The Marginal Impacts of Energy Prices on Carbon Price Variations: Evidence from a Quantile-on-Quantile Approach

Kun Duan[a], Xiaohang Ren[b,c,*], Yukun Shi[d], Tapas Mishra[e], Cheng Yan[f]

[a]*School of Economics, Huazhong University of Science and Technology, Wuhan, 430074, China.*
[b]*Business School, Central South University, Hunan 410083, China.*
[c]*Southampton Statistical Sciences Research Institute, University of Southampton, Southampton, SO17 1BJ, UK.*
[d]*Adam Smith Business School, University of Glasgow, Glasgow G12 8QQ, UK.*
[e]*Southampton Business School, University of Southampton, Southampton, SO17 1BJ, UK.*
[f]*Essex Business School, University of Essex, Colchester, CO4 3SQ, UK.*

Abstract

We uncover the marginal impacts of energy prices on carbon price variations across carbon-energy price distributions in Phase III of the European Union Emission Trading Scheme (EU ETS). Applying a novel Quantile-on-Quantile (QQ) regression and the causality-in-quantiles approach, our empirical results demonstrate asymmetric and negative impacts of energy prices on carbon prices. The impacts are stronger at lower carbon quantiles and relatively smaller at higher quantiles (in absolute terms). Concerning different energy sources, the impacts of both oil and coal prices show a quasi-monotonic increase along with a rise in carbon quantiles; the absolute values of their impacts are much greater than that of the gas price impacts, depicting a relatively flat pattern. The results are consistent with our theoretical explanations which identify the two effect-transmission channels from energy to carbon prices, viz. *the aggregated carbon demand effect* and *the fuel-switching effect*. Thanks to the differences in energy sources and variability over their price distributions, the observed differential in carbon price-response is an indication of non-unique carbon market dynamics, the efficient management of which would require differentiated policy interventions. Robustness checks further confirm the accuracy of our conclusions.

Keywords: Carbon futures prices, Energy futures prices, EU ETS, Quantile-on-Quantile, Causality-in-quantiles

*Corresponding author

Email addresses: kunduan@hust.edu.cn (Kun Duan), X.Ren@soton.ac.uk (Xiaohang Ren), yukun.shi@glasgow.ac.uk (Yukun Shi), T.K.Mishra@soton.ac.uk (Tapas Mishra), cheng.yan@essex.ac.uk (Cheng Yan)

1. Introduction

To circumvent mounting problems in global climate change, the European Union (EU) launched the first CO_2 emission trading system in 2005: the European Union Emission Trading Scheme (EU ETS). Founded on the principle of 'cap-and-trade', the EU ETS has proved to be an effective mitigation tool for European carbon emissions (Yu et al., 2015a). It has rapidly grown into the largest carbon markets worldwide covering over 50% of total CO_2 emissions produced by more than 11,000 heavy energy-using installations in 31 European countries.[1] The 'cap-and-trade' mechanism limits the use of carbon by the margin of a 'cap'. In other words, companies seeking to use more carbon basically engage in a 'trade' with the ones which have a surplus. Beyond the cap, an intended additional unit of carbon consumption would cost a hefty amount as competition effects led by demand pressure from various carbon-consumed sectors could give rise to the differential response of 'sell price' of an extra unit of carbon.[2] Thanks to the movement of energy prices, carbon prices can demonstrate heterogeneous response characterized by an asymmetric pattern at varied locations of carbon-energy price distributions (see, e.g. Chevallier, 2011; Hammoudeh et al., 2014b). Despite an inherent policy significance, a sparse body of literature has so far been dedicated to an in-depth study of this asymmetric effect.

Why energy prices would drive carbon prices over time? A quick survey reveals a variety of reasons. First, there is a strong linkage between markets of (fossil) energy and carbon and economic activities.[3] The consumption of fossil energy serves as the main source of aggregate carbon emissions, intensely driving multitudinous aspects of economic development and human lives involving energy production, modern transportation, industrial operation process, and land-use changes, etc. (Balcılar et al., 2016). Hence, energy prices are natural predictors of carbon prices, at least in light of the fact that the largest source of total carbon emissions can be traced to fossil energy combustion (Christiansen et al., 2005). Second, when prices of carbon-consumption-led energy resources (i.e., fossil energy) are low (high), the demand of energy consumption will accordingly expand (shrink) given that the supply is constant and exogenous. This would result in a rise (decline) in carbon emissions followed by a rise in carbon allowance prices (Zhang and Sun, 2016).[4] Third, frequent proliferation of policy uncertainty

[1]EU ETS is organized in four phases: Phase I was considered as a 'trial period' in 2005-2007; Phase II coincided with the period of Kyoto Protocol commitment in 2008-2012; Phase III currently runs in 2013-2020 to help meet the European mitigation target of green gas emissions by 20% in 2020 in contrast to 1990; Phase IV would start from 2021 until 2030 to reduce the European green gas emissions by at least 40% by 2030 compared with the levels in 1990.

