Rapport Final

Contrat de recherche « Finance Carbone – Marchés d'options, information et efficience »

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Synthèse

Avant-propos

Nous avons le plaisir de remettre notre rapport de fin de projet de recherche pour le projet « Finance Carbone ». Le projet a permis à ce jour la réalisation de 5 papiers de recherche dont 4 ont été publiés dans des revues à comité de lecture classées A (3/4) ou B (1/4) par le CNRS. Le 5$^{\text{ème}}$ papier est actuellement en soumission dans une revue de catégorie identique. L'ensemble de ces contributions a permis de traiter les sujets qui ont été proposés au CFE lors de la remise du projet.

A ce jour, les fonds obtenus grâce au CFE ont permis :

1. Des déplacements multiples afin de permettre aux chercheurs de se rencontrer et de travailler ensemble.
2. Des présentations à des séminaires invités et à des colloques nationaux et internationaux.
3. L'achat de données, de petits matériels informatiques et de logiciels dédiés au projet.

Les présentations à des colloques, tout particulièrement, ont permis de donner une meilleure visibilité à nos travaux et, à notre sens, ont mis en valeur le soutien financier du CFE. De plus, les présentations ayant eu lieu lors de colloques portant sur des champs différents de l'économie (économie de l'énergie, économie générale, finance), la reconnaissance du CFE en tant que financeur de la recherche en économie de l'énergie n'en est que plus large. Précisons que lors de chaque communication le soutien financier du CFE a été mentionné.

Dans la suite de ce document de synthèse, nous présentons d'une manière brièvement la contribution de chaque papier. Le CFE pourra trouver ensuite un long résumé (en français) pour chaque article ainsi que la dernière version du document de travail (avant publication) en version originale (anglais).

Synthèse des contributions académiques

Nous présentons à présent les principaux résultats de notre travail dont les résumés longs en français suivent.

Les trois premiers articles s'intéressent à l'analyse de l'efficience du marché européen du carbone. C'est le premier point qui avait été proposé dans notre projet initial.

Dans «**Testing the martingale difference hypothesis in CO2 emission allowances** » par Amélie Charles *et alii*, nous montrons que le marché du carbone est efficient au sens faible (pas d'information dans les cours passés exploitable pour la prévision des cours futurs) lors de la phase II. Des résultats sont également fournis pour la phase I qui ne présentait pas une efficience au sens faible sur l'ensemble de sa durée. Il semble donc que l'efficience du marché soit progressivement apparue, peut-être à la suite d'un phénomène d'apprentissage des agents économiques opérant sur ce marché. Cela est de bon augure pour la phase III à venir.

Dans « **Testing the speculative efficiency hypothesis on CO2 emission allowance prices: Evidence from Bluenext** » par Amélie Charles *et alii*, nous nous sommes intéressés à une autre dimension de l'efficience, en particulier l'absence d'arbitrage entre marché spot et marché à terme. Par le biais de tests de cointégration entre ces deux séries, il apparait que les deux marchés ne sont pas reliés à long terme ce qui met en lumière une inefficience spéculative du marché du carbone.

Dans « **EUA and sCER Phase II Price Drivers: Unveiling the reasons for the existence of the EUA-sCER spread** » par Julien Chevalier *et alii*, nous élargissons la notion d'efficience évoquée dans les deux premiers papiers en considérant la relation entre le marché européen (EUA) et le marché mondial du carbone (CER). Nous montrons que la relation d'arbitrage est en fait imparfaite en raison de limitations sur le type d'acteurs pouvant exercer cette opération et le seuil maximal d'intervention pour ces opérateurs.

Le quatrième article s'intéresse à la question de l'impact de l'introduction du marché d'options sur le marché sous-jacent du carbone. Il s'agit du deuxième sujet proposé dans le projet.

Dans notre article « **Option introduction and volatility in the EU ETS** » par Julien Chevallier *et alii*, nous proposons une analyse économétrique complète de la période autour de la date d'introduction du marché option (en tenant compte également des volumes échangés qui seront de plus en plus importants). Il semble que la mise en place d'un marché option n'ait pas eu d'effet déstabilisateur sur le marché original du carbone. Ce résultat est robuste à l'introduction d'un ensemble de variables de contrôle. D'autre part, il semble que les options permettent une amélioration de l'efficience informationnelle du marché en réduisant la persistance de la volatilité.

Enfin, le cinquième article propose une modélisation de la volatilité des prix du carbone, en utilisant les données intra-journalières disponibles pour ce marché. C'est le troisième point du projet scientifique proposé.

L'article « **On the realized volatility of the ECX CO2 emissions 2008 futures contract: distribution, dynamics and forecasting** » par Julien Chevalier et Benoît Sévi suggère une modélisation autorégressive de la volatilité réalisée sur l'EU ETS qui capte de manière satisfaisante l'ensemble des faits stylisés relevés (mémoire longue de la volatilité réalisée notamment). De plus, nous montrons que la distribution inconditionnelle des rendements standardisés est quasiment normale ce qui valide l'hypothèse avancée en finance de mélange des lois normales. Nous montrons également, à titre d'illustration, que le modèle a des performances très supérieures au modèle GARCH standard.

Testing the martingale difference hypothesis in CO2 emission allowances

Auteurs : Amélie Charles, Olivier Darné et Jessica Fouilloux

Publication : **Economic Modelling**, 28, 27–35 (2011)

Colloques : Association Française de Finance (AFFI), Brest, 2010; Association Française de Science Economique (AFSE), Nanterre, 2010.

Le système communautaire d'échange de quotas d'émission (SCEQE) ou *European Union Emission Trading System* (EU ETS), créé en 2005, est un mécanisme de l'Union Européenne visant à réduire l'émission globale des gaz à effets de serre, en particulier le CO2, et à atteindre les objectifs de l'Union Européenne dans le cadre du protocole de Kyoto. C'est le plus grand système d'échange de crédits d'émissions de gaz à effet de serre dans le monde. Afin d'améliorer la fluidité du EU ETS, des marchés de négociation et d'échange de droits d'émission de gaz à effet de serre ont été créés, notamment les marchés Bluenext en France, ECX à Londres et Amsterdam, EEX en Allemagne, SendeCO2 en Espagne, EXAA en Autriche et Nord Pool en Norvège.

Une question importante est de savoir si les mécanismes mis en place par l'EU ETS ont permis au marché d'opérer de manière efficiente d'un point de vue informationnel. En d'autres mots, est-ce que les prix d'échanges de droits d'émission reflètent toute l'information disponible telle qu'il ne soit pas possible pour un investisseur de réaliser un arbitrage ? L'étude de cette question est cruciale car l'objectif du EU ETS est de permettre aux pays participants d'assurer le respect de l'environnement d'une manière rentable et économiquement optimale, qui tous deux exigent implicitement que le marché lui-même soit efficient. L'efficience du marché du CO2 est particulièrement importante pour les entreprises d'émission, les gestionnaires de risque et les investisseurs dans la nouvelle classe des fonds de pension dans l'énergie et de carbone. L'efficience du marché du carbone est destinée à permettre aux entreprises de réaliser leurs réductions d'émissions au moindre coût. Une implication politique de l'inefficacité des marchés est un plus grand besoin de règlement visant à améliorer les flux d'information et de réduire les manipulations de marché.

L'hypothèse de marché efficient (*efficient market hypothesis* ou EMH), et plus précisément l'hypothèse de marché informationnel au sens faible, stipule que les informations contenues dans les prix passés sont immédiatement, pleinement et sans cesse reflétées dans le prix actuel de l'actif. Cela implique que les prix suivent une marche aléatoire ou une martingale. En conséquence, les variations de prix futurs basées sur des informations passées des prix sont imprévisibles et fluctuent seulement en réponse au flux aléatoire de nouvelles informations. En outre, étant donné que l'ajustement des prix à un nouvel élément d'information est instantané et précis, les rentabilités ne peuvent être prédites. Cela signifie que les variations de prix historiques ne peuvent pas être utilisées pour former des prévisions supérieures ou de réaliser des bénéfices au-dessus du niveau justifié par le risque supposé. La plupart des études sur l'EMH des marchés financiers teste l'efficience au sens faible au travers de l'hypothèse de différence de martingale (*martingale difference hypothesis* ou MDH) où le prix actuel est le meilleur prédicteur du prix futur des prix et les rendements sont indépendants (ou ne sont pas corrélés avec) les valeurs du passé. Si le marché des émissions de CO2 est efficient au sens faible, alors les changements dans les prix spot du CO2 suivent une séquence de différence de martingale (*martingale difference sequence* ou MDS), et les variations de prix sont imprévisibles. Cela signifie qu'il est impossible pour un opérateur d'obtenir un rendement excédentaire au fil du temps grâce à la spéculation. Si le marché n'est pas efficient au sens faible, alors les variations de prix sont prévisibles. Ainsi, les traders peuvent générer des rendements anormaux par la spéculation. Pour ces raisons, la prévisibilité des rendements est un enjeu important dans l'efficacité du marché du carbone.

Dans cet article, nous étudions l'EMH au sens faible sur les marchés EU ETS de quotas d'émission de carbone, en utilisant les prix au comptant (prix spot) négociés sur BlueNext (France), European Energy Exchange (EEX, Allemagne) et Nordic Power Exchange (Nord Pool, Norvège), au cours de la Phase I et de la Phase II, ainsi que les prix à terme négociés sur BlueNext et ECX au cours de la Phase II (données quotidiennes et hebdomadaires). La non prévisibilité des changements de prix spot et à terme du CO2, qui est une implication de l'efficience de marché au sens faible, est évaluée en utilisant deux tests économétriques : (1) le test de bootstrap du rapport des variances automatique. Ce test de ratio de variances est robuste à l'hétéroscédasticité et à la non-normalité qui sont présents dans les prix de quotas d'émission de CO2 et possèdent des propriétés souhaitables en petits échantillons. (2) Le test spectral généralisé qui permet de capturer la présence possible de non linéarité.

Pour la Phase I, les résultats montrent que les variations de prix spot des trois marchés sont prévisibles, ce qui suggère la possibilité d'arbitrage, sauf pendant la sous-période allant d'avril 2006 à octobre 2006, à savoir après la divulgation (avril 2006) des premières informations fiables sur les émissions réelles de l'année 2005 révélant que la plupart des installations disposaient d'excédents de quotas – qui a été accompagné par un effondrement soudain des prix d'allocation – et avant l'annonce (octobre 2006) par la Communauté Européenne de la validation du Plan National d'Allocation des Quotas (PNAQ) II plus stricte – qui a renforcé l'effet dépressif sur les prix. Nous mettons aussi en évidence que la divulgation en avril 2006 d'information sur les émissions de l'année 2005 ne semble pas avoir influencé la prévisibilité des changements de prix. Enfin, nous montrons que les changements des prix spot et à terme ne sont pas prévisibles au cours de la Phase II, car nous n'avons pas réussi à rejeter la MDH basée sur des données quotidiennes et hebdomadaires. Ces marchés sont donc efficients au sens faible.

Testing the speculative efficiency hypothesis on CO2 emission allowance prices: Evidence from Bluenext

Auteurs : Amélie Charles, Olivier Darné et Jessica Fouilloux

Publication : Document de travail du LEMNA (2011) – étude préliminaire

Colloques : Association Française de Finance (AFFI), Montpellier, 2011.

En janvier 2005, le système communautaire d'échange de quotas d'émission (SCEQE) ou *European Union Emission Trading System* (EU ETS) est entré en vigueur. L'EU ETS est une des plus importantes initiatives prises pour réduire les gaz à effet de serre (principalement CO2) causés par le changement climatique (protocole de Kyoto). L'EU ETS inclut environ 11 500 installations participantes à travers vingt-sept États membres. En 2010, il prend en compte 45% des émissions CO2 en Europe.

L'EU ETS présente un système de « *cap and trade* », qui fonctionne par la création et l'allocation de quotas aux installations. Puisque les quotas sont limités, ils sont échangés sur des marchés et leur prix dépendent de l'offre et de la demande. La distribution de ces droits est gratuite. Le plan fonctionne au cours de périodes discrètes, avec une première période test de 2005 à 2007 (la Phase I) et une deuxième période correspondant à la première période d'engagement du Protocole de Kyoto. Cette période s'étendra de 2008 à 2012 (la Phase II) et sera suivie par une troisième période de 2013 à 2020 (la Phase III). L'objectif de l'Union Européenne est de réduire de 8% les émissions par rapport au niveau d'émission de 1990 et ce durant la période 2008-2012.

L'EU ETS inclut 6 plateformes de négociations sur lesquelles sont échangés des contrats au comptant, des contrats à terme et des options avec une valeur marchande totale de 72 milliards d'Euros en 2010. Les échanges de contrats à terme représentent une large part de cette valeur (environ 87 % en 2010). La compréhension de la relation entre les prix au comptant (prix spot) et des prix des contrats à terme (futures) est ainsi d'une importance cruciale pour tous les participants au marché carbone. En effet, pour que le marché soit efficient et que les prix soient justes, il faut que la relation de *cost-of-carry* soit respectée, c'est-à-dire qu'il ne soit pas possible de réaliser un arbitrage entre le marché des futures et le marché au comptant. Les marchés du carbone ne peuvent se développer que si les prix sont à leur vraie valeur et si ces marchés fournissent assez de liquidité.

On peut considérer qu'un marché financier est efficient si les prix reflètent entièrement toutes les informations disponibles et qu'aucune occasion d'arbitrage n'est laissé inexploitée. Cette forme d'efficience est connue comme étant l'efficience au sens faible ou l'hypothèse d'efficience spéculative. En utilisant ce modèle, l'efficience impliquera nécessairement que le prix du marché reflète entièrement toutes les informations disponibles et ainsi qu'il n'existe aucune stratégie permettant de réaliser un gain certain. Une façon d'évaluer l'efficience d'un marché est de tester le lien entre le prix au comptant et le prix des futures à l'aide de tests de cointégration. Le fait que les prix des futures soient parfaitement cointégrés aux prix au comptant par la relation de *cost-of-carry* montre qu'il n'existe pas de possibilité d'arbitrage.

Bien que des papiers appropriés aient été publiés sur le comportement des prix au comptant des quotas d'émission et des prix de futures, les études sur l'efficience des marchés de CO2 sont plutôt rares. Ces travaux étudient la relation entre les prix au comptant et les prix des futures dans le modèle de *cost-of-carry* sur la Phase I. Cependant, certains auteurs émettent des doutes sur l'applicabilité de ce modèle à cause de l'immaturité de l'EU ETS. Dans notre étude, nous examinons l'hypothèse d'efficience spéculative sur le principal marché européen du carbone, Bluenext, en utilisant les prix au comptant et les prix des futures des quotas de CO2 au cours de la Phase II. Nous appliquons plusieurs tests de racine unitaire ainsi que les tests de cointégration linéaires et non-linéaires. Les résultats indiquent une absence de relations de cointégration linéaire et non linéaire entre les prix au comptant et les prix futures. Nous montrons ainsi que l'efficience au sens faible n'est pas vérifiée au cours de la Phase II sur le marché Bluenext.

Les résultats de ce papier seront prolongés dans une prochaine étude en examinant l'hypothèse d'efficience spéculative à partir de la relation de *cost-of-carry*.

EUA and sCER Phase II Price Drivers: Unveiling the reasons for the existence of the EUA-sCER spread

Auteurs : Julien Chevallier, Emilie Alberola, Maria Mansanet-Bataller et Morgan Hervé-Mignucci

Publication : **Energy Policy** 39, 1056-69 (2011)

Cet article étudie la transmission du prix entre le marché européen du CO2 et le marché "mondial" du CO2. Côté européen, l'unité de carbone échangeable est appelée *European Union Allowance* (EUA). Côté mondial, l'unité de carbone échangeable est appelée *Certified Emissions Reduction* (CER). Le but de cet article consiste à identifier les mécanismes de formation du prix propre à chaque actif, ainsi que l'existence de possibilités d'arbitrage entre les deux marchés.

En effet, il est possible pour un opérateur intervenant sur le marché européen du CO2 d'utiliser soit des EUAs, soit des CERs, pour assurer sa conformité avec la contrainte d'émissions. Les CERs sont des actifs fongibles, à hauteur de 13,4% en moyenne dans les pays membres de l'Union Européenne, avec les EUAs, et ils peuvent donc légitimement être utilisés dans les registres nationaux.

Cette opération d'enregistrement dans les registres européens de quotas délivrés au niveau international (par le Comité exécutif du *Clean Development Mechanism Executive Board*) est ouverte à des agents possédant effectivement des installations dans le périmètre européen, et pouvant effectuer la double opération d'écriture entre le registre international et le registre européen. Cette opération est donc exclue pour des intervenants purement financiers sur le marché du CO2, telle que les banques d'investissements agissant en compte propre. Des agents possédant à la fois des installations et des bureaux de trading sont éligibles à l'opération d'arbitrage. On peut penser dans ce cas aux principaux acteurs sur le marché électrique.

Si une différence de prix existe entre les deux actifs financiers (les EUAs et les CERs), il peut devenir profitable pour un agent économique d'utiliser la source de carbone la moins chère en vue d'assurer sa conformité. En cas de divergence positive de prix entre les deux actifs, on comprend donc bien l'intérêt que représente le fait de vendre des quotas EUAs et d'acheter des quotas CERs, soit de vendre le *spread* EUA-CER.

L'article montre de façon intéressante que les agents économiques attendent que l'écart de prix entre les deux actifs soit maximal (au-delà de six euros par tonne de CO2) avant de bénéficier de la possibilité d'échanger un quota carbone contre un autre. Sur ces marchés environnementaux, une possibilité de « free lunch » demeure donc en permanence, contrairement à la théorie financière. Cette situation peut se comprendre aisément si l’on intègre le fait que seuls certains acteurs peuvent bénéficier de l’opération d’arbitrage, et que cette possibilité est limitée quantitativement. Effectivement, les opérateurs ne peuvent pas convertir plus de 200 millions de tonnes de CO2 provenant du marché mondial en vue d’assurer leur position de conformité sur le marché européen. Par ailleurs, l’évènement de conformité n’intervient qu’avec une fréquence annuelle sur le marché européen du CO2, ce qui laisse aux agents la possibilité de lisser leur position de conformité dans le temps.

A travers l’analyse économétrique, l’article retrace progressivement quels sont les déterminants du prix du CO2 européen et du prix du CO2 mondial à partir de régressions multiples avec effets GARCH. L’étude basée sur un modèle vectoriel autoregressif, sur la notion de cointégration et de modèle vectoriel à correction d’erreur, montre qu’une relation de long-terme existe entre les deux actifs, et que les déséquilibres tendent à être corrigés par le prix EUA. En effet, le marché européen est à ce jour le marché du carbone le plus liquide et le plus développé (plus que le marché du CER).

Ces résultats peuvent être utiles non seulement dans la sphère académique, pour comprendre les inter-relations entre les marchés du CO2, mais aussi et surtout aux pouvoirs publics avant de corriger éventuellement des brèches dans la régulation environnementale. Notons qu’à ce sujet la Commission Européenne a revu à la baisse le nombre de quotas CER pouvant être importés dans le système européen, notamment en fixant des critères environnementaux et technologiques plus stricts sur la provenance de la réduction des émissions.

Enfin, ces résultats peuvent trouver un public attentif parmi les traders, brokers et analystes financiers reliés au marché du CO2, étant donné qu’une opportunité d’arbitrage existe, et que les compétences requises pour en bénéficier ont été clairement identifiées dans l’article.

Option introduction and volatility in the EU ETS

Auteurs : Julien Chevallier, Yannick Le Pen et Benoît Sévi

Publication : **Resource and Energy Economics** 33, 855-80 (2011)

Colloques : International IAEE Conference, San Francisco, 2009 ; European Association of Environmental and Resource Economists (EAERE) Annual Conference, Amsterdam, 2009 ; IAEE European Conference, 2009, Vienne; Université de Stirling, 2009; Chaire Finance Carbone Dauphine, 2011.

L'objectif de cet article est d'évaluer l'effet de l'ouverture le 13 octobre 2006 d'un marché d'options par le European Climate Exchange (ECX) sur la volatilité du marché sous-jacent du CO2. Les options peuvent déstabiliser le marché sous-jacent en donnant des opportunités de spéculation ou améliorer sa liquidité et son efficacité. Les travaux menés jusqu'à présent n'ont pas permis de déterminer quel effet l'emportait.

Nous cherchons à détecter l'impact du fonctionnement effectif du marché des options sur le niveau et la dynamique de la volatilité du marché future. Une question importante est celle de la date à partir de laquelle nous pouvons considérer que le marché des options fonctionne effectivement. L'examen du volume des transactions nous incite à choisir la date du 18 mai 2007 plutôt que celle de son ouverture officielle. En effet, les transactions sur le marché des options atteignent pour la première fois le volume de 1 Mton (pour les calls) ce jour-là.

Nous choisissons les contrats *futures* comme actif sous-jacent en raison du comportement atypique du prix spot pendant la phase I (2005-2007) de l'EU-ETS. Nous étudions les prix des futures et des options pour les contrats de maturité de décembre 2008 et 2009. Afin de contrôler l'effet des variables susceptibles d'agir sur la volatilité des futures, nous considérons les prix des sources d'énergie primaire (pétrole brut, charbon, gas naturel), le prix de l'électricité (y compris le *clean dark spread*, le *clean spark spread*, le prix *switch*) et un indice global du prix des matières premières (l'indice Reuters/Commodity Research Bureau). Nous disposons de 756 observations quotidiennes du 22 avril 2005 au 4 avril 2008.

Nous employons la modélisation AR-GARCH en permettant une modification de la valeur des paramètres après le 18 mai 2007. Les résultats nous amène à conclure que la volatilité a diminué après le 18 mai 2007. Cet effet est robuste à l'introduction des variables de contrôle. La recherche de changements structurels dans le niveau de la volatilité met aussi en évidence un brusque accroissement en avril et mai 2006. Cette période coïncide avec la publication par la Commission Européenne du premier rapport sur les émissions vérifiées. Les différents intervenants sur le marché du CO2 ont bénéficié alors d'un afflux d'informations. L'estimation d'un modèle AR-GARCH sur des fenêtres d'observations roulantes, révèle aussi des changements dans la dynamique de la volatilité. La période de mai 2006 fait apparaître un premier changement structurel. L'impact des chocs sur la volatilité s'accroît nettement après cette date. Nous retrouvons l'effet du premier rapport sur les émissions vérifiées. Nous observons un second changement en février 2007 et l'attribuons à la publication du deuxième rapport sur les émissions.

Conclusion Nos résultats montrent que l'ouverture d'un marché d'options a réduit la volatilité du marché sous-jacent. Elle ne semble donc pas avoir eu d'effet déstabilisant. Des modifications dans le niveau et la dynamique de la volatilité coïncidente aussi avec d'autres évènements, notamment la publication des rapports sur les émissions vérifiées. Une extension de ce travail consisterait à ajouter à notre échantillon les données les plus récentes afin d'étudier si la volatilité a subi d'autre changement ou si elle s'est stabilisée. Une autre extension serait d'utiliser des données intra-journalières afin de détecter des changements structurels dans la volatilité réalisée.

On the realized volatility of the ECX CO2 emissions 2008 futures contract: distribution, dynamics and forecasting

Auteurs : Julien Chevallier et Benoît Sévi

Publication : **Annals of Finance** 7, 1-29 (2011)

Colloques : Atelier Finance et Risque, Nantes, 2009 ; "Carbon Markets Workshop",LSE, 2009, Londres; 6th MONDER Conference, Rio de Janeiro, 2009 ; IEW Workshop, Venise, 2009 ; European Meeting if the Econometric Society (ESEM), Barcelone, 2009 ; European IAEE Conference, Vienne, September 2009.

Le papier s'intéresse à la modélisation de la volatilité et indirectement des rendements sur le marché européen du carbone (contrat futures 2008 échangé sur la bourse ECX). L'originalité de cette recherche réside dans le caractère récent de ce marché qui n'a pas encore pas fait l'objet de ce type d'étude, ainsi que du type de données utilisées, qui sont des données intra-journalières, et qui nécessite l'utilisation de techniques économétriques et statistiques récentes.

Le postulat généralement rencontré lorsque l'on s'intéresse à la modélisation stochastique de séries de prix (rendements) observés sur les marchés financiers est que les rendements sont normalement distribués et que la volatilité, dont on s'accorde à dire qu'elle est elle-même stochastique, est log-normalement distribuée (cela signifie que le logarithme de la volatilité est normalement distribuée). Les contributions récentes en finance empirique ont montré l'apport important qu'ont pu constituer l'accès à des donnés haute-fréquence pour l'étude de ces aspects liés aux distributions. Dans notre article, nous étudions les rendements à une fréquence journalière et la volatilité à la même fréquence mais en utilisant le concept de volatilité réalisée. Celle-ci se calcule en sommant les rendements intra-journaliers pris à un intervalle de 5 minutes (voir la discussion sur ce sujet dans le papier). Lorsqu'on applique une transformation logarithme à ces volatilités réalisées quotidiennes, elles sont bien normalement distribuées, en tous cas si on ne considère pas des tests de normalité trop contraignants.

Un autre postulat est que le flux d'information joue le rôle d'horloge pour le processus de rendement. En effet, un flux d'information important va créer de la volatilité. C'est pour cette raison que l'hypothèse de flux d'information aléatoire se transforme en volatilité stochastique qui entraîne une déviation par rapport à la normalité pour les rendements observés. Une façon de revenir à la normalité (courbe gaussienne) est de rapporter les rendements (standardiser) au niveau de volatilité observé. Ainsi, les auteurs montrent que les rendements standardisés sont apparemment normalement distribués. En utilisant les mesures de volatilité réalisée calculées comme indiqué plus haut, nous pouvons standardiser les rendements quotidiens et, là-encore, la normalité approximative est obtenue pour notre série de rendements sur le marché du carbone.

Ces deux résultats montrent que le modèle sous-jacent de diffusion à volatilité stochastique généralement choisi dans la littérature pour les diverses applications telles que valorisation de produits dérivés, calcul de la valeur à risque (VaR) ou autre allocation d'actifs, est pertinent dans le cas du marché du carbone.

La deuxième partie de l'article s'intéresse à la question de la modélisation de la dynamique de la volatilité quand celle-ci est estimée par le biais de rendements intra-journaliers. Cette dynamique est estimée par le biais d'un modèle autorégressif qui permet de rendre compte du comportement de mémoire longue observé dans les données. Ce modèle HAR propose en effet d'estimer des retards à 1, 5 et 22 jours avec un chevauchement qui crée une forme de pseudo-mémoire longue tout en limitant les aspects liés aux procédures d'inférence.

Nos estimations montrent que ce modèle est tout à fait apte à reproduire les caractéristiques empiriques de la série de volatilité réalisée estimée. En outre, et c'est l'objet de la dernière section de l'article, les résultats en terme de prévision sont significativement améliorés lorsqu'on recourt à des données intra-journalières et au modèle HAR, si on compare ces résultats à des modèles GARCH standards. Il faut noter que la comparaison des prévisions de la volatilité ne peut se faire que par le biais d'une mesure dite « robuste » (cf. Patton, 2011) et c'est cette mesure que nous adoptons dans notre papier. Ce résultat confirme que dans le cas du contrat 2008 du carbone le gain à utiliser des données haute-fréquence est bien réel.

En résumé, notre article est le premier à utiliser des données de transactions (*tick-by-tick*) dans le cas du marché européen du carbone. Notre étude a porté sur le contrat futures 2008 car celui-ci a été assez liquide sur la période considérée. Nos résultats montrent que le recours à ce type de données est fructueux à la fois pour tester des hypothèses en matière de distribution mais aussi pour prévoir la volatilité. Ce dernier point est d'une grande importance pour l'ensemble des investisseurs intervenants sur ce marché.

Testing the Martingale Difference Hypothesis in the EU ETS Markets for the CO_2 Emission Allowances: Evidence from Phase I and Phase II*

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Abstract

This study examines the martingale difference hypothesis (MDH) for the market of carbon emission allowances within the European Union Emission Trading Scheme (EU ETS) during the Phase I and the Phase II, using both daily and weekly data over the period 2005–2009. The weak-form efficient market hypothesis for spot prices negotiated on BlueNext, European Energy Exchange and NordPool is tested with new variance ratio tests developed by Kim (2009). For the Phase I, the results show that these three markets of the European Union allowances seems to be efficiency, except after the European Commission announcements of stricter Phase II allocation in October 2006. Finally, we find that the CO_2 spot prices seem to be weak-form efficiency during the Phase II since the MDH is failed to reject from both daily and weekly data.

Keywords: CO_2 emission allowances; market efficiency; martingale difference hypothesis; variance ratio test.

JEL Classification: G14; Q53; C14.

1 Introduction

The Kyoto protocol is designed to cut six major greenhouse gases (GHGs) emission, particularly carbon dioxide (CO_2)[1] by making the polluter start paying for climate change. Most countries have signed and ratified the Kyoto protocol to the Union Nation Framework Convention on Climate Change.[2] The protocol is based on a "cap and trade" system. Each country is agreed with the intention of reducing their overall emissions by 8% of their 1990 levels by the end of 2012. For the 5-years compliance period from 2008 until 2012, entities (nations or companies) that emit less than their quota are able to sell emission credits to entities that exceed their quota. It is also possible to sponsor carbon projects that provide a generating tradable carbon credits. To aid countries in achieving their reduction objectives, the Protocol includes three flexibility mechanisms: the creation of an international carbon market, Joint Implementation and the Clean Development Mechanism.[3]

Several national and regional emission markets have been established in which a variety of specialized financial instruments are traded. Europe has emerged as a leader in the emissions trading industry with the European Union Emission Trading Scheme (EU ETS) being the world's largest single market for CO_2 emission allowances, which covers up to 40% of European CO_2 emissions. Indeed, the EU ETS markets are the largest, most liquid and most developed. Its main objective consists in giving incentives to industrials to reduce emissions and to contribute to the promotion of low carbon technologies and energy efficiency among CO_2 emitting plants. Most important combustion entities manage their compliance between their allocation and

[1] The CO_2 belongs to the GHG group with the methane CH_4, nitrous oxide N_2O, hydroflurocarbons HFC_s, perfluorocarbons PFC_s and sulphur hexafluoride SF_6.

[2] In October 16, 2008, 183 countries had signed and ratified the Kyoto protocol. The United States is the only country why has not ratified the protocol.

[3] Joint Implementation (JI) projects do not create credits, but rather transfer reduction units from one country to another. The aim of Clean Development Mechanism (CDM) projects is to promote investments in developing countries by industrialized nations and to encourage the transfer of low-emission technologies.

annual verified emissions by buying or selling European Union Allowances (EUAs) to emit a ton of carbon.

The EU ETS was initiated in January 2005 as the central framework that EU member states should employ in order to fulfill their obligations under the Kyoto protocol, i.e., to reduce the anthropogenic contribution of the greenhouse gas emissions (primarily CO_2) in the atmosphere. The EU ETS has been designed to operate in two initial phases. The first phase (2005–2007, Phase I) is a pilot phase during which the trading volume increased from 262 million metric tons in 2005 to 818 million metric tons in 2006 to 1.4 billion in 2007. The value of trades reached 30 billion euros in 2007. Phase I established a strong carbon market and provided new business development opportunities for risk management and market operators. The second phase (2008–2012, Phase II) coincides with the period when the EU must meet the 8% decrease from 1990 levels under the Kyoto Protocol. For the post-2012 period, the European Commission has decided to continue the operation of the market with the EU member states having already agreed to reduce up to 2020 their greenhouse gas emissions by an additional 12% over the obligatory levels under the Kyoto protocol.[4] In order to improve the fluidity of the EU ETS, organized allowance trading has been segmented across trading platforms: European Climate Exchange (ECX) based in London and Amsterdam started in April 2005, Nordic Power Exchange (Nord Pool) in Norway began in February 2005, BlueNext in France started in June 2005[5], European Energy Exchange (EEX) in Germany began in March 2005, Energy Exchange Austria (EEA) in Austria began in June 2005, and SendeCO2 in Spain started at the end of 2005.

Several relevant research papers have been published in the economics literature on the emission allowance market mechanisms, policies and their implications.[6] Recently, a growing empirical research has been undertaken from a financial market framework,

[4]See Daskalakis and Markellos (2008) for a discussion on the EU ETS.

[5]Powernext Carbon became BlueNext on January 2008

[6]See, for example, Rubin (1996), Kling and Rubin (1997), Boemare and Quirion (2002), Kosobud, Stokes and Tallarico (2002), Svendsen and Vesterdal (2003), Vesterdal and Svendsen (2004), Böhringer and Lange (2005), Ellerman (2005) and Ellerman, Buchner and Carraro (2007), Stern (2007), and the Special issue in *Oxford Review of Economic Policy*, (2008, Volume 24, Number 2), among others.

especially on the behavior of emission allowance spot and futures prices, e.g., Alberola et al. (2008), Daskalakis and Markellos (2008), Paolella and Taschini (2008), Seifert et al. (2008), Benz and Trück (2009), and Boutaba (2009).[7]

An important question is whether the chosen mechanics of the EU ETS have allowed the market to operate efficiently during the Phase I (2005–2007) and since implementing the Phase II (2008–2012). In other words, do emission allowance prices reflect all available information to the extent that no investor can systematically gain excess returns (see, Fama, 1970, 1991, 1998; Fama and French, 1988; Lo and MacKinlay, 1988; among others)? Investigating this issue is crucial, since the prime aim of the EU ETS is to allow the participating countries to achieve environmental compliance in a cost-effective and economically optimal manner, both of which implicitly require that the market itself is efficient. The efficiency of the CO_2 market is particularly important for emission intensive firms, policy makers, risk managers and for investors in the emerging class of energy and carbon hedge funds. Carbon market efficiency as the objective of carbon markets is to enable firms to achieve their emissions reductions at minimum cost. If markets are inefficient the policy implications are that there is a greater role for regulation to improve information flows and reduce market manipulation.

Since the seminal papers of Samuelson (1965) and Fama (1965), the efficient market hypothesis (EMH thereafter) states that efficient market prices follow a random walk or a martingale[8], and always fully and instantaneously reflect all available and relevant information, where the information set consists of past prices and returns. As a result, future prices are purely unpredictable based on past price information and fluctuate only in response to the random flow of news (Fama, 1970; 1991). Moreover,

[7]Some others papers focused on the relationship between spot and futures markets for EUAs, e.g., Uhrig-Homburg and Wagner (2007), Milunovich and Joyeux (2007), Trück et al. (2007), Alberola and Chevallier (2009), Daskalikas et al. (2009).

[8]The terms "random walk" and "martingale" have been interchangeably used in the literature. However, strictly speaking, the innovations series is $i.i.d.$ for "random walk", while it is a martingale difference sequence for "martingale". See Escanciano and Lobato (2009) for a discussion.

since price adjustment to a new piece of information is instantaneous and accurate, returns cannot be predicted. This means that historical prices cannot be used to form superior forecasts or to accomplish trading profits above the level justified by the risk assumed. Most of the EMH studies on financial markets tested for the weak-form efficiency through the martingale difference hypothesis (MDH thereafter)[9], where the current price is the best predictor of the future price and the returns are independent (or uncorrelated) with the past values. If the CO_2 spot price follows a martingale difference sequence (MDS thereafter), then the market is weak-form efficient, and hence not predictable. This means that it is impossible for a trader to gain excess returns over time through speculation. If the spot price is predictable, then the market is not weak-form efficient. This means that the traders can generate abnormal returns through speculation. For these reasons, the predictability of return is an important issue to this concerned with carbon market efficiency. Nevertheless, little attention has been devoted on the weak-form efficiency in the CO_2 markets. Seifert et al. (2008) showed that the daily CO_2 spot price negotiated on BlueNext from June 24, 2005 to December 15, 2006, seems to be relatively efficient, using autocorrelation tests. Daskalakis and Markellos (2008) assessed the weak-form efficiency by analyzing spot and futures market data from BlueNext, Nord Pool and ECX, using daily prices covering the period from the first available quote up to December 12, 2006. They found that BlueNext and Nord Pool markets are not consistent with weak-form efficiency from variance ratio tests and technical analysis trading rules.

In this paper we extend the examination of the weak-form EMH in the EU ETS markets for CO_2 emission allowances in two ways. First, this study is based on a more extensive sample. We study daily data for three spot markets, BlueNext, EEX and NordPool, during the Phase I (2005–2008) and the Phase II (2008–2009) in order to compare the evolution between the two initial phases and these markets. We also investigate the EMH over various sub-periods in order to analyze the effects of the

[9] Note that if the MDH is based on the theory of efficiency, the EMH does not imply that prices follow a martingale difference sequence (MDS). Therefore, if prices do not follow a MDS, this does not imply inefficiency of the market. See Lo and MacKinlay (2001) for a discussion on MDH and EMH.

important structural change due to the first disclosure of 2005 verified emissions on April 2006 revealing the long position of each plant which was accompanied by a sudden allowance price collapse, as well as the European Commission announcements of stricter National Allocation Plans II validation in October 2006 which reinforced the depressive effect on prices. Furthermore, we analyze the weekly data for the three spot markets in order to consider a market as perfectly weak-form efficient if it is found to behave randomly at any level of data frequency. This avoids the shortcomings with the high and medium/low frequency data (e.g., non-trading, bid-ask spread, asynchronous prices). Second, the weak-form EMH is evaluated from powerful method, namely the variance-ratio [VR] test.[10] More precisely, we apply the bootstrapped automatic VR test suggested by Kim (2009). This VR test is robust to heteroscedasticity and non-normality which are present in CO_2 emission allowance prices (e.g., Milunovich and Joyeux, 2007; Daskalakis and Markellos, 2008; Benz and Trück, 2009) and is powerful in small finite sample.

The remainder of this paper is organized as follows: Section 2 presents the bootstrapped automatic VR test; Section 3 summarizes the characteristics of the data, and the empirical results on the MDH are given in Section 4. The conclusion is drawn in Section 5.

2 Variance ratio tests

Since the seminal work of Lo and MacKinlay (1988, 1989) and Poterba and Summers (1988), the standard variance ratio [VR] test or its improved modifications have been widely used for testing market efficiency, including the multiple variance ratio test of Chow and Denning (1993), sign and rank tests of Wright (2000), wild bootstrap test of Kim (2006), and power-transformed test of Chen and Deo (2006).[11]

[10] Lo and MacKinlay (1989) examined the VR, Dickey-Fuller unit root and Box-Pierce serial correlation tests and found that VR test was more powerful than the others under the heteroscedastic random walk.

[11] See Hoque, Kim and Pyun (2007) and Charles and Darné (2009) for a review.

The VR test is based on the property that, if return is purely random, the variance of k-period return (or k-period differences), $y_t - y_{t-k}$, of the time series y_t, is k times the variance of the one-period return (or the first difference), $y_t - y_{t-1}$. Hence, the VR at lag k, $VR(k)$, defined as the ratio of $1/k$ times the variance of k-period return to that of one-period return, should be equal to one for all values of k.

The VR test evaluates the hypothesis that a given time series or its first difference (or return), $x_t = y_t - y_{t-1}$, is a collection of independent and identically distributed observations (i.i.d.) or that it follows a MDS. Define the VR of k-period return as

$$\begin{aligned} V(k) &= \frac{Var(x_t + x_{t-1} + \cdots + x_{t-k+1})/k}{Var(x_t)} \\ &= \frac{Var(y_t - y_{t-k})/k}{Var(y_t - y_{t-1})} = 1 + 2\sum_{i=1}^{k-1}\left(\frac{(k-i)}{k}\right)\rho_i \end{aligned}$$

where ρ_i is the i-th lag autocorrelation coefficient of $\{x_t\}$. $V(k)$ is a particular linear combination of the first $(k-1)$ autocorrelation coefficients, with linearly declining weights. The central idea of the variance ratio test is based on the observation that when returns are uncorrelated over time, we should have $Var(x_t + \cdots + x_{t-k+1}) = kVar(x_t)$, i.e. $V(k) = 1$.

A test can be constructed by considering the statistic based on an estimator of V(k). Following Wright (2000), the VR statistic can be written as

$$VR(x;k) = \left\{(Tk)^{-1}\sum_{t=k}^{T}(x_t + \cdots + x_{t-k+1} - k\hat{\mu})^2\right\} \div \left\{T^{-1}\sum_{t=1}^{T}(x_t - \hat{\mu})^2\right\} \tag{1}$$

where $\hat{\mu} = T^{-1}\sum_{t=1}^{T} x_t$. If the return follows a MDS, the expected value of $VR(x;k)$ should be equal to unity for all horizons k. Lo and MacKinlay (1988) proposed the asymptotic distribution of $VR(x;k)$. Moreover, Cochrane (1988) showed that the estimator of $V(k)$ can be interpreted in terms of the frequency domain. This estimator which uses the usual consistent estimators of variance is asymptotically equivalent to 2π the normalized spectral density estimator at the zero frequency.

To implement the test, one should test for the null hypothesis that the VR is equal to one for a set of (holding periods) k values. For example, popular choices in empirical applications include $k \in \{2,5,10,30\}$ for daily return, while $k \in \{2,4,8,16\}$ for weekly return (see, for example, Belaire-Franch and Opong, 2005; and Fong et al., 1997). However, these choices are entirely arbitrary and adopted without any concrete statistical justifications. In view of this, Choi (1999) proposed an automatic variance ratio (AVR, thereafter) test, in which the optimal value of holding period k is determined automatically using a completely data-dependent procedure.

Let x_t denote asset return at time t, where $t = 1,...,T$. Choi's (1999) AVR test is based on a VR estimator related to the normalized spectral density estimator at zero frequency, namely,

$$\widehat{VR}(k) = 1 + 2\sum_{i=1}^{T-1} h(i/k)\widehat{\rho}(i), \tag{2}$$

where $\hat{\rho}(i) = \hat{\gamma}(i)/\hat{\gamma}(0)$ is the sample autocorrelation of order i, $\hat{\gamma}(i)$ is the sample autocovariance of order i, and $h(x)$ is the quadratic spectral kernel defined as

$$h(x) = \frac{25}{12\pi^2 x^2}\left[\frac{\sin(6\pi x/5)}{6\pi x/5} - \cos(6\pi x/5)\right],$$

According to Choi (1999), under the condition that x_t is is serially uncorrelated,

$$AVR(k) = \sqrt{T/k}[\widehat{VR}(k) - 1]/\sqrt{2} \rightarrow_d \mathbf{N}(0,1), \tag{3}$$

as $T \rightarrow \infty$, $k \rightarrow \infty$, and $T/k \rightarrow \infty$, when x_t is an $i.i.d.$ sequence with finite fourth moment. To test for $H_0 : VR(k) = 1$, a choice for the value of lag truncation point k should be made, which is equivalent to the value of holding period in the time domain. Choi (1999) proposed a data-dependent method of choosing k optimally, following Andrews (1991). The AVR test statistic with the optimally chosen lag truncation point is denoted as $AVR(k^*)$. The $AVR(k^*)$ test is an asymptotic test which may show deficient small sample properties, especially under conditional heteroscedasticity. When x_t is subject to conditional heteroscedasticity, Kim (2009) suggested to employ the wild bootstrap of Mammen (1993) to improve small sample properties, as in Kim (2006) who applied the wild bootstrap to the Lo-MacKinlay and Chow-Denning tests.

Kim's (2009) wild bootstrap AVR test is conducted in three stages as follows:

1. Form a bootstrap sample of size T as $x_t^* = \eta_t x_t$ $(t = 1, ..., T)$ where η_t is a random variable with zero mean and unit variance;

2. Calculate $AVR^*(k^*)$, the $AVR(k^*)$ statistic calculated from $\{x_t^*\}_{t=1}^T$;

3. Repeat 1 and 2 B times, to produce the bootstrap distribution of the AVR statistic $\{AVR^*(k^*; j)\}_{j=1}^B$.

The test for H_0 against the two-tailed alternative is conducted to using the p-value, which is estimated as the proportion of the absolute values of $\{AVR^*(k^*; j)\}_{j=1}^B$ greater than the observed statistic $AVR(k^*)$. Alternatively, one may use the $100(1-2\alpha)$ per cent confidence interval $[AVR^*(\alpha), AVR^*(1-\alpha)]$, where $AVR^*(\alpha)$ denotes the α^{th} percentile of $\{AVR^*(k^*; j)\}_{j=1}^B$. As advocated by Kim (2009), the number of bootstrap iterations is set to 500.

Kim (2009) found that the wild bootstrap AVR significantly improves the size and power properties of the AVR test. Furthermore, this wild bootstrap AVR test compares favorably to the other alternatives such as the wild bootstrap Chow-Denning test of Kim (2006), the power-transformed test of Chen and Deo (2006) and the joint sign test of Kim and Shamsuddin (2008), where the choice of holding periods k is arbitrarily made.

3 Data description

The spot data of the study consists of the daily closing prices for EUA negotiated on BlueNext, EEX and Nordpool. For the Phase I, the dataset covers the period from June 24, 2005 to April 25, 2008 (708 observations) for BlueNext, August 04, 2005 to March 20, 2008 (664 observations) for EEX, and October 25, 2005 to March 31, 2008 (610 observations) for NordPool. For the Phase II, they cover the period from February 26, 2008 to November 11, 2009 (435 observations) for BlueNext, January 16, 2009 to November 11, 2009 (209 observations) for EEX, and April 15, 2008 to November 11, 2009 (395 observations) for NordPoll. Figures 1 and 2 provide a graphical representation of these series. We also examine the weekly spot data where the prices are observed on Wednesday or on the next day if the markets are closed on Wednesday. We use the both frequencies to overcome issues like biasness with daily and weekly data (e.g., non-trading, bid-ask spread, asynchronous prices).

Table 1 presents summary statistics for the returns calculated as the first differences in the logs of the EUA prices. During the Phase I, the CO_2 markets display negative mean returns of about -0.01% per day whereas during the Phase II the mean returns are very low ($\pm 0.001\%$). Note that the risk measured as the standard deviation is higher for the Phase I (close to 0.100) than that for the Phase II (close to 0.030). All the returns are highly non-normal, i.e. showing evidence of significant excess skewness and excess kurtosis during the Phase I, as might be expected from daily returns. Note that there is no evidence of excess skewness during the Phase II. Moreover, the kurtosis is significant and very high for the Phase I, implying that the distribution of the returns is leptokurtic and thus the variance of the CO_2 spot prices is principally due to infrequent but extreme deviations. A leptokurtic distribution has a more acute peak around the mean and fat tails. The Lagrange Multiplier test for the presence of the ARCH effect indicates clearly that the prices show strong conditional heteroscedasticity, which is a common feature of financial data. In other words, there are quiet periods with small prices changes and turbulent periods with large oscillations.

For the weekly data (Table 1), the returns show the same characteristics than those for the daily data. Note that NordPool for the Phase I and EEX for the Phase II do not exhibit conditional heteroskedasticity.

4 Testing the efficient market hypothesis

We investigate the weak-form EMH for BlueNext, EEX and Nordpool by testing the MDH from wild bootstrapped AVR test. The Table 2 displays the results for daily (Panel A) and weekly (Panel B) data during the Phase I and the Phase II. The results show that the MDH is rejected for EEX at the level 5% and for BlueNext and NordPool at the level 10% whereas the results are consistent with the MDS in the EUAs spot

Table 1: Statistical analysis of returns

Market	Obs.	Mean	SD	Skewness	Kurtosis	ARCH(10)
			Daily			
Phase I						
BlueNext	707	-0.011	0.096	-0.669[a]	18.876[a]	37.583[a]
EEX	663	-0.010	0.125	0.726[a]	18.857[a]	54.682[a]
NordPool	609	-0.011	0.121	-0.176	29.321[a]	51.361[a]
Phase II						
BlueNext	434	-0.001	0.028	-0.125	4.346[a]	34.332[a]
EEX	208	0.001	0.031	0.166	4.007[a]	25.608[a]
NordPool	394	-0.002	0.029	0.020	4.630[a]	18.705[a]
			Weekly			
Phase I						
BlueNext	146	-0.054	0.161	-1.351[a]	6.320[a]	10.286
EEX	134	-0.052	0.212	-0.621[a]	8.531[a]	59.103[a]
NordPool	124	-0.062	0.171	-1.191[a]	5.605[a]	9.773
Phase II						
BlueNext	88	-0.004	0.064	-0.424	4.437[a]	31.114[a]
EEX	41	0.004	0.072	-0.316	3.949[a]	13.992
NordPool	80	-0.007	0.067	-0.430	4.543[a]	29.529[a]

Notes: The skewness and kurtosis statistics are standard-normally distributed under the null of normality distributed returns. ARCH(10) indicates the Lagrange multiplier test for conditional heteroscedasticity with 10 lags. [a] means significant at the levels 5%.

prices during the Phase II for the three markets from the daily data. These results are confirmed from the weekly data. The finding on the Phase I confirms that of Daskalakis and Markellos (2008) for BlueNext and NordPool on a shorter period. Therefore, it seems that CO_2 spot markets for BlueNext, EEX and NordPool can be considered perfectly weak-form efficient during the Phase II because they behave randomly at all levels of data frequency.

