-0.77)
κ_5	NA	0.0003^{**} (1.98)
Switching		
β_1	0.150^{*} (10.14)	0.076^{*} (11.92)
β_2	NA	0.446^{*} (12.14)

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists, β is the parameter for intenstity of choice. *,**,*** denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.4: In-sample estimation results for coal market during normal times

	Coal	
	neutral	uncertainty
ζ	0.0004 (0.73)	0.0003 (0.51)
κ_1	$-1.68E-05^{**}$ (-2.55)	$-2.24E-05^{***}$ (-1.74)
κ_2	NA	0.0003^{**} (2.29)
κ_4	$6.68E-05$ (1.13)	-0.0002^{**} (-2.83)
κ_5	NA	0.0001^{*} (4.51)
Switching		
β_1	0.472^{*} (9.05)	1.06^{*} (4.29)
β_2	NA	0.028^{*} (12.13)

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists, β is the parameter for intenstity of choice. *,**,*** denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.5: In-sample estimation results for electricity market during normal times

	Electricity	
	neutral	uncertainty
ζ	-0.0005 (-0.58)	-0.0003 (-0.32)
κ_1	-0.0003^{**} (-2.00)	-0.0002^{***} (-1.84)
κ_2	NA	NA
κ_4	0.0004^{*} (2.80)	-0.0001 (-0.34)
κ_5	NA	0.0006^{*} (3.82)
Switching		
β_1	2.702^{*} (5.95)	2.13^{*} (3.47)
β_2	NA	0.090^{*} (11.95)

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists, β is the parameter for intenstity of choice. *,**,*** denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.6: In-sample estimation results for oil market during extreme movements (without uncertainty)

	Oil	
	neutral	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.036^{*} (−16.07)	0.033^{*} (18.72)
κ_1	$-3.40E-05^{***}$ (−1.71)	$2.78E-05^{*}$ (2.63)
κ_2	NA	NA
κ_4	0.0002^{*} (4.08)	$-9.77E-05^{**}$ (−1.77)
κ_5	NA	NA

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists. θ denotes quantile level, respectively 5% and 95% for downside and upside. *,**,*** denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.7: In-sample estimation results for gas market during extreme movements (without uncertainty)

	Gas	
	neutral	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.059^{*} (-16.50)	0.063^{*} (18.89)
κ_1	-0.0001^{**} (-2.27)	-0.0001^{**} (-2.40)
κ_2	NA	NA
κ_4	0.0005^{***} (1.80)	$-2.70E-05$ (-0.70)
κ_5	NA	NA

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists. θ denotes quantile level, respectively 5% and 95% for downside and upside. *,**,*** denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.8: In-sample estimation results for coal market during extreme movements (without uncertainty)

	Coal	
	neutral	
	Downside $\theta = 5\%$	Upside $\theta = 95\%$
ζ	-0.030^{*} (−12.98)	0.027^{*} (18.60)
κ_1	-0.0002^{**} (−2.51)	4.06^{**} (2.47)
κ_2	NA	NA
κ_4	0.0003^{*} (5.52)	$-6.47E-05$ (−0.99)
κ_5	NA	NA

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists. θ denotes quantile level, respectively 5% and 95% for downside and upside. *,**,*** denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.9: In-sample estimation results for electricity market during extreme movements (without uncertainty)

	Electricity	
	neutral	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.024^{*}	0.024^{*}
	(-20.22)	(16.20)
κ_1	0.0018^{*}	-0.0026^{*}
	(4.81)	(-8.52)
κ_2	NA	NA
κ_4	0.0019^{*}	-0.0012
	(11.32)	(-1.42)
κ_5	NA	NA

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists. θ denotes quantile level, respectively 5% and 95% for downside and upside. *,**,*** denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.10: In-sample estimation results for oil market during extreme movements (with uncertainty)

	Oil	
	uncertainty	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.036^{*}	0.033^{*}
	(-21.80)	(21.40)
κ_1	$-8.12E-05^{**}$	$2.68E-05^{**}$
	(-2.08)	(2.55)
κ_2	0.0002^{**}	$-2.03E-05$
	(2.01)	(-0.14)
κ_4	$-6.49E-06$	$-8.98E-05$
	(-0.09)	(-1.13)
κ_5	0.0003^{*}	-0.0001^{**}
	(7.54)	(-2.22)

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists. θ denotes quantile level, respectively 5% and 95% for downside and upside. *,**,*** denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.11: In-sample estimation results for gas market during extreme movements (with uncertainty)

	Gas	
	uncertainty	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.061^{*}	0.063^{*}
	(-17.17)	(14.79)
κ_1	0.0002	$-9.73E-05^{**}$
	(0.66)	(-2.20)
κ_2	-0.001^{**}	-0.0004^{**}
	(-2.20)	(-2.30)
κ_4	0.0005	-0.0009
	(1.08)	(-0.77)
κ_5	0.0007^{**}	0.0002^{**}
	(2.09)	(-2.29)

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists. θ denotes quantile level, respectively 5% and 95% for downside and upside. $^{*},^{**},^{***}$ denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.12: In-sample estimation results for coal market during extreme movements (with uncertainty)

	Coal	
	uncertainty	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.033^{*}	0.027^{*}
	(-10.75)	(17.84)
κ_1	-0.0002^{*}	$3.51E-05$
	(2.72)	(0.42)
κ_2	0.001^{***}	0.0005^{*}
	(1.66)	(8.81)
κ_4	-0.0006^{*}	-0.0006
	(-3.12)	(-0.40)
κ_5	0.0006^{*}	$5.73E-05^{*}$
	(4.77)	(2.79)

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists. θ denotes quantile level, respectively 5% and 95% for downside and upside. *,**,*** denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.13: In-sample estimation results for electricity market during extreme movements (with uncertainty)

	Electricity	
	uncertainty	
	Downside	Upside
	$\theta = 5\%$	$\theta = 95\%$
ζ	-0.023^{*} (−19.95)	0.025^{*} (15.39)
κ_1	0.0018^{*} (5.35)	-0.0026^{*} (−7.75)
κ_2	NA	NA
κ_4	0.0013^{***} (1.65)	-0.0010 (−1.20)
κ_5	0.0021^{*} (11.17)	-0.0011^{*} (−2.58)

Notes: ζ is for the constant term, κ denotes respectively the demand from neutral fundamentalists, averse fundamentalists, neutral chartists, and averse chartists. θ denotes quantile level, respectively 5% and 95% for downside and upside. $^{*},^{**},^{***}$ denotes significance at 1, 5, and 10% level respectively. Between parentheses t-stats.

Table 4.14: Conditional Predictive Ability Test

Model strategy	RW			
	Oil	Gas	Coal	Electricity
HAM model	200.83 (0.00*)	180.90 (0.00*)	270.92 (0.00*)	196.87 (0.00*)
	[0.70^{+}]	[0.85^{+}]	[0.98^{+}]	[0.60^{+}]

Notes: Between parentheses p-values. * denotes rejection of the null hypothesis at 1% significance level. Between brackets the proportion of time the method in the column outperforms the method in the row over the out-of-sample period, according to the Giacomini and White (2006)'s decision rule. $^{+}$ indicates that the HAM outperforms RW model more than 50% of the time.

Chapter 5

On the links between stock and commodity markets' volatility

Introduction [1]

Throughout the last decade, commodity prices experienced an exceptional volatility, with simultaneous and alternating phases of rising and falling trends. This evolution can be compared to that of financial markets, as illustrated by Figures 5-1 and 5-2 representing the Standard and Poor's 500 (S&P 500) and Commodity Research Bureau (CRB) price returns' volatility. As shown in Figure 5-3—which displays the dynamics of the S&P 500 and CRB price indexes—commodity prices have experienced a drop during the 2007-2008 financial crisis, and their link to stock prices seems to have strengthened since that turmoil. At the same time, commodities increasingly become part of portfolio allocation, together with stock classes.

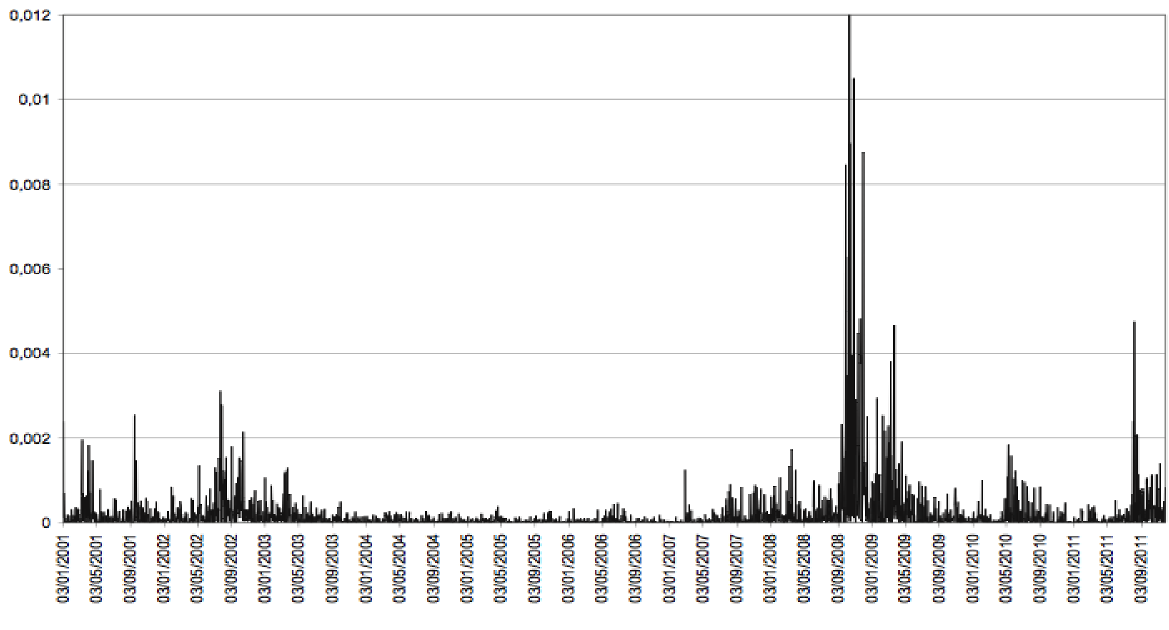

Figure 5-1: S&P 500 stock returns volatility (01/03/2001 - 11/28/2011)

[1] A first version of this chapter has been published as Creti, A., Joëts, M., and Mignon, V., 2013, On the links between stock and commodity markets' volatility, Energy Economics, 37, 16-28.