[2]The design of EU ETS is argued to further result in the fluctuating relationship between carbon-energy prices in Europe (Lutz et al., 2013).

[3]According to International Energy Agency (2019), more than 80% of global energy consumption comes from fossil energy, while 75% of CO_2 emissions are attributed to the combustion of fossil energy.

[4]Energy price decrease (increase) could be due to either an expansion (a contraction) in the energy

and turbulence in the macroeconomic-financial systems might result in a rather close interaction between prices in energy and carbon markets in addition to their commodity features (Fan et al., 2013; Zhang and Huang, 2015).

What implications can one draw from the effect of changes in energy prices on carbon prices? Given that carbon prices form an essential cost component of carbon-consumed installations from regulated industrial sectors, a primary implication concerns mitigation of carbon emissions and carbon price fluctuations. Therefore, uncovering the impacts of energy prices on carbon prices can provide useful information to the regulated installations to responsibly adjust their energy consumption structure to ensure cost efficiency and to meet their carbon emission targets in the long-run (Zhang and Sun, 2016). Moreover, understanding energy price impacts is pivotal to ensuring effectiveness of EU ETS, and this can be reflected through EU ETS's strong predictive ability of carbon price movements, as these are driven by underlying market fundamentals including energy prices (Lutz et al., 2013).[5] At the same time, due to rapid development of worldwide financial markets, the correlation among various asset and commodity markets is becoming increasingly large and complex. Thus, analyzing the relationship between carbon and energy markets equips practitioners with useful information regarding asset allocations and portfolio optimization (Subramaniam et al., 2015; Zhang and Sun, 2016). Finally, a precise interpretation of energy price impacts on carbon prices can help ensure an effective environmental regulatory process for lowering carbon emissions and favoring cleaner energy sources, while ensuring a healthy and prosperous market development (Hammoudeh et al., 2014a).

While a robust body of research has investigated the effects of energy prices on carbon price changes in Phases I and II of EU ETS,[6] the current paper is probably among the few attempts that examine the energy price impacts in Phase III. This latter phase is vastly different from the previous two phases, for instance, with regard to allocation mechanism, cap-setting, banking limitations, market role, market liquidity and expertise, respectively.[7] Specifically, Phase III uses *auctioning* as the main allocation mechanism of carbon emission allowances instead of the *grandfathering*, i.e., free carbon allowance allocation based on historical emissions, mainly employed in both Phases I and II.[8] Second, Regarding the cap-setting, instead of an indirect way of approving

supply or a contraction (an expansion) in the energy demand. This may further result in a prosperous (tight) carbon market and heightened (lowered) carbon prices.

[5]Following Creti et al. (2012) and Hammoudeh et al. (2014a), we do not consider weather conditions as their impacts are indirect and can be captured by the sudden demand shocks in energy prices.

[6]See, e.g., Mansanet-Bataller et al. (2007); Alberola et al. (2008); Creti et al. (2012); Zhang and Sun (2016).

[7]New updates in Phase III are documented in Directive 2009/29/EC (European Parliament and Council, 2009).

[8]As the free allocation setting is replaced by 'auctioning' in Phase III, the carbon allowance demand and price formation reflect more about market participants' expectation of energy price movements and energy structure adjustments of the installations, and vice versa, leading to a closer bi-directional

the National Allocation Plans (NAPs) employed in Phases I and II, in Phase III the European Commission (EC) directly sets the EU-wide carbon emission cap, indicating a stricter and more effective cap-setting (Lutz et al., 2013). Moreover, greater amounts of carbon-consumed sectors, including production and processing of non-ferrous metals, are regulated since the start of Phase III. Third, in terms of the banking limitation, neither banking nor borrowing of carbon allowance credits were allowed between Phases I and II, leading to a self-contained market in Phase I that is unrelated to future caps (Daskalakis et al., 2009). In contrast, the limitation was then released so that the subsequent Phases II and III can be well connected via banking. Allowing banking of spare allowances across different phases contributes to reducing the risk of dramatic price declines.