We re-examine the weak-form EMH during the Phase I for the three markets due to the presence of a structural break[12] on the April 25, 2006 which can biased

[12] The structural break has been detected using the Bai and Perron (1998, 2003) tests.

Table 2: Results of AVR* tests for Phase I and Phase II.

	BlueNext	EEX	NordPool
		Daily	
Phase I	-3.154^b (0.072)	-3.555^a (0.047)	-3.640^b (0.059)
Phase II	0.437 (0.583)	0.689 (0.446)	0.566 (0.497)
		Weekly	
Phase I	1.908^a (0.035)	2.373^b (0.057)	2.021^b (0.056)
Phase II	0.064 (0.827)	-0.185 (0.675)	0.043 (0.877)

[a] and [b] Significant at the levels 5% and 10%, respectively. We report the VR statistic for each test. Phase I covers the period from June 24, 2006 to April 25, 2008, and Phase II covers the period from February 26, 2008 to September 22, 2008.

the VR tests (Lee and Kim, 2006). Indeed, the first disclosure of 2005 verified emissions on April 2006 revealing the long position of each plant was accompanied by a sudden allowance price collapse (more than 50%).[13] On the May 15, 2006 the European Commission confirmed verified emissions were about 80 million tons or 4% lower than yearly allocation. This break highlights that when the cap is not set below business-as-usual emissions, allowance trading does not necessarily guarantee a carbon price high enough to provide incentives to reduce CO_2 emissions since the stringency of the cap did not appear sufficient for market agents, and consequently the allowance price collapsed (Alberola et al., 2008). Furthermore, from October 2006 to the end of 2007 CO_2 prices tend towards zero following the European Commission (EC) announcement of stricter National Allocation Plans (NAPs) II validation, until the end of Phase I. This price pattern suggests that allowance trading was based on heterogeneous anticipations prior to information disclosure. Among the main explanations of low allowance prices towards the end of Phase I, previous literature identifies over-allocation concerns, early abatement efforts in 2005 due to high

[13] Beginning at 8 euros on January 1, 2005 EUA prices rose to 25–30 euros until the end of April. On the last week of April 2006 prices collapsed when operators disclosed 2005 verified emissions data and realized the scheme was oversupplied. After this considerable adjustment by 54% in four days, EUA prices moved in the range from 15 euros to 20 euros until October 2006.

allowance prices, and possibly decreasing abatement costs in 2006 due to abnormal temperatures and switching from coal- to gas-fired electricity in a context of falling natural gas prices compared to coal (Ellerman and Buchner, 2008; Mansanet-Bataller et al., 2007; Alberola et al., 2008; Hintermann, 2010). Alberola and Chevallier (2009) suggested that low allowance prices may also be explained by banking restrictions between 2007 and 2008. Given the impossibility of using Phase I allowances in Phase II (no bankability), the overall excess in allowances led to a decrease in their price which finally dropped to zero.[14]

Therefore, we investigate the effects of these events on the efficiency of the EUAs spot market during the Phase I, by re-running the VR tests for the following subperiods: Beginning of the spot price negociations (2005) [BSPN05] to April 24, 2006, and April 25, 2006 to the end of the spot price negociations (2008) [ESPN08], namely before and after the compliance break, as well as April 25, 2006 to October 26, 2006 to ESPN08, namely before and after the EC announcement of stricter NAPs II.

Table 3 displays the results of bootstrapped AVR tests on the sub-periods for daily data (Panel A) and weekly data (Panel B). The structural change due to the first disclosure of 2005 verified emissions on April 2006 does not seem to have an impact on the weak-form efficiency since the test statistics are significant at the levels 5% or 10% for the three markets from the daily data. Nevertheless, the MDH is rejected before the compliance break from the weekly data.

The EC announcement of stricter Phase II allocation appears to have a negative effect on the EUAs spot markets since after this announcement in October 2006. The CO_2 spot prices in BlueNext, EEX and Nordpool are not coherent with the MDS at the level 5% from both daily and weekly data. This indicates that before October 2006 the daily data reflected the most up-to-date information about CO_2 spot prices, and thus it is impossible for a trader to generate excess returns over time through speculation. However, there was possibility of abnormal returns through speculation after October 2006.

[14]See Hintermann (2010) for a discussion on the allowance price drivers in the Phase I of the EU ETS.

Table 3: Results of AVR* tests in Phase I sub-periods.

	BlueNext	EEX	NordPool
Daily			
Compliance break			
BSPN05 – April 2006	3.077^a (0.006)	1.948^b (0.077)	2.208^b (0.062)
April 2006 – ESPN08	-3.414^a (0.027)	-3.407^a (0.026)	-3.685^a (0.039)
Stricter NAPs II			
April 2006 – Oct 2006	0.034 (0.955)	−0.662 (0.665)	−0.023 (0.954)
Oct 2006 – ESPN08	-3.043^a (0.039)	-2.908^a (0.043)	-3.120^a (0.033)
Weekly			
Compliance break			
BSPN05 – April 2006	−0.009 (0.935)	0.001 (0.995)	−0.424 (0.334)
April 2006 – ESPN08	2.000^a (0.020)	2.024^b (0.092)	2.244^a (0.028)
Stricter NAPs II			
April 2006 – Oct 2006	0.357 (0.637)	0.457 (0.556)	0.416 (0.466)
Oct 2006 – ESPN08	1.617^a (0.035)	2.211^a (0.019)	1.911^a (0.023)

[a] and [b] Significant at the levels 5% and 10%, respectively. We report the VR statistic for each test. BSPN05: Beginning of the spot price negociations (2005); ESPN08: End of the spot price negociations (2008).

5 Conclusion

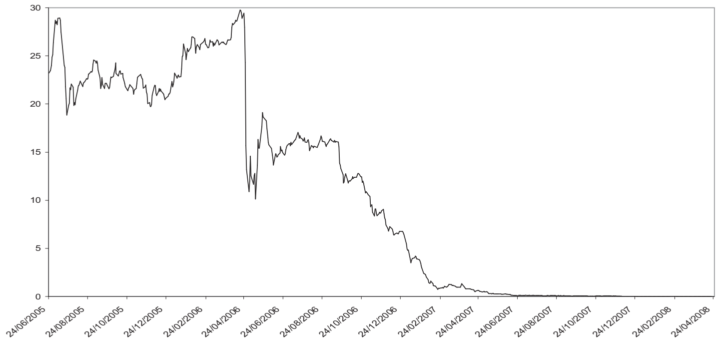
This paper explored the weak-form efficiency in the EU ETS markets for carbon emission allowances, using both daily and weekly spot prices negotiated on BlueNext, EEX and Nordpool, during the Phase I and Phase II. For that, we used new variance ratio tests, which are robust to heteroscedasticity and non-normality – present in EUAs spot prices – and powerful in small sample, namely the bootstrapped automatic VR tests developed by Kim (2009).

For the Phase I, the results showed that these three markets of the EUAs seems to be efficiency, except after the European Commission announcements of stricter Phase II allocation in October 2006, suggesting the possibility of abnormal returns through speculation. Note that the first disclosure of 2005 verified emissions implying a sudden allowance price collapse in April 2006 did not appear to affect the efficiency. Finally, we found that the CO_2 spot prices seem to be weak-form efficiency during the Phase II since the MDH is failed to reject from both daily and weekly data.

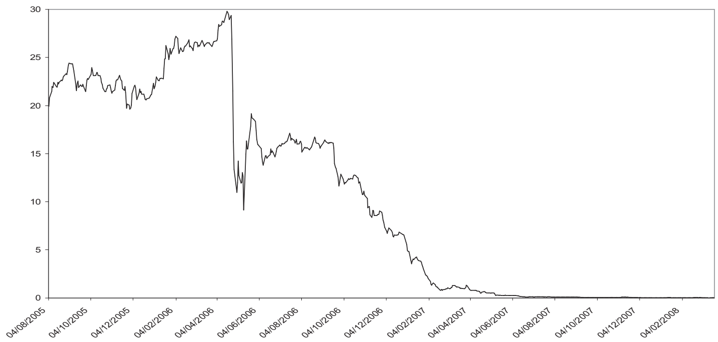
Daskalakis and Markellos (2008) argued that allowing for short selling and for allowance banking between successive phases may increase liquidity and improve the efficiency of the market. It is imperative that policy makers address these issues during the eminent reviewing process, in order to ensure that the EU ETS evolves into a mature, efficient and internationally competitive market.

Further research should investigate the weak-form efficiency on the futures markets.

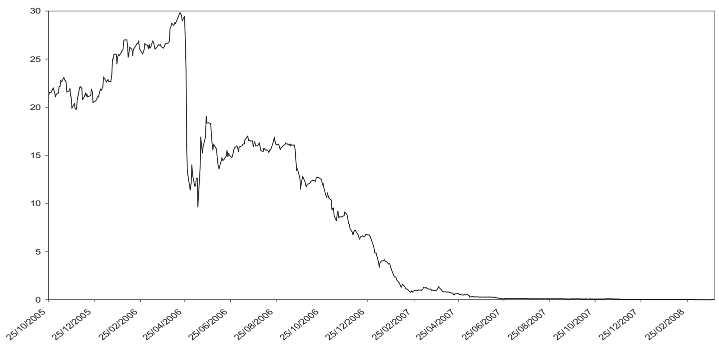
Figure 1: Daily spot prices during Phase I



(a) BlueNext

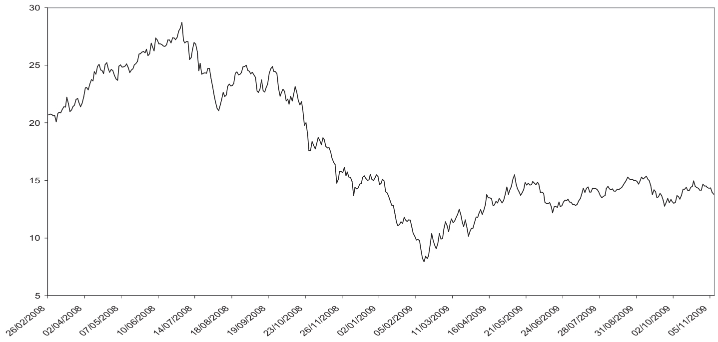


(b) EEX

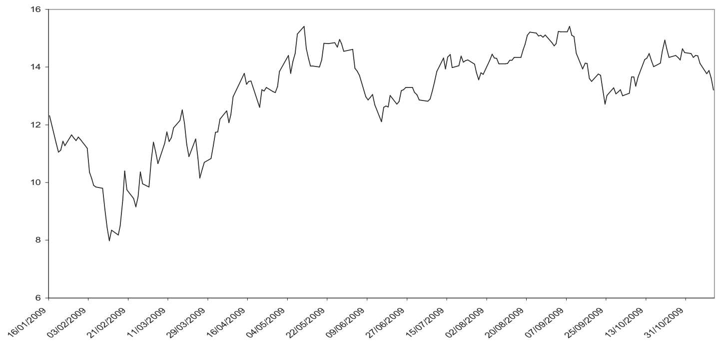


(c) NordPool

Figure 2: Daily spot prices during Phase II



(a) BlueNext



(b) EEX

(c) NordPool

References

[1] Alberola E. and Chevallier J. (2009). European carbon prices and banking restrictions: Evidence from Phase I (2005–2007). The Energy Journal, 30, 51–80.

[2] Alberola E., Chevallier J. and Chèze B. (2008). Price drivers and structural breaks in European carbon prices 2005–2007. Energy Policy, 36, 787–797.

[3] Bai J. and Perron P. (1998). Estimating and testing linear models with multiple structural changes. Econometrica, 66, 47–78.

[4] Bai J. and Perron P. (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18, 1–22.

[5] Benz E. and Trück S. (2009). Modeling the price dynamics of CO_2 emission allowances. Energy Economic, 31, 4–15.

[6] Boemare C. and Quirion P. (2002). Implementing greenhouse gas trading in Europe: Lessons from economic literature and international experiences. Ecological Economics, 43, 213–230.

[7] Böhringer C. and Lange A. (2005). On the design of optimal grandfathering schemes for emission allowances. European Economic Review, 49, 2041–2055.

[8] Boutaba M.A. (2008). Dynamic linkages among European carbon markets. Economics Bulletin, 29, 513–525.

[9] Charles A. and Darné O. (2009). Variance ratio tests of random walk: An overview. Journal of Economic Surveys, 23, 503–527.

[10] Chen W.W. and Deo R.S. (2006). The variance ratio statistic at large horizons. Econometric Theory, 22, 206–234.

[11] Choi I. (1999). Testing the random walk hypothesis for real exchange rates. Journal of Applied Econometrics, 14, 293-308.

[12] Chow K.V. and Denning C. (1993). A simple multiple variance ratio test. Journal of Econometrics, 58, 385–401.

[13] Daskalakis G. and Markellos R.N. (2008). Are the European carbon markets efficient? Review of Futures Markets, 17, 103–128.

[14] Daskalakis G., Psychoyios D. and Markellos R.N. (2009). Modeling CO_2 emission allowance prices and derivative: Evidence from the European trading scheme. Journal of Banking and Finance, 33, 1230–1240.

[15] Ellerman A.D. and Buchner B.K. (2008). Over-allocation or abatement? A preliminary analysis of the EU ETS based on the 2005-2006 emissions data. Environmental and Resource Economics, 41, 267–287.

[16] Ellerman A.D., Buchner B. and Carraro C. (2007). The allocation of European Union allowances: Lessons, Unifying Themes and General Principles. Cambridge University Press, Cambridge.

[17] Escanciano J.C. and Lobato I.N. (2009b). Testing the Martingale Hypothesis. In Patterson K. and Mills T.C. (eds) Palgrave Hand-book of Econometrics, Palgrave, MacMillan.

[18] Fama E. (1970). Efficient capital markets: A review of theory and empirical work. Journal of Finance, 25, 383–417.

[19] Fama E. (1991). Efficient capital markets: II. Journal of Finance, 46, 1575–1617.

[20] Fama E. (1998). Market efficiency, long-term returns, and behavioral finance. Journal of Financial Economics, 49, 283–306.

[21] Fama E. and French K.R. (1988). Permanent and temporary components of stock prices. Journal of Political Economy, 96, 246–273.

[22] Hintermann B. (2010). Allowance price drivers in the first phase of the EU ETS. Journal of Environmental Economics and Management, 59, 43–56.

[23] Hoque H.A.A.B., Kim J.H. and Pyun C.S. (2007). A comparison of variance ratio tests of random walk: A case of Asian emerging stock markets. International Review of Economics and Finance, 16, 488–502.

[24] Kim J.H. (2006). Wild bootstrapping variance ratio tests. Economics Letters, 92, 38–43.

[25] Kim J.H. (2009). Automatic variance ratio test under conditional heteroskedasticty. Finance Research Letters, 6, 179-185.

[26] Kim J.H. and Shamsuddin A. (2009). Are Asian stock markets efficient? Evidence from new multiple variance ratio tests. Journal of Empirical Finance, 15, 518–532.

[27] Kling C. and Rubin J.D. (1997). Bankable permits for the control of environmental pollution. Journal of Public Economics, 64, 101–115.

[28] Kosobud R.F., Stokes H.H. and Tallarico C.D. (2002). Tradable environmental pollution credits: A new financial asset. Review of Accounting and Finance, 4, 69–88.

[29] Lee Y-S., Kim T-H. and Newbold P. (2006). Spurious rejections by variance ratio tests in the presence of a break in drift. Working paper, Durham University.

[30] Lo A.W. and MacKinlay A.C. (1988). Stock market prices do not follow random walk: Evidence from a simple specification test. Review of Financial Studies, 1, 41–66.

[31] Lo A.W. and MacKinlay A.C. (1989). The size and power of the variance ratio test in finite samples: A Monte Carlo investigation. Journal of Econometrics, 40, 203–238.

[32] Lo A.W. and MacKinlay A.C. (2001). A Non-Random Walk Down Wall Street. Princeton University Press, Princeton.

[33] Mammen E. (1993). Bootstrap and wild bootstrap for high dimensional linear models. Annals of Statistics, 21, 255–285.

[34] Mansanet-Bataller M., Pardo A. and Valor E. (2007). CO_2 prices, energy and weather. The Energy Journal, 28, 67–86.

[35] Milunovich G. and Joyeux R. (2007). Market efficiency and price discovery in the EU carbon futures market. Working paper, Macquarie University.

[36] Paolella M.S. and Taschini L. (2008). An econometric analysis of emission allowance prices. Journal of Banking and Finance, 32, 2022–2032.

[37] Rubin J.D. (1996). A model of intertemporal emissions trading, banking, and borrowing. Journal of Environmental Economics and Management, 31, 269–286.

[38] Schleich J., Ehrhart K.-M., Hoppe C. and Seifert S. (2006). Banning banking in EU emissions trading? Energy Policy, 34, 112–120.

[39] Seifert J., Uhrig-Homburg M. and Wagner M. (2008). Dynamic behavior of CO_2 spot prices. Journal of Environmental Economics and Management, 56, 180–194.

[40] Stern N. (2007). The Economics of Climate Change: the Stern Review. Cambridge University Press, Cambridge.

[41] Svendsen G.T. and Vesterdal M. (2003). How to design greenhouse gas trading in the EU? Energy Policy, 31, 1531–1539.

[42] Trück S., Borak S., Härdle W. and Weron R. (2007). Convenience yields for CO_2 emission allowance futures contracts. Working paper, Humboldt-University of Berlin.

[43] Uhrig-Homburg M. and Wagner M. (2007). Futures price dynamics of CO_2 emission certificates – An empirical analysis. Working paper, University of Karlsruhe.

[44] Vesterdal M. and Svendsen G.T. (2004). How should greenhouse gas permits be allocated in the EU? Energy Policy, 32, 961–968.

Testing the Speculative Efficiency Hypothesis on CO_2 Emission Allowance Prices: Evidence from Bluenext[*]

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Abstract

In this paper, we attempt to examine the speculative efficiency hypothesis on CO_2 emission allowance prices negotiated on Bluenext, by testing the relationship between futures and spot prices from the Fama (1970) framework. This approach is based on the joint hypothesis of no risk premium and unbiasedness of futures prices. Cointegration tests are performed to confirm the legitimacy of futures and spot prices being included in the regression, following the approach proposed by Balke and Fomby (1997). The results indicate the absence of linear and nonlinear cointegration relationship between spot and futures prices. The speculative efficiency hypothesis did not hold even if the joint hypothesis is not rejected because of the existence of serial correlation in the residuals.

Keywords: CO_2 emission allowances; Cointegration; Spot and futures prices; Market efficiency.

JEL Classification: G13; G14; Q50.

1 Introduction

On January 2005, the European Union Emission Trading Scheme (EU ETS) went into effect. The EU ETS is one of the most important initiatives taken to reduce the greenhouse gas (GHG) emissions (primarily CO_2) that cause climate change (Kyoto protocol). The European Union (EU)[1] includes approximately 11,500 participating installations spread across twenty-seven member states. In 2010, it is estimated that the sources to which the trading scheme applies account for 45 per cent of CO_2 emissions and a little less than 40 per cent of total GHG emissions in that year.

The EU ETS introduces a cap-and-trade system, which operates through the creation and distribution of tradable rights to emit, usually called EU allowances (EUAs), to installations. Since a constraining cap creates a scarcity rent, these EUAs have value. The distribution of these rights for free is called allocation and is the unique feature of cap-and-trade system. The cap-and-trade scheme operates over discrete periods, with the first or pilot period (Phase I, 2005-2007) and with the second period corresponding to the first commitment period of the Kyoto Protocol. This period will extend from 2008 to 2012 (Phase II) and will be followed by a third period from 2013 to 2020 (Phase III). The EU target is a reduction of 8 per cent below 1990 emissions in the 2008-2012 period. To help countries in achieving their reduction objectives, the Protocol includes three flexibility mechanisms: The creation of an international carbon market, Joint Implementation and the Clean Development Mechanism.[2]

The EU ETS includes spot, futures, and option markets with a total market value of

[1]To improve the fluidity of the EU ETS, organized allowance trading has been segmented across trading platforms: Nordic Power Exchange (Nord Pool) in Norway began in February 2005, European Energy Exchange (EEX) in Germany began in March 2005, European Climate Exchange (ECX) based in London and Amsterdam started in April 2005, BlueNext in France and Energy Exchange Austria (EEA) in Austria began in June 2005, and SendeCO2 in Spain started at the end of 2005.

[2]Joint Implementation (JI) projects do not create credits, but rather transfer reduction units from one country to another. The aim of Clean Development Mechanism (CDM) projects is to promote investments in developing countries by industrialized nations and to encourage the transfer of low-emission technologies.

72 billion Euros in 2010. Futures contracts account for a wide part of this value (about 87% in 2010).. Understanding the relationship between spot and futures prices is thus of crucial importance for all participants in the carbon market. Carbon trading works only if markets for carbon provide enough liquidity and pricing accuracy, i.e., markets provide prices that are useful for hedgers and other users of carbon markets. The efficiency of the CO_2 market is particularly important for emission intensive firms, policy makers, risk managers and for investors in the emerging class of energy and carbon hedge funds.

As pointed out by Fama (1970), a financial market can be considered as efficient if prices fully reflect all available information and no profit opportunities are left unexploited known as the weak-form efficiency or speculative efficiency hypothesis. Speculative efficiency is essential for an operator who wants to hedge on the futures market against any possible price fluctuations. According to the futures markets literature, the model that futures prices are unbiased estimators of future spot prices is the appropriate framework to test efficiency. Using this model, efficiency will necessarily imply that the market price fully reflects available information and thus there exists no strategy that traders can speculate in the futures market on the future levels of the spot prices exploiting profits consistently. One way to test the link between spot and futures prices is to use cointegration tests.[3] In others words, it should expect spot and futures prices for any commodity to be linked through a long-run equilibrium relationship because it can be argued that spot and futures prices are driven by the same fundamentals. Evidence of no cointegration seems to be consistent with the speculative market hypothesis. Indeed, economic theory suggests that cointegration is unlikely to be observed in efficient markets (Granger, 1986). Another way to test whether futures prices are the best predictors of the spot prices is to use the regression proposed by Fama (1970). In this approach, market efficiency requires that futures prices should be unbiased predictors of future spot prices and

[3]Cointegration is a necessary condition for market efficiency but nor a sufficient condition. A test for serial correlation is needed to infer about market efficiency.

residuals of the regression are not serially correlated. Simple empirical tests are based on the joint hypothesis of market efficiency and unbiasedness of futures prices (risk neutrality).

Although relevant papers have been published on the behavior of emission allowance spot and futures prices (see, e.g., Alberola et al., 2008; Daskalakis and Markellos, 2008; Paolella and Taschini, 2008; Seifert et al., 2008; Benz and Trück, 2009), studies on CO_2 market efficiency are rather sparse. Alberola and Chevallier (2009), Uhrig-Homburg and Wagner (2009) and Joyeux and Milunovich (2010) study the relationship between spot and futures prices from the cost-of-carry model. However, Daskalakis and Markellos (2008) and Daskalakis et al. (2008) have some doubts on the applicability of a cost-of-carry model because of the EU ETS is a very young market means that significant differences in terms of stakeholders, liquidity, information and pricing may exist between spot and futures markets. Recently, Chevallier (2010) analyzes the relation between spot and futures prices using daily data from February 26, 2008 to April 15, 2009.[4] He rejects a cointegrating relationship between CO_2 allowances spot and futures prices when accounting for the presence of a structural break in February 2009, possibly due to the delayed impact of the "credit crunch" crisis. A vector autoregression analysis indicates that futures prices are relevant for price information in the spot market (the opposite is not true). Charles et al. (2011) examine the martingale difference hypothesis (MDH) within the EU ETS during the Phase I and the Phase II, using both daily and weekly data over the 2005-2009 period. Their results indicate that for the Phase I, the spot price changes are predictable, suggesting the possibility of abnormal returns through speculation. The authors fail to rejet the MDH during the Phase II, meaning that the European carbon market seems to be weak-form efficient.

The aim of this paper is to investigate the speculative efficiency hypothesis between spot and futures prices in order to provide empirical evidence for efficiency on the EU

[4] Note that Chevallier (2010) employ the daily spot prices negotiated on BlueNext and the daily futures prices negotiated on ECX when investigating the relation between spot and futures prices.

ETS. We thus study the daily spot et futures prices negotiated on Bluenext, covering the period from February 22, 2008 to October 20, 2010, namely the Phase II.[5] We test the joint hypothesis of market efficiency and unbiasedness of futures prices from the Fama (1970) regression. As it is well known that appropriate tests for efficiency and unbiasedness are necessarily dependent upon the underlying time-series properties of the data, we first use various unit roots tests, and we then apply linear (Johansen, 1995) and nonlinear (Seo, 2006) cointegration tests following the approach proposed by Balke and Fomby (1997).

The remainder of this paper is organized as follows: Section 2 presents the speculative efficiency hypothesis. The empirical framework is discussed in Section 3. The conclusion is drawn in Section 4.

2 The Speculative Efficiency Hypothesis

Theoretically, if spot and futures markets operate efficiently and are frictionless, futures contracts should be traded at a price known as the fair value. The starting point of most studies is the arbitrage free or cost-of-carry model in which the futures price is represented as

$$F_t = S_t e^{(r+u-d)(T-t)} \tag{1}$$

where F_t is the futures price at time t; S_t is the spot price at time t; r is the risk-free interest rate; u is the storage cost; d is the convenience yield; and T is the expiration date of the futures contract and $(T-t)$ is the time of expiry of the futures contract. Taking logarithms of both sides of equation (1) gives

$$\mathrm{Ln}(F_t) = \mathrm{Ln}(S_t) + (r+u-d)(T-t) \tag{2}$$

[5]BlueNext is the most liquid spot CO_2 exchanges operating under the EU ETS. Contrarily to others studies (Uhrig-Homburg and Wagner, 2009; Chevallier, 2010) we take the futures prices negotiated also on Bluenext but not on ECX, which is the most liquid futures exchange for EUAs, to have the data negotiated on the same market.

This equation suggests that the long-term relationship between the logs of the spot and futures prices should be one to one.

In practice, researchers have had difficulty testing the arbitrage relationship embodied in equation (2) due to the unobservable nature of storage costs and convenience yields (Joyeux and Milonovich, 2010). Hence, most studies have focused on the Fama (1970) speculative market efficiency tests of the form

$$S_t = \alpha + \beta F_{t-1} + \varepsilon_t \tag{3}$$

In this approach, market efficiency requires that futures prices should be unbiased predictors of future spot prices. Simple empirical tests of the speculative efficiency hypothesis are based on tests of the joint hypothesis $\alpha = 0$ and $\beta = 1$. Failure to reject the joint hypothesis implies that the futures price determined at time $t-1$ is an unbiased predictor of the spot price for time t. However, statistical rejection of this joint hypothesis means either that there is a risk premium ($\alpha \neq 0$) or that the market is inefficient ($\beta \neq 1$). As underlined by Bilson (1981), it is important to note, however, that best unbiased forecasting by the futures price is not a necessary component of an efficient markets approach. It is easy, for example, to construct a model in which markets are efficient in the sense of removing any opportunities for risk-adjusted excess returns but in which there is a predictable bias in the futures price forecast.

It is well known that appropriate tests for efficiency and unbiasedness are necessarily dependent upon the underlying time-series properties of the data. If the price series are non-stationary, hypothesis tests based on equation (3) will give biased results. Regressing a non-stationary variable, which can only be made stationary by differencing on a deterministic trend, generally leads to the problem of a spurious regression, involving invalid inferences based on t- and F-tests (Granger and Newbold, 1974). In such cases the researcher could falsely conclude that a relationship exists between two unrelated non-stationary series. One way to circumvent the stationary problem is to estimate equation (3) in first-difference form (Hansen and Hodrick, 1980)

$$\Delta S_t = \gamma + \delta \Delta F_{t-1} + \varepsilon_t \tag{4}$$

where Δ is the first-difference operator. Market efficiency and unbiasedness are jointly implied by the restrictions $\gamma = 0$ and $\delta = 1$.

Nevertheless, it is well known that equation (4) are misspecified if the two series (spot and futures prices) are cointegrated, that is to say if they have the same stochastic trend in common. When two price series, such as the future and the spot price series, are both integrated of the same order d, a linear combination of two $I(d)$ series can be integrated of an order lower than d. More specifically, it is possible that two series that are non-stationary and contain a unit root, for example $I(1)$, can generate a linear combination that is stationary, $I(0)$. These two series are said to be cointegrated with a cointegrating relationship of the following form

$$\varepsilon_t = S_t - \alpha - \beta F_{t-1} \tag{5}$$

If the two series are cointegrated, i.e. showing a stable common relationship in the long term, it is possible that the movement of one asset is linked to the movement of other asset. Thus, the establishment of a cointegration relationship is equivalent to the existence of an error correction term, which implies that in the face of a deviation of one asset price from the induced long-run relationship. Indeed this term describes the adjustment process due to disequilibrium. In the case of cointegration relationship between spot and futures prices, it is necessary to use an error correction representation described in Granger (1986)

$$\Delta S_t = -\rho\varepsilon_{t-1} + \theta\Delta F_{t-1} + \sum_{i=2}^{m} \theta_i \Delta F_{t-i} + \sum_{j=1}^{n} \psi_i \Delta S_{t-j} + \nu_t \tag{6}$$

where ε_{t-1} is the error correction term, and ν_t is a stationary white-noise residual term. Cointegration implies $\rho > 0$ because spot price changes respond to deviations from long-run equilibrium. The speculative hypothesis implies the following restrictions $\rho = 1$, $\theta \neq 0$ and $\theta_i = \psi_i = 0$.

3 Empirical results

The study sample consists of the daily closing prices of spot EUA prices from February 22, 2008 to October 20, 2010 (661 observations) and futures EUA prices of maturity

December 2010, December 2011 and December 2012 from April 21, 2008 to October 20, 2010 (624 observations) both negotiated on BlueNext.[6] Figure 1 provides a graphical representation of the spot and futures series. Note that the futures prices are higher than spot prices. This market condition is known as contango. Note that as the futures contract approaches to its maturity date, the difference between futures and spot prices is smaller and diminishes to zero at maturity since spot and futures prices converge.

We apply various unit root tests on spot and futures prices and find that all price series are characterized by a unit root (Table 1). When tests are applied on series in first-difference, they are found to be stationary. In other words, all price series are integrated of order 1. These results confirm those obtained by Alberola et al. (2008), Daskalakis et al. (2009), Chevallier (2009) and Alberola and Chevallier (2009).

Table 2 presents summary statistics for the returns calculated as the first differences in the logs of the EUA spot and futures prices. The kurtosis coefficient is significant for the both series, implying that the distribution of the log-returns is leptokurtic and thus the variance of the CO_2 prices is principally due to infrequent but extreme deviations. A leptokurtic distribution has a more acute peak around the mean and fat tails. The Lagrange Multiplier test for the presence of the ARCH effect clearly indicates that the log-returns show strong conditional heteroscedasticity, which is a common feature of financial data. In other words, there are quiet periods with small price changes and turbulent periods with large oscillations. Moreover, the skewness coefficient is negative and significant only for the spot series, implying that there is more negative log-returns than positive log-returns. This result means that the distribution of the spot price changes is asymmetric. No evidence of skewness is found in the futures log-returns.[7]

To test for cointegration between the spot and futures prices, both linear

[6] Data for Bluenext are available on www.bluenext.fr.

[7] Note that the spot prices display less volatility (measured by standard deviation) than do futures prices. This can suggest that the investors tend to be less conservative in their trading approach and take price shocks in the spot market seriously.

(Johansen,1995) and nonlinear (Seo, 2006) tests following the approach proposed by Balke and Fomby (1997) are used.

We first implement the Johansen maximum likelihood procedure (Johansen, 1988, 1991). This approach consists in estimating a Vector Error Correction Model (VECM) by maximum likelihood, under various assumptions about the trend or intercept parameters and the number r of cointegrating vectors, then conducting likelihood ratio tests. We write a p-dimensional VECM as follows

$$\Delta y_t = A' X_{t-1}(\beta) + u_t$$

with

$$X_{t-1} = \left\{ \begin{array}{ccccc} 1 & w_{t-1}(\beta) & \Delta x_{t-1} & \dots & \Delta x_{t-n} \end{array} \right\}'$$

where x_t is a p-dimensional $I(1)$ time series which is cointegrated with one $(p \times 1)$ cointegrating vector β, $w_t(\beta) = \beta' x_t$ is the $I(0)$ error-correction term, u_t is an error term, and A is a coefficient matrix.

Johansen (1995) considers five restrictions on the deterministic components. In model 1 the level data y_t have no deterministic trends and the cointegrating equations do not have intercepts, giving the most restrictive specification. In model 2 the level data y_t have no deterministic trends and the cointegrating equations have intercepts. In model 3 the level data y_t have linear trends but the cointegrating equations have only intercepts. In model 4 the level data y_t and the cointegrating equations have linear trends. In model 5 the level data y_t have quadratic trends and the cointegrating equations have linear trends, giving the least restrictive specification. These five cases are nested from the most restrictive to the least restrictive. As noted by K*ü*hl (2007), the formulation of the model has important implications for testing the market efficiency hypothesis. To obtain the correct model, statistical inferences must be carefully examined first. A LR test is thus carried out (Johansen, 1994). The form of the LR tests is as follows

$$LR = -T \sum_{i=r+1}^{p} \ln \left[\frac{1-\hat{\lambda}_i^j}{1-\hat{\lambda}_i^k} \right] \qquad \text{with } j,k = 1,\dots,5 \text{ and } j \neq k. \tag{7}$$

From the results reported in Table 3, we concluded that model 1 seems to be the most appropriated to test the cointegration relationship between the spot and futures price series.

Johansen (1988, 1991) proposes two LR test statistics to test whether there is no cointegration under the null against the alternative linear cointegration. The first test, called lambda max test, is based on the log-likelihood ratio

$$\mathrm{LR}(r|r+1) \quad = \quad -T\ln(1-\lambda_{r+1})$$

where T is the sample size, k is the number of endogenous variables, and $r = 0,1,\ldots,k-1$. This LR test tests the null hypothesis that the cointegration rank is equal to r against the alternative that the cointegration rank is equal to $r+1$.
The second test, called the trace test, is based on the log-likelihood ratio

$$\mathrm{LR}(r|k) \quad = \quad -T\sum_{i=r+1}^{k}\ln(1-\lambda_i)$$

where λ_i is the largest eigenvalue of the A matrix in equation, k is the number of endogenous variables, and $r = k-1,\ldots,1,0$. This LR test tests the null hypothesis of r cointegrating relations against the alternative of k cointegrating relations, where k is the number of endogenous variables, for $r = 0,1,\ldots,k-1$.
Results of these tests are given in Table 4.[8]

The null hypothesis of none cointegrating vector between the spot and futures prices cannot be rejected, implying that the linear VECM does not seem to be the most suitable model for the data of interest. This finding is in contradiction with that of Chevallier (2010). This difference can be explained by the fact that Chevallier (2010) employs (i) the daily spot prices negotiated on BlueNext and the daily futures prices negotiated on ECX when investigating the relation between spot and futures prices; and (ii) a shorter period (February 26, 2008 to April 15, 2009) than our period of interest. Evidence of no cointegration seems to be consistent with the speculative effi-

[8]We have to specify the lags of the test VAR to apply the Johansen cointegration tests. We use the traditional criteria (Akaike, Schwarz, Hannan-Quinn, Final Prediction Error) to select the optimal lag length.

ciency hypothesis.[9] Indeed, economic theory suggests that cointegration is unlikely to be observed in efficient markets (Granger, 1986). The Equation 6 means that the price of one asset does not only depend on its own past prices but also on the history of a different asset's prices, implying that the speculative efficiency hypothesis is violated (Richard, 1995).

Nevertheless, as pointed by Balke and Fomby (1997), the concept of cointegration is based on the implicit assumption that the adjustment of the deviations towards the long-run equilibrium is made instantaneously at each period. There are nevertheless serious arguments in economic theory to invalidate this assumption of linearity.[10] Moreover, in the linear cointegration context, increases or decreases of the deviations are deemed to be corrected in the same way. Again, several theoretical arguments may contest this assumption, such as the presence of menu costs (Levy et al., 1997), market power (Ward, 1982) or simply small country versus rest of the world effects. Balke and Fomby (1997) introduce the concept of threshold cointegration.[11] In their nonlinear framework, the adjustment does not need to occur instantaneously but only once the deviations exceed some critical threshold, allowing thus the presence of an inaction or no-arbitrage band. While their work focused on the long-run relationship representation, extension to a threshold VECM has been made by several authors, the threshold effect being applied to the anticipations by the agents of interventionary policy only to the error-correction term (Seo, 2006) or to the lags and the intercept as well (Hansen and Seo, 2002). Moreover, spurious cointegration can occur when there are breaks in the deterministic component (level or slope) of each time series

[9]Cointegration is a necessary condition for market efficiency but not a sufficient condition. A test for serial correlation is needed to infer about market efficiency.

[10]Among them, the presence of transaction costs is maybe the most noteworthy, as it implies that adjustment will occur only once deviations are higher than the transactions costs, and hence adjustment should not happen instantaneously and at each time. Financial theory predicts that even in highly liquid markets a so-called band of no arbitrage may exist where deviations are too small for the arbitrage to be profitable.

[11]See Stigler (2010) for an updated survey on threshold cointegration.

(Leybourne and Newbold, 2003) or in the variance of the innovation errors of each time series (Noh and Kim, 2003).

A nonlinear VECM may be denoted as

$$\Delta y_t = \begin{cases} A_1' X_{t-1}(\beta) + u_t & \text{if} \quad w_{t-1}(\beta) \leq \gamma \\ A_2' X_{t-1}(\beta) + u_t & \text{if} \quad w_{t-1}(\beta) > \gamma \end{cases}$$

with

$$X_{t-1} = \left\{ \begin{array}{ccccc} 1 & w_{t-1}(\beta) & \Delta x_{t-1} & \ldots & \Delta x_{t-n} \end{array} \right\}'$$

where x_t is a p-dimensional $I(1)$ time series which is cointegrated with one $(p \times 1)$ cointegrating vector β, $w_t(\beta) = \beta' x_t$ is the $I(0)$ error-correction term, u_t is an error term, A_1 and A_2 are coefficients matrices that describe the dynamics in each of the regimes, and γ is the threshold parameter.

The approach advocated by Balke and Fomby (1997) is to conduct a two-step analysis: If linear cointegration is not rejected, tests for threshold cointegration with linear under the null should be used. Failure of cointegration in the first step should lead to the use of tests with no cointegration under H_0 and threshold cointegration under the alternative. As the null hypothesis of none cointegrating relations is not rejected, we use the test developped by Seo (2006). The null hypothesis of no-linear cointegration is tested against the alternative of threshold cointegration. This test is superior to its precursors, such as those proposed by Balke and Fomby (1997) and Hansen and Seo (2002), where the standard test for linear cointegration is used for threshold cointegration.[12] The test statistic, denoted supW, is the supremum of the Wald test statistics for the null hypothesis, calculated from a grid of γ values over its parameter space. The statistic is denoted as

$$\text{supW} = \sup_{\gamma \in \Gamma} W_n(\gamma) \tag{8}$$

with γ the threshold parameter. Seo (2006) proves that, under certain conditions, the

[12] According to Seo (p.130, 2006), their approach is misleading and can cause substantial power loss.

supW converges to a function of the Brownian motion, free from nuisance parameters. For improved size and power properties in small samples, Seo (2006) proposes the bootstrap based on residual resampling, which approximates the sampling distribution of the supW statistic under the null. According to his Monte Carlo experiment, the bootstrap test shows desirable size properties and high power, especially when the sample size is as large as or more than 250. The result reported on Table 4 indicates that the null hypothesis of no cointegration cannot be rejected.

Thus, we can conclude that the spot and futures log-returns do not seem to be cointegrated.[13] As the two series are $I(1)$, we can estimate equation (4) to test the speculative efficiency hypothesis. As heteroskedasticity was found in the spot and futures prices (see Table 2), the models are estimated with the White heteroskedastic-consistent standard errors. Estimates of equation (4) is presented in Table 5. The results indicate that there is no evidence of a time-varying risk premiums ($\gamma = 0$). The null hypothesis $\delta = 1$ is rejected at the 5% level, implying that the futures prices of maturity 2010 and 2011 do not seem to be the best forecasts of the future spot prices. Nevertheless, the joint hypothesis of market efficiency and unbiasedness is not rejected, meaning that futures prices of maturity 2010 and 2011 appear to be the unbiased predictors of spot prices. [14] The result of the joint test is not the same of the futures series of maturity 2012. Indeed, the Wald test is rejected implying that futures prices of maturity 2012 are not the best predictors of spot prices. Our findings suggest that cointegration exists on the short term, not on the long-run. This phenomenon can be a particularity of the carbon markets which operates by phases. Market participants may consider 2012 as the end of the second phase and prefer waiting before taking any decision about 2012.

Nevertheless, the acceptance of the restrictions on parameters (γ and δ) are not a necessary and sufficient condition for market efficiency. The serial independence of

[13]Masih and Masih (2002) suggested that cointegration of commodity markets does not exist if there is either a non-stationary risk premium or a non-stationary convenience yield.

[14]The joint test is more powerful than the individual tests.

residuals is an important condition for market efficiency. Indeed, residual correlation implies that spot prices rely on past spot prices in addition to current futures prices, thus violating market efficiency. If the parameter restrictions and serial independence of residuals are met, then the market is efficient and futures prices provide unbiased estimates of future spot prices. The Breusch-Godfrey test is applied to check the presence of serial correlation (Table 5) and indicates that the null hypothesis of no serial correlation is rejected, which casts some doubt on the efficiency of the market. As the two above conditions are not met, the market does not seem to be efficient.

4 Conclusion

This paper investigated the speculative efficiency hypothesis on CO_2 emission allowance prices negotiated on Bluenext, by testing the joint hypothesis of market efficiency and unbiasedness of futures prices. The unit root tests concluded that spot and futures prices are non-stationary in levels but stationary in first-difference. The spot and futures prices are tested for cointegration using both linear (Johansen, 1995) and nonlinear (Seo, 2006) tests following the approach proposed by Balke and Fomby (1997). The results indicate the absence of linear and nonlinear cointegration relationship between spot and futures prices. The speculative efficiency hypothesis did not hold even if the restrictions on the parameters are not rejected because of the existence of serial correlation of residuals.

Understanding the relationship between spot and futures prices is thus of crucial importance for all participants in the carbon market. Carbon trading works only if markets for carbon provide enough liquidity and pricing accuracy, i.e., markets provide prices that are useful for hedgers and other users of carbon markets. The efficiency of the CO_2 market is particularly important for emission intensive firms, policy makers, risk managers and for investors in the emerging class of energy and carbon hedge funds. If carbon markets are inefficient the policy implications are that there is a greater role for regulation to improve information flows and reduce market manipulation (Stout, 1995). It is imperative that policy makers address these issues during the eminent reviewing process, to ensure that the EU ETS evolves into a mature, efficient and internationally competitive market.

Table 1: Results of unit root tests

Data	ERS	NP1	NP2	KPSS	KSS
Series in level					
Spot data	-0.220	-0.252	-0.217	1.431	-0.248
Dec10 Futures data	-0.067	-0.072	-0.068	1.592	-0.294
Dec11 Futures data	-0.152	-0.171	-0.148	1.633	-0.419
Dec12 Futures data	-0.158	-0.183	-0.153	1.667	-0.366
Series in first-difference					
Spot data	-2.368	-10.044	-2.233	0.319	-3.194
Dec10 Futures data	-2.791	-10.141	-2.739	0.298	-4.298
Dec11 Futures data	-3.425	-10.164	-2.902	0.276	-3.667
Dec12 Futures data	-3.355	-10.172	-2.926	0.249	-3.683
Critical value	-1.94	-8.10	-1.98	0.463	-2.93

Notes: The unit root tests are the efficient tests of Elliott, Rothernberg and Stock (1996, ERS) and Ng and Perron (2001, NP1 and NP2), the stationarity test of Kwiatkowski et al. (1992, KPSS), the nonlinear test of Kapetanios et al. (2003, KSS). ^{a} means significant at the 5% level.

Table 2: Statistical analysis of log-returns series

Data	Obs.	Mean (%)	SD	Skewness	Kurtosis	ARCH(10)
Spot data	623	-0.076	0.026	-1.194**	4.733**	15.303**
Dec10 Futures data	623	-0.084	0.025	-0.130	4.735**	16.680**
Dec11 Futures data	623	-0.086	0.025	-0.131	4.836**	15.652**
Dec12 Futures data	623	-0.087	0.024	-0.143	4.939**	14.405**

Notes: The skewness and kurtosis statistics are standard-normally distributed under the null of normality distributed returns. ARCH(10) indicates the Lagrange multiplier test for conditional heteroscedasticity with 10 lags. ** means significant at the 5% level. The futures data are the futures of maturity December 2010.

Table 3: Test for deterministic components in VECM

	Test statistic		
Null hypothesis	Dec10	Dec11	Dec12
Model 1 in model 2	-6.10	-4.75	-4.04
Model 2 in model 3	1.07	1.10	1.13
Model 3 in model 4	-6.76	-8.16	-8.34
Model 4 in model 5	2.15	2.75	3.70

Notes: The test statistic is asymptotically distributed as χ^2 with $(p-r)$ degrees of freedom with p the lag length and r the number of cointegration relationships. ** means significant at the 5% level.

Table 4: Cointegration tests

Hypotheses	*Johansen test*					
	Dec10		Dec11		Dec12	
	t-stat	p-value	t-stat	p-value	t-stat	p-value
Lambda max test						
$r \leq 0$	4.21	0.59	4.36	0.57	4.36	0.57
$r \leq 1$	0.11	0.79	0.27	0.67	0.41	0.59
Trace test						
$r \leq 0$	4.32	0.67	4.63	0.62	4.77	0.60
$r \leq 1$	0.11	0.79	0.27	0.67	0.41	0.59
	Seo test					
	Dec10		Dec11		Dec12	
	t-stat	p-value	t-stat	p-value	t-stat	p-value
no coint / threshold cointegration	20.71	1.00	18.09	1.00	18.93	1.00

Notes: ** means significant at the 5% level.