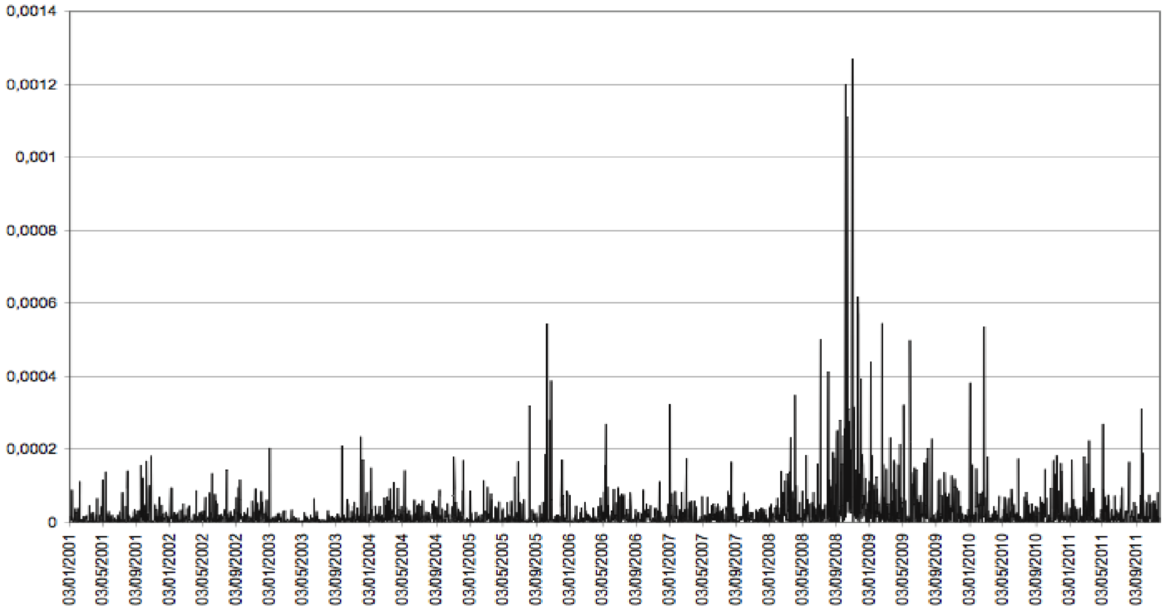

Figure 5-2: Commodity price returns volatility (01/03/2001 - 11/28/2011

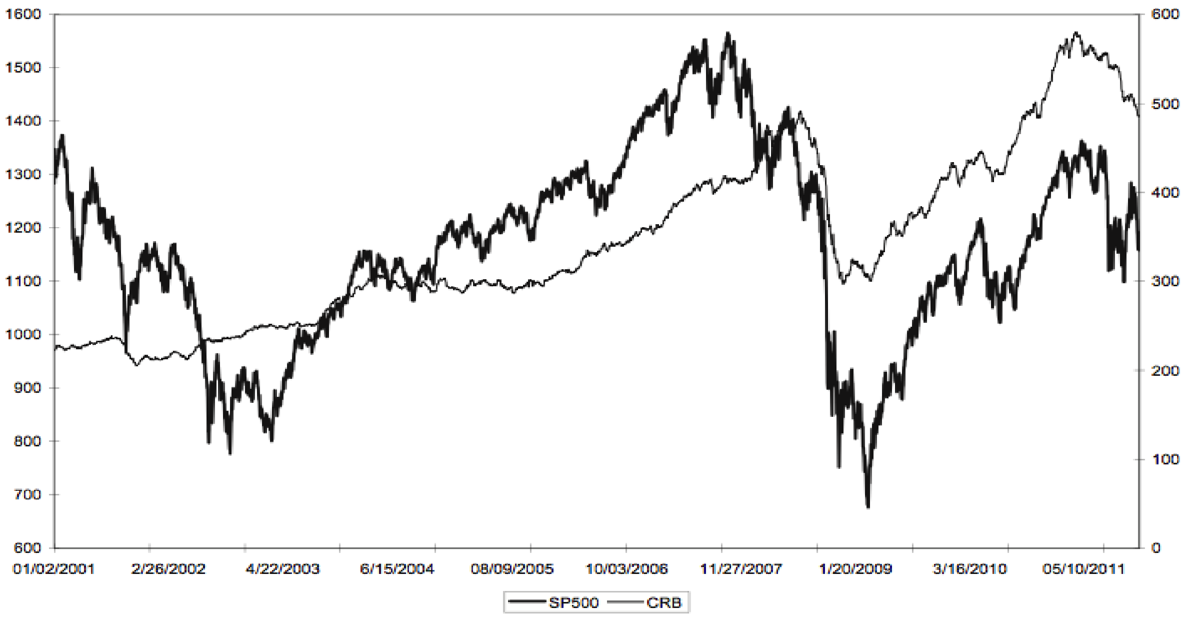

Figure 5-3: Evolution of S&P 500 and CRB indexes (01/03/2001 - 11/28/2011)

At a macroeconomic level, policymakers pay a particular attention to commodity prices and their volatility given their potential to feed inflation pressures. Volatility of commodity prices is thus a central issue for the world economy, as notably illustrated by the G20 which addressed the question of excessive fluctuations and volatility of commodity prices in its September 2009 Pittsburgh summit. Moreover, analyzing the links between commodity and stock markets is of particular interest for financial players as raw materials enter many investment portfolios, together with stock classes (Silvennoinen and Thorp, 2010; Dwyer et al., 2011; Vivian and Wohar, 2012). Furthermore, as documented by Choi and Hammoudeh (2010), commodity traders concurrently look at both stock and commodity markets fluctuations to infer the trend of each market. Comparing the dynamic volatility of raw materials and equities prices provides useful information about possible substitution strategies between commodity and stock classes. In particular, volatility plays a key role regarding hedging possibilities, and impacts asset allocation across raw materials and their risk-return trade-off. Building on the observed links between commodity and stock markets, a recent literature has emerged regarding the impact of investors' behavior in explaining the increase in both level and volatility of commodity prices.[2] However, as underlined by Vivian and Wohar (2012), no clear-cut conclusion has been reached so far.

In this chapter, we contribute to the emerging empirical literature dealing with the relationships between commodity and stock markets. More specifically, we focus on the dynamics of the correlations between both markets, and analyze whether those correlations evolve according to the situation—bullish or bearish—in the stock market. We pay a particular attention to the recent 2007-2008 financial crisis by investigating whether it has strengthened or disrupted the links between stock and commodity markets. From a methodological viewpoint, we follow the dynamic conditional correl-

[2] Recent references include Eckaus (2008), Khan (2009), Masters and White (2009), Capelle-Blancard and Coulibaly (2011), Du et al. (2011), Stout (2011), Valiante (2011), Büyükşahin et al. (2008, 2011), Irwin and Sanders (2012), Vivian and Wohar (2012), and Manera et al. (2012) for a review.

ation (DCC) GARCH approach introduced by Engle (2002) which allows to assess the changes in correlations between commodity and stock returns over time. The DCC-GARCH approach has been followed by Choi and Hammoudeh (2010) in a quite similar context, but our study considerably extends the analysis.[3] Our sample consists of 25 commodities covering various sectors over the period from January 3, 2001 to November 28, 2011. Relying on a large panel of raw materials (energy, metals, agricultural, food, ...) allows us to study whether commodities constitute an homogenous asset class with regard to their links with stock markets, and whether the crisis has engendered a financialization of commodity markets.[4] This kind of relationship has typically been investigated in the case of oil (Doyle et al., 2007; Mouawad, 2009), though the cross-effect on oil and stock market volatility remains globally unclear.

Our results show that correlations between commodity and stock markets are time-varying and highly volatile. The impact of the 2007-2008 financial crisis is noticeable, emphasizing the links between commodity and stock markets, and highlighting the financialization of commodity markets. We also show that, while sharing some common features, commodities cannot be considered a homogeneous asset class: a speculation phenomenon[5] is for instance highlighted for oil, coffee and cocoa, while the safe-haven role of gold is evidenced.

The rest of the chapter is organized as follows. Section 5.1 briefly reviews the literature about the links between commodity and stock markets. Section 5.2 presents the data as

[3] Only five commodities were considered in Choi and Hammoudeh (2010), instead of 25 in our case.

[4] The financialization process refers to a situation in which the price of an individual commodity is not only determined by its primary supply and demand, but also by several financial factors and investors' behavior in derivative markets.

[5] We use the term "speculation" for simplifying purposes to refer to a situation in which investors (i) engage in transactions to profit from short-term fluctuations in the market value of the considered asset or product, and (ii) focus only on price movements rather than on the fundamentals linked to the considered asset or product. Empirically, speculation is assessed here through the dynamics of correlations between oil and commodity markets: increasing correlations in times of rising oil prices, and decreasing—and even negative—correlations during periods of declining stock prices.

well as some stylized facts, and Section 5.3 deals with methodological aspects. Results are displayed in Section 5.4, and Section 5.5 concludes the chapter.

5.1 Literature review

As documented in the introduction, commodity markets share several characteristics with stock markets and financial assets. So far the literature has analyzed this phenomenon mainly by focusing on oil, and looking at the comovements between stock and oil markets. Most of this literature offers substantial evidence on the impact of oil on stock prices, putting forward a negative relationship between oil price and stock market returns.[6] For instance, Jones and Kaul (1996), using a standard cash-flow dividend valuation model, find a significant negative impact of oil price shocks on US and Canadian quarterly stock prices in the postwar period. Several models, relying on some variants of Vector Autoregressive analysis (VAR), highlight similar findings. Park and Ratti (2008), performing a multivariate VAR analysis, find statistically significant impact of oil prices shocks on real stock returns for US and 13 European countries over the period from January 1986 to December 2005. Sadorsky (1999) investigates relationships among monthly oil prices, S&P 500 stock returns, short-term interest rate, and industrial production for the January 1947-April 1996 period by means of an unrestricted VAR model. The author shows that oil prices and oil price volatility both play important roles in affecting S&P 500 stock returns. Papapetrou (2001) estimates a vector error-correction model on monthly data for Greece from January 1989 to June 1999, and concludes that oil prices drive stock price dynamics.