Figure 1: Spot and futures price series in log-returns

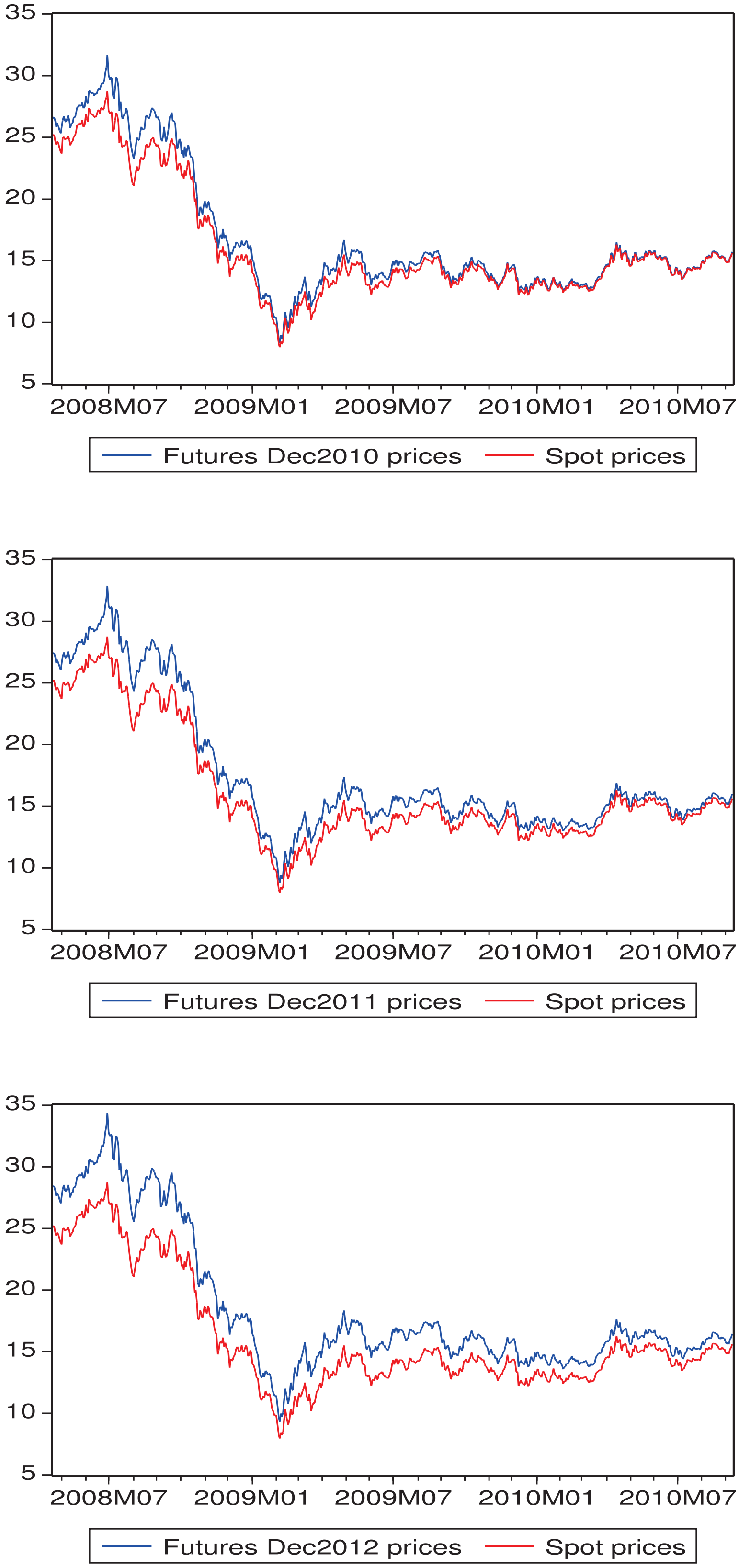

Table 5: Fama's regression

Model	γ	δ	Wald	BG
	Dec10			
$\Delta S_t = \gamma + \Delta F_t + \varepsilon_t$	$7.01 10^{-5}$ (0.80)	0.99^{**} (0.00)	0.75 (0.48)	22.20^{**} (0.00)
	Dec11			
$\Delta S_t = \gamma + \Delta F_t + \varepsilon_t$	$1.03 10^{-4}$ (0.72)	1.00^{**} (0.00)	0.07 (0.93)	14.41^{**} (0.00)
	Dec12			
$\Delta S_t = \gamma + \Delta F_t + \varepsilon_t$	$-6.88 10^{-4}$ (0.50)	0.09^{**} (0.03)	227.72 (0.00)	2.93^{**} (0.00)

Notes: ** means significant at the 5% level. BG represents the Breusch-Godfrey LM test for serial correlation. The test statistic is asymptotically distributed as χ^2 with p degrees of freedom where p represents the lag length.

References

[1] Alberola, E., Chevallier, J. (2009). European carbon prices and banking restrictions: Evidence from Phase I (2005–2007). The Energy Journal, 30, 51–80.

[2] Alberola, E., Chevallier, J., Chèze, B. (2008). Price drivers and structural breaks in European carbon prices 2005–2007. Energy Policy, 36, 787–797.

[3] Balke, N.S., Fomby, T.B. (1997). Threshold cointegration. International Economic Review, 38, 627–645.

[4] Benz, E., Trück, S. (2009). Modeling the price dynamics of CO_2 emission allowances. Energy Economic, 31, 4–15.

[5] Bilson, J. (1981). The speculative efficiency hypothesis. Journal of Business, 54, 435–451.

[6] Breusch, T.S. (1978). Testing for autocorrelation in dynamic linear models. Australian Economic Papers, 17, 334–355.

[7] Charles, A., Darné, O., Fouilloux, J. (2011). Testing the martingale difference hypothesis in CO_2 emission allowances. Economic Modelling, 28, 28–35.

[8] Chevallier, J. (2009). Carbon futures and macroeconomic risk factors: A view from the EU ETS. Energy Economics, 31, 614-625.

[9] Chevallier, J. (2010). A note on cointegrating and vector autoregressive relationship between CO_2 allowances spot and futures prices. Economics Bulletin, 30, 1564–1584.

[10] Daskalakis, G., Markellos, R.N. (2008). Are the European carbon markets efficient? Review of Futures Markets, 17, 103–128.

[11] Daskalakis G., Psychoyios, D., Markellos, R.N. (2009). Modeling CO_2 emission allowance prices and derivative: Evidence from the European trading scheme. Journal of Banking and Finance, 33, 1230–1240.

[12] Elliott, G., Rothenberg, T.J., Stock, J.H. (1996). Efficient tests for an autoregressive unit root. Econometrica, 64, 813–836.

[13] Fama, E. (1970). Efficient capital markets: A review of theory and empirical work. Journal of Finance, 25, 383–417.

[14] Granger, C.W.J (1986). Developments in the study of cointegrated economic variables. Oxford Bulletin of Economics and Statistics, 48, 213–228.

[15] Granger, C.W.J, Newbold, P. (1974). Spurious regressions in econometrics. Journal of Econometrics, 80, 143–159.

[16] Hansen, B.E., Seo, B. (2002). Testing for two-regime threshold cointegration in vector error-correction models. Journal of Econometrics, 110, 293–318.

[17] Hansen, L.P., Hodrick, R.J. (1980). Forward exchange rates as optimal predictors of future spot rates: An econometric analysis. Journal of Political Economy, 88, 829–53.

[18] Johansen, S. (1988). Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12, 231–54.

[19] Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica, 59, 1551–1580.

[20] Johansen, S. (1994). The role of the constant and linear terms in cointegration analysis of nonstationary variables. Econometric Reviews, 13, 205-229.

[21] Johansen, S. (1995). *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*. Oxford: Oxford University Press.

[22] Joyeux, R., Milunovich, G. (2010). Testing market efficiency in the EU carbon futures market. Applied Financial Economics, 20, 803–809.

[23] Kapetanios, G., Shin, Y., Snell, A. (2003). Testing for a unit root in a nonlinear STAR framework. Journal of Econometrics, 112, 359–370.

[24] Kühl, M. (2007). Cointegration in the foreign exchange market and market efficiency since the introduction of the Euro: Evidence based on bivariate cointegration analyses. Discussion Paper CEGE No 68, University of Gottingen.

[25] Kwiatkowski, D., Phillips, P., Schmidt, P., Shin, Y. (1992). Testing the null hypothesis of stationary against the alternative of a unit root: How sure are we that economic time series have a unit root? Journal of Econometrics, 54, 159–178.

[26] Levy, D., Bergen, M., Dutta, S., Venable, R. (1997). Magnitude of menu costs: Direct evidence from large U.S. supermarket chains. The Quarterly Journal of Economics, 112, 791–825.

[27] Leybourne, S.J., Newbold, P. (2003). Spurious rejections by cointegration tests induced by structural breaks. Applied Economics, 35, 1117–21.

[28] Masih, A.M.M., Masih, R. (2002). Propagative causal price transmission among international stock markets: Evidence from the pre and post globalization period. Global Finance Journal, 13, 63–91.

[29] Ng, S., Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. Econometrica, 69, 1519–1554.

[30] Noh, J., Kim, T.H. (2003). Behaviour of cointegration tests in the presence of structural breaks in variance. Applied Economics Letters, 10, 999–1002.

[31] Paolella, M.S., Taschini, L. (2008). An econometric analysis of emission allowance prices. Journal of Banking and Finance, 32, 2022–2032.

[32] Richard, A.J. (1995). Comovements in national stock market returns: Evidence of predictability, but not cointegration, Journal of Monetary Economics, 36, 631–654.

[33] Seifert, J., Uhrig-Homburg, M., Wagner, M. (2008). Dynamic behavior of CO2 spot prices. Journal of Environmental Economics and Management, 56, 180–194.

[34] Seo, M. (2006). Bootstrap testing for the null of no cointegration in a threshold vector error correction model, Journal of Econometrics, 134, 129–150.

[35] Stigler, M. (2010). Threshold cointegration: Overview and implementation in R. Working Paper.

[36] Stout, L.A. (1995). Are stock markets costly casinos? Disagreement, market failure and securities regulation. Virginia Law Review, 81, 611–712.

[37] Uhrig-Homburg, M., Wagner, M. (2009). Futures price dynamics of CO_2 emission certificates – An empirical analysis. The Journal of Derivatives, 17, 73–88.

[38] Ward, R. (1982). Asymmetry in retail, wholesale and shipping point pricing for fresh vegetables. American Journal of Agricultural Economics, 64, 205–212.

MISSION CLIMAT WORKING PAPER

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The EUA-sCER Spread: Compliance Strategies and Arbitrage in the European Carbon Market

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Abstract:

This article studies the price relationships between EU emissions allowances (EUAs) – valid under the EU Emissions Trading Scheme (EU ETS) – and secondary Certified Emissions Reductions (sCERs) – established from primary CERs generated through the Kyoto Protocol's Clean Development Mechanism (CDM). Given the price differences between EUAs and sCERs, financial and industrial operators may benefit from *arbitrage* strategies by buying sCERs and selling EUAs (i.e. selling the EUA-sCER spread) to cover their compliance position between these two assets, as industrial operators are allowed to use sCERs towards compliance with their emissions cap within the European system up to 13.4%. Our central results show that the spread is mainly driven by EUA prices and market microstructure variables and less importantly, as we would expect, by emissions-related fundamental drivers. This might be justified by the fact that the EU ETS remains the greatest source of CER demand to date.

Keywords: EUA-sCER Spread; Arbitrage; Emissions Markets.

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1. Introduction

The European Union Emissions Trading Scheme (EU ETS) is the EU's flagship climate policy forcing industrial polluters to reduce their CO_2 emissions in order to help the European Member States to achieve their Kyoto Protocol target (i.e. to reduce greenhouse gas emissions on average by 8% with respect to 1990 levels). As an emissions cap, industrial operators receive, in Phases I (2005-2007) and II (2008-2012) of the scheme, a yearly allocation of European Union Allowances (EUAs), which represent the right to emit one ton of CO_2 in the atmosphere.[1] The compliance of industrial operators requests the balance between verified emissions and allocated allowances. Besides, industrial operators may cut the costs of reducing their emissions by using credits issued from the Kyoto Protocol Clean Development Mechanism (CDM), called Certified Emissions Reductions (CERs).[2] These CERs correspond to one ton of avoided CO_2 emissions in the atmosphere, and may be obtained through projects development in non Annex-B countries of the Kyoto Protocol that allow to reduce emissions compared to a baseline scenario. Once credits have been issued by the United Nations's CDM Executive Board they may be sold by project developers on the market, and thus become secondary CERs (sCERs). The central goal of this article is to study the price drivers of EUAs and sCERs, and to explain the evolution of the price difference observed between these two assets (the EUA-sCER spread).

Even if both assets allow the emission of one ton of CO_2 in the atmosphere, we observe the existence of a positive spread between EUA and sCER prices that may be due to the partial fungibility between these two carbon assets. Indeed, to provide more flexibility to carbon-constrained installations, the European Commission has allowed industries covered by the EU ETS to use both assets for compliance. However, it has established a limit on the use of CERs (primary or secondary) up to 13.4% of their allocation from 2008 to 2012 on average. To comply with their emissions cap, industrial emitters may thus adopt various strategies: *(i)* surrender EUAs (allocated either to the plant or to others plants of the same company), *(ii)* reduce real emissions (either at the installation-level or abroad, using the Kyoto Protocol's flexibility mechanisms), *(iii)* buy EUAs or/and sCERs, *(iv)* borrow EUAs from future allocation, (*v*) surrender banked EUAs from past allocation. Trotignon and Leguet (2009) document that, in 2008, 96% of the surrendered allowances were EUAs, and only 3.9% were sCERs.[3] The trade-offs between using EUAs or sCERs towards compliance

[1] For Phase III of the EU ETS starting in 2013, the main part of EUAs will be allocated to industrials though auctioning. The power sector will have to buy 100% of its allocation, while sectors faced to international competition and some carbon leakages will keep receiving a free yearly allocation.

[2] Emission Reduction Units (ERUs) generated through the Joint Implementation mechanism (JI) of the Kyoto Protocol fall beyond the scope of this article, and are left for future research.

[3] Note 0.01% were ERUs. No CERs were used towards compliance before that period, due to the lack of connection between the Kyoto Protocol's International Transaction Log (ITL) and the EU ETS' Community Independent Transaction Log (CITL).

in the EU ETS depend on the limit of CERs which can be used for compliance, their respective price trends, and the price difference between them. Carbon traders and brokers are following closely the evolution of the EUA-sCER spread, which reflects the uncertainties embedded in the development of both schemes. In theory, as the sCERs are free of project delivery risks, the prices of EUAs and sCERs should be equal since they represent the same amount of CO_2 emissions reduction (one ton). However, due to the limit of 13.4% on average of the credits surrendered, the sCERs' "exchange rate" is smaller than for EUAs, and therefore sCERs are discounted with respect to EUAs. This premium represents the opportunity cost of using sCERs for compliance instead of EUAs.

Beyond prices, regulatory issues may also explain the variation of the spread between these two carbon assets in the long run. First, with the European Energy Climate package, the EU ETS is confirmed until 2020. However, the details concerning the import of CDM credits within Phase III (2013-2020) are not known with certainty. Indeed, the European Union establishes particular conditions of the emissions trading scheme in Phase III that are dependent on the achievement of a post-Kyoto international agreement. Thus, there exists a wide range of uncertainties arising around the status and recognition of CERs (both primary and secondary) in a revised EU ETS beyond 2012. Second, carbon assets form another class of commodities against which traders need to define specific hedging strategies (Chevallier (2009), Chevallier et al. (2009)).

The existence of spreads between assets has been studied mainly on financial markets. Collin-Dufresne et al. (2001) find that credit spread changes in the U.S. are mainly driven by local supply and demand shocks. Manzoni (2002) characterizes the evolution of credit spreads on the sterling Eurobond market by a cyclical behavior and persistent volatility process. Zhang (2002) examines the predictive power of credit spreads from the corporate bond market in the U.S., and supports Bernanke and Gertler's (1989) credit channel theory as the explanation for the strong forecasting ability of credit spreads. Codogno et al. (2003) show that differentials between Euro zone government's bond spreads may be explained by banking and corporate risk premiums in the U.S. Ramchander et al. (2005) investigate the influence of macroeconomic news on interest rates and yield spreads in the U.S. and they find that Consumer Price Index, non-farm payroll figures, and Fed funds rate release announcements have a significant influence on changes in these spreads. Gómez-Puig (2006) highlights the importance of size and liquidity indicators in explaining sovereign yield spreads following the European Monetary Union. Davies (2008) examines U.S. credit spread determinants with an 85 year perspective. Based on cointegration techniques for the determinants of credit spreads, he demonstrates that key causal relationships exist independently across different inflationary environments. Liu and Zhang (2008) investigate whether the value spread is a useful predictor of returns. They identify mixed evidence, as two related variables, the book-to-market spread (the book-to-market of value stocks minus the book-to-market of growth stocks), and the market-to-book spread (the market-to-book of growth stocks minus the market-to-book of value stocks) predict returns but with opposite signs. Manganelli and Wolswijk (2009) further study the spreads between Euro area government's bond yields, and find that they are related to short-term interest rates, which are in turn related to liquidity risk components.

Compared to previous literature, we provide the first empirical analysis of EUA and sCERs drivers, and the determinants of the EUA-sCER spread during Phase II (2008-2012) of the EU ETS. Mansanet-Bataller et al. (2007), Alberola et al. (2008), and Alberola and Chevalier (2009) have already analyzed the price fundamentals of EUAs during Phase I (2005-2007) of the EU ETS, but not the drivers of EUAs or sCERs during Phase II. Additionally, to our best knowledge, no previous empirical study has focused either on the determination of sCERs drivers or on the arbitrage strategies consisting in buying sCERs and selling EUAs (yielding net profits from the existence of the positive EUA-sCER spread).

Our central results show that EUAs and sCERs share the same price drivers, i.e. these emissions markets prices are mainly determined by institutional events, energy prices, weather events, and macroeconomic variables. Moreover, EUAs are found to determine significantly the price path of sCERs, by accounting for a large share of the explanatory power of sCERs prices. This result emphasizes that EUAs remain the main "money" in the field of emissions market, which is exchanged broadly as the most liquid asset for carbon trading. The trading of sCERs, while growing exponentially, is still mostly determined by the fact that the EU ETS remains the largest emissions trading scheme to date in the world.[4] This result also explains why sCERs are traded at a discounted price from EUAs: absent the project risk which is characteristic of primary CERs, sCERs are still limited by the import limit set within the EU ETS.

Regarding the EUA-sCER spread, our central contribution documents that variables stemming from the market microstructure literature (such as volumes exchanged on each emissions market, see Madhavan (2000) for a review) are the main drivers of the spread, in addition to EUA price levels, institutional and macroeconomic variables, and forecast errors on the delivery of primary CERs. The latter result may indicate that the EUA-sCER spread is traded as a "speculative" product by market participants such as traders and energy utilities companies, since it is possible to obtain a net benefit by simultaneously trading EUAs and sCERs (when the price difference between these two assets is above a certain profitability threshold). Taken together, our results indicate that while the fungibility between emissions markets worldwide is quickly developing, there remain significant opportunities for price arbitrage.

The remainder of the article is organized as follows. Section 2 details compliance strategies in the EU ETS. Section 3 develops a cointegration analysis between EUAs and

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[4] Note that this situation could change with the future developments from the U.S. federal cap-and-trade scheme and other regional initiatives.

sCERs prices. Section 4 reviews the main EUAs price drivers. Section 5 covers the specific sCERs price drivers. Section 6 focuses on the determinants of the EUA-sCER spread. Section 7 summarizes the article with some concluding remarks.

2. Compliance Strategies in the EU ETS

This section briefly reviews background information on the EU ETS, which was launched in 2005 according to the Directive 2003/87/EC to facilitate the EU compliance with its Kyoto commitments. Phase I was introduced as a training period during 2005-2007. Phase II coincides with the commitment period of the Kyoto Protocol (2008-2012). Phase III will cover the period 2013-2020. Around 11,000 energy-intensive installations are covered by the scheme, which accounts for nearly 50% of European CO_2 emissions (Alberola et al., 2009a, 2009b). Emissions caps are determined at the installation-level in National Allocation Plans (NAPs). In what follows, we examine more closely EUAs and CERs contracts, as well as their respective price developments.

2.1. EUAs and CERs contracts

On the one hand, EUAs are the default carbon asset in the EU emissions trading system. They are distributed by European Member States throughout NAPs, and allow industrial owners to emit one ton of CO_2 in the atmosphere. The supply of EUAs is fixed in NAPs, which are known in advance by market participants (2.08 billion per year during 2008-2012).[5]

On the other hand, CERs, which also compensate for tons of CO_2 emitted by their owners, are much more heterogeneous than EUAs. Primary CERs represent greenhouse gases emissions reductions achieved in non-Annex B countries of the Kyoto Protocol. These certificates are issued by the United Nations Clean Development Mechanism Executive Board (CDM EB). CDM projects may associate various partners (ETS compliance buyers, Kyoto-bound countries, project brokers, profit-driven carbon funds, international organizations such as the World Bank, etc.). CDM projects partnerships are governed by emissions reduction purchase agreements (ERPAs).[6] The price of primary CERs will depend on the risk of each project, and on its capacity to effectively issue

[5] However on September 23, 2009, the European Court of First Instance (CFI) overruled the decision of the European Commission concerning NAPs for the second period submitted by Estonia and Poland. The Commission will explore two options: *(1)* issue a new decision based on "proper" criteria before December 23, 2009; and *(2)* appeal the CFI ruling, on a point of law, before November 23, 2009. Six other Eastern European countries may contest NAPs as well. In total, it represents a potential additional 162 million allowances.

[6] The ERPA basically sets forward the duties and rights of the partners. Among the rights of the partners is the right to receive a *pro rata* quantity of the primary CERs.

primary CERs. This price will be the cost of the project divided by the number of primary CERs actually issued. Thus, primary CERs from different projects will have different prices.

Once issued by the CDM EB, primary CERs may either be used by industrial firms for their own compliance, or sold to other participants in the market. In the latter case, it becomes a secondary CER (sCER). Note that as the sCERs are CERs that have been already issued by the CDM EB, their project delivery risk is null. As stated in the introduction, the main difference between the use of EUAs and CERs (including both, primary and secondary) for compliance in the EU ETS lies in the 13.4% (on average) import limit set by the European Commission on CERs, while EUAs may be used without any limit. The CERs import limit for compliance is equal to 1.4 billion tons of offsets being allowed into the EU ETS from 2008-2012.[7]

In this article we focus on the price relationships between EUAs and sCERs. Next, we describe the EUAs and sCERs price developments.

2.2. Price development

In this section, we examine Phase II EUA and sCER prices, which reflect the price of reducing emissions during the commitment period of the Kyoto Protocol (2008-2012).[8] The sCER price series used for this study is the longest historical price series existing for sCERs: the sCER Price Index developed by Reuters. It has been built by rolling over two sCERs contracts with different maturity dates (December 2008 and December 2009). Similarly, we have rolled over EUA futures contracts traded at the European Climate Exchange (ECX) of the corresponding maturity dates (December 2008 and December 2009) to match them with the sCER price series.[9] The sample period considered starts with the beginning of the sCER Price Index (March 9, 2007) and ends on March 31, 2009. As shown in Figure 1, the EUA and the sCER price series follow a similar price path.

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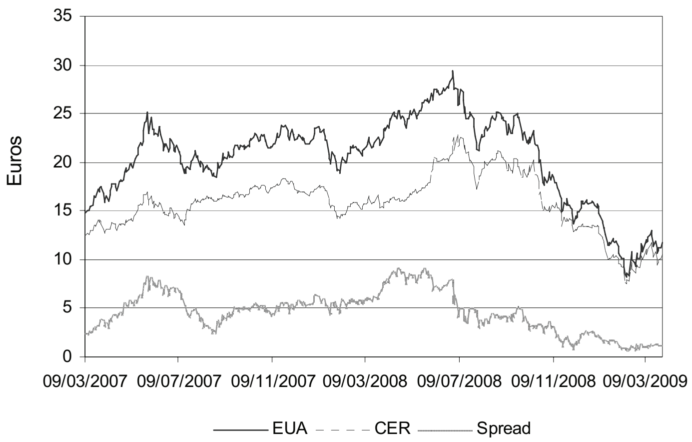
[7] In the absence of a satisfactory international agreement, installations subject to allowances during Phase III will only be able to use the credits left over from Phase II (2008-2012), or a maximum amount corresponding to 11% of the Phase II allocation. These measures are equivalent to capping the potential demand for Kyoto credits to 1,510 Mt between 2008 and 2020. If a post-Kyoto international agreement is achieved, the ceiling on the use of credits from project mechanisms towards the compliance of EU ETS installations will be raised to 50% of the additional reduction efforts. Beyond this issue, the introduction of a new international agreement on climate change would introduce “high quality” as a condition for project credits coming from countries which have signed the international agreement. This would translate into a reduced supply of credits originated from project mechanisms to EU ETS compliance buyers.

[8] Note that banking and borrowing of allowances are allowed within Phases II and III of the EU ETS, contrary to Phases I and II (Alberola and Chevallier (2009)).

[9] Carchano and Pardo (2009) analyse the relevance of the choice of the rolling over date using several methodologies with stock index future contracts. They conclude that regardless of the criterion applied, there are not significant differences between the series obtained.

EUAs were traded at €15 in March 2007, then stayed in the range of €19-25 until July 2008, and decreased steadily afterwards to achieve €8 in February 2009. sCERs started at €12.5 in March 2007, evolved in the range of €12-22 through July 2008, and continued to track EUA prices until €7 in February 2009. Thus, sCERs have always remained below EUAs and consequently the spread has been positive during all the sample period.

Figure 1: Time-series of ECX EUA Phase II Futures, Reuters CER Price Index, and CER-EUA Spread from March 9, 2007 to March 31, 2009



Source: Reuters

Descriptive statistics for EUAs, sCERs, and the spread may be found in Table 1. Given the price paths observed in historical data, it appears interesting to investigate the presence of one cointegrating relationship between EUAs and sCERs in the next section.

Table 1: Summary statistics for all dependent variables

Variable	Mean	Median	Max	Min	Std. Dev	Skew.	Kurt
Raw Prices series							
EUA_t	20.40389	21.52000	29.33000	8.20000	4.459218	-0.765966	3.031938
$sCER_t$	15.85798	16.6875	22.8500	7.484615	2.986495	-0.351494	3.135252
$Spread_t$	4.545912	4.620000	9.043571	0.647857	2.108445	0.047792	2.292397
Nathural Logarithms							
EUA_t	2.986643	3.068983	3.378611	2.104134	0.255164	-1.323179	4.275898
$sCER_t$	2.743941	2.776476	3.128951	2.012850	0.505511	-0.994736	4.182189
Log returns							
EUA_t	-0.000437	0.0001	0.113659	-0.094346	0.026833	-0.060828	4.868026
$sCER_t$	-0.000309	0.0001	0.112545	-0.110409	0.024441	-0.370323	5.961950
VAR(4) Residuals							
EUA_t	0.00001	0.001242	0.108251	-0.094873	0.05903	-0.052333	4.522629
$sCER_t$	0.00001	0.000390	0.111584	0.097672	0.023742	-0.309379	5.520998
First-differences							
Δ Spread	-0.002219	-0.010179	1.070000	-1.740000	0.295605	-0.368420	6.262861

Note: EUA_t refers to ECX EUA Futures, $sCER_t$ to Reuters sCER Price Index, and $Spread_t$ = EUA_t-$sCER_t$ spread. Std.Dev. stands for Standard Deviation, Skew. for Skewness, and Kurt. for Kurtosis. The number of observations is 529. The VAR(4) specification is detailed in Section 2.3.

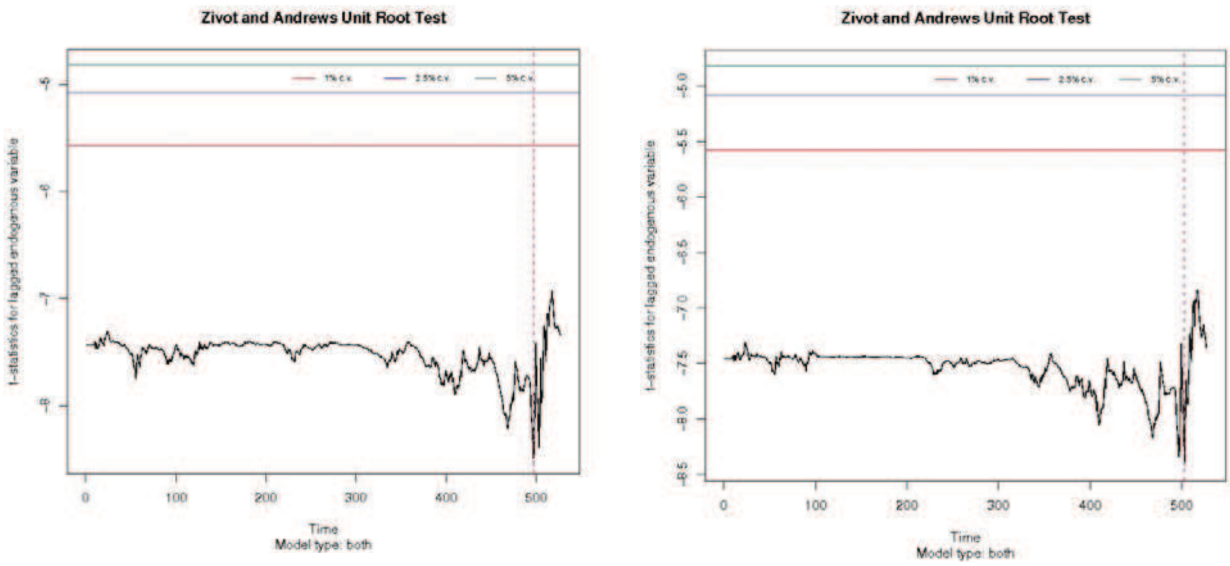
3. Cointegration Analysis

Following the methodology used in Manzoni (2002) and Ramchander et al. (2005), who studied the relationship between bond spreads, we proceed in a first step by identifying the possible cointegration relationship between the two types of assets considered (EUAs and sCERs). We will then analyze the EUA-sCER spread drivers.

3.1. Unit Roots and Structural Break

A necessary condition for studying cointegration involves that both time-series are integrated of the same order. We thus examine the order of integration, noted *d*, of the time-series under consideration based on Zivot and Andrews' (1992) unit root test. This test allows examining the unit root properties of the time-series, while simultaneously detecting endogenous structural breaks for each variable. Figure 2 presents the Zivot-Andrews unit root test statistics for the two EUA and sCER variables transformed to log-returns.

Figure 2: Zivot-Andrews (1992) Test Statistic for the EUA (left) and sCER (right) Variables



The model estimated is a combination of a one-time shift in levels, and a change in the rate of growth of the series. The null of unit root is clearly rejected in favour of the break-stationary alternative hypothesis. One estimated break point is identified for each of the time-series: February 13, 2009 for the EUA variable, and February 20, 2009 for the sCER variable. These breakpoints may be due to a delayed effect of the "credit crunch" crisis on the carbon market (see Chevallier (2009) for a discussion). Both time-series are integrated of order 1 (*I(1)*). The existence of a structural break in the time-series considered, while remaining stationary, means that we need to develop cointegration tests that explicitly include potential breaks, as they have been developed by Lutkepohl et al. (2004).

3.2. VECM and Structural Break

After having validated the necessary condition for studying cointegration (which involves that both time-series should be integrated of the same order), we investigate the existence of a long-term relationship across these two carbon prices by employing a cointegration analysis with the maximum-likehood test procedure established by Johansen and Juselius (1990) and Johansen (1991). Results for the cointegration test with one structural shift at unknown time (Lutkepohl et al (2004)) are shown in Panel A of Table 2. The trace statistic result indicates a cointegration space of $r = 1$, given a 5% significance level. We may conclude that there exists one long-term cointegrating vector between the EUA and sCER variables taken in natural logarithm form.

Table 2: Johansen Cointegration Rank Trace Statistic, Cointegration Vector, Model Weights and VECM with Structural Break for the EUA and the CER Variables.

Panel A: Johansen Cointegration Rank Trace Statistic

Hypothesis	Statistic	10%	5%	1%
$r \leq 1$	5.26	5.42	6.79	10.04
$r = 1$	16.95	13.78	15.83	19.85

Panel B: Cointegration Vector

Variable	EUA (1)	sCER (1)
EUA (1)	1.0000	1.0000
sCER (1)	-0.4955009	-1.519945

Panel C: Model Weights

Variable	EUA (1).	sCER (1)
ΔEUA	-0.06163548	0.00734759
ΔsCER	-0.04490726	0.0182197

Panel D: VECM with Structural Break ($r = 1$)

Variable	ΔEUA	ΔsCER
Error Correction Term (ect)	-0.0197908	-0.0282009
Deterministic constant	0.0106349	0.0154190
Lagged differences		
ΔEUA (1)	-0.0641515	-0.0504123
ΔsCER (1)	0.2307197	0.1423340

Note: EUA refers to ECX EUA Phase II Futures, sCER to Reuters sCER Price Index, transformed to natural logarithms. Critical values are reported in Lutkepohl et al (2004). Lag order in parenthesis. The number of observations is 529.

Next, we proceed to the estimation of the Vector Error Correction Model (VECM), which is useful in making causal inferences among the variables of our system.[10] As shown in Panel D of Table 2, the coefficients of the error correction terms for the EUA and sCER variables are negative, and thus we validate the error correction specification. In terms of short-run dynamics, the error correction terms emerge as important channels of influence in mediating the relationship between the different EUAs and sCERs prices. We notice in Panel D of Table 2 that the error correction term appears stronger for sCERs than for EUAs. This implies that the sCER variable has a stronger behavior to adjust to past disequilibria by moving towards the trend values of the EUA variable. This specification confirms that EUAs constitute a leading factor in the price formation of sCERs. It can also be seen that changes in the respective prices of EUAs and sCERs have a significant causal influence (in the Granger sense) on each other.[11]

3.3. VAR(p) Modeling

In light of the previous results, and in order to proceed with the suitable identification of the price drivers for each variable, we use a VAR(p) in differences with an intervention dummy for February 2009 to model the data-generating process of the EUA and sCER log-series. The VAR(p) model is specified as follows:

$$\Delta y_t = A_0 + A_1 \Delta y_{t-1} + A_2 \Delta y_{t-2} + \ldots + A_p \Delta y_{t-p} + \varepsilon$$

Where $\Delta y_t = \begin{bmatrix} \Delta EUA_t \\ \Delta sCER_t \end{bmatrix}$ is a vector of EUA and sCER log-returns, $A_0 = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix}$ is a vector of constants, and $A_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}$, etc. are the coefficient matrices.

To determine the appropriate lag structure, we computed the following information criteria: Akaike ($AIC(n)$=4), Schwarz (SC(n)=1), Hannan-Quinn ($HQ(n)$=1), and Final Prediction Error ($FPE(n)$=4). Since the Ljung-Box-Pierce Portmanteau test on the residuals

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[10] The VECM is specified as follows:

$$\Delta y_t = A_0 + A_1 Ecm_{t-1} + A_2 \Delta y_{t-1} + \varepsilon$$

Where $\Delta y_t = \begin{bmatrix} \Delta EUA_t \\ \Delta sCER_t \end{bmatrix}$ is a vector of first differences of EUA and sCER prices, $A_0 = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix}$ is a vector of constants, $A_1 = \begin{bmatrix} b_{11} \\ b_{21} \end{bmatrix}$ is a vector measuring the speed of the adjustment to the long-run relationship, and $A_2 = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}$ is a coefficient matrix.

[11] These results are not reproduced in the article to conserve space, and may be obtained upon request.

of the VAR(1) model indicated the presence of autocorrelation, we choose to retain a lag of order $p = 4$. As shown in Table 3, residuals are not auto-correlated for the VAR (4) model.

Table 3: Diagnostic test of VAR(4) Model

Test	Statistic	D. F.	p-value
Portmanteau	57.4878	48	0.16
ARCH VAR	97.1946	9	0.01
JB VAR	147.6817	4	0.01
Kurtosis	143.5005	2	0.01
Skewness	4.1811	2	0.12

Note: Portmanteau is the asymptotic Portmanteau test with a maximum lag of 16, ARCH VAR is the multivariate ARCH test with a maximum lag of order 5, JB is the Jarque Bera Normality test for multivariate series applied to the residuals of the VAR(4). Kurtosis and Skweness stand for separate tests for multivariate skewness and kurtosis. D.F. stands for degree of freedom of the test statistic.

The ARCH effect is very strong, which indicates the necessity to use a GARCH model for further analysis. Figure 3 plots the log-returns and the VAR(4) residuals of the ECX EUA Phase II Futures and sCER Price Index time price series.

Figure 3: Log-returns (left) and VAR(4) residuals (right) of ECX EUA Phase II Futures and Reuters sCER Price index for the sample period from March 9, 2007 to March 31, 2009

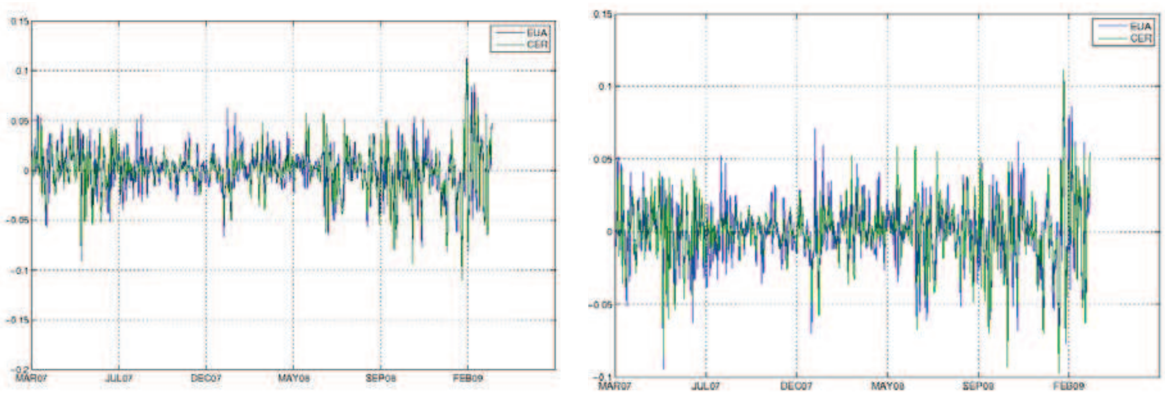
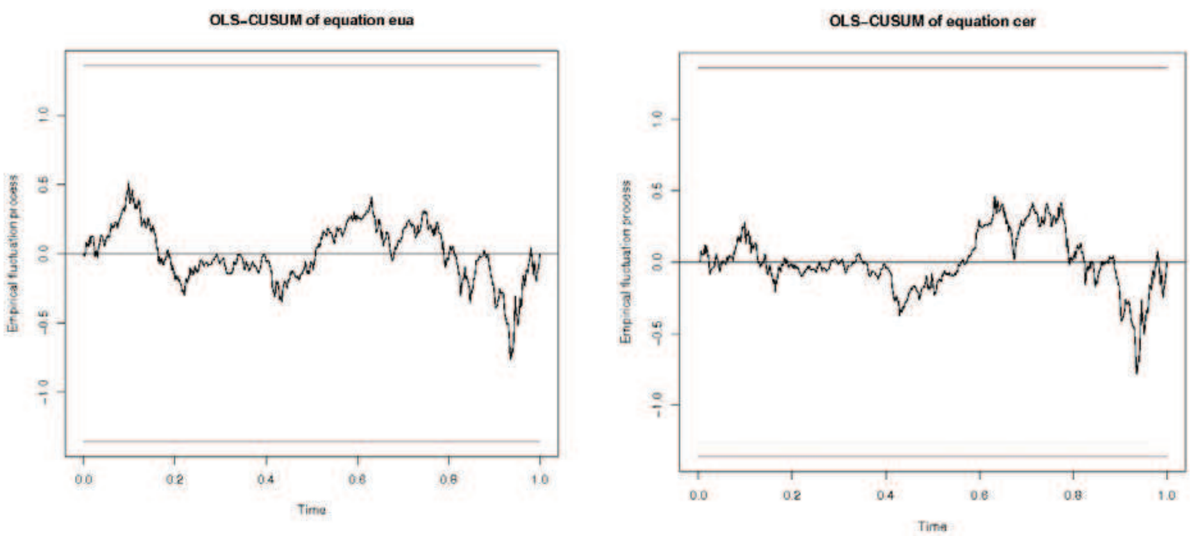


Figure 4 shows the OLS-based CUSUM tests for the VAR (4) residuals. Despite some structural instability around the February 2009 breakpoints, the residuals stay within the interval confidence levels.

Figure 4: OLS-CUSUM Test for the EUA (left) and sCER (right) Variables of the VAR(4) Model



Additional impulse response analysis reveals the traditional "hump" shape between EUAs and sCERs, as shocks pass on both variables and fluctuations dampen at the horizon of 10 lags.[12] The variance decomposition indicates that the variance of the forecast error for the EUA price is due to its own innovations up to 90%. For the sCER price, the variance of the forecast error is due to EUAs up to 70%, and only 30% to its own innovations. These results confirm our findings in Section 2.2.

In the next step of our empirical analysis, we proceed by fitting a suitable GARCH model to the residuals of the VAR (4) model for the EUA and sCER variables.

4. EUAs Price Drivers

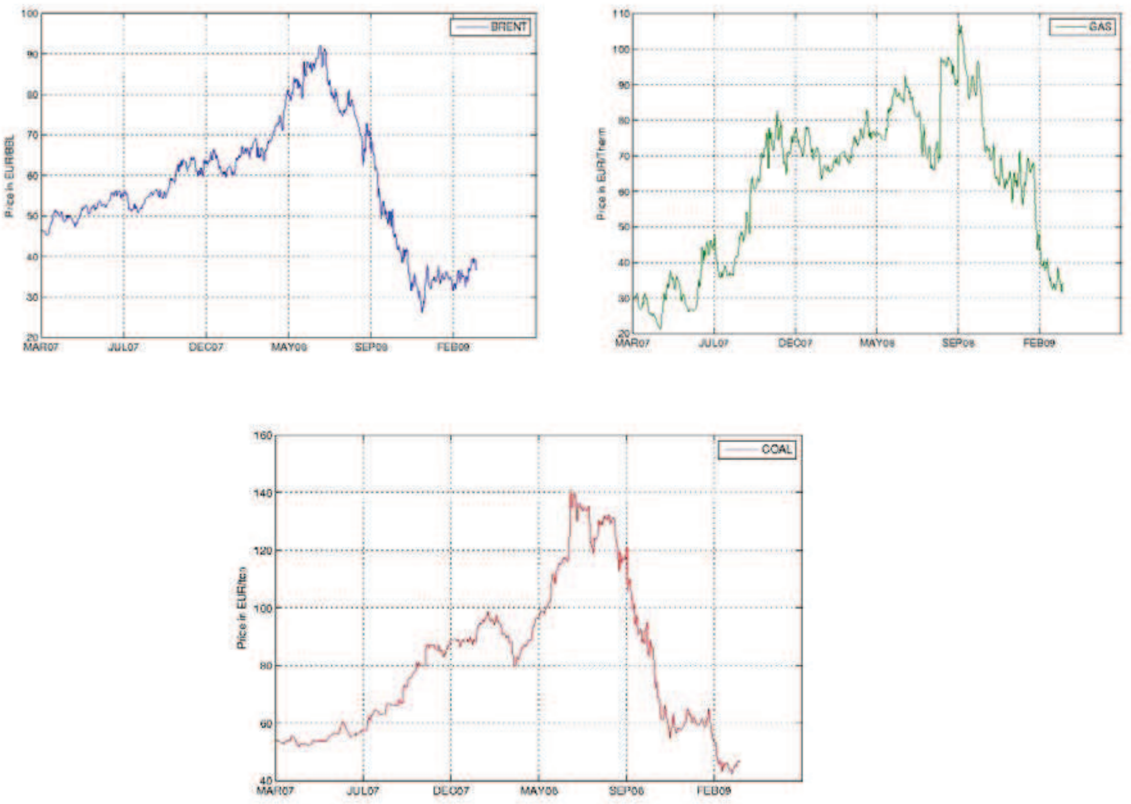
In this section, we focus on the drivers of EUAs using the residuals of the VAR(4) model. As detailed in previous literature, we may distinguish between factors determining the supply and demand of EUAs. The supply of EUAs is fixed by the European Commission in National Allocation Plans that are validated after negotiation between Member States and national industrials covered by the scheme. Announcements relative to the strictness of NAPs have been shown to have a strong influence on EUA prices (Alberola et al. (2008), Chevallier et al. (2009), Mansanet-Bataller and Pardo (2009)). Concerning demand factors, previous literature identifies energy prices, weather events, and the level of industrial production as being the main drivers of EUAs during Phase I (Mansanet-Bataller et al. (2007), Alberola et al. (2009a, 2009b).

[12] These results are not reproduced here to conserve space, and may be obtained upon request.

4.1. Database

We include as EUAs price drivers the most representative energy prices in Europe. That is, the daily Brent and natural gas futures prices traded at the International Petroleum Exchange (IPL) and coal prices CIF ARA.[13] The time-series have been built by rolling over the nearest month ahead contract. As the futures contract on Brent is quoted in US$ per barrel, the futures contract on Natural Gas is quoted in GBP per therm, and the coal contract is quoted in US$ per metric ton, we have converted all price series to Euro by using the daily exchange rate data available from the European Central Bank.[14] Figure 5 shows these energy prices.

Figure 5: IPE Crude Oil Brent, IPE Natural Gas, and Coal CIF ARA Prices from March 9, 2007 to March 31, 2009



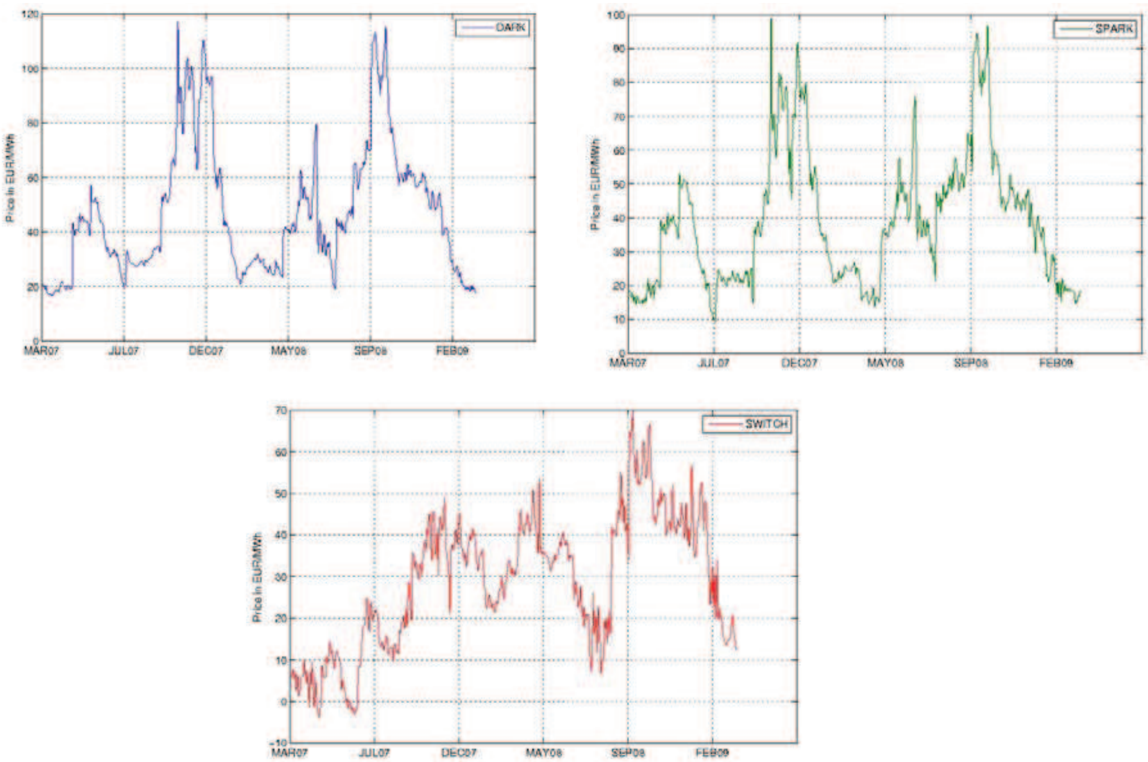
Source: Reuters

[13] CIF ARA defines the price of coal inclusive of freight and insurance delivered to the large North West European ports, e.g. Amsterdam, Rotterdam or Antwerp.

[14] Data available at http://www.ecb.int/stats/exchange/eurofxref/html/index.en.html

Besides, we use the CO_2 *switch* price between coal and gas in €/ton, as computed in the *Tendances Carbone* database.[15] This variable represents the fictional daily price that establishes the equilibrium between the *Clean Dark Spread* and the *Clean Spark Spread*.[16] It therefore represents the price of CO_2 *above* which it becomes profitable in the short term for an electric power producer to switch from coal to natural gas. The economic logic behind the use of these spreads lies in the central role played by power producers in the determination of the EUA price, since they receive around half of the allowances distributed in the EU emissions trading system (Delarue et al. (2008), Ellerman and Feilhauer (2008)). The CO_2 switch price, Clean Dark and Clean Spark Spreads are displayed in Figure 6.