Shifting from the study of comovements to volatility analysis, the most recent literature focuses on volatility spillovers between oil/industrial commodity and stock markets.

[6] For an extensive review of the literature on this topic, see Filis et al. (2011).

Hammoudeh et al. (2004) investigate the spillover effects, day effects, and dynamic relationships among five daily S&P oil sector stock indices and five daily oil prices for the US oil markets[7] from July 17, 1995 to October 10, 2001 using cointegration techniques as well as ARCH-type models. They evidence volatility spillovers from the oil futures market on the stocks of some oil sectors. They also find an oil volatility transmission day effect, Friday having a calming effect on the volatility of oil stocks. Chiou and Lee (2009) examine the asymmetric effects of WTI daily oil prices on S&P 500 stock returns from January 1, 1992 to November 7, 2006, by investigating structure changes in this dependency relationship. Using the Autoregressive Conditional Jump Intensity model with expected, unexpected and negative unexpected oil price fluctuations, they find that high fluctuations in oil prices have asymmetric unexpected effects on stock returns. Malik and Ewing (2009) rely on bivariate GARCH models to estimate the volatility transmission between weekly WTI oil prices and equity sector returns[8] from January 1, 1992 to April 30, 2008 and find evidence of spillover mechanisms. Focusing on the Brent market, Filis et al. (2011) analyze time-varying correlations between oil prices and stock markets by differentiating oil-importing (USA, Germany, and the Netherlands) and oil-exporting (Canada, Mexico, and Brazil) countries. Using the multivariate DCC-GARCH approach from January 1988 to September 2009, they find that the conditional variances of oil and stock prices do not differ for oil-importing and oil-exporting economies. However, time-varying correlations depend on the origin of the oil shocks: the response from aggregate demand-side shocks is much greater than supply-side shocks originated by OPEC's production cuts. Finally, Choi and Hammoudeh (2010) extend the time-varying correlations analysis by considering commodity prices of Brent oil, WTI oil, copper, gold and silver, and the S&P 500 index from January 2, 1990 to May 1, 2006. They show that commodity correlations have

[7] The US oil industry encompasses companies engaged in various phases of oil production and processing. The US oil markets include the West Texas Intermediate (WTI), Cushing spot and the New York Mercantile Exchange (NYMEX) for 1 to 4 month futures prices.

[8] The following sectors are considered: financials, industrials, consumer services, health care, and technology.

increased since 2003, limiting hedging substitutability in portfolios.

Our study extends the previous literature by considerably enlarging the sample of commodities analyzed. We consider 25 different strategic commodities, traded in the US and covering various sectors: energy, precious metals, agricultural, non-ferrous metals, food, oleaginous, exotic and livestock. In addition to the diversity of the sectors covered, two main criteria have guided our choice of commodities: (i) data availability over our whole considered period, and (ii) important trading activity, as apprehended through the transactions volume and the number of large participants in the market (see various reports by the Commodity Futures Trading Commission). The dataset we have built allows us to compare the behavior of each commodity group regarding stock market fluctuations, and to study whether correlations between commodities and equities evolve over time and depend on the situation—bearish or bullish—on the stock market.

5.2 Data and stylized facts

We consider daily spot price series for a large sample of commodities over the January 3, 2001 - November 28, 2011 period (source: Datastream, Thomson Financial).[9] We investigate 25 different commodities covering the following various sectors: energy,[10] precious metals, agricultural, non-ferrous metals, food, oleaginous, exotic and livestock. All price series are quoted in US dollars. We also consider an aggregate

[9] An alternative would have been to rely on futures prices. However, as highlighted by Vivian and Wohar (2012), spot prices are the underlying asset upon which derivatives are based, a fact that is important when analyzing volatility. In addition, relying on spot prices avoids issues related to rollover of futures contracts.

[10] In the group of energy commodities, we have retained electricity rather than coal—although the latter represents the most important input in electricity production—because of the various interesting key changes undergone by the electricity market. In particular, the liberalization of the electricity market has led to the opening of this sector to competition—an evolution which is interesting for our purpose since it may promote the financialization of the electricity trading.

commodity price index, the Commodity Research Bureau (CRB) index. Regarding the equity market, we rely on one of the main US stock market index, namely the S&P 500 index.

Table 5.1 in Appendix provides some descriptive statistics regarding the returns series, defined as $r_t = \ln(P_t/P_{t-1})$, where P_t denotes the price index at time t. The group of energy commodities seems to differ from other groups in terms of volatility: the variance of electricity, gas and to a lesser extent oil price returns is higher than that obtained for the other commodities;[11] being also higher than those of S&P 500 and CRB returns. The electricity series is extremely volatile, as its high kurtosis value shows. This is not surprising given that electricity is not storable and prices reflect the real-time equilibrium between demand and supply, with contingencies that vary greatly from one day to another.[12] Together with high volatility, the group of energy commodities exhibits low returns on average, leading to the lowest benefit-risk trade off compared to the S&P 500 and the CRB indexes, and the group of food and oleaginous commodities which are more profitable on the return-risk basis. Statistics in Table 5.1 also show that all series are characterized by a time-varying volatility, an ARCH effect being present for almost all returns series. Finally, returns tend to be autocorrelated, especially for the energy and the precious metals groups, indicating some persistence phenomenon.

[11] The increasing trend in volatility of oil and gas market prices in the USA has also been documented by Pindyck (2004) among others.

[12] Though the Commodity Futures Trading Commission provides no data regarding the financialization of electricity (see Table 5.2 in Appendix), the latter can also be considered as a financial product. An illustration is given by the Nordic financial electricity market, whose liquidity provided by a number of speculators highlights that it is also important for financial trading purposes. More fundamentally, with the creation of electricity spot markets—including various standardized products—pure financial trading has been progressively growing to the point that the Dodd-Frank Act provides that these markets are monitored within the framework of financial stability measures.

5.3 Methodology

To investigate the time evolution of correlations between the commodity and stock markets, we rely on the dynamic conditional correlation (DCC) GARCH models introduced by Engle (2002). Let r_t be the vector composed of two returns series, $r_t = (r_{1t}, r_{2t})'$. Denoting by $A(L)$ the lag polynomial, we have:

$$A(L)r_t = \mu + e_t \tag{5.1}$$

where e_t is the error-term vector.

The DCC model is based on the hypothesis that the conditional returns are normally distributed with zero mean and conditional covariance matrix $H_t = E\left[r_t r_t' | I_{t-1}\right]$. The covariance matrix is expressed as follows:

$$H_t = D_t R_t D_t \tag{5.2}$$

where $D_t = diag\left[\sqrt{h_{1t}}, \sqrt{h_{2t}}\right]$ is a diagonal matrix of time-varying standard deviations issued from the estimation of univariate GARCH(1,1) processes:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{5.3}$$

and R_t is the conditional correlation matrix of the standardized returns ε_t, with $\varepsilon_t = D_t^{-1} r_t$:

$$R_t = \begin{bmatrix} 1 & q_{12t} \\ q_{21t} & 1 \end{bmatrix} \tag{5.4}$$

The matrix R_t is decomposed into:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{5.5}$$

where Q_t is the positive definite matrix containing the conditional variances-covariances of ε_t, and Q_t^{*-1} is the inverted diagonal matrix with the square root of the diagonal elements of Q_t :

$$Q_t^{*-1} = \begin{bmatrix} 1/\sqrt{q_{11t}} & 0 \\ 0 & 1/\sqrt{q_{22t}} \end{bmatrix} \tag{5.6}$$

The DCC(1,1) model is then given by:

$$Q_t = \omega + \alpha \varepsilon_{t-1} \varepsilon_{t-1}^{'} + \beta Q_{t-1} \tag{5.7}$$

where $\omega = (1 - \alpha - \beta)\,\overline{Q}$. Following Engle (2002), $\overline{Q}$ is treated as the second moment of ε_t, and is proxied by the sample moment of the estimated returns in large systems. However, as noticed by Aielli (2011), the equality $\overline{Q} = E[\varepsilon_t \varepsilon_t^{'}]$ does not hold in the general case, and the interpretation of $\overline{Q}$ as well as its estimation are not straightforward (see Aielli, 2011 for some examples).

The dynamic conditional correlations are finally given by:

$$\rho_{12t} = \frac{q_{12t}}{\sqrt{q_{11t} q_{22t}}} \tag{5.8}$$

Note that, following Engle (2002), the estimation of this model is done using a two-step maximum likelihood estimation method, the likelihood function being given by:[13]

$$L = -\frac{1}{2} \sum_{t=1}^{T} \left(2 \log (2\pi) + 2 \log |D_t| + \log |R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t \right) \tag{5.9}$$

5.4 Results

To assess the evolution of correlations between stock and commodity markets over time, Figures 5-4, 5-5, and 5-7 in Appendix report the dynamic conditional correlations between each commodity and the S&P 500 returns series. The links between markets during periods of financial stress are clearly underlined,[14] putting forward that investment in equities constitutes an alternative to commodities, providing a mechanism for substitution between asset classes. Although there are some specific features for each type of commodity market (as we will explain in detail below), some common characteristics emerge.

First, correlations are highly volatile throughout the period. This confirms the findings of Choi and Hammoudeh (2010) showing the existence of high and low volatility regimes for the correlations between oil, copper, gold and silver and the S&P 500 index over the January 2, 1990 to May, 1, 2006 period. For many raw materials, we find

[13] See Engle (2002).

[14] The grey bands correspond to periods of bearish stock market, the white stripes corresponding to periods of bullish stock market.

that this volatility is particularly marked after the 2007-2008 financial crisis. In all cases, there is an increase in volatility during and following the crisis. Second, in most cases, the largest drop in the correlations appears at the time of the 2008 financial crisis. The stock market collapse has loosened the conditional links between stock and commodity price returns, but only in the very short run. This decrease in correlations during times of high financial markets' stress may be linked to a flight-to-quality phenomenon. When risk market rises, the benefits of diversification are most appreciated and investors tend to choose commodities as refuge instruments. This short-run characteristic could thus explain the temporary disrupted link between both markets (see Silvennoinen and Thorp, 2010; Chong and Miffre, 2010). Third, for almost all of the series, the highest correlations are observed after the crisis, at the end of the period under study. Both markets move upward during episodes of growing world demand for industrial commodities, giving an important role to commercial traders who use commodity futures to hedge their business activities. On the whole, the 2007-2008 financial crisis has caused significant changes in the relationship between stock and commodity markets, as well as increased correlation in the volatility. Regarding the long-run trends, correlations are likely to be governed by industrialization and financialization processes, as well as by commercial and non-commercial traders.