Figure 6: Clean Dark Spread, Clean Spark Spread, and Switch Price from March 9, 2007 to March 31, 2009



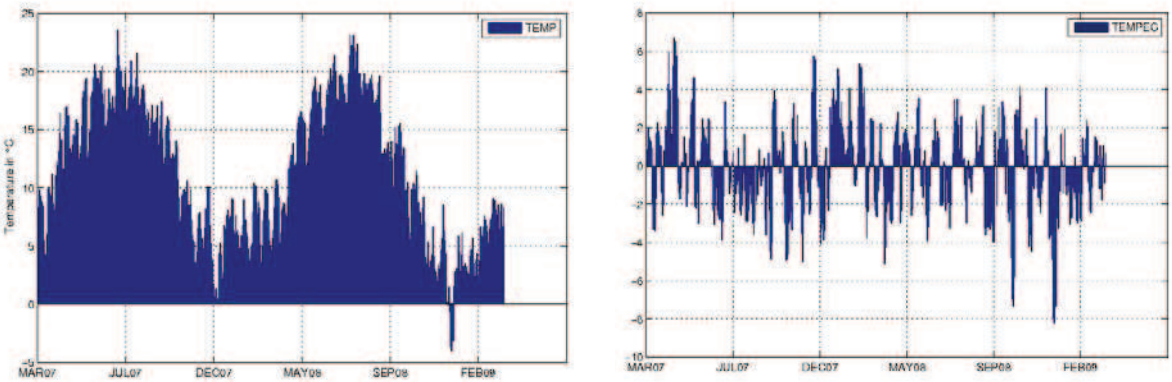
Source: Reuters

[15] *Tendances carbone* is a monthly newsletter on the EU ETS, produced by the Caisse des Dépôts, Mission Climat the research team of CDC Climat department which is in charge of finance carbon activities. It can be found at http://www.caissedesdepots.fr/missionclimat

[16] Note that the *Clean Dark Spread* represents the difference between the price of electricity at peak hours and the price of coal used to generate that electricity, corrected for the energy output of the coal plant. The *Clean Spark Spread* represents the difference between the price of electricity at peak hours and the price of natural gas used to generate that electricity, corrected for the energy output of the gas-fired plant. Both spreads are expressed in €/MWh.

To take into account weather influences, we use the *Tendances Carbone European temperatures index*, which is an average of national temperatures indices of four European countries (France, Germany, Spain and the United Kingdom), weighted by the share of each National Allocation Plan. From this index, we have created three new variables: *tempec* represents the difference between the value of the temperatures index and the decennial average; *temphot* is a dummy variable for extremely hot temperatures (equal to 1 if the value of the temperatures index is higher than the third quartile of the series, and 0 otherwise); and *tempcold* is a dummy variable for extremely cold temperatures (equal to 1 if the value of the temperatures index is lower than the first quartile of the series; and 0 otherwise). The temperatures index and its deviation from decennial average are shown in Figure 7.

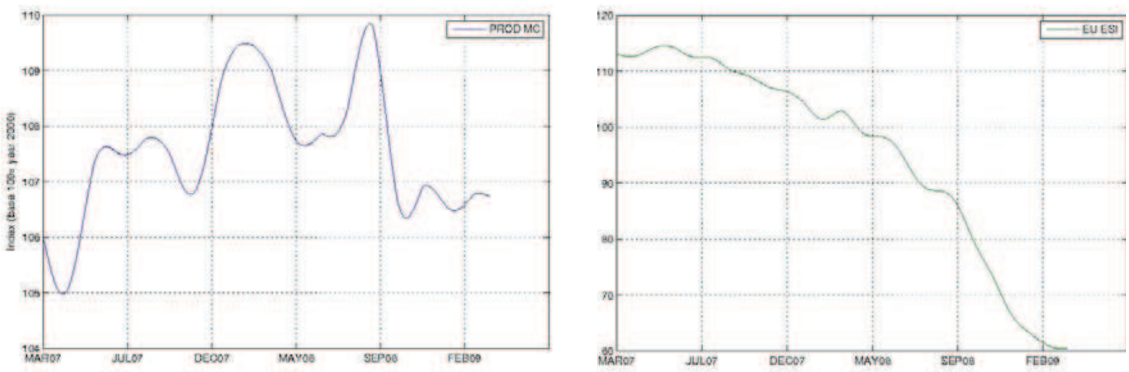
Figure 7: European Temperatures Index and Deviation from Decennial Average from March 9, 2007 to March 31, 2009



Source: Mission Climat Caisse des Dépôts

We have also introduced exogenous variables impacting CO_2 emissions levels. First, we consider the *Tendances Carbone European Industrial Production index* indicator, which uses Eurostat production indices and is a backward-looking indicator tracking past economic trends. Second, we use the *Economic Sentiment Index* published by Eurostat, which reflects overall perceptions and expectations at the individual sector level in a single aggregate index. This index is a forward-looking indicator used to mirror economic sectors' sentiment. Finally, the "credit crunch" crisis may also have an impact on CO_2 emissions levels. To detect this potential influence, we have created the variable *crisis* as a dummy variable equal to 1 from August, 17 2007 onwards and 0 otherwise. This date corresponds to the first cut in interests rates by the U.S. Federal Reserve, and may be considered as the beginning of the financial crisis (Chevallier (2009)). Figure 8 shows the European Industrial Production Index and the European Sentiment Index variables.

Figure 8: Tendances Carbone Industrial Production Index (Weighted by the Share of NAPs) and EU Economic Sentiment Index



Source: Mission Climat - Caisse des Dépôts, Eurostat.

Additionally, we consider three other variables relevant to market trends. First, to take into account the slope of the Euro area yield curve, we have used the *yield* variable, which is available from the European Central Bank.[17] This series is built as the spread between the 5- and the 2-year interest rates. A positive (negative) value of the variable *yield* is expected to indicate an upward-sloping (downward-sloping) interest rate term structure, and hence a trend to cool down (stimulate) the economy (Collin-Dufresne et al. (2001)). Second, we have computed the $momentum_{EUA}$ variable. This variable represents the difference between ECX EUA Phase II Futures prices at time *t* and at time *t-5*, thereby indicating bullish or bearish carbon market trends. Finally, *VIX* is the volatility index published by the Chicago Board Options Exchange (CBOE), which is widely recognized as an indicator of aggregate market volatility among financial practitioners (Collin-Dufresne et al. (2001)). Figure 9 presents the evolution of the three variables.[18]

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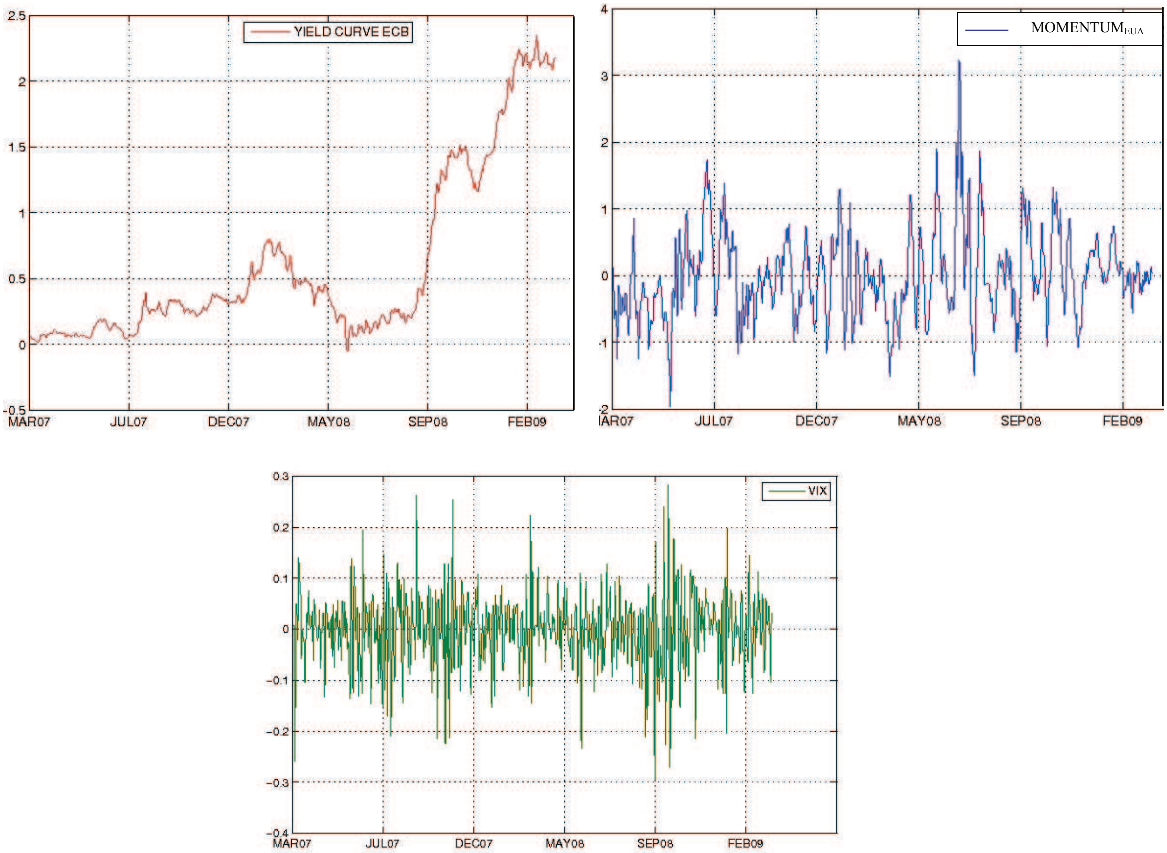
[17] Data can be found at : http://sdw.ecb.europa.eu

[18] Note we leave for further research the investigation of other potential explanatory variables, such as EUA forward curves and the return on investment for EUAs growing at the EURIBOR rate.

Figure 9: Slope of Yield Curve, Market Momentum, and VIX Index from March 9, 2007 to March 31, 2009



Source: European Central Bank, Reuters and CBOE

Regarding news variables that may impact the supply of EUAs, we consider three types of events. First we take into account the arrival of new information concerning *Phase II NAPs*. Second, we consider news related to the extended development of the EU ETS during *Phase III*. These two dummy variables have been constructed by filtering the most reliable and significant announcements on EU ETS developments from the European Commission website.[19] Third, we also take into account the likely impact on EUA prices provoked by the connection between the Kyoto Protocol's International Transaction Log (ITL) and the EU ETS' Community Independent Transaction Log (CITL) on October 10, 2008 throughout the *ITL-CITL* dummy variable. This variable takes the value of 1 when news concerning the connection occurred and 0 otherwise.

After transforming, when necessary, the exogenous variables of our database into stationary variables, we detail in the next section the GARCH modelling for the EUA variable.

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[19] Those announcements are presented in Annex 1. They have been obtained from the European Commission website: http://ec.europa.eu/environment

4.2. GARCH Modeling

We model the EUA variable by using the asymmetric TGARCH (*p,q*) model by Zakoian (1994) with a Student's *t* innovation distribution, estimated by Quasi Maximum Likelihood with the BHHH algorithm:

$$
\begin{aligned}
EUA_t = \alpha + \rho brent_t + \chi coal_t + \delta gas_t + \xi switch_t + \phi tempec_t + \varphi temphot_t + \gamma tempcold_t \\
+ \eta MCprod_t + \varpi EUESI_t + \iota yield_t + \kappa momentum_{EUA t} + \lambda crisis_t + \vartheta VIX_t \\
+ \mu EUETSphaseIII_t + \theta NAPphaseII_t + \nu ITL\_CITL_t + \varepsilon_t
\end{aligned}
$$

$$\sigma_t = \alpha_0 + \alpha^+(L)\varepsilon_{t-1}^+ - \alpha^-(L)\varepsilon_{t-1}^- + \beta(L)\sigma_{t-1}$$

with EUA_t the residuals of the VAR(4) model related to the EUA at time *t*, α the constant, $brent_t$, $coal_t$, and gas_t are the returns of the brent, coal and gas series, $switch_t$ the switch variable, $tempec_t$, $temphot_t$, $tempcold_t$ the temperatures variables, $MCprod_t$ the industrial production index from *Tendances Carbone*, $EUESI_t$ the EU Economic Sentiment Index, $yield_t$ the slope of the Euro area yield curve, $momentum_{EUAt}$ the momentum variable concerning the EUA market, $crisis_t$ the dummy variable accounting for the "credit crunch", VIX_t the CBOE volatility indicator, $EUETSphaseIII_t$ the dummy variable for Phase III news, $NAPphaseII_t$ the dummy variable for Phase II news, ITL_CITL_t the dummy variable for the ITL-CITL connection, ε_t the error term, σ_t the conditional volatility, the subscript index *t* refers to date *t*. $(L)\varepsilon_{t-1}^+$ and $(L)\varepsilon_{t-1}^-$ are the positive and negative errors of the mean equation lagged one period respectively, and $(L)\sigma_{t-1}$ is the conditional volatility lagged one period. Note that in this model $(L)\varepsilon_{t-1}^+$ and $(L)\varepsilon_{t-1}^-$ capture asymmetric effects.

4.3. Estimation results

By estimating the TGARCH model presented in Section 3.2 and removing one by one non-significant exogenous variables, we are able to identify two different sets of regression results. In Table 4, regression (1) includes the main energy variables, while regression (2) contains the *switch* and other market variables. The quality of the regressions is verified following several diagnostic tests: the Adjusted R^2, the Log-Likelihood ratio, the ARCH Lagrange Multiplier (LM) test, the Ljung-Box Q-test statistic with a maximum number of lags of 20 (Q(20) statistic), the Akaike Information Criterion (AIC) and the Schwartz Criterion (SC). For both models, the Ljung-Box-Pierce test indicates that residuals are not autocorrelated, and the Engle ARCH test indicates that heteroskedasticity is adequately captured by the structure of the TGARCH model. Besides, we have investigated the presence of multicolinearity by computing the matrix of partial cross-correlations and the inflation of variance between explanatory variables.[20] These calculations did not reveal serious problematic multicolinearities.

Table 4: TGARCH (1,1) Regression Results for the EUA Price Drivers

Variable	EUA_t	
	(1)	(2)
Constant	0.0008	0.0011
	(0.0008)	(0.0008)
$Brent_t$	0.0013***	
	(0.0003)	
$Coal_t$	-0.0017***	
	(0.0003)	
Gas_t	0.0003***	
	(0.0001)	
$Switch_t$		0.0006***
		(0.0002)
$Momentum_{EUAt}$	0.0082***	0.0083***
	(0.0007)	(0.0007)
NAP phase II_t	-0.0084*	-0.0095*
	(0.0044)	(0.0049)
Adjusted R^2	0.1916	0.1631
Log-Likelihood	1287.749	1274.906
ARCH LM Test	0.7950	0.6360
Q(20) Statistic	26.789	24.322
AIC	-4.7811	-4.8243
SC	-4.9667	-4.7673
N	529	529

*Note: EUA_t refers to the residuals of the VAR(4) model related to the EUA (ECX EUA Phase II Futures). ***,(**),(*) Denotes 1%,(5%),(10%) significance levels. The quality of regressions is verified through the following diagnostic tests: the adjusted R-squared (Adjusted-R^2), the Log-Likelihood, the ARCH Lagrange Multiplier (ARCH LM Test), the Ljung Box Q-test statistic with a maximum number of lags of 20 (Q(20) statistic), the Akaike Information Criterion (AIC), and the Schwarz Criterion (SC). The 1% (5%) critical value for the Ljung-Box portmanteau test for serial correlation in the squared residuals with 20 lags is 37.57 (31.41). N is the number of observations.*

In regression (1), we observe that energy variables have an impact on the *EUA* variable at statistically significant levels, which is conform to previous literature (Mansanet-Bataller et al. (2007), Alberola et al. (2008)).[21] *Brent* and *gas* have a positive impact on EUA price changes: increases in fuel prices are directly transmitted to the CO_2 allowance market. As the most CO_2-intensive fuel, *coal* has a *negative* impact on CO_2 prices. This implies that when the coal price increases, industrials have an incentive to use *less* CO_2-intensive fuels, which decreases the demand and the price of CO_2 allowances. In regression (2), we uncover the influence of two other variables: $momentum_{EUA}$ is positive and statistically significant at the 1% level, while the dummy variable *NAP Phase II* is negative and statistically significant at the 10% level. The sign of the latter variable is conform to our expectations:

[20] This table is not reproduced here to conserve space, and may be obtained upon request.

[21] Note that the energy variables are considered here as contemporaneous variables. Including lags did not fundamentally change the results obtained.

NAPs II allocations were reduced by 10% compared to NAPs I. This stricter constraint did not impact positively *EUAs* due to the context of the economic crisis, which was reflected primarily in the decrease of production outputs (and as consequence in reduced CO_2 emissions from EU ETS installations). The positive sign of $momentum_{EUA}$ may be explained by the fact that EUA price changes responded positively to carbon market trends during our study period.

In regression (2), we uncover the explanatory power of the *switch* variable at the 1% level. Its positive sign confirms that when the coal price increases, it becomes more profitable for power operators to switch from coal to natural gas including CO_2 costs. Both the $momentum_{EUA}$ and *NAP Phase II* variables are also significant with similar coefficients and signs as in regression (1), which confirms the robustness of our previous estimates. Having reviewed the main price drivers of the EUA variable, we extend in the next section our investigation to the fundamentals of sCERs.

5. sCER Price Drivers

We focus in this section on the modeling of the sCER variable defined as the residuals of the VAR(4) model for the sCERs.[22] To our best knowledge, this constitutes the first empirical analysis of sCER price drivers.

5.1. Exogenous variables

As for EUAs, it is important to distinguish between demand and supply factors affecting sCERs. Contrary to the allocation of EUA, the supply of sCERs is unknown. The main sources of uncertainty are due to the fact that (*i*) the supply of primary CERs is unknown and difficult to estimate (as it depends on several risks related to the issuance of primary CERs); and (*ii*) the amount of primary CERs that will be converted into sCERs is also difficult to assess (see Trotignon and Leguet (2009). On the demand side, whereas on the EU ETS the demand comes from private financial or industrial operators, for sCERs the demand comes from a larger number of participants (investors, industrials and Annex-B countries). Most of the CERs demand to date comes from European industrials, which are limited to 13.4% (on average) of surrendered allowances for compliance during Phase II of the EU ETS. Besides, Annex-B countries of the Kyoto Protocol may also use CERs for compliance. Countries with a potential deficit of Assigned Amount Units (AAUs valid under the Kyoto Protocol) in 2012 - such as Japan - are involved in sCERs purchasing. Among other factors that may impact sCERs prices, we identify the same factors as those affecting EUAs prices, since both assets may be used for compliance in the EU ETS.

[22] Note that as the drivers of primary and secondary CER are not the same, it is important to remind here that we are considering secondary CER prices.

Hence, we consider the same explanatory variables as for EUAs in sCERs pricing. That is, energy prices (brent, gas and coal), the *switch* price variable, temperatures variables, variables related to production levels, market volatility, and dummy variables related to the announcements concerning the status of the CDM in Phase III of the EU ETS and the ITL-CITL connection. Note that we have computed a new specific variable, called $momentum_{sCER}$, for the indication of bullish and bearish periods. Similarly to the case of the $momentum_{EUA}$ variable, the $momentum_{sCER}$ variable is obtained as the difference between the sCER variable at time *t* and at time *t-5*.

Besides, we add three variables that take into account the specificities of sCERs (mostly related to the supply side): (i) *CDM EB meeting*, (ii) *linking,* and (iii) *CDMpipeline*.

The dummy variable *CDM EB meeting* is equal to 1 on the publication date of CDM EB's reports, and 0 otherwise. This variable indicates the arrival of new information from the United Nations'CDM Executive Board. The dummy variable *linking* is equal to 1 when there on the announcement date related to the linking of emissions trading schemes worldwide, and 0 otherwise.[23]

Finally, the *CDMpipeline* variable is the forecast error concerning the number of primary CERs actually delivered by the CDM EB. Each month, the UNEP Risoe announces how many primary CERs are expected to be delivered in the CDM Pipeline.[24] This variable is computed following the approach developed by Kilian and Vega (2008):

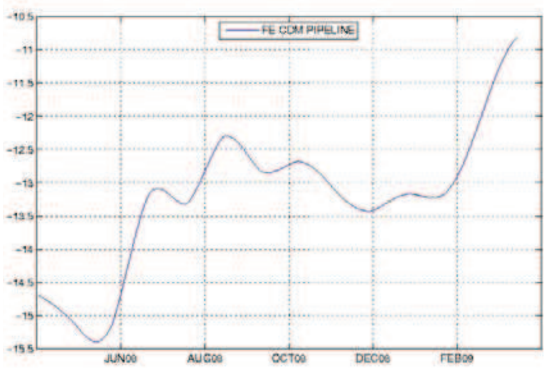
$$CDMpipeline_t = \frac{Realised_t - Expected_t}{\hat{\sigma}}$$

With $Realised_t$ the announced value of the amount of primary CERs delivered by the UNEP Risoe, $Expected_t$ the market's expectation of the amount of primary CERs to be delivered prior to the announcement, calculated by Trotignon and Leguet (2009), and $\hat{\sigma}$ the sample standard deviation of the "unexpected" component. Figure 10 shows the forecast errors for the number of primary CERs available in the CDM pipeline.

[23] Please see Annex I for detailed information on both data.

[24] Available at : http://cdmpipeline.org

Figure 10: Forecast errors for the number of CERs available in the CDM Pipeline from May 2008 to March 2009



Source: UNEP Risoe and Mission Climat Caisse des Dépôts

5.2. GARCH modeling

We model sCER prices by following the same methodology as for EUA Phase II Futures prices:

$$\begin{aligned} sCER_t = {} & \alpha + \rho brent_t + \chi coal_t + \delta gas_t + \xi switch_t + \phi tempec_t + \varphi temphot_t + \gamma tempcold_t \\ & + \eta MCprod_t + \varpi EUESI_t + \iota yield_t + \kappa momentum_{sCERt} + \lambda crisis_t + \vartheta VIX_t \\ & + \mu EUETSphaseIII_t + \nu ITL\_CITL_t + \pi CDMpipeline_t + \varsigma CDMEBmeeting_t \\ & + \upsilon linking_t + \varepsilon_t \end{aligned}$$

$$\sigma_t = \alpha_0 + \alpha^+(L)\varepsilon_{t-1}^+ - \alpha^-(L)\varepsilon_{t-1}^- + \beta(L)\sigma_{t-1}$$

with $sCER_t$ are the residuals of the VAR(4) model related to the sCERs at time t, $momentum_{sCERt}$, $CDMpipeline_t$, $CDMEBmeeting_t$, and $linking_t$ exogenous variables specific to sCERs defined as above. Other variables have been defined previously for the EUA variable.

5.3. Estimation results

Estimation results are presented in Table 5. The quality of the regressions (3) to (5) is verified with the same diagnostic tests as for EUAs. All diagnostic tests are validated for regressions (3) to (5).

In regression (3), we observe that energy prices (*brent*, *coal* lagged one period, and *gas*) have a statistically significant impact on sCER prices with the same signs as for EUAs. This first result confirms that EUAs and sCERs share basically the same price fundamentals with respect to the interaction with energy markets.

In regression (4), *momentum*$_{sCERt}$ and *linking* are statistically significant at the 1% and 10% levels, respectively. The sign and interpretation of *momentum*$_{sCERt}$ is similar to *momentum*$_{EUAt}$ in the case of the EUA variable.

The positive sign of *linking* suggests that news about the future connection between the European and international credits carbon markets tend to increase sCERs prices. Note that sCERs are fungible across regional and domestic markets. Thus, this positive sign is coherent with what we would expect: as the global demand of sCERs increases, the price of sCERs also increases.

In regression (5), we note that *CDMpipeline* is not significant in explaining sCERs price changes. This result is conforming to the view that sCERs have distinct fundamentals from the delivery of primary CERs, since they are free of project delivery risk.

Table 5: TGARCH (1,1) Regression Results for the sCER Price Drivers

Variable		$sCER_t$	
	(3)	(4)	(5)
Constant	0.0008	0.0007	0.0007
	(0.007)	(0.0007)	(0.0013)
$brent_t$	0.0009***		0.0005*
	(0.0002)		(0.0003)
$coal_{t-1}$	0.0008**		-0.0017***
	(0.0001)		(0.0003)
gas_t	0.0002***		0.0002*
	(0.0001)		(0.0001)
$momentum_{CERt}$	0.0093**	0.0098***	
	(0.0009)	(0.0009)	
$Linking_t$		0.0194*	
		(0.0111)	
CDM $pipeline_t$			0.0005
			(0.0013)
Adjusted R^2	0.1582	0.1427	0.0469
Log-Likelihood	1344.581	1339.208	660.743
ARCH LM Test	0.9195	0.9730	0.7560
Q(20) Statistic	25.137	24.396	20.724
AIC	-5.1074	-4.8026	-4.5827
SC	-5.0341	-4.7783	-4.4542
N	529	529	529

*Note: $sCER_t$ refers to the residuals of the VAR(4) model related to sCERs (Reuters sCER Price Index). ***,(**),(*) Denotes 1%,(5%),(10%) significance levels. The quality of regressions is verified through the following diagnostic tests: the adjusted R-squared (Adjusted-R^2), the Log-Likelihood, the ARCH Lagrange Multiplier (ARCH LM Test), the Ljung Box Q-test statistic with a maximum number of lags of 20 (Q(20) statistic), the Akaike Information Criterion (AIC), and the Schwarz Criterion (SC). The 1% (5%) critical value for the Ljung-Box portmanteau test for serial correlation in the squared residuals with 20 lags is 37.57 (31.41). N is the number of observations.*

Having detailed separately EUAs and sCERs price drivers, we now turn to the determinants of the price difference between these two emissions assets.

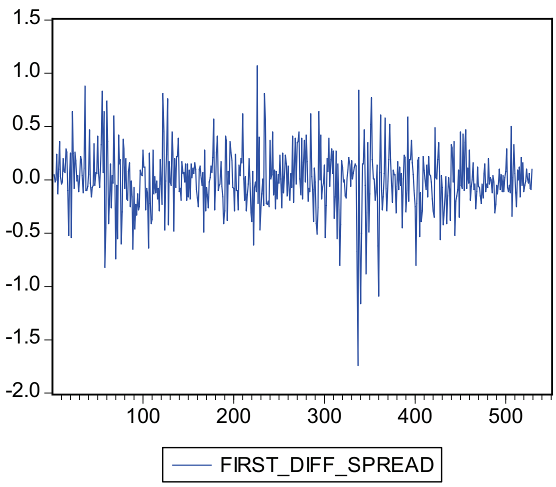
6. EUA-sCER Spread drivers

Following the analysis of EUAs and sCER price drivers, we focus in this section on the variables that may have an explanatory power for the evolution of the EUA-sCER spread defined as follows:

$$Spread_t = EUA_t - sCER_t$$

With EUA_t and $sCER_t$ respectively, the EUA (ECX EUA Phase II Futures prices) and sCER (Reuters sCER Price Index) rolled-over futures contract prices.[25] The EUA-sCER spread is pictured at the bottom of Figure 1. Given its construction, the spread is positive. It is equal to €2 in March 2007, €8 in May 2007, and evolves in the range of €2 to €6 until May 2008. It becomes then relatively close to zero until March 2009. Thus, the spread seems to widen (narrow) depending on bullish (bearish) periods on emissions markets. In Figure 11, we observe that the EUA-sCER spread taken in stationary first-difference transformation exhibits volatility clustering from May to September 2008, and that the volatility decreases near the end of the sample period.

Figure 11: First-difference of the EUA-sCER Spread from March 9, 2007 to March 31, 2009



[25] Note that ECX has implemented a sCER-EUA trading facility that allows trading the spread at reduced transaction costs. To facilitate the understanding of the determinants of the spread, we have chosen the more intuitive definition of the Spread = EUA-sCER, which has the advantage to be positive over the sample period.

The EUA-sCERs spread trading is mostly used by industrial and financial operators involved in short term trading activity. Indeed, the supply and demand for EUA-sCERs spread contracts come from short term price differences between EUAs and sCERs (as shown in Figure1). At time *t*, it appears profitable for investors to swap between these two carbon assets by buying sCERs and selling EUAs, since both assets may be used for compliance in the EU ETS (as long as the import limit on CERs is not reached). However, not all market participants may benefit from this arbitrage strategy. The reason for that situation is twofold: *(i)* there exist different types of market participants with different kinds of obligations and flexibility requirements on the use of sCERs, and *(ii)* technical skills are required to simultaneously buy sCERs and sell EUAs.

The latter point means that while banks may trade EUAs and sCERs on the market, they cannot use them towards their own compliance (and thus benefit from the full scale of the arbitrage strategy), since they are not regulated by the scheme. Conversely, large regulated utilities such as energy trading companies may benefit from opening a carbon trading desk *in-house* and exchange sCERs for EUAs in their own registry account. This type of market participant is therefore able to arbitrate between the two emissions markets by buying sCERs on the market and selling EUAs (registering them in its own registry towards compliance with their emissions target) when the price difference between the two emissions markets is at its maximum. This strategy yields a net "free-lunch" benefit as long as the import limit on CERs is not reached (which is not likely to be reached anytime soon according to the analysis by Trotignon and Leguet (2009)).

6.1. Exogenous variables

Besides the variables that have been previously identified as impacting EUAs and sCERs, we use price thresholds, market activity and liquidity variables stemming from the market microstructure literature (Codogno et al. (2003), Manganelli and Wolswijk (2009)) that may have an explanatory power for the EUA-sCER spread.

Regarding price thresholds, *EUApricelevel* is computed by regressing the EUA-sCER spread against the time-series of EUA prices. This variable reflects the idea that investors would more easily trade the spread if EUAs prices are around €30 than if they drop to €5. Following Zhang (2002), we also use a threshold variable (noted *thresholdSpread*) defined at €6 for the EUA-sCER spread.[26] *Above* this threshold, investors are expected to simultaneously sell EUAs and buy sCERs. Below, they are expected to wait for the widening of the spread to benefit from future more profitable arbitrage opportunities. Note

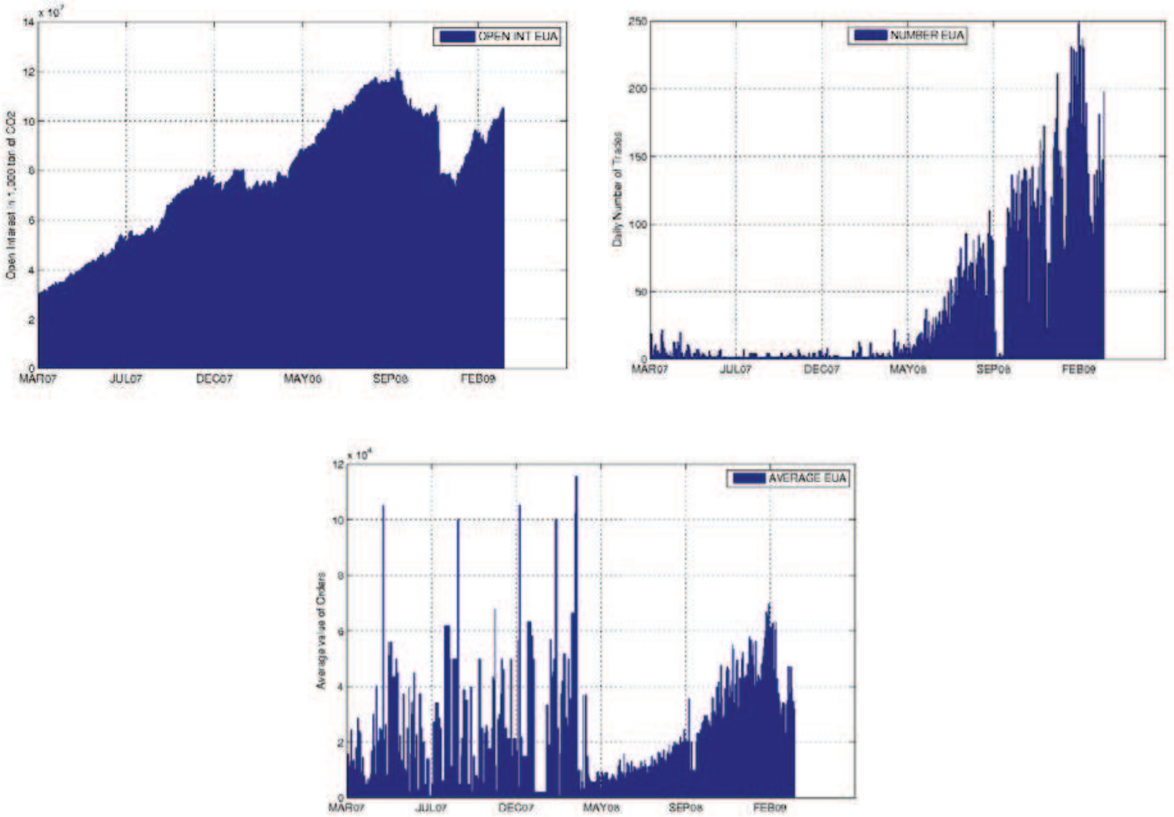
[26] This threshold has been fixed considering the average level of the spread during our sample period. Besides, we experimented with various thresholds, and this variable was found to be statistically significant only as such.

that this behavior is coherent with the fact that the import of CERs in the EU ETS (and thus the arbitrage opportunity) is limited in quantity and through time.

Regarding market activity, we use the average trade size for ECX EUA Phase II Futures prices (*averagetradeEUA*), defined as the daily volume divided by the daily number of trades, in order to track the impact of block trades or quasi-block trades on the spread. One could expect that large primary CER issuance could translate into large movements in the EUA market for cashing on the spread. Additionally, we have defined the variable *openintEUA* as the level of the open interest for the prevailing EUA calendar futures contract. This variable reflects the market overall level of engagement with the underlying asset. Compared to cumulative volumes, the open interest measure has the advantage to neutralize the impact of further transactions on existing futures positions to other market participants. The larger the open interest, the larger the quantity of futures contracts to be settled at a given date. We have also created the variable *CDMmktdvlpt* as a dummy variable equal to 1 during news announcements regarding the ability to trade sCERs (such as the beginning of trading sCER throughout standardized contracts on market places, etc.) and 0 otherwise.[27] We expect more activity on the spread as more announcements are recorded. Moreover, *numbertradeEUA* indicates the daily number of trades performed on ECX EUA Phase II future prices, as a proxy for liquidity in the market. This variable also reflects market participants' increased technical skills, as they may resort to specific algorithms to "slice up" large orders. Figure 12 displays the *openintEUA*, *numbertradeEUA*, and *averagetradeEUA* variables.

[27] See Annex I for announcement dates regarding the ability to trade sCERs.

Figure 12: ECX EUA Futures Open Interest (left), BNX Daily Number of Trades (right), and Average value of Orders (below) from March 9, 2007 to March 31, 2009

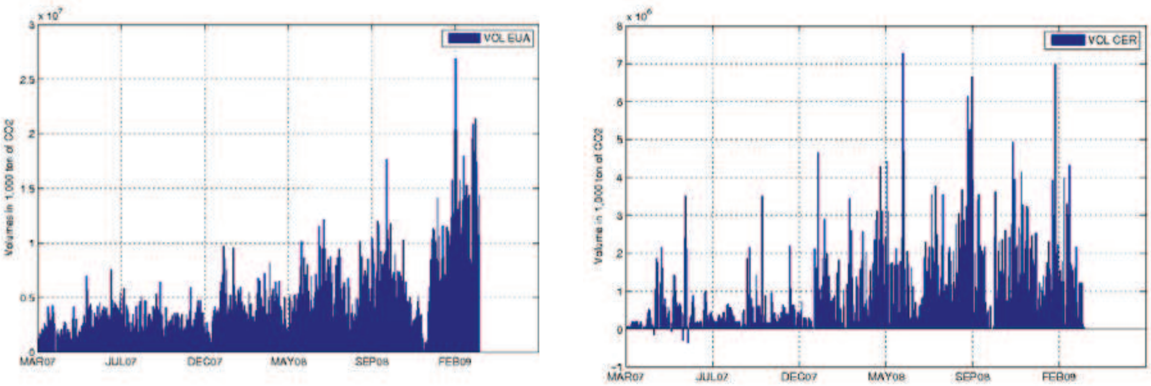


Source: ECX and Bluenext

To detect whether the size of the EUA-sCER spread is affected by changes in market activity and more specifically by market liquidity, we have considered trade-based measures for EUAs and sCERs. More precisely, following Gómez-Puig (2006), we have instrumented the *ΔvolumeEUA* variable, which tracks changes in the volume of EUAs traded, and the *ΔvolumesCER* variable, which tracks changes in sCERs volumes exchanged.[28] Figure 13 shows the evolution of these two variables.

[28] Data from the London Energy Brokers' Association (LEBA) have been used to compute this variable.

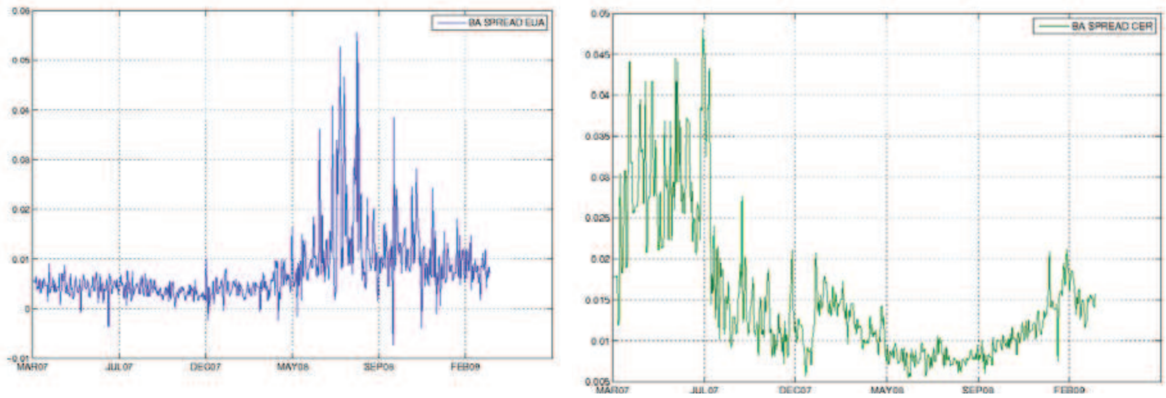
Figure 13: ECX EUA Futures (left) and Reuters CER Index (right) Volumes from March 9, 2007 to March 31, 2009



Source: ECX and LEBA

By using the (intraday) order book for EUAs, we computed relative bid-ask measures for EUAs (*bidaskEUA*). We systematically checked relative bid-ask spreads over 10% and below 1% (i.e. out of the established trend), and manually removed outliers that most likely reflected market orders made without any chance of being fulfilled.[29] Hence, the "cleaned" bid-ask used is a proxy for real liquidity of EUAs. We applied the same methodology with brokers' bid-ask data from the Reuters CER index (*bidasksCER*). The index contains daily average bid and ask prices from eight representative carbon brokers, so that no recalculation was required to proxy market liquidity on a daily basis. Figure 14 shows the *bidaskEUA* and *bidasksCER* variables.

Figure 14: Bid-ask spread for ECX EUA Futures (left) and Reuters CER Index (right) from March 9, 2007 to March 31, 2009



Source: ECX and Reuters

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[29] Bid-ask spreads may be negative according to our calculations since: *(1)* we are interested in daily average bid and ask, hence smoothing any intraday move; and *(2)* some bids or asks could have been posted with no intent of being attractive, but rather by contractual obligations (for market makers), or to deceive. Those bids and asks distort our estimation of bid-ask spreads. There is no economic rationale behind a negative bid-ask for a single quote, but it could indicate strong intraday activity.

Finally, we use *Panic* as a dummy variable equal to 1 from October 10 to 17, 2008; and 0 otherwise. This variable reflects the sharp increase in the volatility of EUA prices that may be observed in October 2008, as regulated utilities were "rushing to cash" in search for liquidity, in order to cope with the credit crunch crisis according to market observers.[30]

6.2. GARCH modeling

We model the EUA-sCER spread by following the same methodology as for the determinants of EUA and sCER variables:

$$\begin{aligned} Spread_t = {} & \alpha + \kappa momentum_{EUA\,t} + \upsilon VIX_t + \pi CDMpipeline_t + \lambda crisis_t + \mu EUETSphaseIII_t \\ & + \nu ITL\_CITL_t + \Pi panic_t + \varsigma CDMEBmeeting_t + \nu linking_t + \omega CDMmktdvlpt_t \\ & + \phi numbertradeEUA_t + \psi open\operatorname{int} EUA_t + \chi EUApricelevel_t + \eta \Delta averagetradeEUA_t \\ & + \xi \Delta volumeEUA_t + \beta \Delta volumesCER_t + \varpi bidaskEUA_t + \varsigma bidasksCER_t \\ & + \gamma thresholdSpread_t + \varepsilon_t \end{aligned}$$

$$\sigma_t = \alpha_0 + \alpha^+(L)\varepsilon_{t-1}^+ - \alpha^-(L)\varepsilon_{t-1}^- + \beta(L)\sigma_{t-1}$$

with $Spread_t$ the first-differenced EUA-sCER spread, $CDMmktdvlpt_t$, $numbertradeEUA_t$, $openintEUA_t$, $EUApricelevel_t$, $averagetradeEUA_t$, $volumeEUA_t$, $volumesCER_t$, $bidaskEUA_t$, $bidasksCER_t$, $thresholdSpread_t$ are the exogenous variables specific to the EUA-sCER spread commented above. Other variables have been defined previously for the analysis of EUA and sCER price drivers. Exogenous variables have been transformed to stationary when needed.

6.3. Estimation results

Table 6 presents the estimation results for the EUA-sCER spread. All diagnostic tests are validated for regressions (6) and (7).

Note that a statistically significant positive (negative) coefficient means that the spread is widening (narrowing) following changes in the underlying explanatory variable.

[30] See editorial by Trevor Sikorski (Barclays Capital) in issue #35 of the *Tendances Carbone* newsletter, Mission Climat Caisse des Dépôts, Paris.

Table 6: TGARCH(1,1) Regression Results for the EUA-sCER Spread Drivers

Variable	$Spread_t$ (6)	$Spread_t$ (7)
Constant	0.0145	-0.0080
	(0.0111)	(0.0134)
EUA price $level_t$	-0.9562***	-0.6726***
	(0.0322)	(0.0469)
Δ volume EUA_t	0.0007**	0.0001***
	(0.0004)	(0.0001)
Δ volume $sCER_t$	0.0013**	
	(0.0007)	
$Momentum_{EUAt}$	-0.0945***	-0.0997***
	(0.0121)	(0.0151)
$Linking_t$	0.2610***	
	(0.0733)	
VIX_t		0.3364***
		(0.1213)
$Crisis_t$		-0.4299***
		(0.0711)
CDM EB $meeting_t$		-0.0901***
		(0.0541)
$ThresholdSpread_t$		0.0764***
		(0.0134)
CDM $pipeline_t$		-0.0161***
		(0.0013)
Open interest EUA_t		0.0001***
		(0.0001)
Adjusted R^2	0.5800	0.5658
Log-Likelihood	141.5910	79.0179
ARCH LM Test	0.5540	0.5278
Q(20) statistic	36.765	26.371
AIC	-0.5023	-0.4699
SC	-0.4209	-0.3016
N	529	529

*Note: $Spread_t = EUA_t\text{-}sCER_t$. EUA refers to ECX EUA Phase II Futures prices. $sCER_t$ refers to Reuters sCER Price Index. ***,(**),(*) Denotes 1%,(5%),(10%) significance levels. The quality of regressions is verified through the following diagnostic tests: the adjusted R-squared (Adjusted-R^2), the Log-Likelihood, the ARCH Lagrange Multiplier (ARCH LM Test), the Ljung Box Q-test statistic with a maximum number of lags of 20 (Q(20) statistic), the Akaike Information Criterion (AIC), and the Schwarz Criterion (SC). The 1% (5%) critical value for the Ljung-Box portmanteau test for serial correlation in the squared residuals with 20 lags is 37.57 (31.41). N is the number of observations.*

In regression (6) we observe that the $EUApricelevel_t$ variable has a strong and statistically significant explanatory power for the determination of the EUA-sCER spread. As highlighted previously, sCER and EUA prices have followed similar price paths over the period. Thus, changes in EUA prices have a strong effect on the EUA-sCER spread. The sign of the $EUApricelevel_t$ coefficient is negative, which suggests that when EUA prices increase, the EUA-sCER spread diminishes. This result supports the intuition that at higher EUA price levels, investors and market operators have higher incentives to take adequate positions in both emissions markets to take advantage of the EUA-sCER spread. On the contrary, at low levels of EUA prices, the EUA-sCER is narrowing, which yields less profitable arbitrage opportunities. Interestingly, the coefficients of the $\Delta voumelEUA_t$ and $\Delta voumelsCER_t$ variables are statistically significant and *positive*. This result indicates that increased trading of EUAs and sCERs translates into wider EUA-sCER spread. This view is conform to the use of the EUA-sCER spread as a speculative product by rational investors and arbitrageurs: the volumes exchanged for EUAs and sCERs are found to be the highest when the EUA-sCER spread is at its maximum – thereby reflecting the strategy to maximize net profits.

The $momentum_{EUAt}$ and $linking_t$ variables have a statistically significant impact on variation of the EUA-sCER spread. The sign of $momentum_{EUAt}$ is positive, which suggests that when this variable is increasing (on a bullish carbon market), the EUA-sCER spread is narrowing. This result illustrates in a similar way the profit-maximizing strategy of rational market participants in the carbon market through the use of the EUA-sCER spread. Conversely, on a bearish carbon market (indicated by decreases in the $momentum_{EUAt}$ variable), the EUA-sCER spread is widening, which provides future opportunities for market participants to make the spread transaction at better conditions.

As indicated by the positive coefficient of the *linking* variable at the 1% level, the development of an international carbon market accepting sCERs as compliance assets tends to widen the EUA-sCER spread. Indeed, the prospects for growing sCERs demand outside of the European trading system might lead to a partial decorrelation from EUAs in a near future.

News regarding Phase III of the EU ETS, the ITL-CITL connection and market liquidity (as proxied by bid-ask spreads) could not be identified as statistically significant variables in regression (6).

Regression (7) is similar to regression (6), and reveals the explanatory power of six additional variables. The $EUApricelevel_t$, the $\Delta volumesEUA_t$, and the $momentum_{EUAt}$, coefficients may be interpreted identically. Changes in the *VIX* index, which are obtained from the implied volatility of S&P option prices, are used as a proxy of the evolution of aggregate financial markets' volatility. Its positive and statistically significant coefficient indicates that the EUA-sCER spread widens when the stock market volatility increases. This increase in the spread may indicate that the risk of holding sCER is perceived as higher than holding EUAs, which translates into a higher risk premium for the sCERs.

The *crisis* dummy variable appears statistically significant with a negative coefficient. Since the start of the global financial crisis, the EUA-sCER spread has narrowed, which suggests a strong interest in selling EUAs. Two facts may help to understand this negative coefficient. First, the global financial downturn has caused a decrease in industrial production and energy demand (and thus in the energy production of CO_2-intensive plants). The need for CO_2 allowances has dropped drastically, which fostered incentives to sell EUAs and contributed to the decline of the EUA-sCER spread. Second, as a consequence of the crisis, funding needs have increased. From this perspective, selling EUAs (which are only needed for compliance on April 30th of the year *N+1*) constitutes a sound strategy in order to obtain the cash needed from companies, especially in a credit-constrained economic environment. Thus, massive sales of EUAs for this purpose may explain the narrowing of the spread.

The coefficient of the dummy variable *ThresholdSpread$_t$*, is statistically significant and positive. Thus, when the EUA-sCER spread goes beyond the €6 level, the spread is widening more. This result confirms that market participants wait for the €6 threshold of the EUA-sCER spread to be achieved before taking advantage of the arbitrage strategy, thereby maximizing net profits from this free-lunch activity.

The coefficients of the two variables *CDMpipeline$_t$* and *CDMEBmeeting* are negative and statistically significant. Positive (negative) expected amount of primary CERs issued and news about CDM EB meetings are associated with a narrowing (widening) of the EUA-sCER spread. Increasing the delivery of CERs reduces the counterparty risk of a secondary CER, since the supply of primary CER is rising. Thus, the premium for holding EUAs instead of sCER decreases, which further narrows the spread.

Finally, the *openintEUA$_t$* variable may be interpreted similarly to the results relative to changes in carbon assets' volumes. As for the *ΔvolumeEUA$_t$* and *ΔvolumesCER$_t$* variables, increases in the open interest position on EUA futures is translated into a wider EUA-sCER spread.

Taken together, these results contribute to the clear identification of three categories of drivers for the EUA-sCER spread. First, the spread reacts to the EUA price levels as the EU ETS remains to date the major source of CER demand (both primary and secondary). Second, the spread is explained by variables reflecting the use of sCERs as a flexibility mechanism for EU ETS compliance buyers. This may be proxied by looking at *(1)* emissions prospects (i.e. demand for compliance) and the compliance profile of buyers (i.e. their ability to surrender a given quantity of CERs for compliance) and *(2)* the relative supply of EUAs (based on the levels of NAPs) and CERs (from the CDM pipeline) which will end up being used in the EU ETS. Third, and most importantly, we uncover that the EUA-sCER spread may be explained by market microstructure variables (e.g. trading activity proxies) justifying the "speculation"-related nature of this instrument. This result constitutes our central contribution with regard to the identification of the EUA-sCER spread drivers, since it appeared obvious to most market observers that this trading facility was used for speculative purposes, yielding net profit free-of-risk (that may be truly called a 'free-lunch' activity for arbitrageurs). Thus, we provide the first formal empirical analysis of such rational behavior of investors in the context of the EU ETS Phase II.

7. Conclusion

This article provides the first complete empirical analysis of both EUAs and sCERs price drivers, as well as the determinants of the EUA-sCER spread during Phase II (2008-2012) of the EU ETS. To our best knowledge, no previous empirical study has focused either on the determination of sCERs drivers or on the arbitrage strategies consisting in buying sCERs and selling EUAs (yielding net profits from the existence of a positive EUA-sCER spread during the sample period). We may decompose our findings in three main contributions.

First, the fundamentals of EUAs during Phase II have been clearly identified. As the supply of allowances was fixed by allocations through negotiations between the European Commission and Member States, price uncertainties typically depend on the level of demand factors. Conform to previous literature, we find that the demand for Phase II EUA prices also depends, in the short term, on the level of CO_2 emissions. The EUA variable classically evolves during the sample period as a function of primary energy prices and news related to Phase II NAPs. However, economic growth and weather conditions were not identified as significant influences, contrary to what has been observed during Phase I.

Second, our analysis of sCERs (i.e. CERs already issued by the CDM Executive Board of the United Nations) has confirmed that EUAs determine significantly the sCERs price path. We show that there exists one long-term cointegrating vector between EUAs and sCERs taken in natural logarithm transformation. Besides, the sCER variable has a stronger tendency to adjust to past disequilibria by moving towards the trend values of the EUA variable, which confirmed that EUAs are the leading factor in the price formation of sCERs. This result emphasizes that EUAs remain the most widely recognized "money" on emissions market. EUAs are exchanged broadly as the most liquid asset for carbon trading, which may be explained by the fact that Europe remains to date the major source of demand for that kind of credits. We also find that energy prices, variables referring to the linking of international carbon markets, and $\text{momentum}_{\text{sCER}}$ variables have an impact on sCERs prices. We conclude that sCERs pricing differs from EUAs since it embodies a greater level of uncertainty. Market participants are lacking the exact information concerning either the supply of CERs, or the total expected demand by 2012. Indeed, the future of credit offset mechanisms beyond 2012 is currently in definition with the current international negotiations for an international climate framework successor of the Kyoto protocol and with the current expectation on the regional carbon markets development, while the use of CERs in Europe is confirmed only until 2020.

Our third and main contribution concerns the determinants of the observed difference between EUA and sCER prices, namely the EUA-sCER spread. We identify statistically the influence of three key factors: *(i)* the evolution of EUA price levels, *(ii)* the regulatory information concerning both sCERs and EUAs, and *(iii)* trading activity proxies. Hence, we confirm the view that the EUA-sCER spread may be used as a 'speculative' instrument by rational investors and market participants on the EU ETS, who are able to trade simultaneously EUAs and sCERs when the price difference is large enough to justify the arbitrage activity. When 'free-lunch' opportunities exist on financial markets, they should be instantly identified by market agents.

The existence of the EUA-sCER spread may thus be chiefly explained by the conjunction of three factors: (i) the demand and supply of the EUA and sCER are different with higher uncertainty related to the sCERs, (ii) the European Commission has set an import limit of 13.4% on average concerning the use of CERs towards compliance within the European emissions trading system and (iii) the EUA and sCERs are not perfectively fungible for all market participants but only for those with compliance obligations. This limits the exploitation of the arbitrage opportunities that, in high volumes reduce the spread. Consequently, the arbitrage opportunities of exchanging cheaper sCERs by EUAs for compliance are limited in quantity and through time and benefit mainly to energy trading companies which possess large supplies of EUAs and their own carbon trading desk. In this paper, we uncover a salient characteristic of these newly created emissions markets: they allow the existence of temporary free-lunch activities (i.e. arbitrage opportunities are not necessarily transformed once they are identified, which is contrary to fundamental theories of finance), and foster the adoption of arbitrage operations (i.e. purchasing the EUA-sCER spread and thereby making a net risk-free profit) once the EUA-sCER spread has reached a given threshold. This empirical analysis of emissions markets reveals in fine the rational behavior of investors: profit-maximizing strategies are elaborated given the very unusual – compared to other financial markets – institutional characteristics of emissions markets. The arbitrage activity between EUA and sCERs also requires an expert knowledge that only banks with carbon trading desks, major energy trading companies, and specialized brokers are able to offer as of today. As the range of carbon markets develops worldwide, we may expect this kind of trading activities to develop rapidly, as the trading of spread for crude oil futures has recently demonstrated.

The evolution of the spread will depend crucially on sCER supply and its European demand, which will be defined gradually until the end of Phase II. Two scenarios are possible. If the supply of CERs is less than 1,400 Mt (including both primary and secondary), the price of sCER should rise towards that of the EUAs, and the spread should shrink. Conversely, if the supply of CERs is more than 1,400 Mt, the price of sCERs will disconnect from that of the EUAs.

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References

Alberola, E. and Chevallier, J. 2009. European Carbon Prices and Banking Restrictions: Evidence from Phase I (2005-2007). *The Energy Journal* 30(3), 51-80.

Alberola, E., Chevallier, J. and Chèze, B. 2008. Price drivers and structural breaks in European Carbon Prices 2005-07. *Energy Policy* 36 (2), 787-797.

Alberola, E., Chevallier, J. and Chèze, B. 2009a. Emissions Compliances and Carbon Prices under the EU ETS: A Country Specific Analysis of Industrial Sectors. *Journal of Policy Modeling* 31(3), 446-462.

Alberola, E., Chevallier, J. and Chèze, B. 2009b. The EU Emissions Trading Scheme: the Effects of Industrial Production and CO_2 Emissions on European Carbon Prices. *International Economics* 116, 95-128.

Bernanke, B. and Gertler, M. 1989. Agency Costs, Net Worth and Business Fluctuations. *American EconomicReview* 79, 14-31.

Carchano, O., Pardo, A., 2009. Rolling Over Stock Index Futures Contracts. *Journal of Futures Markets* 29, 684-694.

Chevallier, J. 2009. Carbon Futures and Macroeconomic Risk Factors : A view from the EU ETS, *Energy Economics* 31(4), 614-625.

Chevallier, J., Ielpo, F. and Mercier, L. 2009. Risk Aversion and Institutional Information Disclosure on the European Carbon Market: a Case-Study of the 2006 Compliance Event. *Energy Policy* 37(1), 15-28.

Codogno, L., Favero, C., and Missale, A. 2003. Yield spreads on EMU government bonds. *Economic Policy* 18(37), 503-532.

Collin-Dufresne, P., Goldstein, R.S., and Spencer Martin J. 2001. The Determinants of Credit Spread Changes. *The Journal of Finance* 56(6), 2177-2208.

Davies, A. 2008. Credit spread determinants: An 85 year perspective. *Journal of Financial Markets* 11(2), 180-197.

Delarue, E.D., Ellerman, A.D., and D'haeseleer, W. 2008. Short-Term CO2 Abatement in the European Power Sector. *MIT CEEPR Working Paper* #2008-008.

Ellerman, A.D., and Feilhauer, S. 2008. A Top-down and Bottom-up Look at Emissions Abatement in Germany in Response to the EU ETS. *MIT CEEPR Working Paper* #2008-017.

Gómez-Puig, M. 2006. Size matters for liquidity: Evidence from EMU sovereign yield spreads. *Economics Letters* 90, 156-162.

Johansen, S. and Juselius, K. 1990. Maximum Likelihood Estimation and Inference on Cointegration with Applications to the Demand for Money, *Oxford Bulletin of Economics and Statistics* 52, 169-210.

Johansen, S. 1991. Estimation and Hypothesis Testing of Cointegrating Vectors in Gaussian Vector Autoregressive Models, *Econometrica*, 59 1551-1580.

Kilian, L., and Vega, C. 2008. Do Energy Prices Respond to U.S. Macroeconomic News? A Test of the Hypothesis of Predetermined Energy Prices. *International Finance Discussion Papers, Board of Governors of the Federal Reserve System*, # 957.

Liu, N., and Zhang, L. 2008. Is the value spread a useful predictor of returns? *Journal of Financial Markets* 11(3), 199-227.

Lutkepohl, H., Saikkonen, P., and Trenkler, C. 2004. Testing for the cointegrating rank of a VAR with level shift at unknown time. *Econometrica* 72(2), 647-662.

Madhavan, A. 2000. Market Microstructure: A Survey. *Journal of Financial Markets* 3 (3), 205-258.

Manganelli, S., and Wolswijk, G. 2009. What drives spreads in the euro area government bond market? *Economic Policy* 24(58), 191-240.

Mansanet-Bataller, M., Pardo, A., and Valor, E., 2007. CO2 Prices, Energy and Weather. *The Energy Journal* 28 (3), 67-86.

Mansanet-Bataller, M. and Pardo, A., 2009. Impacts of Regulatory Announcements on CO_2 Prices. *The Journal of Energy Markets* 2(2), 1–33.

Manzoni, K. 2002. Modeling credit spreads: An application to the sterling Eurobond market. *International Review of Financial Analysis* 11, 183-218.

Ramchander, S., Simpson, M.W., and Chaudhry, M.K. 2005. The influence of macroeconomic news on term and quality spreads. *The Quarterly Review of Economics and Finance* 45, 84-102.

Trotignon, R., and Leguet, B., 2009. How Many CERs by 2013. *Mission Climat Working Paper* 2009-5.

Zakoian, J.M. 1994. Threshold Heteroskedastic Models. *Journal of Economic Dynamics and Control* 18 (5), 931-944.

Zhang, Z. 2002. Corporate Bond Spreads and the Business Cycle. *Bank of Canada Working Paper* #2002-15.

Zivot, E., and Andrews, D.W.K. 1992. Further evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis. *Journal of Business & Economic Statistics* 10(3), 251-270.

Annex 1: Dummy variables

Date	NAPs Phase II	EU ETS Phase III	CDM EB meeting	CDM mktdvlpt
25/03/2007			1	
26/03/2007	1			
26/03/2007	1			
02/04/2007	1			
16/04/2007	1			
18/04/2007			1	
04/05/2007			1	
04/05/2007	1			
15/05/2007	1			
30/05/2007			1	
01/06/2007				1
04/06/2007	1			
05/06/2007				1
06/06/2007			1	
11/06/2007			1	
11/06/2007				1
22/06/2007			1	
11/07/2007			1	
13/07/2007	1			
18/07/2007			1	
18/07/2007	1			
27/07/2007			1	
13/08/2007				1
29/08/2007			1	
31/08/2007	1			
01/10/2007			1	
05/10/2007			1	
19/10/2007			1	
22/10/2007	1			
26/10/2007	1			
26/10/2007	1			
26/10/2007	1			
12/11/2007			1	
14/11/2007			1	
20/11/2007			1	
30/11/2007			1	
07/12/2007	1			
16/01/2008			1	
23/01/2008		1		
01/02/2008			1	
06/02/2008				1
21/02/2008				1
26/02/2008				1
27/02/2008			1	
28/02/2008		1		
03/03/2008		1		
14/03/2008			1	

Date	EU ETS Phase III	CDM EB meeting	CDM mktdvlpt	Linking	ITL-CITL
14/03/2008			1		
23/04/2008			1		
30/04/2008		1			
16/05/2008		1			
19/05/2008			1		
20/05/2008				1	
23/05/2008			1		
29/05/2008			1		
30/05/2008		1			
05/06/2008	1				
06/06/2008	1				
06/06/2008				1	
09/06/2008			1		
11/06/2008	1				
17/06/2008		1			
04/07/2008					1
09/07/2008	1				
16/07/2008		1			
02/08/2008		1			
04/08/2008			1		
06/08/2008					1
12/08/2008			1		
12/08/2008			1		
10/09/2008		1			
26/09/2008		1			
07/10/2008	1				
08/10/2008		1			
08/10/2008	1				
15/10/2008			1		
15/10/2008	1				
20/10/2008	1				
24/10/2008			1		
25/10/2008		1			
28/10/2008					1
12/11/2008		1			
28/11/2008		1			
04/12/2008	1				
08/12/2008			1		
17/12/2008	1				
17/12/2008	1				
17/12/2008	1				
28/01/2009		1			
02/02/2009			1		
03/02/2009			1		
10/02/2009		1			
13/02/2009		1			
16/02/2009			1		

The dummy variables refer to new information disclosure concerning NAPs Phase II (NAPs Phase II), the development of the EU ETS during Phase III (EU ETS Phase III), the day of publication of the CDM Executive Board report (CDM EB meeting), the CER market development (CDM mktdvlpt), the linking of emission trading schemes worldwide (linking) and the ITL-CITL connection (ITL-CITL). Sources: UNFCCC, European Commission, European Council, European Parliament, European Economic and Social Committee, Committee of the Regions, Nordpool, ECX, EEX, Bluenext, ICE, Point Carbon, CNN.

Options introduction and volatility in the EU ETS[1]

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Abstract: To improve risk management in the European Union Emissions Trading Scheme (EU ETS), the European Climate Exchange (ECX) has introduced option instruments in October 2006. The central question we address is: can we identify a potential destabilizing effect of the introduction of options on the underlying market (EUA futures)? Indeed, the literature on commodities futures suggest that the introduction of derivatives may either decrease (due to more market depth) or increase (due to more speculation) volatility. As the identification of these effects ultimately remains an empirical question, we use daily data from April 2005 to April 2008 to document volatility behavior in the EU ETS. By instrumenting various GARCH models, endogenous break tests, and rolling window estimations, our results overall suggest that the introduction of the option market had the effect of decreasing the level of volatility in the EU ETS while impacting its dynamics. These findings are fairly robust to other likely influences linked to energy and commodity markets.

JEL Classification: G13, G18, Q57, Q58.

Keywords: EU ETS, option prices, volatility, GARCH, rolling estimation, endogenous structural break detection.

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1 Introduction

To what extent does the introduction of options tend to destabilize tradable permits markets? Indeed, allowing for option trading may have some consequences on volatility in the underlying market. According to Weaver and Banerjee (1990), the introduction of options may affect the volatility of the underlying market, since they affect producers' decisions through intertemporal arbitrage. Conversely, it may also very well increase the liquidity and the informational efficiency of the underlying market. Back (1993) shows that options may guide producers' decisions based on a mix of true information and speculators' noise signals. Since allowance price stability is an important determinant of the performance of cap-and-trade programs, an analysis of how the introduction of options trading affected volatility in the European Union Emissions Trading Scheme (EU ETS) is worthwhile.

Previous empirical literature provides mixed conclusions concerning the introduction of options. In an exhaustive survey on this topic, Mayhew (2000) shows ambiguous effects of the introduction of derivatives on the volatility of the underlying asset, *i.e.* it may be either positive or negative depending on the market under consideration (equities, bonds, or commodities). Fleming and Ostdiek (1999) have contributed to the analysis of the introduction of derivatives instruments on the underlying crude oil market and derived products. The authors provided evidence of a short-run effect on the level of volatility while the long-run effect may be due to exogenous factors, such as the deregulation of energy markets. Thus, detecting whether the introduction of options has increased or decreased volatility in the EU ETS remains an empirical issue worth of investigation.

The EU ETS is a *compliance* market, which means that each installation of the approximately 10,600 covered installations needs to surrender each year a number of allowances, fixed by each Member State in its National Allocation Plan (NAP), equal to its verified emissions (Ellerman and Buchner (2008), Alberola *et al.* (2009)). To comply with their emissions target, installations may exchange quotas either over-the-counter, or through brokers and market places.[5] *Bluenext*[6] is the market place dedicated to CO_2 allowances based in Paris. It has been created on June 24, 2005 and has become the most liquid platform for spot trading.[7] The *European Climate Exchange* (ECX) is the market place based in London. It has been created on April 22, 2005 and is the most liquid platform for futures and option trading.[8]

Following the rapid development of spot and futures trading on these exchanges[9], more sophisticated carbon products have been progressively introduced, thereby offering to market participants a greater flexibility in the management of their compliance requirements. Option prices have been introduced by ECX on October 13, 2006.[10] The introduction of carbon options naturally raises the

[5] To guarantee compliance, any reported violation may be associated with a high penalty (Stranlund *et al.* (2005)). The existence of a hedging (option) instrument may facilitate compliance, and as such be viewed as a complement of enforcing policies.

[6] Formerly called *Powernext Carbon*.

[7] 72% of the volume of spot contracts are traded on Bluenext (Reuters).

[8] 96% of the volume of futures contracts are traded on ECX (Reuters).

[9] Other exchanges are worth mentioning: *(i) NordPool*, which represents the market place common to Denmark, Finland, Sweden, Norway, and is based in Oslo; *(ii)* the *European Energy Exchange* (EEX), based in Leipzig, trading spot and derivatives products for emissions allowances rights; and *(iii)* the *New York Mercantile Exchange* (NYMEX), based in the U.S., which is also trading European futures and options emissions rights. The price of products exchanged on these market places are strongly correlated, which is also a feature of stock markets.

[10] Note that options have also been introduced by EEX on March 5, 2008. However, we do not have enough historical data at

question of their utility for market agents. There are mainly two uses of options: *(i)* for *speculation* purpose in order to make a profit from trading, and *(ii)* for *hedging* purpose, in order to reduce or eliminate the risk in a position. The second use obviously allows industrials to lower the economic, political and financial uncertainties attached to market developments in the EU ETS. Böhringer *et al.* (2008) emphasize that overlapping instruments should be avoided to achieve efficiency in global environmental policy. The main "environmental policy"-related risk for industrials would then consist in permits price changes, which could be strongly reduced by using hedging instruments such as options.

Empirical studies of the EU ETS option market remain scarce. Uhrig-Homburg and Wagner (2007) describe extensively derivative instruments in the EU carbon market based on qualitative surveys. Chesney and Taschini (2008) provide an application of CO_2 price dynamics modeling to option pricing. Chevallier *et al.* (2009) provide a case-study of investors' changes in risk aversion around the 2006 compliance event using both futures and options. To our best knowledge, no prior study has investigated the impact of the options introduction in the EU ETS on the characteristics of the underlying carbon price in terms of volatility.

When introducing option trading in October 2006, the ECX may have indirectly increased the volatility of the underlying futures market. Indeed, the higher the leverage effect associated with option trading, the higher speculation about fuel substitution develops, which translates into rising volatility. This effect has been observed in some other markets and is generally viewed as a negative externality. More specifically, we examine the following central questions: what is the impact of the option market on the carbon price in terms of volatility? Is the introduction of the option market the only cause behind volatility changes? The latter question leads us to consider other factors such as institutional decisions, energy and global commodity markets to which volatility changes could be attributed as well.

Our empirical study departs from previous literature on several aspects. First, we develop a GARCH model with a dummy variable to study the impact of the introduction of the option market (Antoniou and Foster (1992), Antoniou and Holmes (1995), Gulen and Mayhew (2000)). As in Antoniou and Foster (1992), we decompose our sample into two sub-periods to identify any impact on the nature (the dynamics) of the volatility through changes in GARCH coefficients. This econometric analysis is finally taken one step further by using rolling estimations with a window of 200 observations. Then, we proceed with an endogenous structural break test (Inclán and Tiao (1994), Sansó, Aragó and Carrion (2004)) to detect more precisely the influence of options introduction. To the best of our knowledge, this kind of test has not been used for such a purpose yet.

After taking into account the volatilities of several energy- and commodity-related variables, we do observe an impact of the introduction of the option market on the level of the volatility of carbon futures prices. The results are fairly robust to various specifications of the conditional volatility including different combinations of exogenous variables. These findings therefore suggest that the observed changes in the unconditional component of volatility for EUA futures returns and the introduction of options are linked. In addition, we show a significant change in the dynamics of volatility which might be related to the introduction of options (while this latter effect needs to be

hand for this product and liquidity was known to be very low. So, we decide to focus on ECX option prices only. The study of discrepancies between ECX and EEX option prices is left for further research.

interpreted cautiously). Overall, our article brings a better understanding of the role played by the option market on the volatility of the carbon price in the EU ETS.

The remainder of the paper is organized as follows. Section 2 presents the carbon futures and option markets. Section 3 summarizes the data used. Section 4 details the econometric methodology, along with estimation results. Section 5 concludes.

2 Overview of the futures and option markets in the EU ETS

In what follows, we detail first the structure and main features of EU ETS derivatives, and second we provide a liquidity analysis with a specific focus on the daily liquidity in option contracts.

2.1 Structure and main features of EU ETS derivatives

The EU ETS has been created by the Directive 2003/87/CE. Across its 27 Member States, it covers large plants from CO_2-intensive emitting industrial sectors with a rated thermal input exceeding 20 MW. One allowance exchanged on the EU ETS corresponds to one ton of CO_2 released in the atmosphere, and is called a European Union Allowance (EUA). 2.2 billion allowances per year have been distributed during Phase I (2005-2007). 2.08 billion allowances per year will be distributed during Phase II (2008-2012). With a value of around €20 per allowance, the launch of the EU ETS thus corresponds to a net creation of wealth of around €40 billion per year. On January 2008, the European Commission has extended the scope of the EU trading system to other sectors such as aviation and petro-chemicals by 2013, and confirmed its functioning Phase III until 2020. As for many commodities markets, carbon allowances may be traded through on-exchange markets and through over-the-counter derivatives markets (see Daskalakis et al. (2009), Benz and Hengelbrock (2008) and Rotfuss (2009) for exhaustive descriptions of the EUA derivatives markets). We present below the main features of futures and options contracts written on EUAs.

We choose to model the behavior of the ECX futures prices for the carbon time-series in this article. One reason is that, due to the banking restrictions implemented between 2007 and 2008 (Alberola and Chevallier, 2009), spot prices show a non-reliable behavior during Phase I.[11] The futures contract is a deliverable contract where each member with a position open at cessation of trading for a contract month is obliged to make or take delivery of emission allowances to or from national registries. The unit of trading is one lot of 1,000 emission allowances. Each emission allowance represents an entitlement to emit one ton of carbon dioxide equivalent gas. Market participants may purchase consecutive contract months to March 2008, and then December contract months from December 2008 to December 2012.[12] Delivery occurs by mid-month of the expiration contract date. Trading occurs from 07.00AM to 05.00PM GMT.

Besides, we introduce ECX options into our econometric analysis. ECX option trading started on October 13, 2006. The underlying security for option trading is the ECX futures contract of corre-

[11] Besides, in the EU ETS, allowances need to be surrendered only on a yearly basis during the compliance event by mid-May, which makes the distinction between spot and forward prices less relevant than on other commodity markets such as the crude oil or the electricity market where storage costs are important. Note by contrast that storage costs are zero for CO_2 allowances.

[12] Note *spreads* between two futures contracts may also be traded.

Table 1
Expiration dates for ECX options contracts
Source: Bloomberg

Month	Last Trade	Expiration
November 2006	11/22/06	11/22/06
December 2006	12/19/06	12/19/06
December 2007	12/24/07	12/24/07
December 2008	12/10/08	12/10/08
January 2009	1/21/09	1/21/09
February 2009	2/18/09	2/18/09
December 2009	12/9/09	12/9/09
December 2010	12/15/10	12/15/10
December 2011	12/14/11	12/14/11
December 2012	12/14/12	12/14/12

sponding maturity. Options have been introduced on ECX as *European*-style options, *i.e.* options convey the right, but not the obligation to buy (call) or sell (put) the underlying asset at a specified strike price and expiration date.[13] Similarly, the contract size is 1,000 emissions allowances. Expiration dates for ECX options contracts are summarized in Table 1.

2.2 Liquidity analysis

During Phase I (2005-2007), the total volume of allowances exchanged in the EU ETS has been steadily increasing. The number of transactions has been multiplied by a factor four between 2005 and 2006, going from 262 to 809 million tons. This increasing liquidity of the market has been confirmed in 2007, where the volume of transactions recorded equals 1.5 billion tons. This peak of transactions may be explained by the growth of the number of contracts valid during Phase II, with delivery dates going from December 2008 to December 2012, which amount for 4% of total exchanges in 2005, and 85% in 2007. These transactions reached €5.97 billion in 2005, €15.2 billion in 2006, and €24.1 billion in 2007, thereby confirming the fact that the EU ETS represents the largest emissions trading scheme to date in terms of transactions. In 2008, the carbon market was worth between €89-94 billion, up more than 80% year-on-year (Reuters). The launch of secondary certified emission reduction (CER)[14] contracts on ECX certainly fostered this growth rate of transactions.

The trading of ECX futures started on April 22, 2005 with varying delivery dates going from De-

[13] An *American* option is like an European option, except it can be exercised *at any time* prior to maturity.
[14] According to the article 12 of the Kyoto Protocol, Credit Development Mechanisms (CDM) projects consist in achieving GHG emissions reduction in non-Annex B countries. After validation, the UNFCCC delivers credits called Certified Emissions Reductions (CERs) that may be used by Annex B countries for use towards their compliance position. CERs are fungible with EU ETS allowances with a maximum limit of around 13.4% on average.

cember 2005 to December 2012. Futures contracts with vintages December 2013 and 2014 were introduced on April 8, 2008. For the December 2009 futures contract, futures trade at €13.32/ton of CO_2 as of January 15, 2009, and have reached a maximum price of €32.90/ton of CO_2 in 2008.[15] From April 2005 to January 2009, the total volume of ECX futures exchanged for all vintages is equal to 40.67 billion.

The volume of options contracts traded from October 13, 2006 to January 16 2009 for the futures contracts of maturity December 2008 and December 2009 are presented in Table 2, along with the average volume contract for each strike. The total volume of options contracts traded is equal to 235Mton of CO_2 for the December 2008 contract, and to 73 Mton of CO_2 for the December 2009 contract (as of January 16, 2009). Calls are more actively traded than puts with an average volume of, respectively, 163 Mton and 72 Mton of CO_2 for the December 2008 contract. This pattern is reversed for the December 2009 contract with a total volume of calls and puts traded equal to, respectively, 31 Mton and 42 Mton of CO_2. This latter result may be explained by anticipations of carbon price decreases due to economic uncertainties by market participants. We may notice that the volume of call prices exchanged is clustered around the strikes ranging between €25 and €28. Conversely, the volume of put prices exchanged is clustered around the strikes ranging from €15 to €24. These asymmetries reflect the hedging strategies constructed by market agents to reduce the risk of their position with regard to high/low carbon price changes. They also reflect the uncertainties affecting the allowance market concerning the possible range of price changes in a moving institutional context.

Compared to 1.9 billion CO_2 futures traded in 2008, the size of the option market (235 Mton) during the same year provides evidence that options are actively traded despite it remains an emerging market. This is of central importance for our empirical analysis, since we want to assess whether options have an effect on the carbon price volatility. Since it is possible that the liquidity in options contracts was not instantaneously effective at the date of the introduction of the options market, we focus next on the *daily* liquidity in options contracts[16].

Figure 1 shows the daily liquidity in options contracts during our study period. This figure confirms that, on average, calls are more traded than puts in the EU ETS. More importantly, we notice that the liquidity in options contracts seemed to increase from 500,000 tons to 1Mton for the first time on May 18, 2007 for calls and on June 27, 2007 for puts. Besides, we may observe the very high degree of concentration of options trading during January 2008. During that period, the daily volume of calls traded is often superior to 1Mton, with a maximum of 4.450Mton on January 28, 2008. Similarly, for puts we have a peak at 3.8Mton on January 04, 2008. Figure 1 therefore reveals that the options market becomes increasingly liquid through time, as one can expect, and that the highest volumes of options exchanged seem to coincide with anticipations of yearly compliance events.

[15] In the longer term, analysts forecast EUA prices of €20-25/ton of CO_2 over Phase II and €25-30/ton of CO_2 over Phase III (Reuters).

[16] We wish to thank an anonymous reviewer for highlighting this point.

Table 2
Volume of options contracts traded on ECX from October 13, 2006 to January 16 2009 for the futures contracts of maturity December 2008 and December 2009 (in 1,000 tons)
Source: European Climate Exchange

	Strikes in €	**07**	**08**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
December 2008	**Call prices**	N/A	N/A	N/A	N/A	N/A	N/A	200	350	700	300	500	2,060	5,575	1,650	5,150	6,785	5,370
	Put prices	N/A	400	3,690	1,145	2,425	1,290	4,218	11,380	2,173	2,010	3,875	3,015	8,440	4,820	2,600	4,500	9,650
	Total	N/A	400	3,690	1,145	2,425	1,290	4,418	11,730	2,873	2,310	4,375	5,075	14,415	6,470	7,750	11,285	15,020
December 2009	**Call prices**	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1,000	500	2,100	3,550	500	3,700	N/A	1,000	250	N/A
	Put prices	642	600	4,305	1,242	2,300	2,300	5,450	8,250	4,500	2,000	900	15	1,350	300	4,700	N/A	1,450
	Total	642	600	4,305	1,242	2,300	2,300	5,450	9,250	5,000	4,100	4,450	515	5,050	300	5,700	250	1,450

	Strikes in €	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**37**	**38**	**40**	**45**	**46**	**50**
December 2008	**Call prices**	27,495	10,106	14,273	10,013	1,780	18,300	1,400	3,250	625	3,050	25,200	100	200	14,900	500	400	3,200
	Put prices	1,700	1,100	2,100	1,000	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Total	29,195	11,206	16,373	11,013	1,780	18,300	1,400	3,250	625	3,050	25,200	100	200	14,900	500	400	3,200
December 2009	**Call prices**	3,055	550	2,850	700	10	1,300	500	N/A	N/A	300	2,410	100	500	1,500	1,000	400	2,950
	Put prices	N/A	1,500	N/A	150	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
	Total	3,055	2,050	2,850	850	10	1,300	500	N/A	N/A	300	2,410	100	500	1,500	1,000	400	2,950

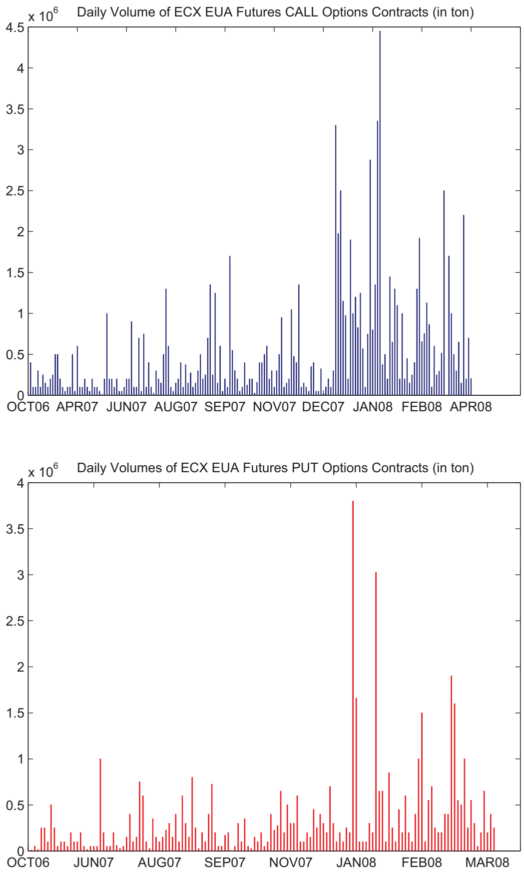

Figure 1
Daily volumes (in ton) of options contracts for ECX EUA Futures Calls (top) and Puts (bottom) from October 13, 2006 to April 03, 2008
Source: European Climate Exchange

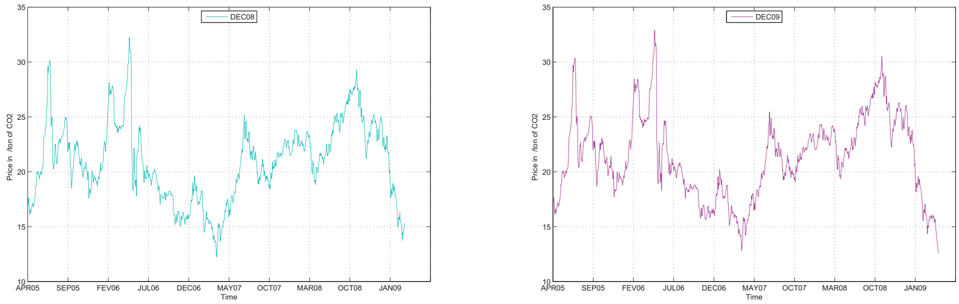

Figure 2
Carbon futures prices of maturities December 2008 (left) and 2009 (right) from April 22, 2005 to January 16, 2009
Source: European Climate Exchange

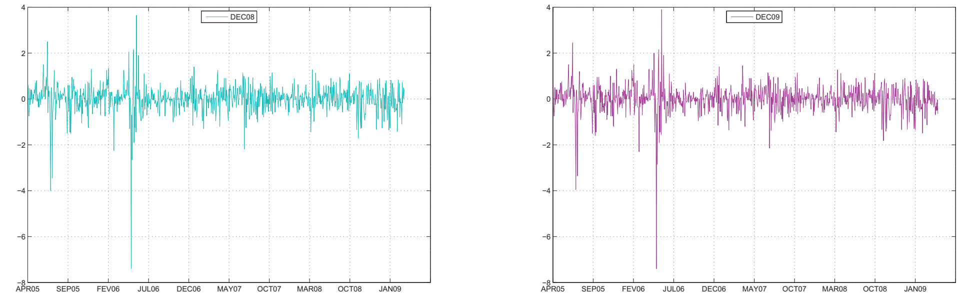

Figure 3
Returns on ECX Carbon Futures Prices of maturities December 2008 (left) and 2009 (right) from April 22, 2005 to January 16, 2009

3 Data

Our sample period goes from April 22, 2005 to April 04, 2008. We gather a full sample of 756 daily observations. The source of the data is ECX, Bloomberg and Reuters.

3.1 Carbon Price

For carbon allowances, we use daily futures and options for the December 2008-2009 contracts traded in €/ton of CO_2 on ECX. Figure 2 shows the futures price development for contracts of maturities December 2008 and 2009 from April 22, 2005 to January 16, 2009. We may observe that futures prices for delivery during Phase II (2008-2012) proved to be much more reliable than futures prices for delivery during Phase I (2005-2007) due to the banking restrictions enforced between the two Phases (Alberola and Chevallier, 2009). Besides, we note that post-2007 futures convey a coherent price signal - around 20 €/ton of CO_2 - throughout the historical available data for the second phase of the scheme. The futures price development features a lower bound around 15€/ton of CO_2 in April 2007, and an upper bound around 35€/ton of CO_2 in November 2008.

Table 3
Descriptive Statistics of ECX EUA Futures Returns and Energy and Global Commodity Markets Returns from April 22, 2005 to January 16, 2009
Source: European Climate Exchange, Reuters

Full Period	Mean	Median	Max	Min	Std. Dev.	Skew.	Kurt.	N
Carbon Futures Returns								
EUA_{DEC08}	-0.0018	0.0200	3.6500	-7.4000	0.6149	-2.2450	29.7930	936
EUA_{DEC09}	-0.0047	0.0200	3.9000	-7.4000	0.6169	-2.1299	29.1426	957
Energy and Global Commodity Markets Returns								
$Brent$	-0.0135	0.0381	11.0876	-15.6324	1.6227	-0.8159	19.0411	830
$Coal$	0.0034	0.0100	8.2900	-5.5600	0.6566	1.1207	46.3338	830
CRB	0.0619	0.4000	30.5700	-38.8100	5.3023	-0.8334	12.9586	830
$CleanDark$	0.0151	-0.0250	50.1700	-40.1400	4.2297	1.4064	50.5866	830
$Ngas$	0.0009	-0.0700	42.4500	-20.5200	3.2438	3.3141	49.2934	830
$Power$	0.0121	-0.0200	43.7100	-39.7800	4.1482	0.5050	44.8046	830
$CleanSpark$	0.0137	-0.0300	45.5000	-42.2200	4.8714	0.0109	33.3175	830
$Switch$	0.0001	0.0001	0.0500	-0.0300	0.0053	1.3380	18.8594	830

Note: EUA_{DEC08} and EUA_{DEC09} refer respectively to the carbon futures returns of maturity December 2008 and December 2009, CRB to the Reuters/Commodity Research Bureau Futures Index, $StdDev.$ refers to the standard deviation, $Skew.$ refers to the skewness, $Kurt.$ refers to the kurtosis, and N refers to the number of observations.

Descriptive statistics of ECX futures contracts of maturity December 2008 and 2009 are presented in Table 3. We may observe that ECX futures of all maturities present negative skewness and excess kurtosis[17]. These summary statistics therefore reveal an asymmetric and leptokurtic distribution.[18]

We also present in Figure 4 the empirical autocorrelation function of EUA returns and squared returns for the futures contracts of maturity December 2008 and December 2009. For both series, although the returns themselves are largely uncorrelated, the variance process exhibits some correlation. This is consistent with the earlier discussion on the necessity to use GARCH modeling for CO_2 price series[19].

3.2 Energy Prices

According to previous literature, energy prices are the most important drivers of carbon prices due to the ability of power generators to switch between their fuel inputs (Delarue *et al.* (2008), Ellerman and Feilhauer (2008)). This option to switch from natural gas to coal in their inputs represents an abatement opportunity to reduce CO_2 emissions in the short term. High (low) energy prices contribute to an increase (decrease) of carbon prices. This logic is described by Kanen (2006) who identifies brent prices as the main driver of natural gas prices which, in turn, affect power prices and ultimately carbon prices. Bunn and Fezzi (2009) also identify econometrically that carbon prices react significantly to a shock on gas prices in the short term. Descriptive statistics for energy and

[17] Note for a normally distributed random variable skewness is zero, and kurtosis is three.
[18] Such a fat-tailed distribution may suggest a GARCH modeling as GARCH models better accommodate excess kurtosis in the data.
[19] Note however that it appears difficult to motivate other type of models, for example processes that are able to account for long memory, given the relatively short time horizon at hand since the creation of the EU ETS.

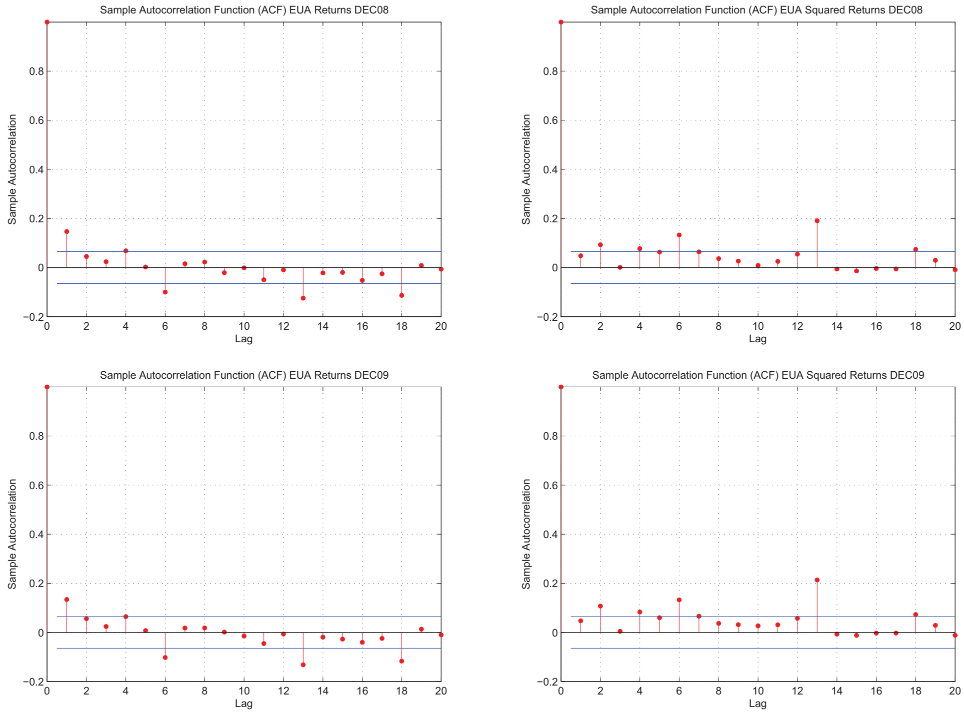

Figure 4
Empirical autocorrelation function of EUA returns (left) and squared returns (right) for the ECX futures contracts of maturity December 2008 (top) and December 2009 (bottom)

global commodity markets returns may also be found in Table 3.

3.2.1 Brent, Natural Gas, and Coal Prices

For energy prices, we use the daily Intercontinental Exchange (ICE) Crude Oil Brent Free-of-Board in $/barrel, the daily ICE Natural Gas 1-Month Forward contract traded in UK pence/Therm, and the daily coal futures Month Ahead price CIF ARA[20] traded in €/ton. Price series are converted to € using the daily exchange rate provided by the European Central Bank.

Figure 5 presents the price development for the Zeebrugge natural gas next month, Rotterdam coal futures, and NYMEX crude oil futures price series from April 22, 2005 to January 16, 2009. Natural gas prices exhibit a strong volatility compared to coal prices. In November 2005 and September 2008, natural gas prices soared to 90€/MWh, and steadily decreased afterwards to 40€/MWh in February 2008 and December 2008. The competitiveness of natural gas compared to coal may be more specifically captured during the period going from December 2006 to July 2007. The brent price series peaked over 80€/barrel from May to August 2008.

[20] CIF ARA defines the price of coal inclusive of freight and insurance delivered to the large North West European ports, *e.g.* Amsterdam, Rotterdam or Antwerp.

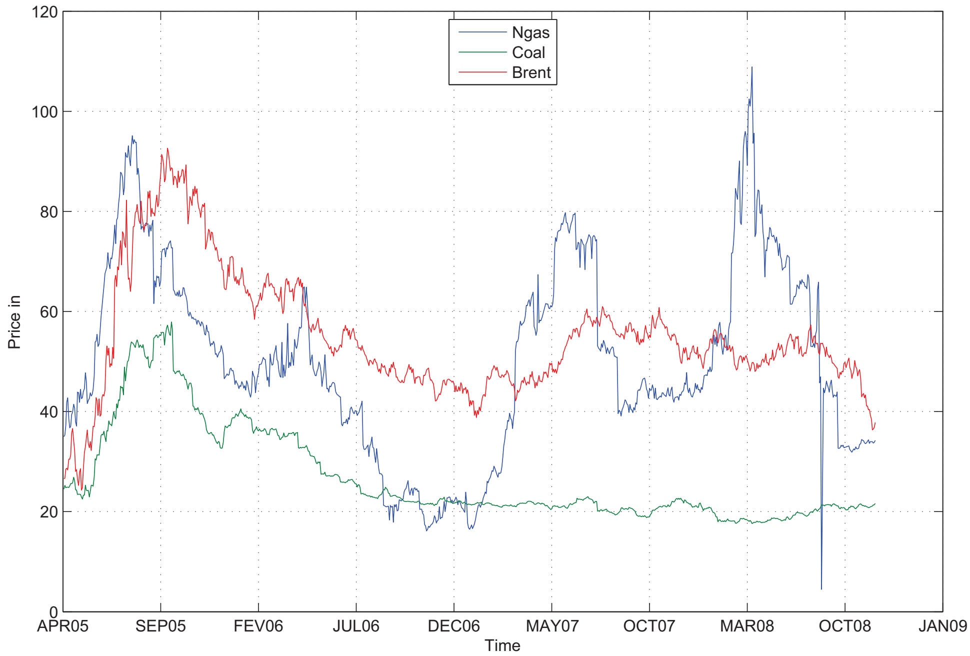

Figure 5
Zeebrugge natural gas, Rotterdam coal futures, and NYMEX crude oil futures prices from April 22, 2005 to January 16, 2009
Source: Reuters

3.2.2 Power, *Clean Spark*, *Clean Dark*, and *Switch* Prices

The price of electricity Powernext (*elec* in €/MWh) is the contract of futures Month Ahead Base. To take account of abatement options for energy industrials and relative fuel prices, three specific spreads are included.

First, the Clean Dark Spread (*clean dark spread* expressed in €/MWh) represents the difference between the price of electricity at peak hours and the price of coal used to generate that electricity, corrected for the energy output of the coal plant and the costs of CO_2:

$$clean\ dark\ spread = elec - (coal * \frac{1}{\rho_{coal}} + p_t * EF_{coal}) \tag{1}$$

with ρ_{coal} the net thermal efficiency of a conventional coal-fired plant.[21], and EF_{coal} the CO_2 emissions factor of a conventional coal-fired power plant[22].

Second, the Clean Spark Spread (*clean spark spread* expressed in €/MWh) represents the difference between the price of electricity at peak hours and the price of natural gas used to generate that electricity, corrected for the energy output of the gas-fired plant and the costs of CO_2:

[21] *i.e.* 35% according to Reuters.
[22] *i.e.* 0.95 tCO_2/MWh according to Reuters.

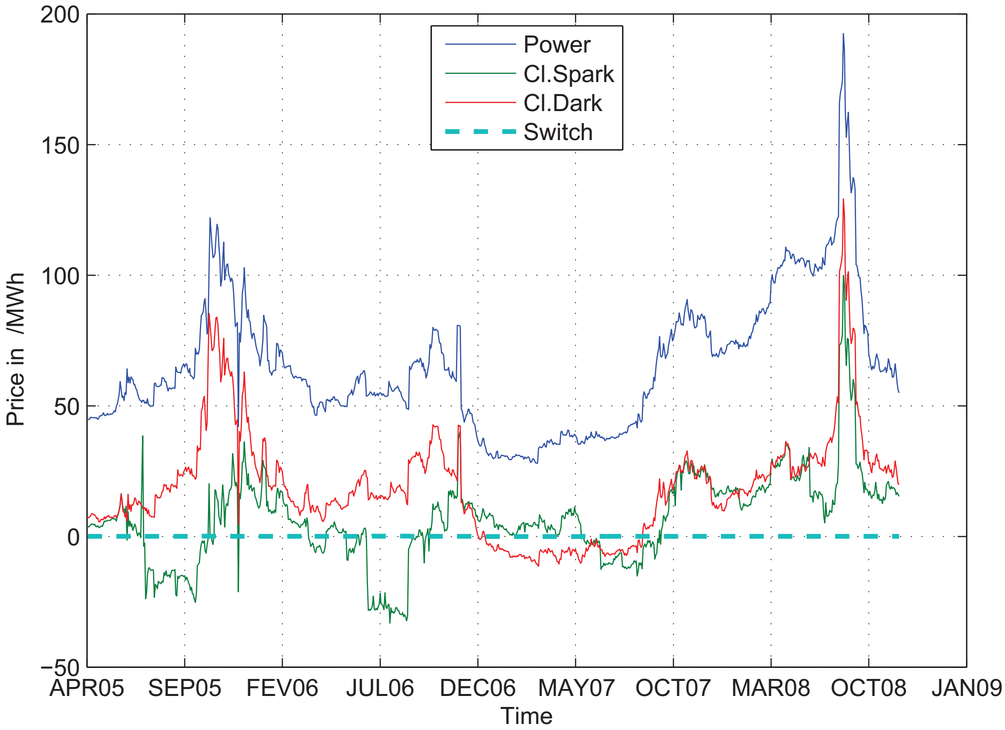

Figure 6
Powernext electricity futures, *Clean Spark Spread*, *Clean Dark Spread*, and *Switch* prices from April 22, 2005 to January 16, 2009
Source: Reuters

$$clean\ spark\ spread = elec - (ngas * \frac{1}{\rho_{ngas}} + p_t * EF_{ngas}) \tag{2}$$

with ρ_{ngas} the net thermal efficiency of a conventional gas-fired plant.[23], and EF_{ngas} the CO_2 emissions factor of a conventional gas-fired power plant[24].