Let us now look more specifically at the different types of markets, starting by the energy group. Oil is clearly the commodity the most related to the stock market, confirming previous studies focusing on the oil market (Jones and Kaul, 1996; Hammoudeh et al., 2004; Filis et al., 2011; and references in Section 5.1). From a theoretical viewpoint, the fundamental value of any asset is given by its expected discounted cash flows. Consequently, an oil price increase will generate a rise in production costs, leading to restraining profits and, in turn, to a diminution in shareholders' value. In times of rising stock prices, the correlations between stock and oil markets increase. During periods of declining stock prices, correlations tend to decrease and become negative during the 2007-2008 crisis. This is also consistent with the well documented oil speculation phenomenon, the increase in crude prices being accentuated in times of rising stock market. From this perspective, oil cannot be seen as a means of portfolio diversification. Gas and electricity display a quite similar evolution in terms of dynamic correlations. Correlations tend to increase at the beginning of the period under study and then remain relatively stable, regardless of the situation on the stock market. Correlations are often negative between stock and electricity markets, putting forward that the behavior of the electricity market is mainly driven by its own market fundamentals (i.e. non-storability, inelasticity of the supply,...).

Turning to the precious metals group, gold is different from the other commodities. Indeed, correlations are mostly negative and diminish in times of declining stock prices, highlighting adverse evolution in the markets. This is consistent with a safe-haven role of gold (see for instance Baur et al., 2010). For the other precious metals, the dynamics are relatively close, with increased correlations' volatility after the 2007-2008 crisis followed by a rise in correlations until mid-2010. Such close dynamics between those precious metals are consistent with the increasing correlations obtained by Choi and Hammoudeh (2010) after the 2003 Iraq war.

The group of exotic commodities also displays an interesting pattern. While the dynamics of correlations for sugar has no particular link with the US stock market trends, coffee and cocoa show a specific profile. As for oil, the correlations tend to grow in times of rising stock prices, and to diminish in periods of declining equity prices. This is in line with a speculation phenomenon in these commodities (see also Gilbert and Morgan, 2010).

Regarding the other groups, two main findings can be highlighted: (i) volatility evolves over time, being quite stable before the 2007-2008 crisis and becoming relatively high during the financial turmoil, and (ii) correlations tend to rise during the crisis, showing increased links between stock and commodity markets.

On the whole, our results show that the 2007-2008 crisis has played a key role in the evolution of the links between stock and commodity markets. Indeed, higher correlations between both markets are generally observed during the financial turmoil, reflecting the phenomenon of financialization of commodity markets that starts to be documented by the literature (see Tang and Xiong, 2010; Silvennoinen and Thorp, 2010). This growing financialization of commodities can be illustrated by the notional values provided by the Commodity Futures Trading Commission (CFTC): as shown in Table 5.2 in Appendix, these notional values—and especially short nominal values—have increased for all products between 2007 and 2011.[15] This phenomenon is particularly noticeable for oil, a result which is consistent with the fact that it is the most financiarized commodity according to the CFTC—the long and short notional values being respectively estimated at $69.4bn and $26.7bn at the end of November 2011 (see Table 5.2 in Appendix). In addition, our findings show that raw materials cannot be aggregated in an homogeneous asset class: they are certainly influenced by common macroeconomic factors but also by their own market determinants.

To complement these figures, Tables 5.3 to 5.7 in Appendix report the estimation results of DCC-GARCH(1,1) models for the whole period, as well as for four sub-periods: (i) two bearish stock market sub-periods: January 3, 2001-March 11, 2003 and October 13, 2007-March 6, 2009, and (ii) two bullish stock market sub-periods: March 12, 2003-October 12, 2007 and March 7, 2009-November 28, 2011.[16] Looking at the sum of the coefficients $\alpha + \beta$ (see Equation (5.7)), our results show that volatility is highly

[15] Note that whereas our sample contains 25 commodities, Table 5.2 reports values for only 15 of them—CFTC providing no detailed data for the remaining 10 commodities of our panel.

[16] The models have been estimated using one lag in the lag polynomial $A(L)$ in Equation (5.1). We have applied various diagnostic tests, namely Ljung-Box test for the absence of residuals autocorrelation, ARCH test for no remaining conditional heteroskedasticity, and Jarque-Bera normality test. All the considered models have successfully passed the tests at the conventional significance levels (to save space, due to the large number of estimated models, complete results are not reported but are available upon request to the authors).

persistent given that this sum is very close to 1 for the majority of commodity series. Comparing the two bullish sub-periods, it is interesting to note that the important change observed for oil concerning the sum of the coefficients $\alpha + \beta$ is also obtained for corn. This finding may be linked to the increasing bioethanol production from corn in the United States. Indeed, this development would provide an alternative method for producing fuel that may be used in case of rising oil prices or oil scarcity. Overall, while being high for all considered periods, persistence tends to be higher during the second, bullish stock market sub-period for 12 commodities, including all precious metals. This result illustrates that the persistence of volatility goes along with the financialization of commodities.

5.5 Conclusion

This chapter investigates the links between commodity and stock markets. To this end, we rely on the dynamic conditional correlation (DCC) GARCH methodology to establish whether the correlations between both markets evolve over time and depend on the situation—bearish or bullish—on the stock market.

Our main findings can be summarized as follows. In our panel of 25 commodities over the period from January 2001 to November 2011, first, the correlations between commodity and stock returns evolve through time, being highly volatile, particularly since the 2007-2008 financial crisis. While the stock market collapse has loosened the links between both markets on the very short run, the highest correlations are observed during the financial turmoil, showing increased links between stock and commodity markets. Second, some commodities are characterized by a speculation phenomenon, especially oil, coffee and cocoa: while their correlations with S&P 500 returns grow in times of increasing stock prices, they diminish in times of bearish financial markets. Third, the safe-haven role of gold is evidenced, as its correlations with stock returns are mostly negative and diminish in times of declining stock prices. Fourth, while sharing some common features, commodities can not be considered as an homogeneous asset class.

On the whole, our findings show that the 2007-2008 financial crisis has played a key role, emphasizing the links between commodity and stock markets, and highlighting the financialization of commodity markets. This evolution in commodity and stock correlations reduces their potential substitutability in portfolios. At the idiosyncratic level, the main exceptions are gold, coffee and cocoa for which risk management strategies are possible, with increased risk diversification allowed by their adverse evolution compared to the stock market in times of declining equity prices.

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Appendix of Chapter 5

Table 5.1: Daily returns summary statistics (whole sample)

	Mean	S. dev.	Var	Kur.	Skew.	LB test	ARCH test
Energy							
Oil	0.0004	0.025	0.0006	8.29	0.01	56.77 (0.00)	299.7 (0.00)
Gas	-0.0004	0.043	0.0019	9.62	0.34	155.0 (0.00)	325.1 (0.00)
Electricity	-0.0002	0.112	0.0126	16.75	0.12	138.0 (0.00)	159.7 (0.00)
Precious Metals							
Gold	0.0006	0.011	0.0001	7.10	-0.34	68.55 (0.00)	122.7 (0.00)
Silver	0.0006	0.022	0.0005	12.27	-0.57	30.23 (0.40)	241.2 (0.00)
Platinium	0.0002	0.015	0.0002	16.61	-0.48	58.76 (0.00)	137.4 (0.00)
Palladium	-0.0001	0.023	0.0005	7.91	-0.36	53.96 (0.00)	79.26 (0.00)
Agricultural							
Cotton	0.0001	0.021	0.0004	15.74	-0.58	35.33 (0.23)	0.48 (0.48)
Lumber	4.66E-05	0.021	0.0004	5.95	0.75	33.99 (0.28)	8.96 (0.00)
Non-ferrous Metals							
Aluminium	8.74E-05	0.014	0.0002	5.34	−0.33	26.28 (0.61)	98.85 (0.00)
Copper	0.0005	0.019	0.0003	6.66	-0.15	44.43 (0.03)	408.9 (0.00)
Zinc	0.0002	0.021	0.0004	5.24	-0.23	32.71 (0.33)	220.6 (0.00)
Tin	0.0004	0.019	0.0003	8.65	-0.24	32.22 (0.35)	156.64 (0.00)
Lead	0.0005	0.023	0.0005	5.68	-0.22	30.14 (0.45)	100.4 (0.00)
Nickel	0.0003	0.026	0.0006	6.08	-0.11	25.69 (0.69)	193.2 (0.00)
Food							
Corn	0.0003	0.019	0.0003	5.39	0.17	61.33 (0.00)	59.09 (0.00)
Wheat	0.0003	0.021	0.0004	5.20	0.17	44.59 (0.04)	64.03 (0.00)
Oleaginous group							
Palm oil	0.0004	0.020	0.0004	9.94	0.44	69.22 (0.00)	39.99 (0.00)
Soybean oil	0.0004	0.016	0.0002	5.14	0.13	28.41 (0.54)	108.4 (0.00)
Exotic group							
Cocoa	0.0003	0.020	0.0004	5.83	-0.30	43.89 (0.04)	2.14 (0.14)
Coffee	0.0004	0.020	0.0004	5.76	-0.23	47.33 (0.02)	31.38 (0.00)
Sugar	6.34E-06	0.023	0.0005	7.55	-0.63	30.97 (0.41)	88.63 (0.00)
Livestock							
Lean hogs	0.0001	0.020	0.0004	25.68	0.43	11.98 (0.99)	0.14 (0.70)
Feeder cattle	0.0001	0.009	8.64E-05	6.54	-0.35	54.60 (0.00)	72.59 (0.00)
Live cattle	0.0001	0.010	0.0001	8.81	0.12	52.02 (0.00)	20.83 (0.00)
Standard & Poor's	-7.05E-06	0.013	0.0001	10.98	-0.16	59.56 (0.00)	786.8 (0.00)
CRB index	0.0002	0.004	2.50E-05	8.05	-0.60	125.1 (0.00)	239.8 (0.00)

Notes: Between parentheses: p-values. The number of observations is 2844 for each series.
Ljung-Box statistics correspond to a test of the null of no autocorrelation with $h = 30$.
ARCH Lagrange multiplier statistics correspond to a test of the null of no ARCH effect.