Third, the *switch* price of CO_2, expressed in €/MWh, is used as a proxy of the abatement cost:

$$switch = \frac{cost_{ngas}/MWh - cost_{coal}/MWh}{tCO2_{coal}/MWh - tCO2_{ngas}/MWh} \tag{3}$$

with $cost_{ngas}$ the production cost of one MWh of electricity on base of net CO_2 emissions of gas in €/MWh, $cost_{coal}$ the production cost of one MWh of electricity on base of net CO_2 emissions of coal in €/MWh, $tCO2_{coal}$ the emissions factor in CO_2/MWh of a conventional coal-fired plant, and $tCO2_{ngas}$ the emissions factor in CO_2/MWh of a conventional gas-fired plant as detailed above.

The *Switch* price represents the fictional daily price of CO_2 that establishes the equilibrium between the *Clean Dark* and *Clean Spark* spreads. It is advantageous in the short term to switch from coal to natural gas, when the daily CO_2 price is *above* the *Switch* price, and conversely.

[23] *i.e.* 49.13% according to Reuters.
[24] *i.e.* 0.41 tCO_2/MWh according to Reuters.

As shown in Figure 6, the use of coal appeared more profitable than natural gas during 2005-2006. Since the beginning of 2007, the difference between both spreads has been narrowing. This situation therefore provides incentives for power operators to switch the use of natural gas instead of coal, as represented by the $Switch$ price series. Besides, we may note a peak in the price of electricity from September to November 2008.

3.3 Global commodity markets

Several indices may be used to capture the influence of risk factors linked to global commodity markets. The main index which is used as the barometer of commodity prices is the Reuters/Commodity Research Bureau (CRB) Futures Index. This index is composed of 17 commodities in different sectors such as energy, grains, industrials, livestock, precious metals and softs. It may be viewed as a broad measure of overall commodity products.[25]

The constituent commodities and the economic weighting of these indices aim at minimizing the idiosyncratic effects of some individual commodity markets.[26] As a commodity, the dynamics of futures allowance prices are very likely to be impacted by the price volatility on global commodity markets, and thus we include the Reuters/CRB Futures Index as an exogenous factor in our estimates.

Energy and global commodity markets returns are presented in Figure 7.

3.4 Correlation between energy and global commodity markets

We are able to alleviate correlation concerns among energy and global commodity markets by looking at the correlation matrix between the returns of potential explanatory variables in Table 4.

The correlation levels remain reasonable, *i.e.* strictly inferior to 60%. We thus may use the returns on energy and global commodity markets as potential factors affecting changes in volatility without only limited collinearities. Since it is possible to have low correlations together with collinearity, we have investigated the presence of multicolinearity by computing the inflation of variance between explanatory variables. These calculations did not reveal serious problematic multicolinearities.[27]

In the next section, we present the econometric methodology used along with our estimation results.

[25] Other indices coming from brokers in the banking industry may also be used for sensitivity tests purposes. The Dow Jones-American International Group Commodity Index (DJ-AIGCI) is a benchmark for commodity investments composed of 20 commodities within the energy, petroleum, precious metals, industrial metals, grains, livestock and softs sectors. The Standard & Poor's Commodity Index (SPCI) is a cross section of 17 agricultural and industrial commodities traded in the energy, fibers, grains, meat and livestocks, metals and softs sectors. The Deutsche Bank Commodity Index (DBCI) is composed of six commodities in the crude oil, heating oil, aluminium, gold, wheat and corn industries, and is designed to track the performance of investments in a small set of commodities in a variety of currencies.

[26] See Geman (2005) for a more detailed analysis of the construction, the coverage, the liquidity, and the weighting of each index.

[27] To conserve space, those results are not presented here, and may be obtained upon request to the authors.

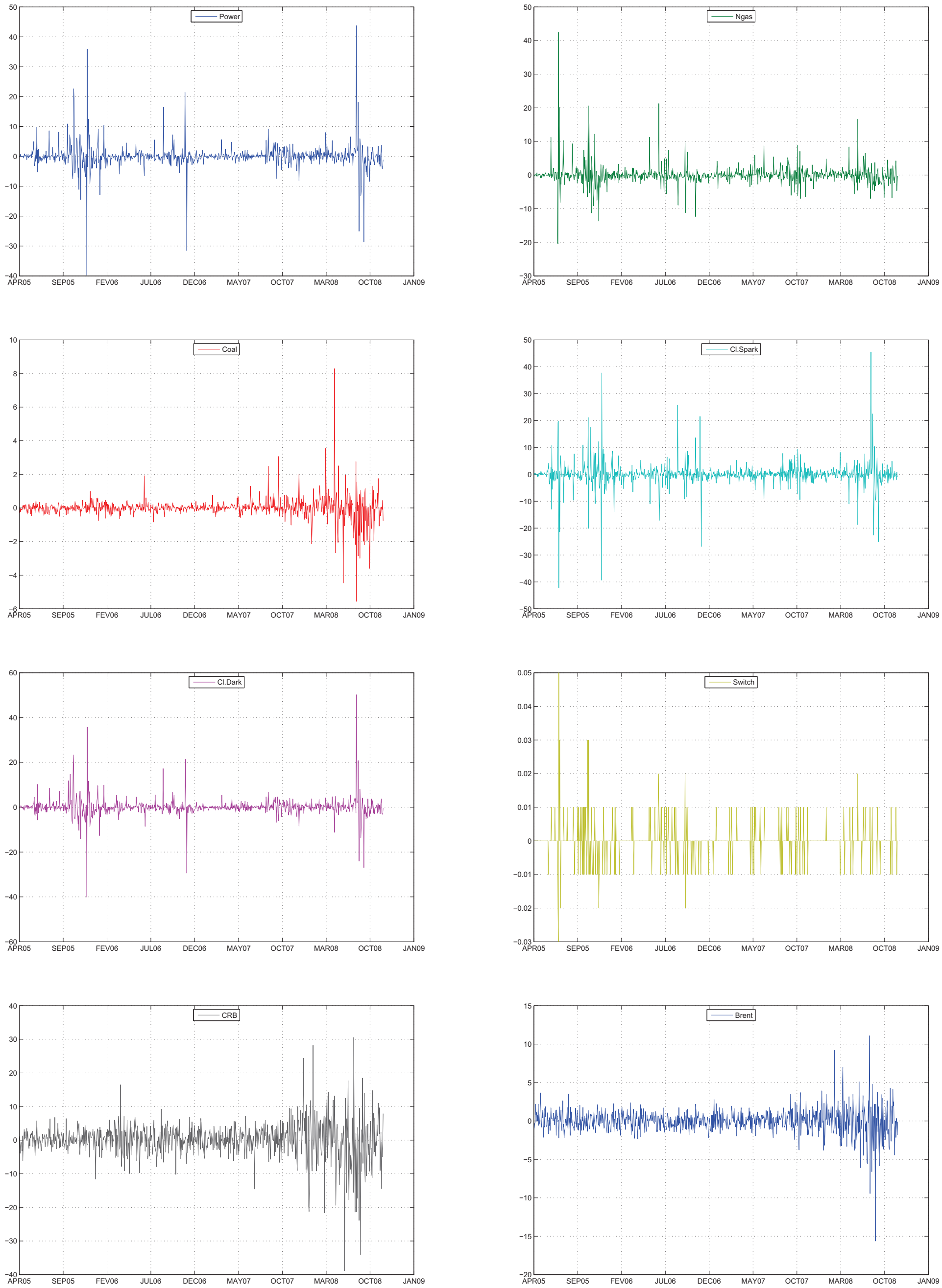

Figure 7
Returns on Energy and Global Commodity Markets Variables from April 22, 2005 to January 16, 2009

Table 4
Matrix of Cross-Correlations Between Energy and Commodity Variables

	CRB	$CleanSpark$	$CleanDark$	$Switch$	$Ngas$	$Brent$	$Power$	$Coal$
CRB	1							
$CleanSpark$	0.053	1						
$CleanDark$	0.128	0.596	1					
$Switch$	0.223	0.714	0.513	1				
$Ngas$	0.214	0.028	0.234	0.314	1			
$Brent$	0.008	0.066	0.219	0.112	0.086	1		
$Power$	0.020	0.274	0.260	0.361	0.125	0.159	1	
$Coal$	0.313	0.037	0.091	0.014	0.214	0.085	0.333	1

Note: CRB refers to the return on the Reuters CRB global commodity index, $CleanSpark$ refers to the return on the *Clean Spark Spread*, $CleanDark$ refers to the return on the *Clean Dark Spread*, $Switch$ refers to the return on the *Switch*, $Ngas$ refers to the natural gas return, $Brent$ refers to the Brent crude oil return, $Power$ refers to the electricity return, and $Coal$ refers to the coal return.

4 Empirical analysis

Our econometric methodology may be broadly summarized in four different steps: *(i)* we estimate a GARCH model with a dummy variable to compare the level of (unconditional) volatility of the underlying allowance market *before* and *after* the introduction of the option market[28]; *(ii)* we include other factors in the variance equation of the GARCH model to control for exogenous effects from relevant variables; *(iii)* we discuss volatility dynamics issues during sub-periods; and *(iv)* we finally run rolling estimations to further identify the effects of the introduction of the option market on the volatility dynamics of the EU ETS.

4.1 GARCH model

The GARCH modeling approach adopted here is common for financial time-series, and has been applied to carbon prices in previous literature (Paolella and Taschini (2008), Benz and Truck (2009)). GARCH models allow to take into account volatility clustering, indicated by fat-tails in the distribution of financial time-series.

The impact of options trading is tested by amending the conditional variance equation of the GARCH model with a dummy variable which takes values 0 for the pre-option period, and 1 for the post-option period. This methodology has been applied by Antoniou and Holmes (1995), Gulen and Mayhew (2000) for financial markets, and Antoniou and Foster (1992) for the crude oil market.[29] Then, we adopt the structure of a GARCH(1,1) model:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \epsilon_t \tag{4}$$

$$\epsilon_t \sim \sqrt{h_t} e_t \qquad \text{with} \qquad e_t \sim iid(0,1)$$

$$h_t = E(\epsilon_t^2 \mid \phi_{t-1}) = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1} + \gamma DF_t \tag{5}$$

with R_t the daily return on carbon futures prices, ϕ_{t-1} is the set of past information, and ϵ_t the error term in Eq. (4). In the conditional variance Eq. (5), DF_t is a dummy variable taking the value of 0 before the 'true' effect of the introduction of options, and 1 thereafter. This dummy variable allows to test for the influence of the introduction of options on the volatility of the underlying carbon market. When creating the dummy variable DF_t, it is crucial to classify the beginning of the impact such that it is not too far from the beginning of the 'true' effect of the introduction of options. In light of the liquidity analysis derived from Figure 1, we have set the beginning of the 'true' effect of the introduction of options on May 18, 2007 (instead of October 13, 2006 which is the official creation of the options market)[30].

[28] To avoid any confusion, we recall that the dummy variable in the volatility equation of a GARCH model has an effect on the unconditional level of volatility as it is invariant through time.

[29] Fleming and Ostdiek (1999) also consider the issue of the impact of derivatives trading on the spot crude oil market, but using GMM methods as in Bollen (1998).

[30] Recall that this date was chosen when the volume of calls traded doubled and hit the 1Mton daily volume for the first time. Also, May 18, 2007 for calls is chosen instead of June 27, 2007 for puts since calls are more actively traded than puts in the EU ETS. We wish to thank an anonymous reviewer for suggesting to adopt this methodology.

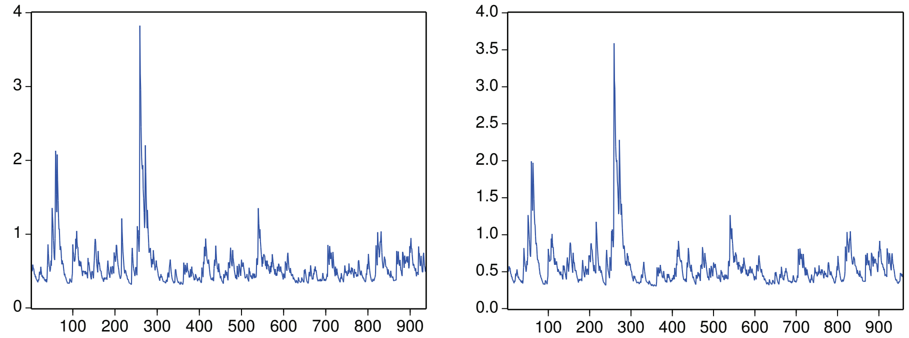

Figure 8
From left to right: conditional standard deviation for the December 08 and 09 returns from a GARCH (1,1)

4.1.1 Estimation

We first test Eq. (4) and (5) with a GARCH(1,1) model *without* the dummy accounting for the introduction of the options market in the variance equation. A preliminary analysis of the returns autocorrelation shows that modeling the conditional mean as an AR(1) eliminate the autocorrelation for each contract. Those results, presented in Table 5 (regressions (1) and (3)), reveal a strongly persistent process, as the sum of α_1 and α_2 is close to 1.[31] This characteristic is a classic feature of financial time-series, and applies for both carbon futures contract of maturity December 2008 and 2009. The time profile of the estimated conditional standard errors from this GARCH model are respectively displayed in Figure 8 for the December 2008 and 2009 contracts. These graphs are very similar for both contracts. During our study period, we observe that the carbon market has been more volatile during the first 300 days, and that the level of volatility is quite lower after April 2006.

4.1.2 Modeling the option market introduction

We estimate Eq. (4) and (5) by introducing the dummy variable DF_t capturing the changes in volatility due to the 'true' effect of the introduction of options. Recall that DF_t takes the value of 0 before the 'true' impact (that was identified from Figure 1) on May 18, 2007, and 1 thereafter.

Estimation results are presented in Table 5 (regressions (2) and (4)).[32] In Table 5, regressions (2) and (4), we may observe that DF_t is statistically significant and negative at the 1% level. Despite the fact that we do not consider here any exogenous factor (see next section), this result appears as a first evidence of the impact of options introduction in the carbon market. Because options enable a more complete and liquid market, and a greater flexibility for market participants to hedge their position on the carbon market, they seem to have a significant impact on the level of volatility in the futures market. This effect may also be related, while it is difficult to consider it empirically, to the increasing maturity of the carbon futures market. This is a common argument in finance when

[31] Namely 0.96 and 0.98 for regressions (1) and (3) respectively.

[32] Note that we tested for various GARCH specifications, such as the GARCH-M developed in Antoniou and Foster (1992), which is convenient for the modeling of a time-varying risk premium. None of them provided superior results. Similarly, various innovation distributions have been implemented (Student t, asymmetric Student t, GED) to better accommodate residual kurtosis, without further improving the results presented here.

Table 5
GARCH(1,1) model estimates *with* and *without* dummy variable for the carbon futures returns of maturity December 2008 and December 2009

	EUA_{DEC08}		EUA_{DEC09}	
	(1)	(2)	(3)	(4)
Mean equation				
β_0	0.0023**	0.0019**	0.0020	0.0017*
	(0.001)	(0.001)	(0.001)	(0.001)
β_1	0.1398***	0.1324***	0.1348***	0.1255***
	(0.048)	(0.049)	(0.048)	(0.048)
Variance equation				
α_0	7.74e-05***	9.39e-05***	5.41e-05***	7.17e-05***
	(1.45e-05)	(1.90e-05)	(1.24e-05)	(1.77e-05)
α_1	0.3039***	0.2870***	0.2638***	0.2518***
	(0.027)	(0.029)	(0.025)	(0.027)
α_2	0.6544***	0.6681***	0.7120***	0.7156***
	(0.037)	(0.041)	(0.034)	(0.039)
D_F		-4.62e-05***		-3.69e-05***
		(1.47e-05)		(1.34e-05)
LL	1680.86	1625.43	1694.26	1638.99

Notes: The dependent variables are the EUA carbon futures return for the contract of maturity December 2008 and December 2009, depending on the column under consideration. Other variables are explained in eq(4) and (5). Standard errors in parenthesis. *** indicates significance at 1%, ** at 5% and * at 10%. LL refers to the log-likelihood.

efficiency is under examination. In our framework, because we are more interested in volatility than in autocorrelation and efficiency, the same argument may not really apply. Indeed, as markets become more mature and the number of traders is larger, because information is more quickly reflected in prices the volatility may be expected to increase in view of the well-known volatility-volume relation. The latter result does not imply however necessarily that the dynamic component of volatility has not been impacted, as we discuss below. In addition, it is worth noting that the estimation results obtained in Table 5 concerning the introduction of the option market may be driven by exogenous factors affecting the volatility of carbon futures returns. As shown by Mansanet et al. (2007), Alberola *et al.* (2008), Chevallier (2009) and Hintermann (2010), the carbon market is impacted by various energy prices and macroeconomic risk factors. In other words, a change in the level of the volatility may be hidden by the presence of other risk factors. To deal with this issue, we now introduce exogenous factors in the variance equation of the GARCH model.

4.2 Exogenous variables in the conditional variance equation

A problem in Section 4.1 is that the date of the dummy variable is chosen *a priori*. Of course, this choice is intuitive since we are interested in modeling how the introduction of the option market affects volatility in the EU ETS. However, the impact of the introduction of the option market may have arisen at a date different from its official opening. Furthermore, other structural breaks may have affected the carbon market and the dynamics of conditional volatility. Detecting these breaks appears crucial to obtain a correct modeling of the conditional standard error. To do so, we implement below a test for structural breaks in the unconditional variance at unknown location.

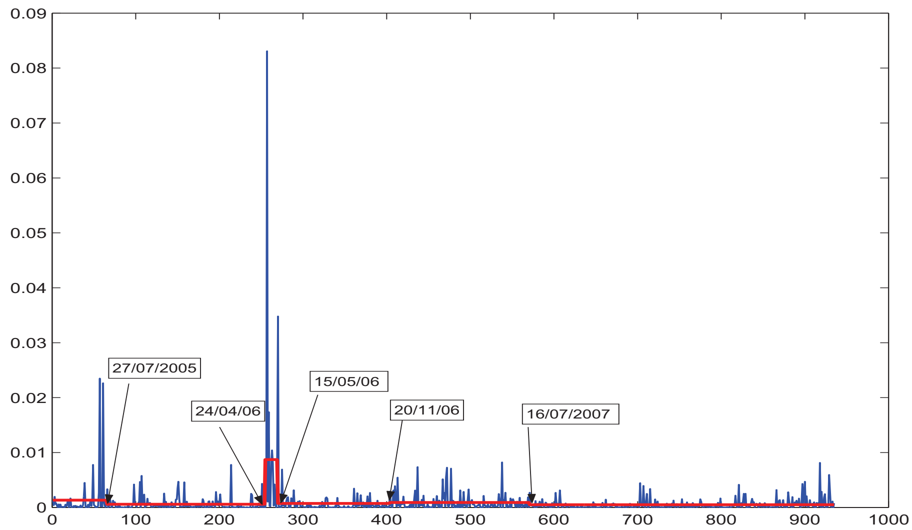

Figure 9
Unconditional variances with break
Note: the blue line represents the squared returns and the red line represents the time profile of the sample variance for the different periods detected from the breaks.

4.2.1 Structural breaks in the unconditional variance

Inclán and Tiao (1994) and Sansó, Aragó and Carrion (2004) have proposed a test for detecting a break in the unconditional variance at unknown date.[33]

Our sample of returns $\{R_t\}_{t=1}^{T}$ contains T observations. The test statistic is $AIT = sup_k|T^{-0.5}G_k|$ where $G_k = \hat{\lambda}^{-0.5}[C_k-(k/T)C_T]$, $C_k = \sum_{t=1}^{k} R_t^2$, $\hat{\lambda} = \hat{\gamma}_0+2\sum_{l=1}^{m}[1-l(m+1)^{-1}]\hat{\gamma}_l$, $\hat{\gamma}_l = T^{-1}\sum_{t=l+1}^{T}(R_t^2-\hat{\sigma}^2)((R_{t-l}^2-\hat{\sigma}^2)$, $\hat{\sigma}^2 = T^{-1}C_T$. $\hat{\gamma}$ represents a nonparametric adjustment factor used to correct for non dependent processes. It is based on a Bartlett kernel with the lag truncation parameter *m*.[34] The value of *k* that maximises $|T^{-0.5}G_k|$ is the estimate of the break date. Critical values are given in Sansó, Aragó and Carrion (2004).

Inclán and Tiao (1994) developed the Iterated Cumulative Sum of Squares (ICSS) algorithm for detecting multiple breaks in variance.[35] We apply this algorithm to our *AIT* statistics to find possible break dates in the unconditional variance of returns.

The *AIT* test statistic and the ICSS algorithm leads us to detect five breaks in the unconditional volatility. Figure 9 shows these breaks with their date. This graph also displays the time profile of the sample unconditional variance for the six periods defined by these breaks and the squared returns, considered as a proxy for the shocks hitting the market.

One obvious break in unconditional volatility occurs during the third (and shortest) period from *t=24/04/06* to *t=15/05/06*. During this time period, the market is highly volatile, as reflected by the high values of the squared returns. The sample variance reaches its highest value for this time period. This increase in unconditional variance can be connected with the first compliance break

[33] Tests for breaks in the unconditional variance have been recently extended by Andreou and Ghysels (2002). See also Rapach and Strauss (2008).
[34] The lag truncation parameter is chosen as $m = E[A(T/100)^{1/4}]$ where T is the number of observations.
[35] A complete description of this algorithm can be found in their paper.

in the time-series of CO_2 returns due to the verification of 2005 emissions in April 2006 (Alberola *et al.* (2008)).

We identify two periods where the unconditional volatility increases: the first one going from the beginning of the sample to t_1 *=27/7/05*, and the second one from t_4 *=20/11/06* to t_5*=16/07/07*. We observe however that during these periods the sample variance does not increase significantly, and thus we do not further comment these breaks. In addition, only a minor increase in volatility is detected using the algorithm around the time options begin to be traded with significant volumes (*i.e.* March 2007).

More importantly, to control for the sharp increase in volatility due to the 2006 compliance event, we include the dummy variable D_{APR06} which takes the value of 1 during the period going from April 25 to June 23, 2006, and 0 otherwise. This variable reflects the institutional development of the EU ETS that occurred in April 2006 during Phase I (Alberola *et al.*, 2008).

4.2.2 Introducing exogenous variables

As highlighted in previous literature (Christiansen *et al.* (2005), Mansanet-Bataller *et al.* (2007), Alberola *et al.* (2008), Chevallier (2009), Hintermann (2010)), the main risk-driving factors on the carbon market are linked to institutional decisions and energy prices. Another source of risk may be linked to the variation of global commodity markets, which may be captured by various indices.

To take into account the impact of these factors on the volatility of carbon futures (besides considering the impact of the option market), we include the volatility of several energy- and commodity-related factors. We compute the sample standard deviations by using a moving window of 25 days (about one trading month) for all factors described in the data section. This methodology is in line with Hadsell and Shawky (2006) and Oberndorfer (2008), and has more formal support than "demeaning" the mean equation (as in Bologna and Cavallo (2002) for instance) when the quantity of interest is the volatility.

For energy variables, we use the volatility of returns on Brent, coal and natural gas prices, as well as the volatility of clean dark and clean spark spreads and the switch price, to proxy for the influence of power producers' fuel-switching behavior on carbon price changes. The relationship between carbon price changes and power producers' fuel-switching behavior appears especially important to bear in mind. Fuel-switching constitutes an important determinant of the CO_2 price, given the proportion of allowances distributed to the power sector, and the arbitrages being made by producers concerning their energy-mix including the CO_2 costs (Delarue *et al.* (2008), Ellerman and Feilhauer (2008)). For global commodity markets, we include the Reuters/Commodity Research Bureau (CRB) index.

We test below for the potential impact of *vol brent, vol gas, vol coal, vol power, vol clean spark, vol clean dark, vol switch*, and *vol CRB* on ECX futures returns volatility modelled using a GARCH framework, by including the estimated volatility of returns of these potential explanatory variables into the variance equation.

4.2.3 Results

Equation (5) is modified as follows:

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1} + \gamma DF_t + \varphi X_t \quad (6)$$

with X_t a vector of exogenous variables including the dummy variable D_{APR06} for the April 2006 structural break, estimated standard deviations for energy and the CRB variables.

As shown in Table 6, estimates from our extended model feature the statistical significance of several factors for 2008 contract (regressions (1) to (4)) and for the December 2009 (regressions (5) to (8)) as well. Some of these significant variables are not exactly the same for both contracts and their significance is more robust for the December 2009 contract.

Concerning energy variables, *vol clean spark* and *vol clean dark* are significant for both the December 2008 and 2009 contracts alone or in conjunction with other regressors.

The dummy is almost always significant at the 1 or 5% level thereby providing evidence that our result in the previous section are not driven by exogenous factors.

Concerning energy variables, *vol clean spark*, *vol clean dark*, *vol oil*, *vol coal* and *vol power* are significant for the December 2008 contract while *vol oil*, *vol clean spark* and *vol clean dark* significantly impact the volatility of the December 2009 futures contract. The rationale behind the negative role of coal on CO_2 price volatility is that, when confronted to a rise of the price of coal relative to other energy markets, firms have an incentive to adapt their energy mix towards less CO_2 intensive sources, which yields to less needs of EUAs. This result is conform to previous literature (Mansanet-Bataller *et al.* (2007), Alberola *et al.* (2008)). The negative sign of *vol spark* for both contracts may be explained by the rather decreasing price pattern of natural gas by contrast to coal during our sample period[36]. *vol oil* positively impacts the volatility returns of CO_2 prices for the December 2009 contract. This positive impact can result from the fact that oil is an input of installations covered by the ETS and that changes in its price also affect economic activity. Therefore, an increase in oil price volatility induces uncertainty about economic perspectives which can increase volatility on the CO_2 market. Finally, note that the D_{APR06} dummy for institutional developments is statistically significant (regressions (2) and (6)), but not the CRB proxy for global commodity markets. The *vol switch* variable is never significant in our regressions, so we do not report results related to this variable (regressions (1) and (5)).

To conclude, we have shown that even after controlling for other relevant energy, institutional and risk factors, the DF_t dummy variable accounting for the introduction of the option market remains significant. This result is very robust to the introduction of factors known as carbon price drivers, such as institutional decisions, energy and global commodity markets (Christiansen *et al.* (2005), Mansanet-Bataller *et al.* (2007), Alberola *et al.* (2008), Hintermann (2010)). The finding appears robust enough to be an evidence of the impact of the introduction of options. We therefore conclude that options introduction had a noticeable impact on the unconditional volatility of CO_2 returns.

[36] While the *clean spark spread* is the profit contribution of using gas for electricity production, the *clean dark spread* is the profit contribution for using coal for electricity production. Depending on the relative price of gas and coal, power producers *switch* between their fuel inputs when one source of energy becomes relatively cheaper to the other. Hence our comments of the *vol clean spark* variable based on that economic logic.

Table 6
GARCH(1,1) model estimates with the dummy variable for the carbon futures returns of maturity December 2008 and December 2009 and exogenous factors in the variance equation

	EUA_{DEC08} (1)	EUA_{DEC08} (2)	EUA_{DEC08} (3)	EUA_{DEC08} (4)	EUA_{DEC09} (5)	EUA_{DEC09} (6)	EUA_{DEC09} (7)	EUA_{DEC09} (8)
Mean equation								
β_0	0.0019*	0.0015	0.0017*	0.0025***	0.0017*	0.0015	0.0020**	0.0018*
	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0009)
β_1	0.1323***	0.1342***	0.1331***	0.1239**	0.1256***	0.1200**	0.1302***	0.1232***
	(0.0487)	(0.0467)	(0.0481)	(0.0534)	(0.0486)	(0.0470)	(0.04772)	(0.0479)
Variance equation								
α_0	9.99e-05**	0.0001***	0.0001***	0.0002***	8.69e-05***	0.0001***	-0.0001***	7.04e-05*
	(3.96e-05)	(2.25e-05)	(4.08e-05)	(5.23e-05)	(3.05e-05)	(2.19e-05)	(2.52e-05)	(4.06e-05)
α_1	0.2854***	0.2224***	0.2434***	0.4189***	0.2485***	0.2058***	0.2281***	0.2101***
	(0.0295)	(0.0349)	(0.0304)	(0.0419)	(0.0.0276)	(0.0332)	(0.0309)	(0.0324)
α_2	0.6702***	0.6148***	0.6934***	0.5523***	0.7207***	0.6658***	0.7090***	0.7230***
	(0.0415)	(0.0473)	(0.0434)	(0.0391)	(0.0386)	(0.0465)	(0.0438)	(0.0442)
DF_t	-4.52e-05***	-4.47e-05***	-6.46e-05***	-5.72e-05**	-3.42e-05***	-4.15e-05***	-4.80e-05	-3.82e-05**
	(1.47e-05)	(1.72e-05)	(1.85e-05)	(2.74e-05)	(1.32e-05)	(1.56e-05)	(1.51e-05)	(1.69e-05)
$DAPR06_t$		0.0012***				0.0010***		
		(0.0001)				(0.0001)		
vol CRB	-0.0021				-0.0054			
	(0.0113)				(0.0079)			
vol oil				0.0080***				0.0098*
				(0.0007)				(0.0052)
vol clean spark			-6.88e-06***	-1.45e-05***			-8.08e-05***	-8.15e-06***
			(1.85e-06)	(2.34e-06)			(1.76e-06)	(1.73e-06)
vol clean dark				9.75e-06***			6.94e-05***	6.22e-06***
				(3.16e-06)			(2.15e-06)	(2.25e-06)
vol coal			-0.0007	-0.0123***				-0.0052
			(0.0030)	(0.0042)				(0.0034)
vol power				0.0005***				8.00e-05
				(0.0002)				(0.0001)
LL	1625.45	1637.89	1629.08	1629.64	1639.23	1648.42	1650.70	1652.73

Notes: The dependent variables are the EUA carbon futures return for the contract of maturity December 2008 and December 2009, depending on the column under consideration. Other variables are explained in Eq. (4) and (6). The algorithm for optimization is BHHH. Standard errors in parenthesis. *** indicates significance at 1%, ** at 5% and * at 10%. LL refers to the log-likelihood.

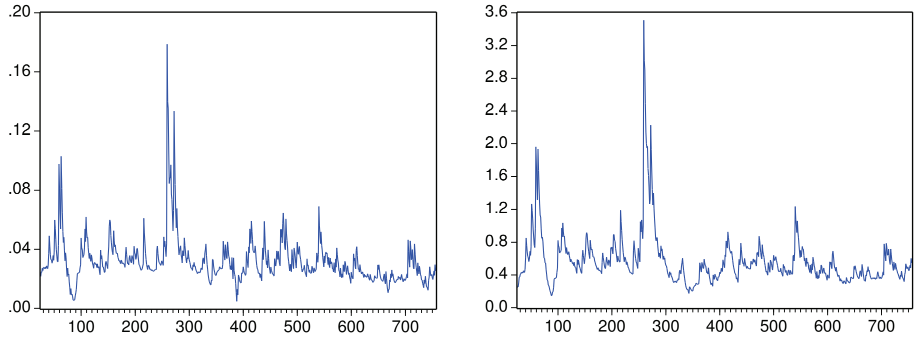

Figure 10
From left to right: conditional standard deviation for the December 08 and 09 returns from a GARCH (1,1) with a dummy for the option market

The conditional variances for both contracts displayed in Figure 10 show indeed a slight decrease in variance in the post "options introduction" period.

4.3 Sub-period decomposition

Besides, we estimate GARCH models during two sub-periods to study the changes in volatility dynamics of carbon futures returns *before* and *after* the introduction of options. According to Antoniou and Foster (1992), this procedure allows to investigate empirically the effects of the introduction of the option market by using both pre- and post-options volatility measures. Here, we do not precisely deal with the impact of the introduction of the option market on the unconditional variance, but rather on its *dynamics* (the *nature* of volatility) in the spirit of Antoniou and Foster (1992), who studied the volatility of futures and spot prices for brent crude oil products.

The methodology consists in comparing the GARCH coefficients *before* (Sample #1) and *after* (Sample #2) the introduction of the option market, by running separate estimates during sub-periods. Estimation results are presented in Table 7 (regressions (1) to (4)).

Our results are as follows. First, regarding the behavior of the autoregressive coefficient, we observe a significant decrease. The coefficients which were significant and of a value around 0.18 are not significant anymore, thus leading to confirm a convergence towards the random walk in the second sub-period.[37] Second, ARCH and GARCH coefficients are quite different in the two subperiods. For Sample #1 (Table 7, regressions (1) and (3)), the process is very persistent.[38] For Sample # 2 (Table 7, regressions (2) and (4)), we observe that the value $\alpha_1 + \alpha_2$ is close to 0.90, which suggests that the variance process as a whole is less persistent. However, the level of the ARCH coefficient, which represents the reaction to new information, is quite low in the second sub-period in comparison with its level in the first sub-period, suggesting that the informational efficiency of the carbon market has decreased. Indeed, the ARCH coefficient being an indicator of how news are impacting the

[37] We provide some additional informations on this decrease using rolling estimation in the next section. A formal analysis of the efficiency of the carbon market remains nevertheless beyond the scope of the present paper and is left for future research.

[38] There is only a limited interest in estimating the so-called IGARCH model (Engle and Bollerslev, 1986) by constraining the sum of the ARCH and GARCH coefficients to one as the estimates in the present regressions do not bind the constraints.

Table 7
GARCH(1,1) model estimates *before* and *after* the May 18, 2007 (volumes in option trading reached 1Mton daily) for the December 2008 and 2009 carbon futures returns

	EUA_{DEC08} (1)	(2)	EUA_{DEC09} (3)	(4)
Mean equation				
β_0	0.0025**	0.0009	0.0023*	0.0009
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
β_1	0.1904**	0.0012	0.1864***	0.0041
	(0.0640)	(0.0740)	(0.0652)	(0.0733)
Variance equation				
α_0	0.0001***	2.61e-05	8.05e-05***	2.42e-05
	(2.24e-05)	(1.72e-05)	(2.00e-05)	(1.55e-05)
α_1	0.3857***	0.1073*	0.3124***	0.1116**
	(0.0359)	(0.0555)	(0.0350)	(0.0538)
α_2	0.5745***	0.8358***	0.6638***	0.8332***
	(0.0437)	(0.0832)	(0.0438)	(0.0790)
LL	1134.57	555.51	1140.14	561.64

Note: The dependent variables are the EUA carbon futures returns for the contracts of maturity December 2008 and December 2009, depending on the column under consideration. Other variables are explained in Eq. (4) and (6). Standard errors in parenthesis. *** indicates significance at 1%, ** at 5% and * at 10%. LL refers to the log-likelihood.

volatility, a lower value for the ARCH coefficient is an indication of a **less** informationally efficient market (the variance adjustment following the arrival of new information is slower)[39][40]. In other words, a market where the GARCH coefficient is dominating exhibits higher autocorrelation[41] in variance which is the case in sample # 2.[42]

We did not find evidence of the influence of energy variables on the volatility of CO_2 returns during sub-periods. Overall, these results suggest that the dynamics and nature of the variance are quite different *before* and *after* the introduction of the options market, which may be inferred from GARCH standard deviations plots in Figure 8. However, note that the presented difference in the estimated parameters (in particular the lower coefficient in second period) is not necessarily a result of the introduction of options. Therefore, we may carefully conclude from these results that the estimated coefficients are not constant over the period of interest[43].

4.4 Checking the time dependency of the model

In this section, we use a rolling estimation procedure to detect some change in the dynamics of the conditional volatility. We estimate the same GARCH (1,1) model as in section 4.1.1. for a rolling window of *L*=200 observations. We obtain a sequence of time indexed estimates of the autoregressive coefficient $\{\beta_{1|t-L+1,t}\}$ and the coefficients of the GARCH model: $\{\alpha_{0|t-L+1,t}\}$, $\{\alpha_{1,t-L+1,t}\}$

[39] See Conrad et al. (2010) for other techniques to investigate the reactions of returns or volatility of returns to new information.
[40] Recall that informational efficiency examined through the values for the GARCH coefficients of the efficiency generally examined using estimates of the autocorrelation of returns are two different, but non-contradictory, concepts of efficiency.
[41] Persistence in the volatility process (sum of ARCH and GARCH coefficients) and autocorrelation in the volatility process (GARCH coefficient) are distinguishable features of the volatility process.
[42] The same pattern with the December 2009 contract.
[43] We wish to thank one anonymous reviewer for highlighting this point.

and $\{\alpha_{2,t-L+1,t}\}$ where the *t-L,t* denotes the sample used for each estimation. Our first estimation is obtained for the sample ending in *t=200=03/02/2006*.

Figure 11 shows the rolling estimate of the autoregressive coefficient in the conditional mean regression. Figures 12 and 13 show the estimates for the ARCH and GARCH coefficients, respectively.[44] The estimates of the GARCH model clearly show some instability in the estimated coefficients. Changing patterns in the GARCH coefficients therefore indicate changes in the dynamics of conditional volatility.

A first sudden break appears at date *t = 258 = 05/05/2006* when the ARCH coefficient rises from 0.4 to 1, and the GARCH coefficient decreases from around 0.6 to 0.4. Both of these changes suggest that the impacts of shocks on conditional volatility were especially important during this time period. It coincides with the strong adjustment of market operators' expectations following the publication of the first report of verified emissions by the European Commission (Alberola *et al.*, 2008).

The second change in the estimated coefficient occurs at time *t=451=05/02/2007*. The ARCH coefficient suddenly drops after this date, while the GARCH coefficient increases. This result may also be interpreted in light of the 2007 compliance event, which relates to the verification of 2006 emissions. Market operators have anticipated the release of the report of the European Commission, and therefore the adjustment in market expectations occurs earlier than in 2006. Due to the "youth" of this commodity market and rules in the making concerning the second trading period (2008-2012), the first years of operation of the EU ETS were characterized by strong reversals in expectations around yearly compliance events (Chevallier *et al.*, 2009).[45] Overall, these rolling windows estimates do not support the view of a strong effect of option introduction on volatility dynamics. Nevertheless, the continuing change in volatility may be partly due to option introduction, despite this hypothesis could hardly be investigated further.

Once agents have integrated this information, we do not observe visually other changes in the estimates of the ARCH coefficient, except for the GARCH coefficient which increases after *t=636=11/10/2007*.

5 Conclusion

This article investigates the effects of the introduction of the option market on the volatility of the EU ETS. Following a brief review of key design issues on the EU ETS, we have presented the main characteristics of both the futures and option markets on ECX. Then, we have detailed our econometric methodology, which consists in capturing both unconditional and dynamic components of the volatility of carbon futures returns with GARCH models, rolling estimates and endogenous structural break detection following the introduction of ECX options. Based on the liquidity of traded options on a daily basis, we have been able to pinpoint the more 'correct' date of the introduction of options as being May 18, 2007. This date has been identified as the number of calls traded hitting for the first time the daily volume of 1Mton, and is thus different from the official creation date of the options market (October 13, 2006). This methodology has been robust to document changes in volatility on equity markets, but has not been applied yet on the carbon market.

[44] Note that during the occurrence of large shocks (such as compliance breaks), volatility explodes which yields to larger confidence intervals as displayed by the blue dashed lines.

[45] In particular, National Allocation Plans for Phase II were more strictly validated than during the first trading period.

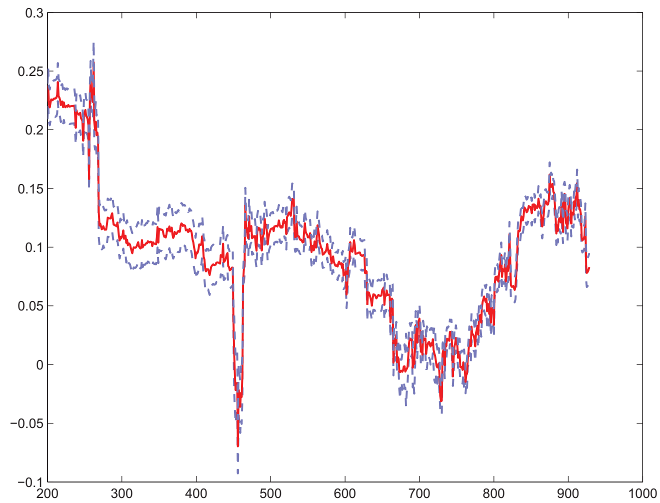

Figure 11
Rolling estimation of the autoregressive coefficient

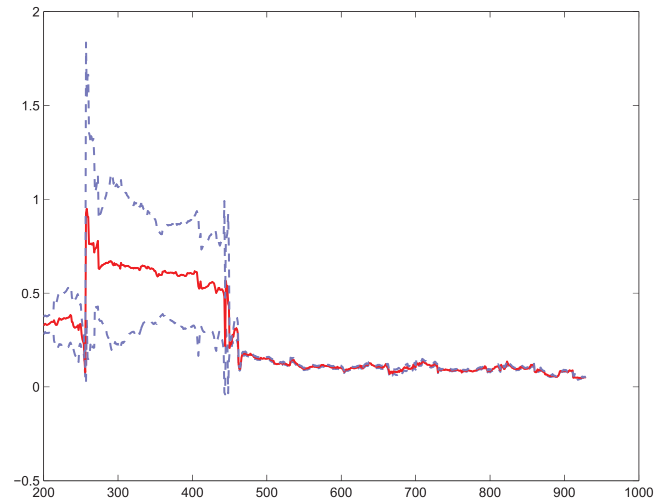

Figure 12
Rolling estimation of the ARCH coefficient

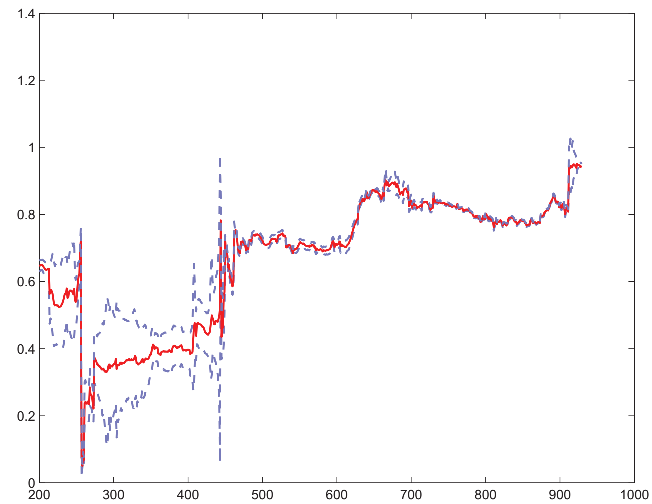

Figure 13
Rolling estimation of the GARCH coefficient

Based on daily data from April 2005 to April 2008, our results from our GARCH analysis suggest that the level of volatility has been significantly modified around this period. This static analysis is taken one step further with the investigation of the dynamic behavior of CO_2 return volatilities using rolling estimates with a window of 200 days. These estimations reveal the presence of shocks related to yearly compliance events in the EU ETS during April 2006 and February 2007. Additional analysis through an endogenous break test (Inclán and Tiao, 1994) provides evidence of breaks in the unconditional volatility during the period under consideration while it appears difficult, due to the nature of these tests (CUSUM), to relate these breaks to options introduction. As in Antoniou and Foster (1992), we also find that GARCH estimates are statistically different *before* and *after* the introduction of the derivatives market, thus leading to conclude that the nature (dynamics) as well as the level of volatility have changed. We have run sensitivity tests with institutional variables, energy and global commodity markets to capture the likely influence of other factors on the volatility of futures returns. Collectively, these results are conform to the view that options do not systematically impact the stability of the underlying market and may even have a stabilizing effect. Our results using the two sub-periods indicate a convergence to the random walk (in view of the decreasing autoregressive coefficient), while informational efficiency seems to have decreased (as indicated by a larger GARCH coefficient during the second sub-period).

A potential extension of this work using intraday data may be pursued relying on Liu and Maheu (2009), who test for breaks in realized volatility with Bayesian estimation and an autoregressive modeling of realized volatility (Corsi (2004), Andersen *et al.* (2007, 2009)). These methods have not been used to detect structural breaks following the introduction of derivative products yet.

References

ALBEROLA, E., CHEVALLIER, J., 2009. European carbon prices and banking restrictions: Evidence from Phase I (2005-2007). *Energy Journal* 30, 51-80.

ALBEROLA, E., CHEVALLIER, J., CHÈZE, B., 2008. Price drivers and structural breaks in European carbon prices 2005-2007. *Energy Policy* 36, 787-797.

ALBEROLA, E., CHEVALLIER, J., CHÈZE, B., 2009. Emissions Compliances and Carbon Prices under the EU ETS: A Country Specific Analysis of Industrial Sectors. *Journal of Policy Modeling* 31, 446-462.

ANDREOU, E., GHYSELS, E., 2002a. Rolling sample volatility estimators: some new theoretical, simulation and empirical results. *Journal of Business and Economic Statistics* 20, 363-376.

ANDREOU E, GHYSELS E., 2002b. Detecting multiple breaks in financial market volatility dynamics. *Journal of Applied Econometrics* 17, 579-600.

ANTONIOU, A., FOSTER, A.J., 1992. The effect of futures trading on spot price volatility: evidence for Brent crude oil using GARCH. *Journal of Business Finance and Accounting* 19, 473-484.

ANTONIOU, A., HOLMES, P., 1995. Futures trading, information and spot price volatility: evidence for the FTSE-100 Stock Index Futures contract using GARCH. *Journal of Banking and Finance* 19, 117-129.

BACK, K., 1993. Asymmetric information and options. *Review of Financial Studies* 6, 435-472.

BENZ, E., TRUCK, S., 2009. Modeling the Price Dynamics of CO_2 Emission Allowances. *Energy Economics* 1, 4-15.

BENZ, E., HENGELBROCK, J., 2008. Liquidity and Price Discovery in the European CO_2 Futures Market: An Intraday Analysis. *University of Bonn Working Paper*.

BOLLERSLEV, T, WOOLDRIDGE, J.M., 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews* 11, 143-172.

BOLLEN, N.P.B., 1998. A note on the impact of options on stock return volatility. *Journal of Banking and Finance* 22, 1181-1191.

BOLOGNA, P., CAVALLO, L., 2002. Does the introduction of stock index futures effectively reduce stock market volatility? Is the "futures effect" immediate? Evidence from the Italian stock exchange using GARCH. *Applied Financial Economics* 12, 183-192.

BUNN, D., FEZZI, C., 2009. Structural Interactions of European Carbon Trading and Energy Prices. *Journal of Energy Markets* 2(4), 53-69.

CHAN, K., CHUNG, Y.P., FONG, W.-M., 2002. The informational role of stock and option volume. *Review of Financial Studies* 15, 1049-1075.

CHESNEY, M., TASCHINI, L., 2008. The endogenous price dynamics of the emission allowances: an application to CO_2 option pricing. *Swiss Finance Institute Research Paper Series*, 08-02.

CHEVALLIER, J., 2009. Carbon futures and macroeconomic risk factors: A view from the EU ETS. *Energy Economics* 31, 614-625.

CHEVALLIER, J., IELPO, F., MERCIER, L., 2009. Risk aversion and institutional information disclosure on the European carbon market: a case-study of the 2006 compliance event. *Energy Policy* 37, 15-28.

CHRISTIANSEN, A.C., ARVANITAKIS, A., TANGEN, K., HASSELKNIPPE, H., 2005. Price determinants in the EU emissions trading scheme. *Climate Policy* 5, 15-30.

CONRAD, C., RITTLER, D., ROTFUSS, W., 2010. Modeling and Explaining the Dynamics of European Union Allowance Prices at High-Frequency. *Discussion Paper Series #497*, University of Heidelberg.