Table 5.2: Index investment data: notional values (in Billions U.S. dollars)

	December 31, 2007		November 30, 2011	
	Long	Short	Long	Short
Oil (WTI)	46.7	7.0	69.4	26.7
Gas	13.2	1.8	16.2	4.1
Gold	8.4	1.1	30.0	9.5
Silver	2.4	0.3	6.9	1.6
Cotton	3.2	0.6	4.3	1.5
Copper	3.1	0.3	7.9	2.2
Corn	9.5	1.9	19.2	7.2
Wheat	10.2	2.1	10.7	4.8
Soybean oil	2.5	0.3	4.0	1.3
Cocoa	0.5	0.1	1.1	0.4
Coffee	2.8	0.6	5.3	2.0
Sugar	3.9	0.7	8.4	2.4
Lean hogs	3.0	0.9	5.2	1.7
Feeder cattle	0.6	0.1	0.8	0.2
Live cattle	5.9	1.3	9.1	2.9

Notes: Source: CFTC, http://www.cftc.gov/MarketReports/IndexInvestmentData/index.htm. Short (resp. long): denotes the gross short (resp. long) notional value and refers to the case where investors are short (resp. long) a commodity index.

Table 5.3: Estimation results of DCC-GARCH(1,1) models (whole sample)

	Oil	Gas	Elec	Gold	Silver
μ	8.2e-04 (3.6e-04)*	-7.2e-04 (5.5e-04)	2.7e-03 (1.2e-03)*	5.3e-04 (1.5e-04)*	3.8e-04 (2.3e-04)
ω	1.2e-05 (6.9e-07)*	3.1e-05 (2.5e-06)*	1.0e-03 (2.2e-05)*	1.8e-06 (7.8e-08)*	5.1e-06 (4.3e-07)*
α	0.061 (1.6e-03)*	0.111 (2.4e-03)*	0.230 (4.7e-03)*	0.042 (9.9e-04)*	0.088 (1.4e-03)*
β	0.917 (1.5e-03)*	0.876 (1.9e-03)*	0.683 (3.2e-03)*	0.943 (7.8e-04)*	0.906 (1.2e-03)*
$\alpha+\beta$	0.978	0.987	0.913	0.985	0.994
	Platinum	Palladium	Cotton	Lumber	Aluminium
μ	-3.6e-04 (1.6e-04)*	7.2e-05 (2.4e-04)	3.0e-04 (3.0e-04)	1.8e-04 (3.5e-04)	4.5e-05 (2.0e-05)*
ω	4.1e-06 (2.3e-07)*	1.7e-05 (3.1e-07)*	8.0e-06 (3.5e-07)*	1.1e-06 (1.0e-07)*	1.3e-06 (1.0e-07)*
α	0.107 (1.7e-03)*	0.079 (1.4e-03)*	0.054 (7.8e-04)*	0.010 (2.2e-04)*	0.033 (5.7e-04)*
β	0.879 (1.4e-03)*	0.889 (9.4e-04)*	0.931 (6.4e-04)*	0.987 (2.0e-04)*	0.960 (4.9e-04)*
$\alpha+\beta$	0.986	0.968	0.985	0.997	0.993
	Copper	Zinc	Tin	Lead	Nickel
μ	4.7e-04 (1.5e-04)*	1.5e-04 (1.8e-04)	5.3e-04 (2.3e-04)*	3.9e-04 (2.5e-04)	4.5e-04 (3.0e-04)
ω	3.5e-06 (2.2e-07)*	2.5e-06 (1.9e-07)*	1.4e-05 (4.0e-07)*	5.1e-06 (2.6e-07)*	1.0e-05 (5.7e-07)*
α	0.047 (8.8e-04)*	0.037 (6.8e-04)*	0.109 (0.002)*	0.038 (7.8e-04)*	0.046 (0.001)*
β	0.941 (8.1e-04)*	0.956 (5.9e-04)*	0.856 (0.001)*	0.951 (6.5e-04)*	0.936 (9.7e-04)*
$\alpha+\beta$	0.988	0.993	0.965	0.989	0.982
	Corn	Wheat	Palm oil	Soybean oil	Cocoa
μ	6.3e-04 (1.4e-04)*	4.5e-04 (2.8e-04)	7.2e-04 (2.9e-04)*	7.1e-04 (2.5e-04)	2.9e-04 (3.3e-04)
ω	5.1e-06 (2.3e-07)*	5.0e-06 (3.8e-07)*	5.9e-06 (2.1e-07)*	3.8e-06 (2.1e-07)*	3.4e-06 (1.6e-07)*
α	0.038 (8.9e-04)*	0.039 (9.5e-04)*	0.063 (1.1e-03)*	0.035 (1.0e-03)*	0.017 (4.4e-04)*
β	0.947 (7.0e-04)*	0.949 (8.8e-04)*	0.923 (8.0e-04)*	0.948 (9.1e-04)*	0.974 (4.0e-04)*
$\alpha+\beta$	0.985	0.985	0.986	0.983	0.991
	Coffee	Sugar	Lean	Feeder	Live
μ	5.0e-04 (3.4e-04)	2.1e-04 (3.7e-04)	1.6e-04 (3.7e-04)	1.5e-04 (1.2e-04)	2.0e-04 (2.0e-04)
ω	2.1e-06 (1.4e-07)*	1.0e-05 (6.2e-07)*	8.6e-05 (6.5e-07)*	1.0e-06 (3.5e-08)*	1.2e-06 (1.7e-06)*
α	0.013 (3.2e-04)*	0.059 (0.001)*	-4.0e-03 (1.4e-03)*	0.012 (3.3e-04)*	0.062 (8.6e-03)*
β	0.981 (3.1e-03)*	0.923 (0.001)*	0.804 (1.4e-03)*	0.975 (2.8e-04)*	0.164 (0.015)*
$\alpha+\beta$	0.994	0.982	0.808	0.987	0.226

Note : Standard errors are in parentheses.* denotes rejection of the null hypothesis at 1%, 5% or 10% significance level.

Table 5.4: Estimation results of DCC-GARCH(1,1) models (sample period: 2001/01/03-2003/03/11)

	Oil	Gas	Elec	Gold	Silver
μ	9.5e-04 (9.5e-04)	1.8e-04 (1.4e-04)	7.8e-04 (3.1e-03)	6.2e-04 (2.4e-04)*	1.1e-04 (3.7e-04)
ω	5.7e-05 (4.2e-06)*	2.5e-04 (2.1e-05)*	6.3e-04 (3.3e-05)*	2.4e-05 (8.9e-07)*	3.4e-05 (1.9e-06)*
α	0.095 (6.4e-03)*	0.214 (0.014)*	0.250 (0.011)*	0.221 (0.017)*	0.133 (0.019)*
β	0.816 (6.9e-03)*	0.689 (0.011)*	0.740 (4.6e-03)*	0.442 (0.018)*	0.583 (0.018)*
$\alpha + \beta$	0.911	0.903	0.990	0.663	0.716
	Platinum	Palladium	Cotton	Lumber	Aluminium
μ	6.4e-04 (4.1e-04)*	-2.0e-03 (6.9e-04)*	4.0e-05 (2.2e-05)*	1.2e-04 (0.0007)	-3.8e-04 (2.0e-04)
ω	1.4e-05 (7.5e-07)*	1.5e-04 (3.7e-06)*	-2.0 (1.0e-06)*	4.5e-04 (1.2e-05)*	2.1e-04 (1.0e-06)*
α	0.118 (7.5e-03)*	0.160 (0.019)*	-9.1e-03 (1.0e-06)*	0.116 (0.053)*	0.037 (0.002)*
β	0.805 (6.7e-03)*	0.508 (0.010)*	0.900 (1.0e-04)*	0.080 (0.066)	0.942 (0.002)*
$\alpha + \beta$	0.923	0.668	0.909	0.196	0.979
	Copper	Zinc	Tin	Lead	Nickel
μ	-1.1e-04 (2.2e-04)	-4.5e-04 (3.7e-04)	-7.6e-05 (4.4e-04)	-1.5e-04 (4.4e-04)	-1.1e-04 (7.4e-04)
ω	2.8e-05 (1.0e-06)*	9.5e-05 (4.4e-04)*	1.2e-05 (1.4e-04)*	3.6e-06 (1.0e-06)*	8.8e-06 (5.5e-07)*
α	0.004 (8.0e-04)*	0.183 (0.045)*	0.105 (0.008)*	0.022 (0.001)*	0.011 (8.1e-04)*
β	0.976 (8.0e-04)*	0.081 (0.033)*	0.779 (0.006)*	0.957 (0.001)*	0.963 (1.3e-03)*
$\alpha + \beta$	0.980	0.264	0.884	0.979	0.974
	Corn	Wheat	Palm oil	Soybean oil	Cocoa
μ	2.4e-04 (5.6e-04)	8.0e-05 (4.9e-04)	3.5e-04 (6.4e-04)	5.0e-04 (4.9e-04)	2.0e-03 (9.0e-04)
ω	6.1e-06 (4.4e-07)*	2.3e-06 (2.3e-07)*	1.3e-07 (2.5e-07)	1.3e-05 (8.8e-07)*	4.7e-05 (3.2e-06)*
α	0.026 (2.4e-03)*	6.8e-03 (6.6e-04)*	0.010 (4.1e-04)*	0.024 (4.6e-03)*	0.063 (6.9e-03)*
β	0.941 (2.2e-03)*	0.983 (7.8e-04)*	0.983 (5.6e-04)*	0.905 (4.5e-03)*	0.844 (6.8e-03)*
$\alpha + \beta$	0.967	0.989	0.993	0.929	0.907
	Coffee	Sugar	Lean	Feeder	Live
μ	3.3e-04 (1.0e-03)	-4.6e-04 (8.1e-04)	-3.7e-04 (0.001)	-4.0e-04 (2.1e-04)	6.7e-05 (1.2e-04)
ω	9.6e-05 (4.6e-06)*	3.9e-04 (2.0e-05)*	9.6e-05 (1.5e-06)*	4.4e-06 (3.3e-08)*	4.4e-07 (3.3e-09)*
α	0.033 (7.5e-03)*	0.226 (0.032)*	0.006 (0.002)*	0.067 (0.006)*	0.011 (1.4e-05)*
β	0.817 (7.4e-03)*	0.014 (0.035)	0.864 (0.002)*	0.854 (0.005)*	1.006 (1.0e-05)*
$\alpha + \beta$	0.850	0.240	0.858	0.921	1.017

Note : Standard errors are in parentheses.* denotes rejection of the null hypothesis at 1%, 5% or 10% significance level.