DASKALAKIS, G., PSYCHOYIOS, D., MARKELLOS, R.N., 2009. Modeling CO_2 emission allowance prices and derivatives: Evidence from the European trading scheme. *Journal of Banking and Finance* 33, 1230-1241.

DELARUE, E.D., ELLERMAN, A.D., AND D'HAESELEER, W. 2008. Short-Term CO_2 Abatement in the European Power Sector. *MIT CEEPR* Working Paper 2008-008.

ELLERMAN, A.D., BUCHNER, B.K., 2008. Over-allocation or abatement? A preliminary analysis of the EU ETS based on the 2005-06 emissions data. *Environmental and Resource Economics* 41, 267-287.

ELLERMAN, A.D., AND FEILHAUER, S. 2008. A Top-down and Bottom-up Look at Emissions Abatement in Germany in Response to the EU ETS. *MIT CEEPR* Working Papier 2008-017.

ENGLE, R.F., BOLLERSLEV, T., 1986. Modelling the persistence of conditional variances. *Econometric Reviews* 5, 1-50.

FLEMING, J., OSTDIEK, B., 1999. The impact of energy derivatives on the crude oil market. *Energy Economics* 21, 135-167.

FOSTER, D., NELSON, D., 1996. Continuous record asymptotics for rolling sample estimators. *Econometrica* 64, 139-174.

GEMAN, H., 2005. *Commodity and Commodity Derivatives: Modeling and Pricing for Agriculturals, Metals and Energy*. John Wiley and Sons, Ltd. Edition.

GULEN, H., MAYHEW, S., 2000. Stock index futures trading and volatility in international equity markets. *Journal of Futures Markets* 20, 661-685.

HADSELL, L., SHAWKY, H.A., 2006. Electricity price volatility and the marginal cost of congestion: an empirical study of peak hours on the NYISO market, 2001-2004. *Energy Journal* 27, 157-179.

HINTERMANN, B., 2010. Allowance price drivers in the first phase of the EU ETS. *Journal of Environmental Economics and Management* 59, 43-56.

INCLÁN, C., TIAO, G., 1994. Use of cumulative sums of squares for retrospective detection of change of variance. *Journal of the American Statistical Association* 89, 913-923.

KANEN J.L.M., 2006. *Carbon Trading and Pricing*. Environmental Finance Publications.

LIU, C., MAHEU, J.M., 2008. Are there structural breaks in realized volatility? *Journal of Financial Econometrics* 6, 326-360.

MANSANET-BATALLER, M., PARDO, A., VALOR, E., 2007. CO_2 prices, energy and weather. *Energy Journal* 28, 73-92.

MAYHEW, S., 2000. The impact of derivatives on cash markets: what have we learned? Unpublished manuscript, University of Georgia, February.

OBERNDORFER, U., 2009. EU emission allowances and the stock market: evidence from the electricity industry. *Ecological Economics* 68, 1116-1126.

PAOLELLA, M.S., TASCHINI, L., 2008. An econometric analysis of emission trading allowances. *Journal of Banking and Finance* 32, 2022-2032.

RAPACH, D.E., STRAUSS, J.K., 2008. Structural breaks and GARCH models of exchange rate volatility. *Journal of Applied Econometrics* 23, 65-90.

ROTFUSS, W., 2009. Intraday price formation and volatility in the European Emissions Trading Scheme: an introductory analysis. *ZEW Discussion Paper* 09-45, Mannheim.

SANSÓ A, ARRAGOÓ V, CARRION JL, 2004. Testing for change in the unconditional variance of financial time series. *Revista de Economiá Financiera* 4, 32-53.

UHRIG-HOMBURG, M., WAGNER, M., 2007. Derivative instruments in the EU emissions trading scheme - an early market perspective. *Working Paper, Chair of Financial Engineering and Derivatives*, Universitat Karlsruhe.

WEAVER, R.D., BANERJEE, A., 1990. Does Futures Trading Destabilize Cash Prices? Evidence for U.S. Live Beef Cattle. *Journal of Futures Markets* 10, 41-60.

On the realized volatility of the ECX CO_2 emissions 2008 futures contract: distribution, dynamics and forecasting[1]

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Abstract: The recent implementation of the EU Emissions Trading Scheme (EU ETS) in January 2005 created new financial risks for emitting firms. To deal with these risks, options are traded since October 2006. Because the EU ETS is a new market, the relevant underlying model for option pricing is still a controversial issue. This article improves our understanding of this issue by characterizing the conditional and unconditional distributions of the realized volatility for the 2008 futures contract in the European Climate Exchange (ECX), which is valid during Phase II (2008-2012) of the EU ETS. The realized volatility measures from naive, kernel-based and subsampling estimators are used to obtain inferences about the distributional and dynamic properties of the ECX emissions futures volatility. The distribution of the daily realized volatility in logarithmic form is shown to be close to normal. The mixture-of-distributions hypothesis is strongly rejected, as the returns standardized using daily measures of volatility clearly departs from normality. A simplified HAR-RV model (Corsi, 2009) with only a weekly component, which reproduces long memory properties of the series, is then used to model the volatility dynamics. Finally, the predictive accuracy of the HAR-RV model is tested against GARCH specifications using one-step-ahead forecasts, which confirms the HAR-RV superior ability. Our conclusions indicate that *(i)* the standard Brownian motion is not an adequate tool for option pricing in the EU ETS, and *(ii)* a jump component should be included in the stochastic process to price options, thus providing more efficient tools for risk-management activities.

JEL Classification: C5, G1, Q4.

Keywords: CO_2 Price, Realized Volatility, HAR-RV, GARCH, Futures Trading, Emissions Markets, EU ETS, Intraday data, Forecasting.

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1 Introduction

The distribution of financial asset returns is often modeled following mixtures of normal distributions that have different parameters (Dacorogna *et al.*, 2001). The distributional and dynamic properties of volatility appear especially important for risk-management purposes, since different specifications will yield to various pricing structures (Guillaume *et al.*, 1997). The investigation of such properties has been revivified by the recent literature on realized volatility, which relies on the use of intraday data. Since the seminal contributions of Andersen, Bollerslev, Diebold and Labys (henceforth ABDL, 2001), Andersen, Bollerslev, Diebold and Ebens (henceforth ABDE, 2001), and Barndorff-Nielsen and Shephard (henceforth BNS, 2002), among others, the literature on realized volatility measures has been very prolific[4].

This article uses tick-by-tick data of CO_2 emissions allowances, valid for compliance under the EU Emissions Trading Scheme (EU ETS), exchanged on the European Climate Exchange (ECX) based in London. More particularly, we use the futures contract of maturity December 2008 to examine the unconditional and conditional (dynamic) distributions of the ECX CO_2 emissions futures volatility. This new analysis appears important on such an emerging market, where the understanding of the volatility properties of CO_2 prices will allow a better characterization of the relevant stochastic process to price derivatives (Tucker (2001), Chevallier *et al.* (2009)). It appears also of primary importance to hedge against various kinds of institutional, economic or financial risks (see Busch and Hoffman, 2007). Hence, the research question developed in this article may be of precious use for risk-management purposes, which requires a careful understanding of the volatility of CO_2 prices.

The statistical properties of daily realized volatilities in futures markets has been investigated, among others, in Thomakos and Wang (2003). Their analysis of D-Mark, E-Dollar, S&P500 and T-bonds shows that standard deviations exhibit long memory, while standardized returns are serially uncorrelated. They also found that the unconditional distributions of daily returns' volatility are leptokurtic and highly skewed to the right, while the distributions of standardized returns and logarithmic standard deviations are close to a Gaussian distribution.

Luu and Martens (2003) test the *mixture-of-distributions-hypothesis* (MDH) (Clark (1973), Tauchen and Pitts (1983)) by comparing volatility models using daily and intraday data. Our approach consists in applying this research question to the study of ECX CO_2 emissions futures. The first use of intraday data for CO_2 emissions markets may be related to Benz and Klar (2008), who investigate the price discovery between various exchanges. To our best knowledge, our article constitutes the first attempt to derive the volatility properties of CO_2 emissions futures using realized measures.

Our data set contains one year of tick-by-tick data from ECX CO_2 emissions futures, corresponding to the 2008 futures contract. The choice to restrain our analysis to the 2008 contract is motivated by *(i)* the erratic behavior of *spot* prices during 2005-2007 due to banking restrictions (Alberola and Chevallier, 2009), which proved to be less robust than *futures* for price signalling in the medium-term; and *(ii)* the validity of the 2008 contract during Phase II (2008-2012), which offers the "bankability"

[4] Surveys may be found in Zivot (2005), McAleer and Medeiros (2008), Andersen and Benzoni (2009).

of CO_2 emissions allowances until the end of Phase III (2013-2020).

Since the end of 2007, both the liquidity of the EU ETS and the availability of high-frequency data have been increasing. ECX emissions futures are indeed the most heavily traded emissions contracts, followed by spot and option prices. The volume of intraday transactions recorded on the ECX CO_2 emissions futures market is approximately equal to one tenth of Foreign Exchange (FX) markets, which are opened 24 hours. With an average of 700 trades per day and 50 seconds between each transaction, the tick-by-tick data gathered for ECX CO_2 emissions futures is somewhat comparable to the values found on other financial markets, such as the level of daily transactions for the D-Mark as documented in Thomakos and Wang (2003).

This article provides the first empirical application of the methodology by ABDL (2001) and ABDE (2001) to ECX CO_2 emissions futures. We use one year of 15-minute returns[5] from the futures contract to estimate the daily realized volatility, and hence to describe the distribution and time-series properties of ECX CO_2 emissions futures. Compared to previous literature, the estimates of intraday volatility based on realized measures are more accurate than the estimates based on daily data which are used in Paolella and Taschini (2008), Benz and Truck (2009), Daskalakis *et al.* (2009) and Oberndorfer (2009), among others.[6]

Our methodology consists in dealing with the distributional, dynamic, and forecasting properties of realized volatility for ECX CO_2 emissions futures. We study the unconditional distributions of realized volatility measures, while testing for several transformations to approach normality. We also test whether the MDH holds for ECX CO_2 emissions futures. Then, we investigate the dynamics of realized volatility measures using an Heterogeneous Autoregressive Model of the Realized Volatility (HAR-RV) developed in Corsi (2009) versus GARCH specifications. We finally propose a forecasting exercise, by testing the predictive accuracy of the HAR-RV model versus other models of conditional volatility based on daily data.

Our main results may be summarized as follows. We first document the near normality of the logarithmic form of realized volatility measures for the ECX 2008 futures contract. This is standard in financial literature, as the "spot volatility" which governs the Brownian motion is generally assumed to be lognormally distributed. Nevertheless, the standardized returns (using realized volatility) are not normally distributed, which stands against the MDH. Standardized returns using GARCH volatilities are more normally distributed, which is not usual for financial series. Finally, the HAR-RV model with a daily and a weekly component outperforms unambiguously GARCH specifications in terms of dynamic modeling and forecasting accuracy. The latter result is due to the superiority of realized measures in estimation using intraday data over lower frequency variations.

Several directions may be pursued in extension of our work. The investigation of jump components in realized volatility measures appears of primary interest, by using standardized bi-power and tripower

[5]The optimal sampling frequency is chosen so as to limit the impact of market microstructure effects.

[6]Our analysis remains univariate. Using high-frequency data, a multivariate analysis such as Cartea *et al.* (2007) or Bunn and Fezzi (2007) does not seem appropriate, because of the complex relationships linking CO_2 emissions and energy markets. Thus, the study of realized covariance and realized correlations of ECX CO_2 emissions futures with other high-frequency energy futures price series is not considered here.

variation (Andersen, Bollerslev and Diebold, henceforth ABD, 2007). The formal determination of the optimal sampling frequency also appears as a promising area for future research using specific microstructure noise detection tests (see Awartani *et al.*, 2009).

The remainder of the article is organized as follows. Section 2 provides an overview of futures trading on the EU ETS. Section 3 reviews estimation methods for realized volatility, discusses optimal sampling frequency issues and maturity effects characteristic of futures contracts. Section 4 studies the unconditional distribution of ECX CO_2 emissions futures returns and realized volatility, as well as the distributional properties of returns and standardized returns, using several transformations for realized volatility measures. Section 5 investigates realized volatility dynamics, and especially long memory components using the HAR-RV model. Section 6 provides a forecasting exercise to test the accuracy of the HAR-RV model against the predictive power of daily GARCH forecasts. Section 7 concludes.

2 The European CO_2 emissions futures market

In this section, we present first the key design issues on the European CO_2 emissions futures market, second we discuss the main characteristics of futures trading on ECX, and third we proceed with a preliminary analysis of the intraday data used.

2.1 Design and transactions growth

Let us discuss first some key design issues, as well as the growth of transactions recorded on the European CO_2 emissions market since its creation on January 1, 2005.

2.1.1 Key design issues

The European Union Emissions Trading Scheme (EU ETS) has been created by the Directive 2003/87/CE. Across its 27 Member States, the EU ETS covers large plants from CO_2-intensive emitting industrial sectors with a rated thermal input exceeding 20 MWh. One allowance exchanged on the EU ETS corresponds to one ton of CO_2 released in the atmosphere, and is called an European Union Allowance (EUA). 2.2 billion allowances per year have been distributed during Phase I (2005-2007). 2.08 billion allowances per year will be distributed during Phase II (2008-2012). With a value of around €20 per allowance, the launch of the EU ETS thus corresponds to a net creation of wealth of around €40 billion. In January 2008, the European Commission extended the scope of the EU trading system to other sectors such as aviation and petro-chemicals by 2013, and confirmed its functioning for a third Phase until 2020.

2.1.2 Transactions growth

During Phase I of the EU ETS (2005-2007), the total volume of allowances exchanged has been steadily increasing. The number of transactions has been multiplied by a factor four between 2005 and 2006, going from 262 to 809 million tons. This increasing liquidity of the market has been confirmed in 2007, where the volume of transactions recorded is equal to 1.5 billion tons. This peak of transactions may be explained by the growth of the number of contracts with delivery dates from December 2008 to December 2012, which represented 4% of total exchanges in 2005, and 85% in 2007. These transactions reached €5.97 billion in 2005, €15.2 billion in 2006, and €24.1 billion in 2007, thereby confirming the status of the EU ETS as the largest emissions trading scheme to date in terms of transactions.

In 2008, the carbon market was worth between €89 billion and €94 billion, up more than 80% year-on-year, according to analysts (Reuters). The launch of secondary certified emission reduction (CER)[7] contracts on ECX certainly fostered this growth rate of transactions.

2.2 Futures trading

As discussed below, due to the non-reliable behavior of *spot* prices during Phase I (2005-2007), we decide to use *futures* prices valid for Phase II (2008-2012). More specifically, we choose to investigate in this article the volatility dynamics of the December 2008 futures contract traded in €/ton of CO_2 on ECX.

2.2.1 Price development

ECX futures trading started on April 22, 2005 with varying delivery dates going from December 2005 to December 2012. Futures contracts with vintages December 2013 and 2014 were introduced on April 8, 2008. Daily closing prices trade at €13.32/ton of CO_2 as of January 15, 2009, and have reached a maximum price of €32.90/ton of CO_2 in 2008[8].

Insert Figure 1 about here

Figure 1 shows the futures price development for contracts of maturities December 2005 through 2014 from April 22, 2005 to January 16, 2009. We may observe that futures prices for delivery during Phase II (2008-2012) proved to be much more reliable than futures prices for delivery during Phase I (2005-2007), due to the banking restrictions enforced between the two Phases (Alberola and Chevallier (2009)). Market observers noticed a divergence between Phase I spot and futures prices - which decreased towards zero - and Phase II futures prices - which conveyed a medium-term price signal around €20/ton of CO_2 throughout the historical data available for the second phase of the scheme. The price development for Phase II futures comprises a lower bound around 15€/ton of CO_2 in April 2007, and an upper bound around 35€/ton of CO_2 in November 2008.

[7] According to the article 12 of the Kyoto Protocol, Credit Development Mechanism (CDM) projects consist in achieving GHG emissions reduction in non-Annex B countries. After validation, the UNFCCC delivers credits called CERs that may be used by Annex B countries for use towards their compliance position. CERs are fungible with EU ETS allowances with a maximum limit of around 13.4% on average.

[8] In the longer term, analysts forecast EUA prices of €20-25/ton of CO_2 over Phase II and €25-30/ton of CO_2 over Phase III, which will run from 2013-20 (Reuters).

2.2.2 Contract specifications

The ECX CO_2 emissions futures contract is a deliverable contract where each member with a position open at cessation of trading for a contract month is obliged to make or take delivery of emission allowances to or from national registries. The unit of trading is one lot of 1,000 emission allowances. Each emission allowance represents an entitlement to emit one tonne of carbon dioxide equivalent gas. Market participants may purchase consecutive contract months to March 2008, and then December contract months from 2008 to 2012[9]. Trading occurs from 07:00AM to 05:00PM GMT. Allowances delivery typically occurs by mid-month of the expiration contract date. The ECX December 2008 futures contracts expired on December 15, 2008. The first delivery of the underlying CO_2 allowance occurred on December 16, 2008, and the last delivery on December 18, 2008.

2.3 Preliminary analysis of the intraday data

Our sample contains one year of tick-by-tick transactions for the ECX futures contract of maturity December 2008, going from January 2 to December 15, 2008. This is equivalent to 240 days of trading after cleaning the data for outliers, and until the expiration of the contract. Intraday data with a one-year time horizon have been studied, for instance, by Taylor and Xu (1997) for the DM/$ exchange rate. The total amount of intraday observations in our sample is equal to 167,004. The ECX CO_2 emissions futures tick data thus corresponds to one tenth of the transactions recorded on FX markets - which are opened 24 hours and reach more than 15,000 trades per day. However, this level of transactions appears comparable to the values found for other markets. For instance, Thomakos and Wang (2003) note that the average number of price changes per day is 163 for the Eurodollar, 3,366 for the S&P500, and 1,710 for T-bonds. The average amount of transactions for the ECX CO_2 emissions futures tick-by-tick data is equal to 700 trades per day. This corresponds to an average of 50 seconds between each transaction.

In the next section, we detail how to compute realized volatility measures.

3 Estimation of realized volatility

In this section, first we review the theoretical background to derive realized volatility measures from intraday data, second we present different estimation methods, third we discuss the issue of optimal sampling frequency choice and the maturity effect in the futures contract.

3.1 Theory

Let $p(t)$ denote a logarithmic asset price at time t. Abstract from a jump process, the continuous-time diffusion process generally employed in asset and derivatives pricing may be expressed by a stochastic differential equation as:

[9] Note *spreads* between two futures contracts may also be traded.

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) \quad \text{with} \quad 0 \leq t \leq T \tag{1}$$

with $\mu(t)$ a continuous and locally bounded variation process, $\sigma(t)$ a strictly positive càdlàg (right continuous with left limits) stochastic volatility process, and $W(t)$ a standard Brownian motion. Note that the formulation in equation (1) is very general, includes most of the processes generally used in standard asset pricing theory (see ABDL (2001)) and may accommodate for long memory components.

Next, let us consider the quadratic variation (QV) for the cumulative return process $r(t) \equiv p(t) - p(0)$:

$$[r, r]_t = \int_0^t \sigma^2(s)ds \tag{2}$$

The QV simply equals the integrated volatility of the process described in equation (1). Now, assume that returns are sampled on a Δ-period yielding $r_{t,\Delta} \equiv p(t) - p(t - \Delta)$. The *realized variance*[10] (RV) is defined as the sum of the corresponding $1/\Delta$, which is assumed to be an integer for simplicity, high-frequency intraday squared returns, or:

$$RV_{t+1}(\Delta) \equiv \sum_{j-1}^{1/\Delta} r^2_{t+j.\Delta,\Delta} \tag{3}$$

Andersen and Bollerslev (1998) followed by ABDL (2001) and BNS (2002) among others demonstrated that, as the sampling frequency of the underlying returns increases, the RV converges uniformly in probability to the increment of the QV process, or:

$$RV_{t+1}(\Delta) \rightarrow \int_0^t \sigma^2(s)ds \tag{4}$$

when $\Delta \rightarrow 0$. Thus, RV is a consistent estimator for the integrated volatility used throughout asset pricing theory. In other words, as the sampling frequency increases, the estimation error of the RV diminishes.

3.2 Estimation methods

Theory suggests that optimal sampling corresponds to sampling at the highest possible frequency. In practice, this is far from being true as shown in a series of articles starting with Andersen and Bollerslev (1998). In fact, the logarithmic return process which is truly observed does not comply with the hypothesis of a semimartingale for the underlying process, which is a necessary hypothesis for deriving results discussed in the previous section. This issue is discussed in ABDL (2001) and Zhang *et al.* (2005) for instance. The latter authors describe this phenomenon as emerging from market microstructure problems, whose main examples are the existence of a bid-ask spread, non-synchronous trading, etc.

[10] Some authors refer to this as *realized volatility*, but we reserve this term for the square root of realized variance that is also considered in this article.

To mitigate the impact of microstructure noise, various methodologies have been employed in the empirical financial literature. These include the determination of the optimal Δ as described in Aït-Sahalia *et al.* (2005) after the noise has been modelled, the use of subsampling schemes as in Zhang *et al.* (2005), resorting to pre-filtering methods as in Andreou and Ghysels (2002) or kernel-based methodologies as in Zhou (1996) or Hansen and Lunde (2006). In order to investigate the relevance of different sampling methods for the analysis of the ECX emissions futures 2008 contract, we do not only follow ABDL (2001) as is the case in most of the existing empirical literature, but we also consider two other methodologies.

First, we consider the traditional un-weighted estimator used for instance in ABDL (2001) and BNS (2002). This estimator is the natural estimator in view of theoretical developments in quadratic variation and perfectly fits equation (3), as it is the sum of squared realized returns on a given sampling frequency. For each day d and sampling frequency $1/m$, we compute:

$$RV^{d,m} = \sum_{i=1}^{m} r_{i,m}^2 \tag{5}$$

Second, we estimate realized volatility following Zhang *et al.* (2005). Their sub-sampling method appears particularly relevant for use with the ECX emissions futures intraday data, because of the limited number of daily transactions compared to other more actively traded financial assets. The idea behind sub-sampling is that when a given sampling frequency, say $1/m$, is chosen in light of the microstructure noise limited impact, a large share of the data is ignored. To fully account for the available information, Zhang *et al.* (2005) propose to average the measure of realized volatility at $1/m$ frequency but for different starting times. Let:

$$RV^{d,m,p} = \sum_{i=1+p}^{m+p} r_{i,m}^2 \tag{6}$$

be the realized variance measure at sampling frequency $1/m$, but with the first observation chosen at $1+p$ with $p < \frac{1}{m}$. By evaluating $RV^{d,m,p}$ for starting times $1, 1+p, 1+2p, ..., 2$ and keeping the sampling frequency $1/m$, we move our estimation window, and thus exploit a larger part of the data set. Zhang *et al.* (2005) then propose to average the measure considering all starting values.

Third, we retain a kernel-based estimator as first proposed in Zhou (1996). After testing for various kernel estimates, such as the modified Tukey-Hanning kernel, our choice goes to the Bartlett kernel-based estimator, which shows better performance with respect to the variability of the estimators with respect to their inputs[11].

We then consider, as is now common in the literature[12], three different proxies for volatilities. First, we study the realized variance as defined in equation (3) with a sampling frequency of 15 minutes, in view of the volatility signature plots in Figure 3 (see more on this below). Second, following ABDL (2001)

[11] Hansen and Lunde (2006) discuss this issue, and provide more details on the practical application of kernel-based methods.

[12] See ABD (2007) and references therein.

we examine the square root of the realized variance, denoted realized volatility, or $RV_t^{1/2}$. Third, we consider the logarithm of the realized volatility, or $log(RV_t^{1/2})$, also known for its convenient properties in small samples[13]. As will be discussed below, the logarithmic transformation represents one among other power transformations. A better choice may emerge following Gonçalves and Meddahi (2008).

Insert Figure 2 about here

Figure 2 plots the three proxies of volatilities (left, middle and right panels) for the three estimation methods selected (top, middle and bottom panels). The time-series reveal the presence of jumps and structural breaks that may be taken into account using multipower variation measures.[14] Note also that the time-series on the left panel reflect the exclusion of the "once-in-a-generation" (Cai *et al.* (2001), ABDL (2003)) anomalous carbon price movement detected on October 13, 2008 which seems to coincide with the depressing effect of the "credit crunch" crisis on the prices of global commodity markets.

Insert Table 1 about here

Table 1 reports the descriptive statistics for the three proxies of volatility with the three estimation methods. We observe that the daily realized variance and the daily realized volatility in standard deviation form present nonzero skewness and excess kurtosis[15]. These descriptive statistics therefore reveal a "fat tailed" leptokurtic distribution for the ECX CO_2 emissions futures contract of maturity December 2008, except for the daily realized volatility in logarithmic form.

3.3 Optimal sampling frequency and maturity effect

As is usual, we need to estimate the highest frequency at which the microstructure noise can be neglected. To this purpose, we use volatility signature plots, where the realized volatility measure described in equation (5) is computed and plotted at different sampling frequencies.

Insert Figure 3 about here

Figure 3 shows the volatility signature plot for the full (top) and November-December (bottom) samples. As in ABDL (2001) and ABDE (2001), we use these volatility signature plots to estimate the range of sampling frequencies where the volatility is strongly increasing, indicating the increasing presence of microstructure noise.

For the full sample, it appears that the choice of 15-minute returns should allow to minimize the impact of the microstructure noise, while ensuring for each day a sufficient number of observations. The use of 15-minute returns for the ECX carbon tick data also appears as a conservative choice compared to

[13]Some articles (*e.g.* ABD (2007)) consider the series of the logarithm of the realized variance instead of the logarithm of the standard deviation of the realized variance. This is of course equivalent up to a scalar.
[14]This aspect is left for further research.
[15]Note for a normally distributed random variable skewness is zero, and kurtosis is three.

5-minute returns usually chosen for FX markets. Of course, the use of volatility signature plot as a simple graphical tool to determine the optimal frequency is questionable. To overcome this difficulty, Awartani *et al.* (2009) propose a statistical test allowing to assess the incremental impact of the microstructure noise between two possible frequencies. As such, a rolling version of their procedure can be viewed as a statistically robust implementation of the volatility signature plot method in ABDL (2001). Because our contribution remains more empirically-oriented, we choose to proceed with the graphical method.

Looking at Figure 3 reveals different patterns between the full sample and the end-of-year sub-sample. We observe that the level of volatility is slightly higher at the end of the year. This is a quite standard effect on commodity futures markets, also known as the "Samuelson effect". Samuelson (1965) advocated in his seminal article that volatility is increasing near the maturity of futures contract as a response to an increasing flow of information.[16] Thus, to verify the Samuelson hypothesis, we should observe that the futures price volatility increases as the futures contract approaches its expiration date. This characteristic of financial assets has been recently proven to be valid using intraday data for a wide range of futures market, including agricultural futures (Duong and Kalev, 2008).

The inspection of the volatility signature plots for the last months of 2008 tends to confirm this hypothesis. The effects of microstructure noise seem visually more important. More importantly, the dispersion of the estimator is larger due to the low level of observations used to compute the realized variance. For the November-December period, the realized volatility estimate can lie anywhere between 0.01 and 0.025 using a sampling frequency around 15 minutes. This variability is lower for the full sample, which goes from 0.015 to 0.020 for the same sampling frequency. Nevertheless, in view of the moderate effect that we observe at the end of the sample, we choose to keep a 15-minute interval between two observations as being representative of the optimal frequency for the entire sample.

In the next section, we explain the empirical results obtained.

4 Unconditional distribution of futures returns and realized volatility

In this section, we study the unconditional distribution of realized volatilities and returns for the ECX December 2008 futures contract. We first focus on the unconditional distribution of our three proxies for realized volatility. We then study the distributional properties of daily raw returns, RV-standardized and GARCH-standardized-returns.

4.1 Distribution of realized variance and volatility

Insert Figure 4 about here

[16]See also Illueca and Lafuente (2006) for an application of the realized volatility measure to the investigation of the expiration-day effect.

We first plot unconditional distribution of realized variances and realized volatilities in the left and middle panels of Figure 4. The distribution of these volatility measures appears strongly right-skewed.

Insert Table 2 about here

This is confirmed by normality test statistics in Table 2. The kurtosis of the series indicates fat tails compared to a Gaussian distribution.

Insert Figure 5 about here

Quantile-Quantile (QQ) plots against normality in Figure 5 unambiguously reject normality for realized variance and volatility. Next, we turn to the logarithmic transformation, which is common practice since ABDL (2001), to near normality.

4.2 Distribution of the logarithmic transformation of volatility

We begin our analysis by using the logarithmic transformation as in most of the existing literature. The kernel-based distributions plotted in the right panel of Figure 4 indicate a less skewed density than for realized variance or its square root. Indeed, in view of the plotted distributions and quantile-quantile plots in the right panel of Figure 5, it appears that the logarithmic transformation of the realized volatility, while remaining left-skewed, does a better job in nearing normality. It should be noted that our kernel-based distributions are only based on 240 trading days. This limited data availability may explain the departure from normality, which is expected in small sample experiments.

To sum up, our analysis shows that the logarithmic transformation of the daily realized volatility is closer to normality than other forms of volatility. This result is in line with previous literature on the modeling of stochastic volatility (see ABDL (2001, 2003) among others), which has practical applications in option pricing.

4.3 Alternative transformations

The logarithmic transformation is only one transformation among others. Alternative transformations have been proposed to improve the normal approximation in small samples. Chen and Deo (2004)'s transformation is based on a power transformation, from which the exponent is then estimated. Unfortunately, the exponent has to be estimated knowing the asymptotic variance of realized volatility, which is not the case in practice. Gonçalves and Meddahi (2008) thus coin this statistic as "infeasible", and rely on Edgeworth expansions to determine the optimal parameter β of the Box-Cox transformation to retain in order to eliminate the skewness. We tested various values of β to better take into account the residual skewness in our series. We did not find better transformations compared to the initial logarithmic transformation[17].

[17] The results of these tests are no reported here due to space constraints, but are available from the authors upon request.

4.4 Distributional properties of returns and standardized returns

Let R_t be the daily open-to-close continuously compounded return of the futures contract for day t.

Insert Figure 6 about here

Daily raw returns are plotted in Figure 6. As is common for financial time-series, returns exhibit volatility clustering.

Insert Table 3 about here

Descriptive statistics of daily returns are provided in Table 3. We observe that the unconditional distribution of returns is close to normality with a sample skewness of -0.047 and a sample kurtosis of 3.24, thus resulting in a Jarque-Bera statistic value of 0.69 corresponding to a p-value of 0.70.

Next, we compute the series of daily standardized returns. Following Clark's (1973) seminal contribution for cotton futures returns, the standardized returns should follow a normal distribution if the process governing the realized volatility is log-normal and the process governing returns is normal. According to Clark's vocable, the volatility process is the "*directing process*", and the distribution of standardized returns is said to be "*subordinated*" to the distribution of returns. The resulting process is thus a lognormal-normal mixture, so-called the "*mixture-of-distribution hypothesis*" (MDH) in the literature[18].

Insert Figure 7 about here

For the ECX CO_2 emissions 2008 futures data, it is obvious that standardized returns are not normally distributed (see Figure 7). Table 3 indicates a sample skewness of 0.89 and a sample kurtosis of 8.84. Gaussianity is clearly rejected at all confidence levels, and does not need further investigation. As in Areal and Taylor (2002), the rejection of the MDH may be due to *(i)* the imperfect estimation of the logarithmic volatility through the realized estimator[19], and *(ii)* the extreme outlier occurring on October 13, 2008, which strongly deforms our distribution. Another explanation for non-normality may be found in Fleming and Paye (2005), who argue that microstructure noise biases kurtosis estimates for standardized returns. The intuition behind this result is that microstructure noise is less likely to occur for large absolute returns, because large absolute returns are often associated with larger volumes. As such, the realized volatility is underestimated for large absolute return days, thus inflating the tails of the standardized returns distribution. Because of the limited number of observations in the present work, it appears difficult to verify this assumption. This would necessitate many large absolute return days and a thorough analysis of the microstructure bias conditionally on the presence of a large absolute return.

[18] A very clear presentation of the MDH is given in Jondeau *et al.* (2007), sections 3.3 and 3.4. This hypothesis is investigated for futures returns in Areal and Taylor (2002) and Martens and Luu (2003), among others.

[19] Note we did not introduce the possibility of jumps in our analysis through more robust estimators as bipower or tripower estimators (see ABD (2007)). Indeed, the presence of jumps may distort the distribution of standardized returns. This area is left for further research.

The rejection of the MDH for the ECX CO_2 emissions 2008 futures contract has strong implications for derivatives pricing in these markets[20]. The jump-free diffusion process which is commonly assumed for option pricing does not seem suitable for the CO_2 emissions allowance market. There may be two different explanations for that. First, the process may include jumps. Options would then be better priced using jump-diffusion models. Second, the independence assumption between the Brownian motion and the volatility process may be violated. This also has some consequences for the pricing of derivatives, as more complex models need to be considered.

We also investigate graphically the presence of leverage, *i.e.* an increase in volatility following negative returns. Such an asymmetry may have consequences in terms of volatility modeling, because a good working knowledge of returns would help to model volatility.

Insert Figure 8 about here

By contrast, the absence of asymmetric effect seems apparent in Figure 8, which provides a scatterplot of realized volatility in logarithmic form against lagged standardized returns. This conclusion has, of course, to be taken with care in light of the limited number of daily observations in our study.

It is common in the financial literature to examine the parametric modeling of volatility through GARCH or stochastic volatility (SV) models. More precisely, GARCH volatilities may be used to standardize daily returns, and may be compared with realized volatility results. Following Benz and Truck (2009), we specify the AR(1)-GARCH(1,1) model:

$$R_t = \beta_0 + \beta_0 R_{t-1} + \epsilon_t \tag{7}$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1} \tag{8}$$

with R_t the daily returns, and ϵ_t the error term in equation (7). Equations (7) and (8) are estimated by Quasi Maximum Likelihood (QML) (Gourieroux *et al.* (1984)) using the BHHH algorithm (Berndt *et al.* (1974)).

Insert Table 4 about here

Estimation results of the AR(1)-GARCH(1,1) model are presented in Table 4. Residual tests for the chosen specification provide evidence that any autocorrelation in the residuals and squared residuals has been removed[21]. The distribution of GARCH-standardized returns is more normal than the distribution of realized volatility-standardized returns (see Table 3 and Figure 7). This result is unusual in the financial economics literature, as GARCH-standardized returns are generally more fat-tailed than realized volatility-standardized returns. The natural leptokurticity of GARCH models is

[20] European options with various strike prices have indeed been introduced in October 2006 on ECX (see Chevallier *et al.* (2009)).

[21] To conserve space, the autocorrelation and partial autocorrelation functions of the residuals and squared residuals are not reproduced here, and may be obtained upon request to the authors.

generally argued to be insufficient to accommodate the empirical excess kurtosis of financial time-series[22].

Insert Figure 9 about here

Figure 9 plots the time series of the AR(1)-GARCH(1,1) model. We observe that GARCH estimates are significantly smoother than realized estimates. In light of our empirical study, GARCH modeling appears more suitable to reach normality once returns have been standardized. This result highlights the critical role which may be played by jumps in the time-series of ECX CO_2 emissions 2008 futures.

In the next section, we investigate the properties of the conditional distribution of futures returns and realized volatility.

5 Modeling realized volatility dynamics

In this section, we are interested in modeling the conditional distribution of volatility. This investigation has practical applications for forecasting purposes, and may also be of interest for traders who need accurate volatility estimates for derivatives pricing.

We first investigate the autocovariance in the realized variance, the realized volatility, and the logarithm of volatility series.

Insert Figure 10 about here

Figure 10 plots the autocorrelation function (ACF) and partial autocorrelation function (PACF) estimated for the naive estimator[23]. We detect the presence of serial correlation for realized variance and realized volatility at least with one lag. For the log-transformation of the volatility series, the estimated autocorrelation does not appear to decay exponentially, but rather hyperbolically. This may be an indication of the presence of an unit root.

Insert Table 5 about here

The test statistics provided in the first column of Table 5 indicate the rejection of the unit-root hypothesis in all cases. In what follows, we focus on the existence of long memory in the data generating process.

Because the tick-by-tick time-series of ECX CO_2 emissions futures is very short to investigate the presence of long memory, we consider two estimation procedures for the fractional integration coefficient, as in ABDL (2001) and Areal and Taylor (2002). First, let S_T be the variance of the sum of

[22] Log-likelihood based on fat-tailed distributions (generalized error distribution (GED), Student, etc.) is commonly used to accommodate this high degree of kurtosis. We did not find however any improvement in our estimation by using a similar approach.

[23] Similar plots were obtained for the two other estimators, and thus are not reported here to conserve space.

T consecutive observations of, say, logarithm of the realized volatility $log(RV_t^{1/2})$. For long memory processes, the variances S_T follow a scaling law such that:

$$T^{-(2d+1)} S_T \rightarrow C \tag{9}$$

as $T \rightarrow \infty$ with $d > 0$, and C is a constant[24].

Insert Figure 11 about here

Figure 11 plots the sample variances S_T of the partial sums of the realized logarithmic standard deviations against the logarithm of the aggregation level for T. The regression coefficient corresponds to $2d + 1$, and thus leads to an implicit value of the fractional integration coefficient reported in Table 5.

The second methodology to estimate this coefficient is the Geweke-Porter-Hudak's (henceforth GPH, 1983) method (see Brockwell and Davis (1991) for a formal presentation, or Corsi (2009) for a discussion). The GPH estimate is based on the regression of the logarithm of the periodogram estimate of the spectral density against $ln(\omega)$ over a range of frequencies ω with:

$$w^{2d} f(\omega) \rightarrow C \tag{10}$$

as $T\omega \rightarrow 0$ and C a constant. Again, the estimates are comprised in the range of $[0, 0.5]$, which indicates the presence of long memory.

In view of these strong indications of long memory in the log time-series, we choose to rely on Corsi's (2009) parsimonious HAR-RV model for at three main reasons. First, recall that our dataset contains only 240 trading days. This is clearly too few for ARFIMA modeling, despite the presence of long memory[25]. Second, Pong *et al.* (2008) show that long memory may not be distinguished from short memory below 250 trading days. Second, the HAR-RV model succeeds in reproducing the long memory features of the time-series, while being easier to estimate particularly on a shorter time-horizon. Third, the heterogeneous behavior assumed between economic agents may be justified by the fact that traders, utilities and financial institutions operating on the EU ETS have different investment horizons. The HAR-RV model is used in ABD (2007), Corsi *et al.* (2008), and Liu and Maheu (2009) among others. The economic intuition behind this model is that different groups of investors have different investment horizons, and consequently behave differently (see Müller *et al.* (1997) for the presentation of the HARCH original model relying on the Heterogeneous Hypothesis).

The original HAR-RV model by Corsi (2009) is formally a constrained AR(22) model, slightly different from ABDL (2001) and Corsi *et al.* (2008)[26]. The HAR-RV model using daily, weekly and monthly

[24] In comparison, setting $d = 0$ is a feature of short memory.

[25] Note that ARFIMA estimation does not appear suitable alternatives for the one-year ECX emissions futures with tick-by-tick data, since the estimation of formal long memory models would require several years of data.

[26] ABDL (2001) formally use an AR(5). In this article, we adopt an intermediate specification by selecting a simplified HAR-RV model with only a weekly component, thus leading to a constrained AR(5) specification. Note that our choice is also econometrically motivated by the $Q(20)$ test statistics reported in Table 3.

realized-volatility components may be defined as follows:

$$\sqrt{RV_t} = \alpha_0 + \alpha_d \sqrt{RV_{t-1}} + \alpha_w (\sqrt{RV})_{t-5:t-1} + \alpha_m (\sqrt{RV})_{t-22:t-1} + u_t \quad (11)$$

or in logarithmic form:

$$\log RV_t = \alpha_0 + \alpha_d \log RV_{t-1} + \alpha_w (\log RV)_{t-5:t-1} + \alpha_m (\log RV)_{t-22:t-1} + u_t \quad (12)$$

Following ABD (2007), the HAR-RV model for forecasting with the horizon h may be defined in general form by using the multiperiod realized variation (the sum of the corresponding one-period measures):

$$RV_{t,t+h} = h^{-1}[RV_{t+1} + RV_{t+2} + \ldots + RV_{t+h}] \quad (13)$$

and by definition, $RV_{t,t+1} \equiv RV_{t+1}$. The HAR-RV model proposed by Corsi (2009) is a specific case of equation (13) for which $h = 1$, thereby assuming that traders have investment horizons corresponding to one-day ahead, one-week ahead, and one-month ahead forecasts.

As demonstrated below, the ECX CO_2 emissions 2008 futures contract only requires a weekly component, thus simplifying Corsi's initial model. For each estimator and for RV, $RV^{1/2}$ and $log(RV^{1/2})$, we estimate the following specification:

$$RV_{t,t+h} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{t-5,t} + u_t \quad (14)$$

Insert Table 6 about here

Insert Table 7 about here

Insert Table 8 about here

Estimates are reported in Tables 6 to 8. From Table 6, we may observe that the HAR-RV model performs poorly in fitting the daily realized variance, as shown by the low R^2 from 0.0003 (regression (9)) to 0.0109 (regression (1)). These results are in line with previous literature on realized volatility, where the "raw" realized variance is difficult to model. The results displayed in Table 7 show the same pattern for the daily realized volatility, where the values obtained for the R^2 range from 0.0653 (regression (8)) to 0.1211 (regression (1)). This improvement from realized variance to realized volatility is common in other empirical studies (see for instance ABDL (2001, 2003)). The best results are generally achieved using the logarithmic transformation. Table 9 shows indeed a dramatic improvement in the results obtained. The R^2 values obtained for the daily realized volatility in logarithmic form range from 0.2798 (regression (2)) to 0.3691 (regression (4)). These values are comparable to ABD (2007) for FX markets and S&P 500 futures. We may conclude that the fit of the HAR-RV model for the log-series of the ECX CO_2 emissions 2008 futures data is much better than the fit for realized variance or realized volatility. The dramatic improvement in the fit of realized volatility models when using the log-transformation is well documented in the literature (see ABDL (2001, 2003), ABD (2007), and Corsi (2009) among others). A better in-sample fit leads to a better out-of-sample forecasting accuracy.

In the next section, we provide a forecasting exercice using the HAR-RV model versus the GARCH specification.

6 Forecasting

In this section, we use Mincer-Zarnowitz regression techniques, as in ABD (2003, 2005), to investigate the forecasting power of our competing models[27]. To compare the forecasting accuracy of the HAR-RV model versus the GARCH model estimated in the previous section, we run the following regressions:

$$(v_{t+1}) = b_0 + b_1(v_{t+1|t,HAR-RV}) + b_2(v_{t+1|t,GARCH}) + u_{t+1} \tag{15}$$

$$(v_{t+1})^{1/2} = b_0 + b_1(v_{t+1|t,HAR-RV})^{1/2} + b_2(v_{t+1|t,GARCH})^{1/2} + u_{t+1} \tag{16}$$

$$\log(v_{t+1})^{1/2} = b_0 + b_1 \log(v_{t+1|t,HAR-RV})^{1/2} + b_2 \log(v_{t+1|t,GARCH})^{1/2} + u_{t+1} \tag{17}$$

Due to the limited historical dataset for ECX CO_2 emissions futures, we only consider *one-step-ahead* forecasts[28]. The HAR-RV model is estimated with a daily and a weekly component for the three estimators.

Insert Figure 12 about here

The corresponding forecasts for the daily realized variance, the daily realized volatility, and the daily realized volatility in logarithmic form versus actual observations are displayed in Figure 12[29].

If the forecasting properties of the HAR-RV model are satisfactory, the b_0 coefficient should be equal to zero, the b_1 coefficient should be equal to one, and the introduction of an alternative model (here a GARCH model) through the coefficient b_2 should not increase significantly the R^2 of the regression. Thus, we are especially interested in the stability of the b_0 and b_1 coefficients, as well as in the increase of the R^2 between models. The b_2 coefficient depends on the scaling of the different variables, and thus is subject to a wide variability.

Insert Table 9 about here

[27] These are also known as "encompassing regressions".

[28] *i.e.* at each period t we use the data observed until $t-1$, and base our forecasts on the parameters of the model estimated over the period $[0, t-1]$. The first forecast is made using 100 observations, the second forecast 101 observations, and so on.

[29] Note that contrary to Figure 2, we decided to keep in our forecasting exercise the outlier on October 13, 2008, possibly due to the "credit crunch" effect as discussed in Section 3.2.

The main results of our forecasting exercise are presented in Table 9. The model which provides the best results is the logarithmic model. This result is not surprising, since the logarithmic model estimates were characterized by the highest values for the R^2 in Table 8. Our results confirm the robustness of the HAR-RV model. As predicted, we observe that the b_0 coefficients are close to zero, while the b_1 coefficients are close to one in all regressions (RV_t, $RV_t^{1/2}$, $\log(RV_t^{1/2})$). Besides, the GARCH estimates do not seem to improve significantly the R^2 of the regressions, especially in the case of RV_t. For $RV_t^{1/2}$ and $\log(RV_t^{1/2})$, we only observe a slight increase of the R^2, but the GARCH coefficient is only significant at the 10% level for the log-series. This property of GARCH models is widely documented in previous literature. Indeed, GARCH forecasts track much better the broad temporal movements in the volatilities for lower frequency variations, and their accuracy tends to perform poorly at higher frequencies.

Accordingly, our forecasting results do not seem to indicate that the mixture of the HAR-RV and GARCH models improves significantly the forecast accuracy of our estimates. For all regressions, the b_1 coefficients are lower than one, and the values of the R^2 do not seem significantly higher.

Overall, we demonstrate in this section the accuracy of the HAR-RV model, as well as the inaccuracy of GARCH forecasts and their inability to adapt to high-frequency movements. As noted in ABDL (2003)[30], this is due to the superiority of realized measures in estimation. As such, superior estimates of present conditions translate into superior forecasts of the future[31].

7 Conclusion

This article constitutes the first attempt to use realized measures of volatility for a specific energy commodity, namely the ECX CO_2 emissions futures contract of maturity December 2008. We proceed as is standard in the realized volatility literature to assess the distributional and dynamic properties of realized volatility for this contract. Besides, this article constitutes one of the first attempts to analyze the properties of CO_2 prices in the EU ETS using high-frequency data.

Our main findings may be summarized as follows: *(1)* the unconditional distribution of daily returns are near normal; *(2)* any attempt to standardize these returns using realized measures and to a lesser extent GARCH estimates does not lead the distribution to Gaussianity; *(3)* we thereby strongly reject the *mixture-of-distribution-hypothesis* developed by Clark (1973) and Tauchen and Pitts (1983); *(4)* the dynamics of realized volatility is well captured using the HAR-RV model with a daily and a weekly component, which outperforms significantly the GARCH specification; and (5) the predictive accuracy of the HAR-RV model outperforms unambiguously other models of conditional volatility based on daily data.

This work may be extended in several directions. First, the ECX CO_2 emissions futures tick-by-tick

[30] "*We have identified the quadratic variation and its empirical counterpart, the realized volatility, as the key objects of interest for volatility measurement, and we consequently assess our various volatility forecasts relative to this measure. It is perhaps not surprising that models built directly for the realized volatility produce forecasts superior to those obtained from less direct methods*, [...]" (ABDL, 2003, p. 613).

[31] Note the forecasts presented here only constitute a statistical metrics, and not an economic metrics such as the value of CO_2 allowances used for option pricing or portfolio management.

data set considered here only covers one-year with about 240 trading days and 700 transactions per day, thereby multiplying parameter and model uncertainties. These uncertainties could be reduced using bootstrap methods as developed very recently in Gonçalves and Meddahi (2009). These authors mainly resort to the wild bootstrap method to increase the number of available intraday data each day, without suffering from the so-called "*microstructure-noise*" bias.

Second, the inclusion of jumps within realized volatility measures appears necessary to fit the characteristics of CO_2 futures highlighted in previous literature. Daskalakis *et al.* (2009) use a jump-diffusion model to approximate the random behavior of CO_2 prices. Benz and Truck (2009) analyze the spot price behavior with a Markov-switching model. Lin and Lin (2007) model CO_2 prices as a result of mean-reversion with varying trends, combined with state-dependent price jumps and volatility structure, and show that mean-reversion fares better in forecasting futures prices.

Third, the use of realized volatility for ECX CO_2 emissions futures contracts may be useful for option pricing (see Stentoft (2008) for a first application to option stock markets) with a high-frequency measure of volatility. This may be of great help on such an emerging commodity market, as on the EU ETS any attempt to price derivatives is subject to strong uncertainties.

Fourth, the "*maturity effect*" encountered when selecting the sampling frequency here may be checked on other markets for more robust conclusions, and statistical tests may be used to determine the optimal sampling frequency. Indeed, if realized volatility is significantly different at different moments in the life of a futures contract, hedge ratios should be modified accordingly.

References

Aït-Sahalia, Y., Mykland, P., Zhang, L., 2005. How often to sample a continuous-time process in the presence of market microstructure noise. *Review of Financial Studies* 18, 351-416.

Alberola, E., Chevallier, J., 2009. European carbon prices and banking restrictions: Evidence from Phase I (2005-2007). *The Energy Journal* 30, 107-136.

Alberola, E., Chevallier, J., Chèze, B., 2008. Price drivers and structural breaks in European carbon prices 2005-2007. *Energy Policy* 36, 787-797.

Andersen, T.G., Benzoni, L., 2009. Realized volatility. In: Andersen, T.G., Davis, R.A., Kreiß, J.-P., Mikosch, Th. (Eds.) *Handbook of Financial Time Series*, Springer.

Andersen, T.G., Bollerslev, T., 1998. Answering the skeptics: yes, standard volatility models do provide accurate forecasts. International Economic Review 39, 885-905.

Andersen, T.G., Bollerslev, T., Diebold, F.X., 2007. Roughing it up: including jump components in the measurement, modeling and forecasting of return volatility. *Review of Economics and Statistics* 89, 701-720.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Ebens, H., 2001. The distribution of stock return volatility. *Journal of Financial Economics* 61, 43-76.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2001. The distribution of exchange rate volatility. *Journal of the American Statistical Association* 96, 42-55.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2003. Modeling and forecasting realized volatility. *Econometrica* 71, 579-625.

Andersen, T.G., Bollerslev, T., Meddahi, N.,, 2005. Correcting the errors: volatility forecast evaluation using high-frequency data and realized volatilities. *Econometrica* 73, 279-296.

Andreou E, Ghysels E., 2002. Detecting multiple breaks in financial market volatility dynamics. *Journal of Applied Econometrics* 17, 579-600.

Areal, N., Taylor, S.J., 2002. The realized volatility of FTSE-100 futures prices. *Journal of Futures Markets* 22, 627-648.

Awartani, B.M.A., Corradi, V., Distaso, W., 2009. Testing market microstructure effect with an application to the Dow Jones Industrial Average stocks. *Journal of Business and Economic Statistics*, forthcoming.

Barndorff-Nielsen, O., Shephard, N., 2002. Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of the Royal Statistical Society, Series B* 64, 253-280.

Benz, E., Klar, J., 2008. Liquidity and price discovery in the European CO_2 futures market: an intraday analysis. Working Paper, Bonn Graduate School of Business.

Benz, E., Truck, S., 2009. Modeling the Price Dynamics of CO_2 Emission Allowances. *Energy Economics* 1, 4-15.

Berndt, E.K., Robert, E.,Hall, B.H., Hausman, J.A., 1974. Estimation and Inference in Nonlinear Structural Models. *Annals of Economic and Social Measurement* 3, 653–665.

Brockwell, P.J., Davis, R.A., 1991. *Time Series: Theory and Methods.* Springer Series in Statistics, Springer-Verlag, New York.

Busch, T., Hoffman, V.H., 2007. Emerging carbon constraints for corporate risk management. *Ecological Economics* 62, 518-528.

Bunn, D., Fezzi, C., 2007. Interaction of European Carbon Trading and Energy Prices. *Fondazione Eni Enrico Mattei* Working Paper 123.

Cai, J., Cheung, Y.L., Lee, R.S.K., Melvin, M., 2001. "Once-in-a-generation" yen volatility in 1998: fundamentals, intervention, and order flow. *Journal of International Money and Finance* 20, 327-347.

Cartea, Á., Börger, R.H., Kiesel, R., Schindlmayr, G., 2007. A multivariate commodity analysis and applications to risk management. Birkbeck Working Papers in Economics and Finance BWPEF 0709, Birkbeck, University of London.

Chen, W.W., Deo, R.S., 2004. Power transformations to induce normality and their applications. *Journal of the Royal Statistical Association B* 66, 117-130.

Chevallier, J., Ielpo, F., Mercier, L., 2009. Risk aversion and institutional information disclosure on the European carbon market: a case-study of the 2006 compliance event. *Energy Policy* 37, 15-28.

Clark, P.K., 1973. A subordinated stochastic process model with finite variance for speculative prices. *Econometrica* 41, 135-156.

Christiansen, A.C., Arvanitakis, A., Tangen, K., Hasselknippe, H., 2005. Price determinants in the EU emissions trading scheme. *Climate Policy* 5, 15-30.

Corsi, F., 2009. A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics* 7, 174-196.

Corsi, F., Mittnik, S., Pigorsch, C., Pigorsch, U., 2008. The volatility of realized volatility. *Econometric Reviews* 27, 46-78.

Dacorogna, M.M., Gençay, R., Müller, U.A., Olsen, R.B., Pictet, O.V., 2001. *An Introduction to High-Frequency Finance*. Academic Press, San Diego, CA.

Daskalakis, G., Psychoyios, D., Markellos, R.N., 2009. Modeling CO_2 emission allowance prices and derivatives: evidence from the European trading scheme. *Journal of Banking and Finance*, forthcoming.

Duong, H.N., Kalev, P.S., 2008. The Samuelson Hypothesis in futures markets: an analysis using intraday data. *Journal of Banking and Finance* 32, 489-500.

Fleming, J., Paye, B.S., 2005. High-frequency returns, jumps and the mixture of normals hypothesis. Unpublished manuscript.

Geweke, J., Porter-Hudak, S., 1983. The estimation and application of long memory time series models. *Journal of Time Series Analysis* 4, 221-238.

Gonçalves, S., Meddahi, N., 2008. Box-Cox transforms for realized volatility. Unpublished manuscript.

Gonçalves, S., Meddahi, N., 2009. Bootstrapping realized volatility. *Econometrica* 77, 283-306.

Gourieroux, C., Monfort, A., Trognon, A., 1984. Pseudo Maximum Likelihood Methods: Theory. *Econometrica* 52, 680–700.

Guillaume, D.M., Dacorogna, M.M., Davé, R.R., Müller, U.A., Olsen, R.B., Pictet, O.V., 1997. From the bird's eye to the microscope: a survey of new stylized facts of the intra-daily foreign exchange markets. *Finance and Stochastics* 1, 95-129.

Hansen, P.R., Lunde, A., 2006. Realized variance and market microstructure noise. *Journal of Business and Economic Statistics* 24, 127-218.

Illueca, M., Lafuente, J.A., 2006. new evidence on expiration-day effects using realized volatility: an intraday analysis for the Spanish stock exchange. *Journal of Futures Markets* 26, 923-938.

Jondeau, E., Poon, S.-H., Rockinger, M., 2007. *Financial Modeling Under Non-Gaussian Distributions*. Springer-Verlag, Springer.

Liu, C., Maheu, J.M., 2008. Are there structural breaks in realized volatility? *Journal of Financial Econometrics* 6, 326-360.

Lin, Y.N., Lin, A.Y., 2007. Pricing the Cost of Carbon Dioxide Emission Allowance Futures. *Review of Futures Markets* 16, 1-16.

Luu, C.J., Martens, M., 2003. Testing the mixture-of-distributions hypothesis using "realized" volatility. *Journal of Futures Markets* 23, 661-679.

McAleer, M., Medeiros, M.C., 2008. Realized volatility: a review. *Econometric Reviews* 27, 10-45.

Müller, U.A., Dacorogna, M.M., Davé, R.D., Olsen, R.B., Pictet, O.V., 1997. Volatilities of different time resolutions – Analyzing the dynamics of market components. *Journal of Empirical Finance* 4, 213-239.

Oberndorfer, U., 2009. EU emission allowances and the stock market: evidence from the electricity industry. *Ecological Economics* 68, 1116-1126.

Paolella, M.S., Taschini, L., 2008. An Econometric Analysis of Emission Trading Allowances. *Journal of Banking and Finance* 32, 2022-2032.

Pong, S., Shackleton, M.B., Taylor, S.J., 2008. Distinguishing short and long memory volatility specifications. *Econometrics Journal* 11, 617-637.

Samuelson, P.A., 1965. Proof that Properly Anticipated Prices Fluctuate Randomly. *Industrial Management Review* 6, 41-49.

Stentoft, L., 2008. Option pricing using realized volatility. CREATES Research Paper 2008-13, Aarhus Business School.

Tauchen, G.E., Pitts, M., 1983. The price variability-volume relationship on speculative markets. *Econometrica* 51, 485-505.

Thomakos, D.D., Wang, T., 2003. Realized volatility in the futures markets. *Journal of Empirical Finance* 10, 321-353.

Tucker, M., 2001. Trading carbon tradable offsets under Kyoto's clean development mechanism: the economic advantages to buyers and sellers of using call options. *Ecological Economics* 37, 173-182.

Zhang, L., Mykland, P.A., Aït-Sahalia, Y., 2005. A tale of two time scales: determining integrated volatility with noisy high frequency data. *Journal of the American Statistical Association* 100, 1394-1411.

Zhou, B., 1996. High frequency data and volatility in foreign-exchange rates. *Journal of Business and Economic Statistics* 14, 45-52.

Zivot, E., 2005. Analysis of High Frequency Financial Data: Models, Methods and Software. University of Washington, Unpublished Manuscript.

Figure 1: CO_2 futures prices of maturities December 2005 through 2014 from April 22, 2005 to January 16, 2009
Source: ECX

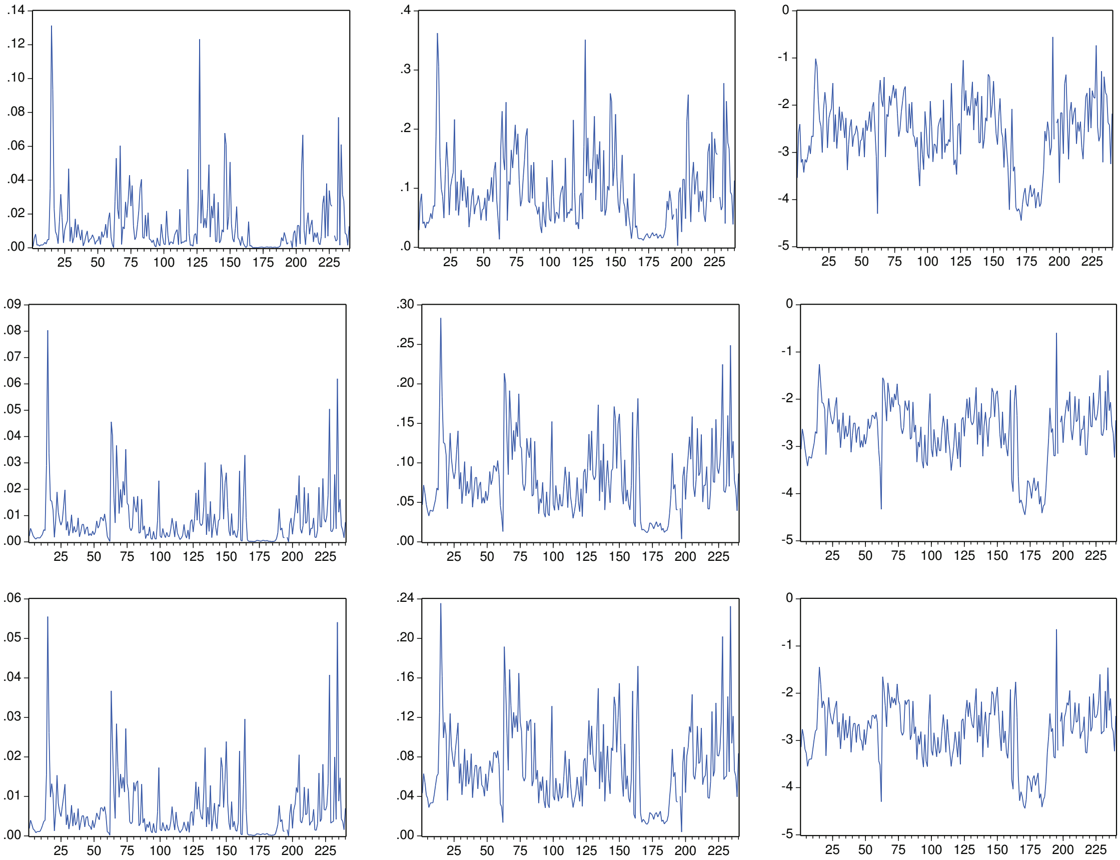

Figure 2: Daily realized variance (RV_t, left panel), daily realized volatility in standard deviation form ($RV_t^{1/2}$, middle panel), and daily realized volatility in logarithmic form ($log(RV_t^{1/2})$, right panel) for the three estimators (naive on the first row, Zhang *et al.* (2005) sub-sampling estimator on the second row, and Bartlett kernel-based estimator on the third row).

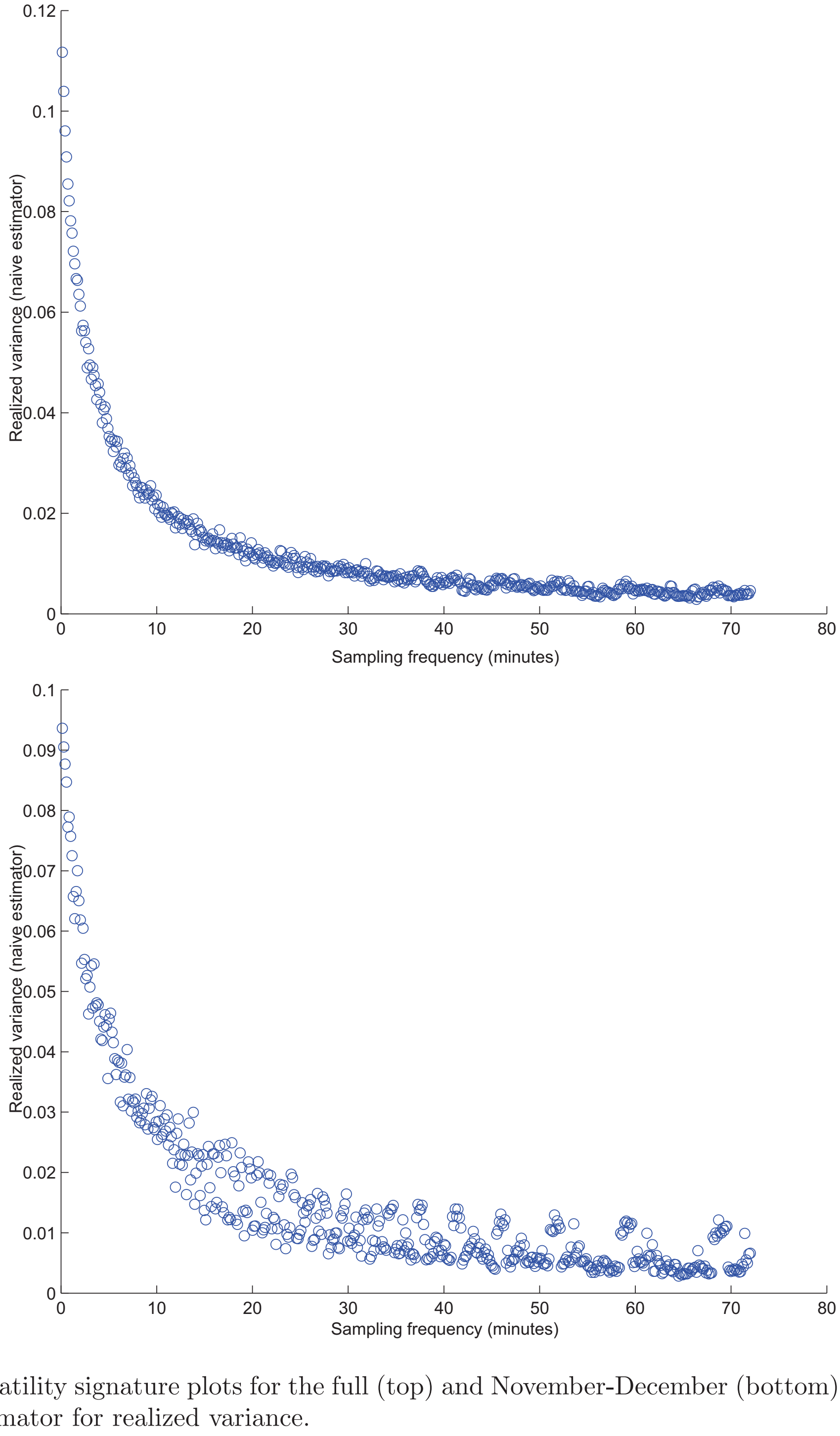

Figure 3: Volatility signature plots for the full (top) and November-December (bottom) samples using the naive estimator for realized variance.

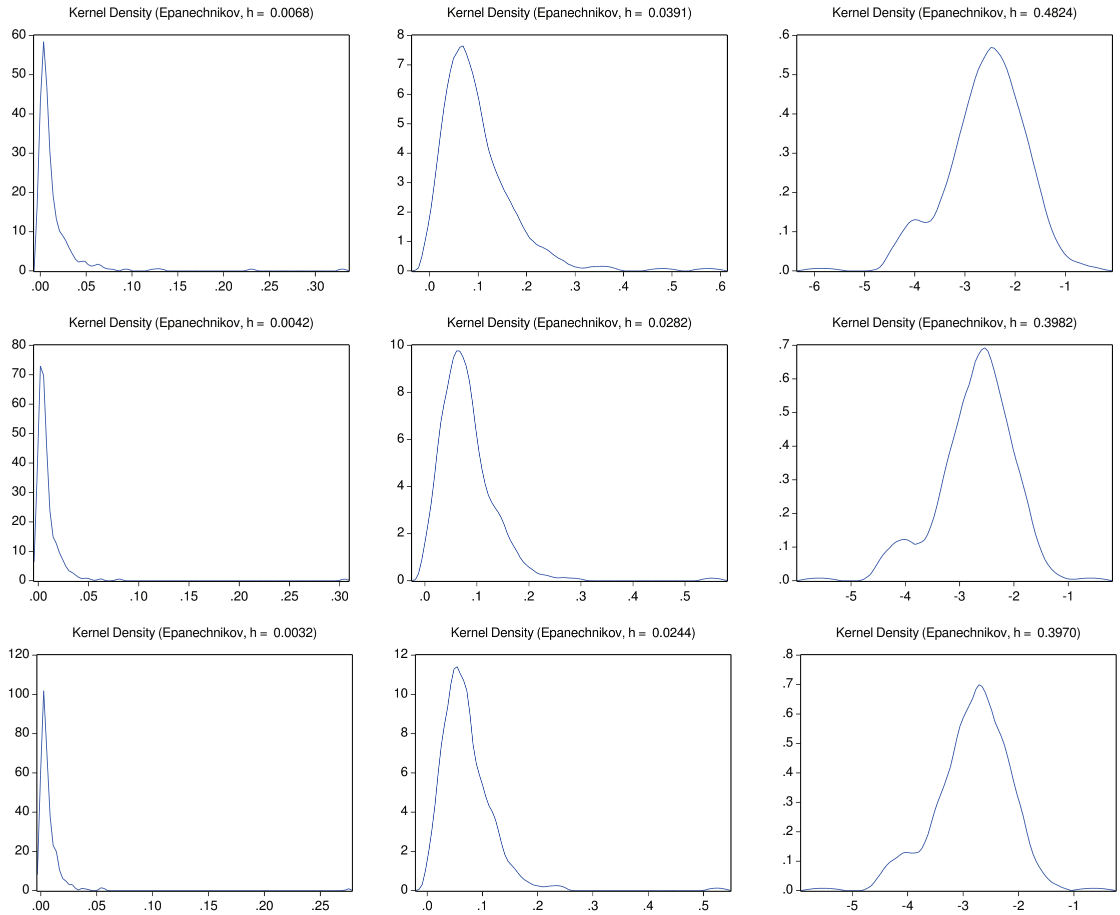

Figure 4: Centered kernel density estimates of the unconditional distribution for the daily realized variance (RV_t, left panel), the daily realized volatility in standard deviation form ($RV_t^{1/2}$, middle panel), and the daily realized volatility in logarithmic form ($log(RV_t^{1/2})$, right panel) based on 15-minute returns. The first row is for the naive estimator, the second row is for the Zhang *et al.* (2005) sub-sampling estimator, and the third row is for the Bartlett kernel-based estimator.

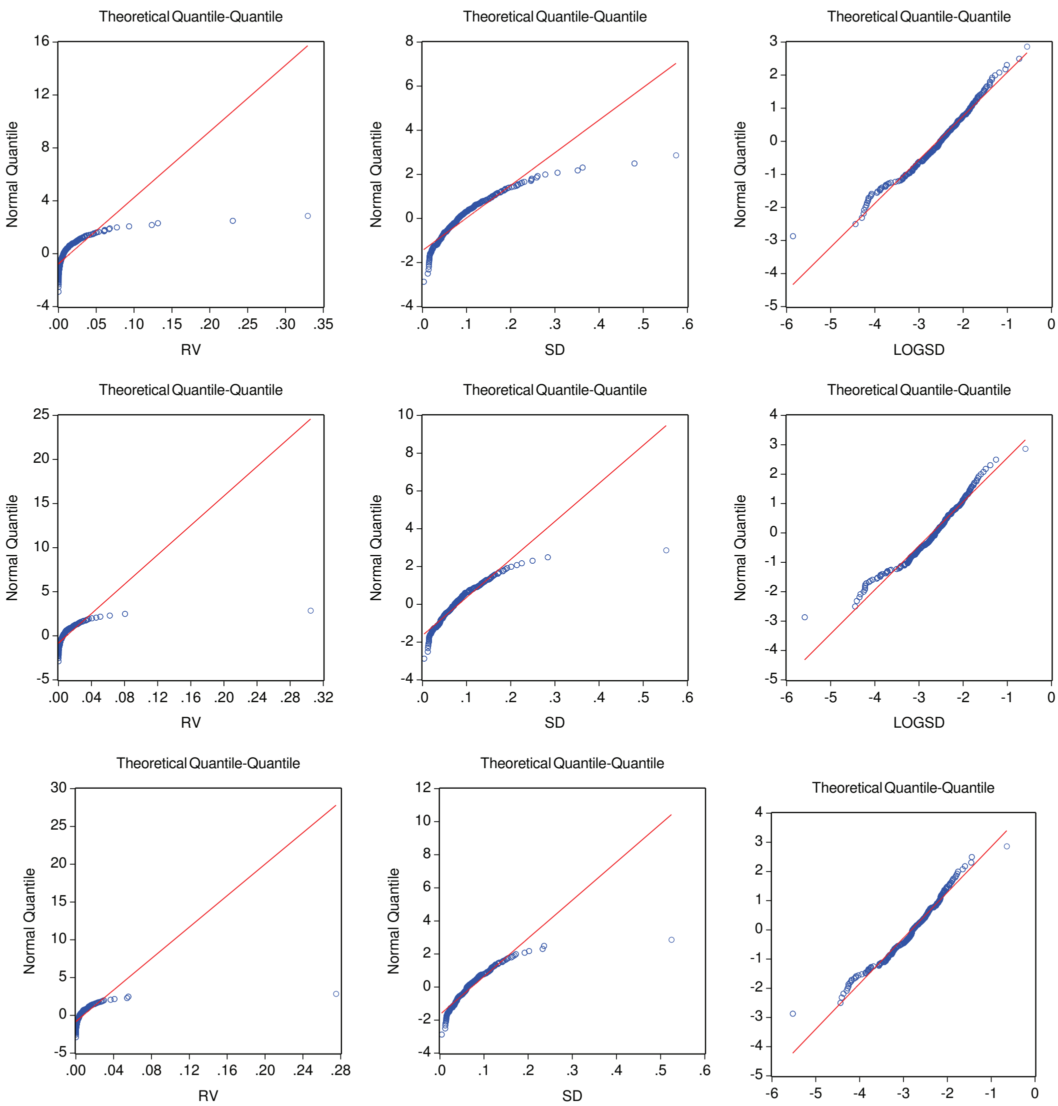

Figure 5: QQ plots for the realized variance (left panel), realized standard deviation (middle panel) and log of the standard deviation (right panel) for the three estimators (naive on the first row, Zhang *et al.* (2005) sub-sampling estimator on the second row, and Bartlett kernel-based estimator on the third row).

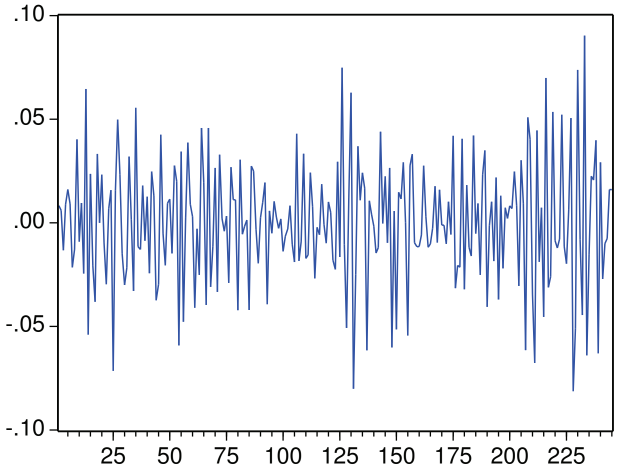

Figure 6: Time-series of daily raw returns.

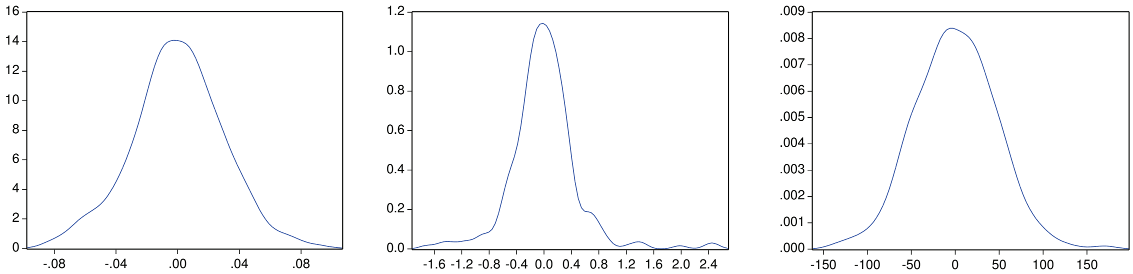

Figure 7: Smoothed Gaussian kernel distribution of daily returns (left panel), realized volatility (naive estimator) standardized returns (middle panel) and GARCH standardized returns (right panel).

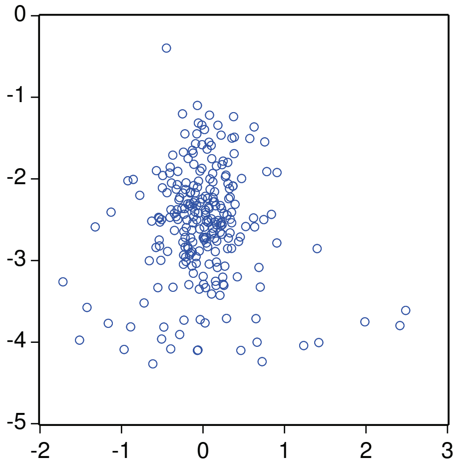

Figure 8: Scatterplot of the logarithmic realized volatility against lagged standardized returns.

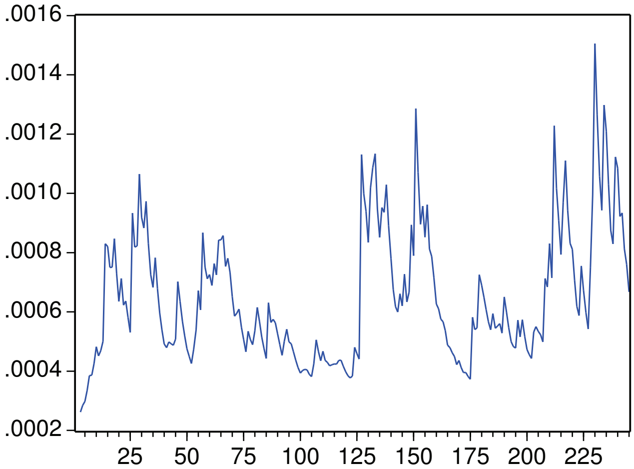

Figure 9: Time series of GARCH volatility measure.

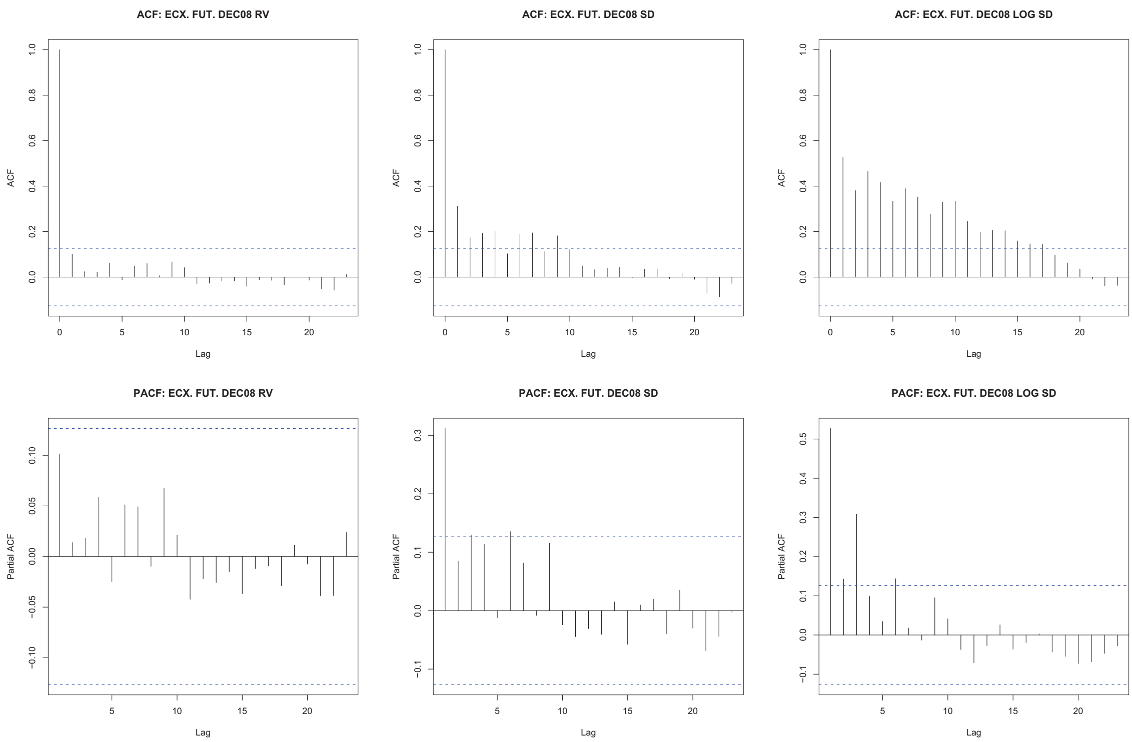

Figure 10: Autocorrelation and partial autocorrelation functions of the daily realized variance (RV_t, left panel), daily realized volatility in standard deviation form ($RV_t^{1/2}$, middle panel), and daily realized volatility in logarithmic form ($log(RV_t^{1/2})$, right panel) for the naive estimator.

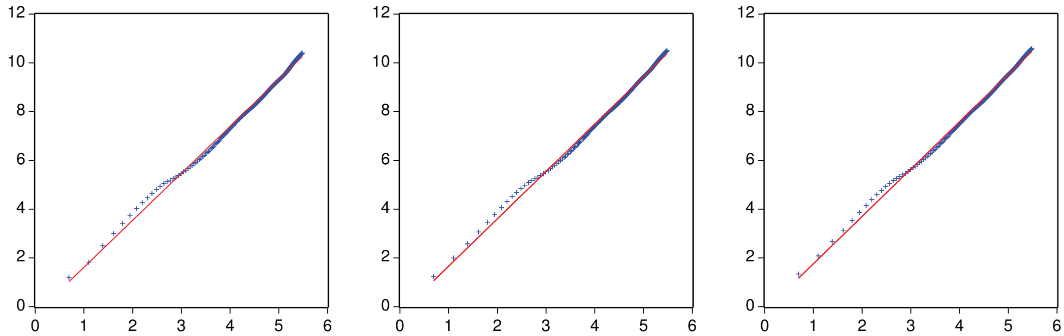

Figure 11: Scaling plot of the sample variances S_T of the partial sums of the realized logarithmic standard deviations against the logarithm of the aggregation level.

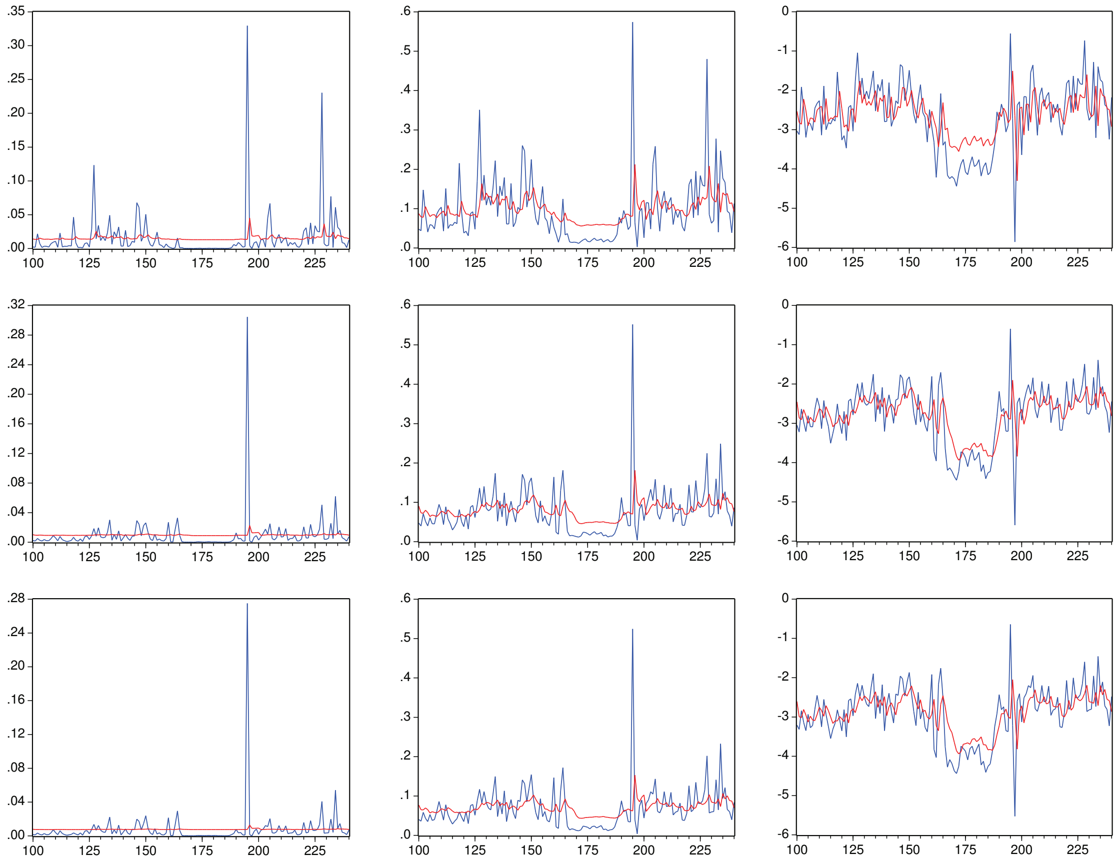

Figure 12: Forecasting of the daily realized variance (RV_t, left panel), the daily realized volatility in standard deviation form (${RV_t}^{1/2}$, middle panel), and the daily realized volatility in logarithmic form ($log({RV_t}^{1/2})$, right panel) with the HAR-RV model for the three estimators (naive on the first row, Zhang *et al.* (2005) sub-sampling estimator on the second row, and Bartlett kernel-based estimator on the third row).

	Mean	SD	Median	Min	Max	Skewness	Kurtosis	Ljung-Box (20)
Naive estimator								
RV_t	0.0130	0.0184	0.0064	0.0001	0.1313	3.2097	16.6500	7.1942
$RV_t^{1/2}$	0.0948	0.0636	0.0800	0.0029	0.0636	1.2998	5.1144	82.886
$log(RV_t^{1/2})$	-2.5652	0.7369	-2.5218	-4.4419	-0.5553	-0.3279	2.9927	420.63
Zhang *et al.* (2005) subsampling estimator								
RV_t	0.0085	0.0104	0.0052	0.0001	0.0804	2.9814	15.7588	3.3318
$RV_t^{1/2}$	0.0798	0.0467	0.0718	0.0037	0.2835	1.1008	4.7061	74.181
$log(RV_t^{1/2})$	-2.6966	0.6551	-2.6313	-4.4489	-0.5944	-0.4657	3.4233	376.51
Bartlett kernel-based estimator								
RV_t	0.0065	0.0079	0.0037	0.0001	0.0555	3.0012	15.4313	2.2043
$RV_t^{1/2}$	0.0702	0.0403	0.0609	0.0040	0.2356	1.1365	4.8489	59.803
$log(RV_t^{1/2})$	-2.8119	0.6264	-2.7932	-4.4386	-0.6454	-0.3229	3.3850	334.17

Table 1: Descriptive statistics of the daily realized variance (RV_t), daily realized volatility ($RV_t^{1/2}$), and daily realized volatility in logarithmic form ($log(RV_t^{1/2})$) for the naive, subsampling, and kernel-based estimators.

Note: The number of trading days is 240. SD stands for standard deviation. Ljung-Box test statistics are computed for a maximum number of 20 lags.

	Lilliefors	Crámer-Von Mises	Jarque-Bera	Watson	Anderson-Darling
Naive estimator					
$RV^{1/2}$	0.127955	1.350926	1080.817	1.089644	8.055166
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$log(RV^{1/2})$	0.062920	0.205757	22.16161	0.164762	1.347298
	(0.0522)	(0.0045)	(0.000015)	(0.0095)	(0.0017)
Zhang *et al.* (2005) subsampling estimator					
$RV^{1/2}$	0.128204	1.047318	4607.472	0.870926	9.000989
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$log(RV^{1/2})$	0.079671	0.353115	34.84085	0.286651	2.259627
	(0.0036)	(0.0001)	(0.0000)	(0.0002)	(0.0000)
Bartlett kernel-based estimator					
$RV^{1/2}$	0.120181	1.171580	8198.267	0.994852	9.903061
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$log(RV^{1/2})$	0.075590	0.264016	25.42408	0.219758	1.671065
	(0.0013)	(0.0009)	(0.0000)	(0.0016)	(0.0003)

Table 2: Normality test statistics for the realized standard deviation and logarithmic transformation with the three estimators.

Note: The values reported in parentheses are the p-values.

	Mean	SD	Skewness	Kurtosis	Jarque-Bera	$Q(20)$	$Q^2(20)$
Daily returns R_t	0.0000337	0.029600	-0.047258	3.242590	0.691953	75.609	51.660
RV-standardized daily returns	0.001904	0.498409	0.893659	8.846009	381.4887	66.923	152.95
GARCH-standardized daily returns	0.3078	46.3145	0.1034	3.4476	2.4622	72.154	19.500

Table 3: Descriptive statistics of continuously compounded daily returns, realized volatility (naive estimator) standardized returns, and GARCH standardized daily returns.

Note: The number of trading days is 240. SD stands for standard deviation, $Q(20)$ and $Q^2(20)$ stand for the Ljung-Box Q test statistics and the Ljung-Box $Q^2(20)$ test statistic computed up to 20 lags for returns and squared returns, respectively.

	Daily returns
Mean equation	
β_0	0.000045
	(0.0015)
β_1	-0.3881***
	(0.0677)
Variance equation	
α_0	0.0000945
	(0.0000668)
α_1	0.1839**
	(0.0945)
α_2	0.6973***
	(0.1572)
R^2	0.1300
Adj. R^2	0.1155

Table 4: AR(1)-GARCH(1,1) model estimates for daily returns

Note: The dependent variable is the daily return. Robust standard errors in parenthesis. *** indicates significance at 1%, ** at 5% and * at 10% levels.

	ADF test	$d(GPH)$	$\hat{d}$ from regression
Naive estimator			
RV_t	-13.9122	0.4376	–
$RV_t^{1/2}$	-11.1715	0.3318	–
$log(RV_t^{1/2})$	-4.2934	0.6849	0.4634
Zhang *et al.* (2005) subsampling estimator			
RV_t	-14.6932	0.4399	–
$RV_t^{1/2}$	-11.3561	0.3247	–
$log(RV_t^{1/2})$	-4.4725	0.6964	0.4588
Bartlett kernel-based estimator			
RV_t	-15.0757	0.4306	–
$RV_t^{1/2}$	-11.8635	0.3066	–
$log(RV_t^{1/2})$	-3.7696	0.6520	0.4711

Table 5: ADF test statistics up to 14 lags, $d(GPH)$ Geweke-Porter-Hudak estimates of the fractional integration parameter, and $\hat{d}$ coefficients estimated from regressions for the daily realized variance (RV_t), the daily realized volatility in standard deviation form ($RV_t^{1/2}$), and the daily realized volatility in logarithmic form ($log(RV_t^{1/2})$) with the naive, subsampling and kernel-based estimators.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	0.0130	0.0137	0.0130	0.0090	0.0093	0.0090	0.0074	0.0075	0.0074
	(0.0028)	(0.0022)	(0.0028)	(0.0019)	(0.0015)	(0.0019)	(0.0016)	(0.0013)	(0.0016)
β_1	0.0810	0.1013		0.0323	0.04683		0.0139	0.0211	
	(0.0746)	(0.0645)		(0.0741)	(0.0648)		(0.0739)	(0.0649)	
β_2	0.0762		0.1556	0.0594		0.0916	0.0283		0.0424
	(0.1505)		(0.1315)	(0.1580)		(0.1395)	(0.1619)		(0.1435)
R^2	0.0109	0.0102	0.0059	0.0026	0.0021	0.0018	0.0005	0.0004	0.0003
Adj. R^2	0.0024	0.0061	0.0017	-0.0059	-0.0020	-0.0024	-0.0080	-0.0037	-0.0039
Log-lik.	484.29	494.19	483.69	564.60	575.98	564.50	595.53	607.52	595.51
AIC	-4.0960	-4.1187	-4.0995	-4.7796	-4.8031	-4.7873	-5.0428	-5.0671	-5.0511
SC	-4.0519	-4.0896	-4.0701	-4.7354	-4.7740	-4.7578	-4.9986	-5.0380	-5.0217

Table 6: OLS estimates for the daily realized variance (RV_t) with the HAR-RV model (three estimators, naive: columns (1) to (3); subsampling: columns (4) to (6); kernel: columns (7) to (9)).

Note: The model estimated is $RV_t = \beta_0 + \beta_1 RV_{t-1} + \beta_2 RV_{t-6,t-1} + u_t$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	0.0490	0.0680	0.0497	0.0388	0.0577	0.0390	0.0366	0.0538	0.0367
	(0.0107)	(0.0076)	(0.0108)	(0.0088)	(0.0061)	(0.0089)	(0.0081)	(0.0054)	(0.0081)
β_1	0.1904	0.3118		0.1522	0.2960		0.1181	0.2554	
	(0.0770)	(0.0615)		(0.0773)	(0.0619)		(0.0775)	(0.0627)	
β_2	0.3174		0.5013	0.3782		0.5281	0.3787		0.4964
	(0.1234)		(0.0996)	(0.1255)		(0.1004)	(0.1298)		(0.1046)
R^2	0.1211	0.0975	0.0980	0.1207	0.0877	0.1060	0.0971	0.0653	0.0881
Adj. R^2	0.1136	0.0937	0.0941	0.1131	0.0839	0.1022	0.0894	0.0613	0.0842
Log-lik.	290.55	293.69	287.49	359.07	362.22	357.12	382.36	386.22	381.19
AIC	-2.4472	-2.4409	-2.4297	-3.0304	-3.0144	-3.0223	-3.2286	-3.2152	-3.2271
SC	-2.4030	-2.4118	-2.4003	-2.9862	-2.9853	-2.9929	-3.1844	-3.1861	-3.1977

Table 7: OLS estimates for the daily realized volatility in standard deviation form ($RV_t^{1/2}$) with the HAR-RV model (three estimators, naive: columns (1) to (3); subsampling: columns (4) to (6); kernel: columns (7) to (9)).

Note: The model estimated is $RV_t^{1/2} = \beta_0 + \beta_1 RV_{t-1}^{1/2} + \beta_2 RV_{t-6,t-1}^{1/2} + u_t$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β_0	-0.6329	-1.2134	-0.6452	-0.6663	-1.1683	-0.6866	-0.7345	-1.2884	-0.7512
	(0.1850)	(0.1479)	(0.1884)	(0.1893)	(0.1493)	(0.1960)	(0.2039)	(0.1581)	(0.2101)
β_1	0.2480	0.5275		0.3299	0.5678		0.3058	0.542864	
	(0.0789)	(0.0549)		(0.0776)	(0.0534)		(0.0781)	(0.0545)	
β_2	0.5041		0.7473	0.4226		0.7449	0.4325		0.7322
	(0.1043)		(0.0713)	(0.1022)		(0.0711)	(0.1045)		(0.0733)
R^2	0.3477	0.2798	0.3200	0.3691	0.3226	0.3200	0.3429	0.2946	0.2995
Adj. R^2	0.3421	0.2768	0.3171	0.3637	0.3197	0.3171	0.3373	0.2916	0.2965
Log-lik.	-220.98	-228.18	-225.88	-190.05	-200.23	-198.87	-184.02	-194.03	-191.54
AIC	1.9062	1.9851	1.9394	1.6430	1.6923	1.7095	1.5917	1.6404	1.6471
SC	1.9504	2.0142	1.9688	1.6872	1.7214	1.7389	1.6358	1.6695	1.6766

Table 8: OLS estimates for the daily realized volatility in logarithmic form ($log(RV_t^{1/2})$) with the HAR-RV model (three estimators, naive: columns (1) to (3); subsampling: columns (4) to (6); kernel: columns (7) to (9)).

Note: The model estimated is $log(RV_t^{1/2}) = \beta_0 + \beta_1 log(RV_{t-1}^{1/2}) + \beta_2 log(RV_{t-6,t-1}^{1/2}) + u_t$.

	b_0	b_1	b_2	R^2
Daily realized variance (RV_t)				
HAR-RV	0.006327	0.5678		0.0011
	(0.02075)	(1.3777)		
GARCH daily	0.01301		1970.17	0.0028
	(0.00434)		(3120.91)	
HAR-RV +	0.00699	0.4156	1788.50	0.0033
GARCH daily	(0.0208)	(1.4074)	(3190.7)	
Daily realized volatility in standard deviation form ($RV_t^{1/2}$)				
HAR-RV	-0.00654	1.0408***		0.1139
	(0.0240)	(0.2419)		
GARCH daily	0.05527		45.8000***	0.0703
	(0.0130)		(13.879)	
HAR-RV +	-0.0069	0.8526***	23.403	0.1281
GARCH daily	(0.0238)	(0.2735)	(15.322)	
Daily realized volatility in logarithmic form ($log(RV_t^{1/2})$)				
HAR-RV	0.1479	1.0656***		0.4704
	(0.2517)	(0.0942)		
GARCH daily	2.3640***		0.6945***	0.1917
	(0.8599)		(0.1188)	
HAR-RV +	1.2419*	0.9724***	0.1854*	0.4800
GARCH daily	(0.7032)	(0.1090)	(0.1113)	

Table 9: Estimates of the Mincer-Zarnowitz regression (equations 15 to 17) using forecasts for the daily realized variance, the daily realized volatility, and the daily realized volatility in logarithmic form obtained from the naive estimator.

Note: The values reported in parentheses are robust standard errors.