Table 5.5: Estimation results of DCC-GARCH(1,1) models (sample period: 2003/03/12-2007/10/12)

	Oil	Gas	Elec	Gold	Silver
μ	8.1e-04 (5.5e-04)	8.9e-04 (1.4e-03)	1.7e-03 (2.3e-03)	5.7e-04 (2.3e-04)*	7.9e-04 (4.5e-04)*
ω	1.1e-05 (3.5e-07)*	1.3e-04 (6.7e-07)*	7.1e-04 (8.9e-05)*	7.5e-07 (7.7e-08)*	7.8e-06 (7.3e-07)*
α	0.029 (5.2e-03)*	0.038 (3.1e-03)*	0.313 (0.009)*	0.024 (9.7e-04)*	0.077 (0.002)*
β	0.943 (5.5e-03)*	0.898 (0.003)*	0.637 (0.003)*	0.968 (8.7e-04)*	0.908 (0.002)*
$\alpha+\beta$	0.972	0.936	0.950	0.992	0.985
	Platinum	Palladium	Cotton	Lumber	Aluminium
μ	7.9e-04 (1.2e-04)*	1.4e-04 (6.2e-04)	1.9e-04 (4.9e-04)	-1.3e-04 (4.9e-04)	2.7e-04 (3.0e-04)
ω	6.8e-06 (5.3e-07)*	1.3e-05 (4.5e-08)*	2.3e-06 (2.2e-07)*	5.3e-06 (3.8e-07)*	3.4e-06 (2.5e-07)*
α	0.149 (0.005)*	0.108 (2.4e-04)*	0.018 (7.2e-04)*	0.014 (1.2e-03)*	0.045 (0.001)*
β	0.812 (0.004)*	0.858 (0.003)*	0.974 (6.6e-04)*	0.968 (1.1e-03)	0.937 (0.001)*
$\alpha+\beta$	0.961	0.966	0.992	0.982	0.982
	Copper	Zinc	Tin	Lead	Nickel
μ	0.001 (4.1e-04)*	0.001 (4.6e-04)*	7.8e-04 (5.7e-04)	0.002 (7.5e-05)*	9.4e-04 (5.9e-04)
ω	3.7e-06 (3.7e-07)*	6.7e-06 (6.5e-07)*	6.1e-05 (2.5e-06)*	5.7e-05 (2.4e-06)*	9.2e-06 (9.6e-07)*
α	0.051 (0.001)*	0.066 (0.002)*	0.086 (0.007)*	0.109 (0.008)*	0.048 (0.001)*
β	0.936 (0.001)*	0.917 (0.002)*	0.752 (0.007)*	0.763 (0.006)*	0.938 (0.001)*
$\alpha+\beta$	0.987	0.983	0.838	0.872	0.986
	Corn	Wheat	Palm oil	Soybean oil	Cocoa
μ	4.8e-04 (4.9e-04)	0.001 (5.7e-04)*	5.1e-04 (6.5e-04)	8.5e-04 (4.0e-04)*	-1.7e-04 (8.4e-04)
ω	3.5e-06 (2.8e-07)*	4.9e-06 (2.8e-07)*	4.9e-05 (1.8e-06)*	5.1e-07 (2.8e-08)*	1.2e-04 (5.1e-06)*
α	0.019 (5.1e-04)	0.005 (7.4e-04)*	0.051 (0.005)*	0.014 (5.0e-04)*	0.015 (9.8e-03)
β	0.969 (8.9e-04)*	0.982 (6.6e-04)*	0.837 (0.005)*	0.983 (4.3e-04)*	0.776 (8.8e-03)*
$\alpha+\beta$	0.988	0.987	0.888	0.997	0.791
	Coffee	Sugar	Lean	Feeder	Live
μ	6.5e-04 (5.5e-04)	1.2e-04 (6.2e-04)	2.5e-04 (9.3e-04)	2.9e-04 (4.8e-04)	2.2e-04 (4.4e-04)
ω	1.4e-06 (5.8e-06)	6.3e-05 (2.7e-06)*	9.2e-04 (2.1e-05)*	4.5e-05 (2.0e-06)*	4.8e-05 (1.9e-06)*
α	0.012 (4.3e-04)*	0.040 (0.004)*	0.013 (0.023)	0.050 (0.009)*	0.044 (0.008)*
β	0.984 (4.1e-04)*	0.811 (0.006)*	0.545 (0.035)*	0.699 (0.011)*	0.682 (0.011)*
$\alpha+\beta$	0.993	0.851	0.658	0.749	0.726

Note : Standard errors are in parentheses.* denotes rejection of the null hypothesis at 1%, 5% or 10% significance level.

Table 5.6: Estimation results of DCC-GARCH(1,1) models (sample period: 2007/10/13-2009/03/06)

	Oil	Gas	Elec	Gold	Silver
μ	9.6e-04 (1.3e-03)	-1.1e-03 (1.7e-03)	3.7e-04 (3.8e-03)	7.2e-04 (8.6e-04)	1.5e-03 (1.2e-03)
ω	1.6e-05 (5.3e-06)*	2.1e-03 (1.2e-04)*	5.0e-04 (1.1e-04)*	7.1e-06 (8.9e-07)*	3.8e-05 (4.2e-06)*
α	0.120 (9.3e-03)*	0.021 (0.014)*	0.240 (0.018)*	0.030 (3.1e-03)*	0.074 (4.8e-03)*
β	0.878 (8.3e-03)*	0.902 (0.063)*	0.713 (0.010)*	0.948 (2.9e-03)*	0.888 (4.3e-03)*
$\alpha+\beta$	0.998	0.923	0.953	0.978	0.962
	Platinum	Palladium	Cotton	Lumber	Aluminium
μ	-5.7e-04 (8.0e-04)	-2.2e-03 (1.9e-03)	5.5e-04 (1.1e-03)	2.2e-03 (1.7e-03)	-1.0e-03 (1.3e-03)
ω	5.2e-04 (4.4e-05)*	1.0e-03 (6.3e-08)*	9.1e-05 (8.7e-06)*	5.1e-04 (2.7e-05)*	8.7e-06 (6.9e-08)*
α	0.168 (0.099)*	0.013 (0.029)	0.142 (0.023)*	0.011 (0.030)	0.076 (0.023)*
β	0.115 (0.096)	0.300 (0.041)*	0.713 (0.017)*	0.375 (0.033)*	0.902 (0.015)*
$\alpha+\beta$	0.283	0.336	0.855	0.386	0.978
	Copper	Zinc	Tin	Lead	Nickel
μ	-6.3 (8.9e-04)	-1.8e-03 (1.2e-03)	7.6e-04 (1.1e-03)	-2.6e-03 (7.1e-03)	-2.8e-03 (1.5e-03)*
ω	9.0e-06 (5.0e-09)*	5.8e-05 (5.1e-06)*	2.0e-05 (2.1e-06)*	1.6e-05 (1.0e-06)*	7.2e-05 (4.9e-08)*
α	0.110 (0.010)*	0.045 (6.0e-03)*	0.089 (5.1e-03)*	0.036 (8.7e-03)*	0.130 (0.013)*
β	0.883 (8.4e-03)*	0.893 (5.6e-03)*	0.885 (4.3e-03)*	0.951 (3.4e-03)*	0.810 (9.8e-03)*
$\alpha+\beta$	0.993	0.938	0.974	0.987	0.940
	Corn	Wheat	Palm oil	Soybean oil	Cocoa
μ	2.1e-03 (1.7e-03)*	-1.1 (1.3e-03)	1.2e-03 (1.2e-03)	1.7e-03 (9.9e-04)	1.8e-03 (1.0e-03)*
ω	1.0e-05 (2.1e-06)*	1.0e-04 (1.3e-05)*	3.0e-05 (1.9e-06)*	9.5e-06 (1.9e-06)*	5.0e-06 (1.1e-06)*
α	0.069 (6.4e-03)*	0.137 (0.019)*	0.069 (4.4e-03)*	0.093 (8.1e-03)*	0.061 (3.4e-03)*
β	0.915 (5.3e-03)*	0.741 (0.017)*	0.898 (6.4e-03)*	0.894 (6.4e-03)*	0.938 (2.6e-03)*
$\alpha+\beta$	0.984	0.878	0.967	0.987	0.999
	Coffee	Sugar	Lean	Feeder	Live
μ	2.9e-04 (8.5e-04)	1.4e-03 (1.1e-03)	1.7e-03 (1.4e-03)	-4.2e-04 (3.4e-04)	-1.2e-04 (5.2e-04)
ω	2.2e-04 (1.4e-05)*	1.1e-05 (3.0e-06)*	3.6e-04 (7.0e-05)*	1.5e-05 (7.1e-07)*	5.9e-06 (1.6e-07)*
α	0.161 (0.027)*	0.119 (9.8e-03)*	0.029 (6.8e-04)*	-7.4e-03 (3.6e-03)*	0.015 (8.8e-04)*
β	0.268 (0.013)*	0.880 (5.6e-03)*	0.383 (0.011)*	0.855 (6.4e-03)*	0.980 (6.5e-04)*
$\alpha+\beta$	0.429	0.999	0.412	0.892	0.995

Note : Standard errors are in parentheses.* denotes rejection of the null hypothesis at 1%, 5% or 10% significance level.

Table 5.7: Estimation results of DCC-GARCH(1,1) models (sample period: 2009/03/07-2011/11/28)

	Oil	Gas	Elec	Gold	Silver
μ	1.2e-03 (7.3e-04)	-1.5e-03 (1.1e-03)	1.3e-03 (3.6e-03)	9.0e-04 (3.1e-04)	0.001 (8.4e-04)*
ω	2.1e-04 (1.0e-05)*	1.6e-05 (1.1e-05)	1.0e-03 (2.9e-04)*	3.5e-06 (1.2e-09)*	1.0e-04 (7.8e-06)*
α	0.071 (0.015)*	0.101 (0.030)*	0.427 (0.127)*	0.065 (0.003)*	0.162 (0.012)*
β	0.575 (0.017)*	0.891 (0.023)*	0.518 (0.065)*	0.907 (0.003)*	0.690 (0.012)*
$\alpha+\beta$	0.646	0.992	0.945	0.972	0.852
	Platinum	Palladium	Cotton	Lumber	Aluminium
μ	1.0e-04 (8.0e-04)	6.3e-04 (1.1e-04)	1.7e-04 (7.5e-04)*	3.6e-04 (8.8e-04)	6.8e-04 (5.5e-04)
ω	2.0e-04 (1.2e-05)*	4.5e-04 (2.8e-06)*	1.5e-06 (3.4e-06)*	5.0e-04 (1.6e-05)*	6.1e-06 (8.5e-07)*
α	0.074 (0.039)*	0.119 (0.035)*	0.048 (0.007)*	0.067 (0.028)*	0.024 (0.001)*
β	0.315 (0.039)*	0.264 (0.036)*	0.951 (0.008)*	0.192 (0.010)*	0.951 (0.001)*
$\alpha+\beta$	0.389	0.383	0.999	0.259	0.975
	Copper	Zinc	Tin	Lead	Nickel
μ	0.001 (5.9e-04)*	1.1e-03 (7.7e-04)	1.1e-03 (6.7e-04)*	0.001 (8.4e-04)	1.0e-03 (6.1e-04)*
ω	1.2e-06 (1.3e-06)*	1.9e-05 (1.5e-06)*	9.1e-05 (1.0e-04)*	2.0e-05 (1.9e-06)*	8.9e-06 (5.8e-07)*
α	0.078 (0.004)*	0.046 (0.022)*	0.114 (0.080)*	0.044 (0.003)*	0.126 (0.015)*
β	0.887 (0.004)*	0.917 (0.044)*	0.666 (0.306)*	0.922 (0.003)*	0.428 (0.022)*
$\alpha+\beta$	0.965	0.963	0.780	0.966	0.554
	Corn	Wheat	Palm oil	Soybean oil	Cocoa
μ	9.0e-04 (7.4e-04)	2.5e-04 (1.1e-03)	6.8e-04 (6.1e-04)	9.4e-04 (4.2e-04)*	9.4e-05 (6.5e-04)
ω	3.2e-04 (1.3e-04)*	9.8e-05 (2.3e-06)*	2.6e-06 (1.9e-07)*	8.4e-06 (6.6e-07)*	1.0e-04 (5.0e-06)*
α	0.097 (0.028)*	0.013 (0.007)*	0.020 (7.7e-04)*	0.043 (0.003)*	0.070 (0.012)*
β	0.183 (0.029)*	0.857 (0.006)*	0.969 (6.5e-04)*	0.908 (0.003)*	0.630 (0.014)*
$\alpha+\beta$	0.280	0.870	0.989	0.951	0.700
	Coffee	Sugar	Lean	Feeder	Live
μ	9.3e-04 (5.6e-04)	0.001 (9.5e-04)	7.2e-04 (6.9e-04)	8.2e-04 (2.9e-04)*	7.8e-04 (4.2e-04)*
ω	8.7e-06 (5.5e-07)*	1.5e-04 (8.5e-06)*	2.4e-04 (4.4e-06)*	6.6e-05 (2.4e-06)*	1.1e-05 (3.7e-07)*
α	0.016 (0.001)*	0.085 (0.012)*	0.044 (0.011)*	0.068 (0.027)*	0.026 (1.9e-03)*
β	0.952 (0.001)*	0.705 (0.011)*	0.334 (0.010)*	0.027 (0.035)*	0.920 (2.7e-03)*
$\alpha+\beta$	0.968	0.790	0.378	0.095	0.920

Note : Standard errors are in parentheses.* denotes rejection of the null hypothesis at 1%, 5% or 10% significance level.

Figure 5-4: Dynamic conditional correlations

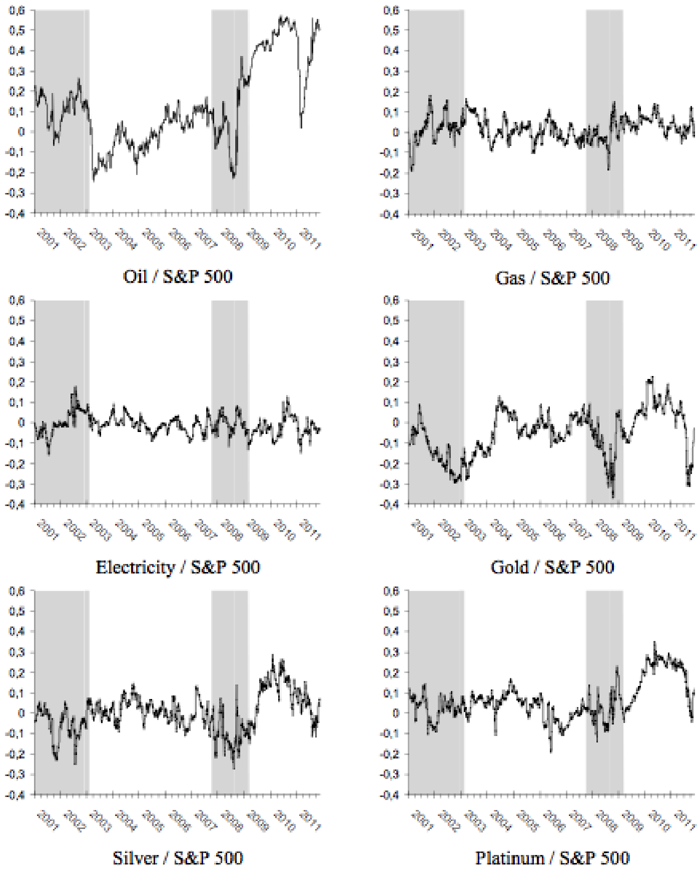


Figure 5-5: Dynamic conditional correlations (2)

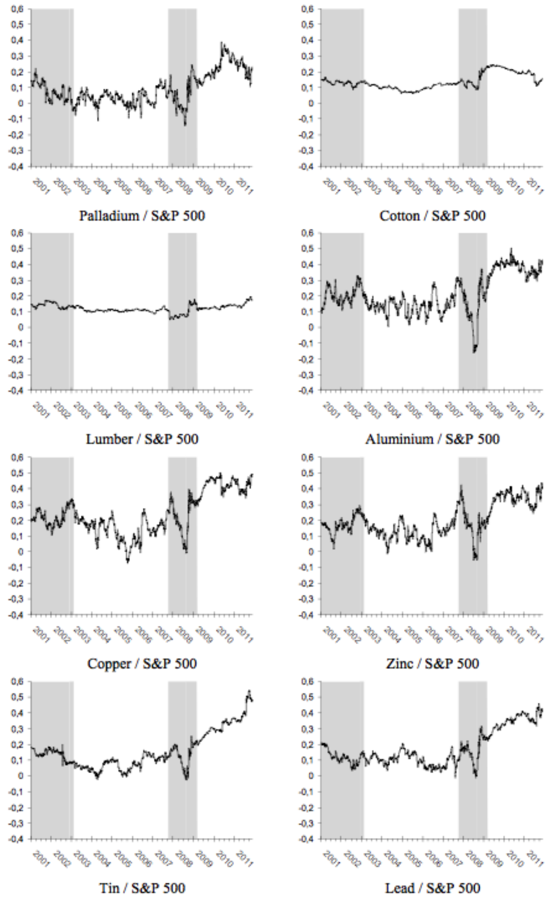


Figure 5-6: Dynamic conditional correlations (3)

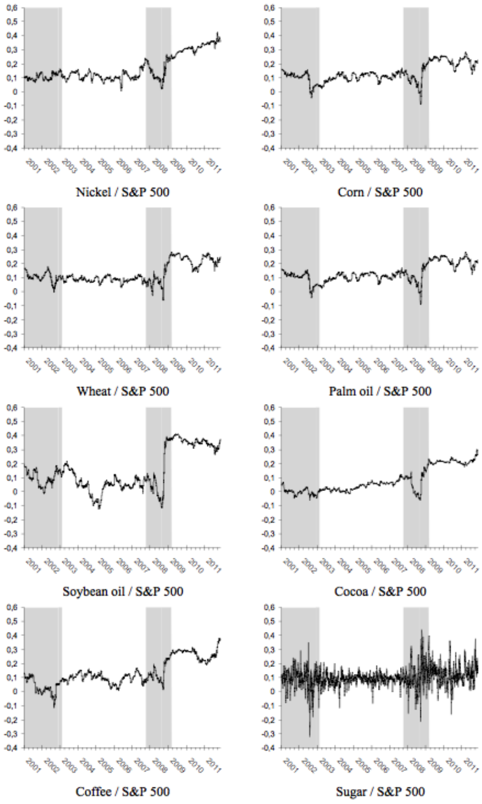
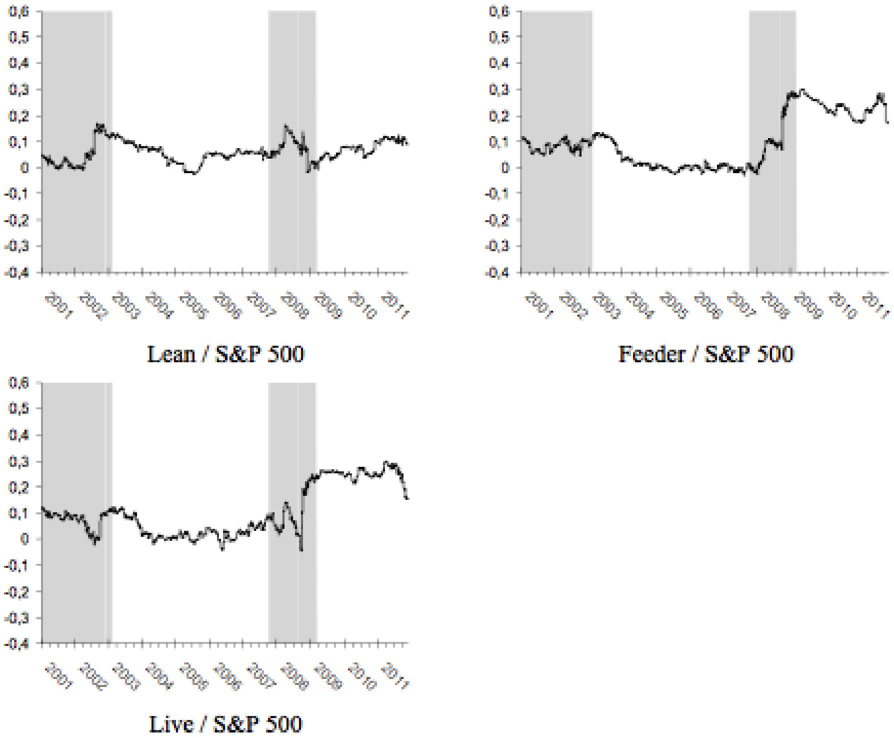


Figure 5-7: Dynamic conditional correlations (4)



Note: The grey bands correspond to periods of bearish stock market, the white stripes corresponding to periods of bullish stock market. These periods have been identified on the basis of the evolution of S&P 500 stock returns using the Bai and Perron (2003) structural break test.

Conclusion générale

Le processus de dérégulation des marchés pose les questions de l'existence d'un monopole et de l'attribution d'un prix plus "juste" pour le consommateur. Il pose aussi les bases d'une modification profonde de la structure des marchés et du processus de formation des prix dans lequel cette dérégulation s'inscrit. Ainsi que nous l'avons vu au cours de cette thèse, cette évolution organisationnelle a donné lieu à la creation de nouveaux moyens d'échanges et à la multiplication du nombre de participants aux horizons divers, rendant la dynamique intrinsèque des prix plus incertaine et sa compréhension plus complexe. Dans un contexte économique en crise et avec une contrainte environnementale grandissante, l'importance des fluctuations des prix des énergies et les causes profondes qui l'accompagnent sont primordiales tant les conséquences peuvent être dommageables pour nombre d'économies.

Cette thèse analyse le rôle de la finance dans la formation des prix des énergies et de matières premières. Plus formellement, elle tente de mettre en lumière les propriétés financières des marchés des commodités qui constituent, pour de nombreux investisseurs institutionnels, un moyen de diversification des risques internationaux face aux fluctuations économiques. Face à l'ampleur de ce phénomène, la question ici abordée vise donc à comprendre ce lien existant entre finance et commodités, et principalement les raisons profondes qui expliquent le comportement des prix. Cette thèse analyse les mouvements des prix en cherchant à comprendre si cette nature "éxhubérante" est le résultat d'une modification des conditions physiques propres à chacun des marchés ou bien la conséquence de comportements purement spéculatifs. Cette question du lien entre énergie et finance est abordée sous trois angles: d'une part la relation entre les prix des différentes énergies et leurs propriétés financières est analysée, d'autre part les aspects émotionnels et comportementaux des marchés sont étudiés, enfin les liens directs entre marchés boursiers et marchés des commodités sont abordés. Notre thèse s'articule autour de cinq chapitres, chacun des chapitres s'inscrivant dans une réflexion progressive.

Peu d'études ont jusqu'alors analysé en profondeur les relations entre les prix des différentes énergies, malgré le caractère essentiel que cette réflexion confère à la compréhension du phénomène de financiarisation des marchés. Pour combler cette insuffisance, le chapitre 1 étudie les relations de long terme entre les prix *forward* du pétrole, du gaz, du charbon et de l'électricité en Europe pour 35 maturités sur la période 2005-2010, période caractérisée par de fortes turbulences économiques. Outre le fait de s'intéresser aux relations de long terme entre les prix à travers une approche en économétrie des données de panel, ce chapitre met en lumière l'ajustement non linéaire et asymétrique des marchés pouvant résulter d'anticipations auto-réalisatrices et de comportements spéculatifs. Il constitue par conséquent la structure de base de notre réflexion, le point d'ancrage vers lequel notre analyse des relations entre finance et énergie s'articule.

Le chapitre 2 s'inscrit dans le prolongement de cette analyse puisqu'il vise à comprendre la nature sous-jacente des interactions entre les prix et cherche à déterminer si ces comportements peuvent être différents selon l'orientation des fluctuations, l'intensité des marchés, et la maturité envisagée. La motivation principale est de faire ressortir les propriétés financières des marchés, à savoir des comportements d'interaction potentiellement plus importants durant les phases d'intenses fluctuations des prix. De nouvelles méthodologies économétriques ont été introduites dans ce chapitre, notamment le développement d'un test statistique permettant d'appréhender la causalité au sens de Granger dans les queues de distribution, se focalisant alors sur les mouvements d'extrême amplitude. Deux principaux résultats émergent de ce chapitre. Dans un premier temps, il apparaît que la dynamique des prix est différente selon l'intensité des fluctuations. En effet, nous observons que la causalité entre les prix des énergies est plus forte durant les mouvements d'extrême ampleur à la baisse que lors des périodes de faible intensité des prix. Ce phénomène est caractéristique des séries financières traditionnelles, ce qui laisse à penser que les prix des énergies possèdent des propriétés financières dont l'origine pourrait être d'ordre spéculatif. Dans un second temps, ce comportement semble se résorber à mesure que l'on considère des maturités plus éloignées, si bien que l'on observe ce que nous qualifions de "Samuelson Causality Effect" rendant les stratégies de diversification entre les actifs énergétiques plus efficientes à long terme, laissant envisager que des facteurs fondamentaux sont davantages la cause de ces changements.

Les conclusions du chapitre 2 insistent sur le caractère financier très particulier des prix *forward* des énergies à 1 mois. Le second thème de notre thèse s'intéresse alors tout particulièrement à ces prix et aux caractères comportemental et émotionnel des marchés. Il se scinde en deux chapitres. Tout d'abord, le chapitre 3 cherche à mettre en relief l'influence des émotions sur la dynamique des prix des énergies. Alors que certaines analyses ont mis en lumière une relation significative entre émotion et prix dans le domaine de la finance[17], rien n'a encore été effectué en économie de l'énergie alors qu'à maints égards les prix des énergies peuvent se comporter comme des actifs financiers traditionnels. A travers la création d'une variable proxy de l'émotion SAD (*Seasonal Affective Disorder*), nous montrons que la dynamique des prix des énergies est fortement impactée par les émotions, principalement durant les mouvements d'extrême baisse des prix. Les sentiments auraient alors une influence sur le comportement des marchés. Dans des situations risquées et incertaines, de nombreux facteurs peuvent influencer le processus de décision des agents économiques, même si ces derniers ne sont pas directement reliés à la décision elle-même. Dans notre réflexion méta-économique des phénomènes, les émotions seraient alors mésattribuées et conduiraient les agents à

[17] Voir Saunders (1993), Cao et Wei (2002), Kamstra et al. (2000), Hirshleifer et Shumway (2003), Kamstra et al. (2003), Dowling et Lucey (2005 et 2008).

se comporter différemment selon l'intensité des fluctuations de prix.

Le chapitre 4 fournit un cadre théorique à cette approche méta-économique des fluctuations puisqu'il construit un modèle comportemental et émotionnel, où différentes catégories d'agents (*i.e.* fondamentalistes et chartistes) co-existent sur les marchés et sont soumis au regret et à l'incertitude. Ce chapitre s'inscrit dans le prolongement du précédent puisque, partant du constat empirique de mésattribution des émotions, nous construisons un cadre d'analyse dans lequel les participants sont en interaction, font face à des mouvements d'incertitudes extrêmes et prennent leurs décisions à travers une perception cognitive et émotionnelle de la réalité économique. Nos résulats mettent en évidence que les marchés des énergies sont composés d'agents hétérogènes qui se comportent différemment selon l'intensité des fluctuations et l'incertitude des mouvements. En particulier, les prix des énergies semblent principalement gouvernés par des agents neutres à l'incertitude (fondamentalistes et chartistes) durant les phases de faible intensité des fluctuations de prix, alors qu'ils sont influencés par des comportements spéculatifs irrationnels durant les phases de fortes fluctuations. Dans cette dernière situation, notre étude met en lumière l'exhubérance irrationnelle ambiante des fluctuations.

Le chapitre 5 revient vers une conception plus traditionnelle de l'économie et propose une analyse fine des relations existantes entre marchés boursiers et prix des matières premières. Ici il n'est plus question d'adopter une analyse méta-économique de la financiarisation des marchés, mais plutôt de considérer une gamme plus large de marchés des commodités afin d'en comprendre les interactions avec les marchés boursiers, mais aussi et surtout de mettre en évidence une potentielle hétérogénéité entre les matières premières. Nous considérons alors les matières premières suivantes sur la période 2001-2011 aux Etats-Unis: énergie, métaux précieux, agro-industriel, métaux non ferreux, alimentaire, oléagineux, exotique, et bétail. Par une approche multivariée de type DCC-GARCH, nous montrons que les corrélations dynamiques entre les marchés des commodités et l'indice Standard & Poor's sont extrêmement volatiles, particulièrement durant la période 2007-2008 de crise financière. Plus précisemment, ce phénomène semble être de plus ou moins grande ampleur selon les phases de hausse ou de baisse des marchés financiers, particulièrement pour les séries des prix du pétrole, du café et du cacao. Par ailleurs, le marché de l'or conserve son rôle de valeur refuge puisque ses corrélations avec le marché des actions se traduisent par une relation négative diminuant durant les périodes de baisse de l'indice. D'un point de vue plus global, certaines commodités semblent être caractérisées par un phénomène de spéculation justifiant le caractère hétérogène des marchés.

Bien entendu cette thèse ne prétend pas répondre à toutes les questions qui se posent concernant la financiarisation des marchés de commodités et les impacts potentiels que ce phénomène implique. Elle s'inscrit dans le courant scientifique actuel qui cherche à comprendre plus en détails le fonctionnement des marchés de commodités en combinant les champs de la macroéconomie, de la finance, de l'énergie et de l'économétrie. Par conséquent, nombreuses sont les extensions pouvant être envisagées. Ainsi, au delà des extensions qui peuvent être apportées par l'application des nouvelles méthodologies en économétrie des données de panel et des séries temporelles, nous pensons que, d'un point de vue économique, deux questions principales se posent pour les prochaines années. En premier lieu, que qualifions-nous de spéculation ou d'excessive spéculation? En deuxième lieu, est-elle domageable en termes de bien être collectif? Ces questions fondamentales nous conduiront ainsi à poursuivre nos travaux sur la financiarisation des marchés des matières premières.