Fourth, in terms of the role of market in emission reductions, the ultimate goal of the EU ETS is to enforce reductions of carbon emissions in the carbon-intensive sectors. As Phase I is widely recognized as a pilot period for newly established regulatory institutes and market participants, it does not possess any clear goal for carbon emission reductions contrary to the later phases.[9] Fifth, in terms of the market liquidity and expertise, considering that Phase I is recognized as a learning period of the EU ETS, market at this initial stage is characterized by low liquidity and highly volatile price movements.[10] Since the start of Phase II when the market becomes increasingly matured, trading volumes have also increased significantly, resulting in a more stable price movement with smaller volatility (Mizrach and Otsubo, 2014). In addition, the types of market transactions have also evolved from spot market dominated transactions (such as bilateral and over-the-counter transactions) in the initial phase to various types of transactions, notably including derivative transactions (such as transactions of futures contracts, options, and swaps) (Lutz et al., 2013).

Having experienced significant institutional development and advances in the market design over phases, Phase III is characterized by a more mature market environment with more enhanced informational efficiency and higher market liquidity compared to previous phases (Chung and Hrazdil, 2010; Mizrach and Otsubo, 2014; Yu et al., 2015b). Therefore, the carbon-energy price linkage becomes even stronger (Koch, 2014), while the changing nature of the carbon price formation driven by energy prices could be better captured in a highly mature market phase alike in Phase III against that in early phases (Lutz et al., 2013; Montagnoli and De Vries, 2010). Moreover, increases in maturity from Phases I to III also support the argument of inconstant carbon-energy price relationship over phases as recently documented (see, e.g., Aatola et al., 2013;

carbon-energy price relationship in Phase III against that in previous phases (Koch, 2014).

[9] The later phases clearly assign their individual reduction targets as already introduced at the beginning of this section.

[10] These are the features in Phase I except after 2006 when both market liquidity and price variation was very low due to the price breakdown. This was caused by the disclosure of the information in April 2006 indicating that the overall emission cap was not restrictive in Phase I. Moreover, no banking of allowance credits was allowed between Phase I and II, further leading to the price breakdown.

Chevallier, 2012; Creti et al., 2012; Ibrahim and Kalaitzoglou, 2016; Tan and Wang, 2017). As a further demonstration, in Table 3 we have summarized important empirical evidence of the fluctuating energy price impacts on carbon prices over different phases.

While it is crucial to extend existing results of energy price impacts on carbon prices to the latest Phase III, the effort is surprising nascent. Although it is widely acknowledged that energy price impacts could be heterogeneous with an asymmetric pattern over carbon-energy price distributions, serious studies have yet to emerge. The current paper fills the literature gap by employing a novel Quantile-on-Quantile (QQ) approach proposed by Sim and Zhou (2015) to uncover the marginal price impacts of the energy sources (i.e., oil, gas, and coal) on carbon prices at different locations of carbon-energy price distributions in Phase III.[11] The results of marginal energy price impacts drawn by the QQ estimation can be further reinforced and extended to the domain of a causal interpretation in a quantile research context. We employ a nonparametric quantile causality method proposed by Jeong et al. (2012), i.e., the causality-in-quantiles test, through which the potential nonlinear and asymmetric causality from energy prices to carbon prices across carbon quantiles is investigated. The results are then explained via two identified effect-transmission channels, i.e., *the fuel-switching effect* and *the aggregated carbon demand effect*.

Unlike many previous studies, we focus on futures rather than spot contracts, as the volumes being traded on futures contracts are much greater than that on spot contracts (Mansanet-Bataller et al., 2007).[12] Second, price dynamics of futures contracts are not exposed to significant structural breaks and abnormal price jumps as being characterized by the spot price series (Bredin and Muckley, 2011). Third, the spot trading market of EUA is relatively immature compared to the futures market (Daskalakis et al., 2009; Aatola et al., 2013), indicating a better capture of the decision making of carbon-consumed installations via the futures price movements (Rickels et al., 2007). Concurrently, futures prices are represented in a return format to measure how growth in energy futures prices affects the growth in carbon futures prices.[13]

[11] It is known that the relationship between contemporaneous terms of carbon and energy prices could be bidirectional, while a failure to account for this would give rise to biased estimation results. To deal with such the endogeneity problem of the simultaneity, following existing related literature (see, e.g. Aldy and Pizer, 2015; Coglianese et al., 2017; Duan et al., 2019), our QQ model specification is determined based on the argument that past energy prices are predetermined with regard to current carbon prices. Accordingly, our employed QQ model uses the time-lagged term of energy prices as the explanatory variable and the contemporaneous term of carbon prices as the dependent variable, through which the potential endogeneity problem can be well mitigated. Moreover, the setting of our employed QQ model is also consistent with Lin and Nelson (2019), suggesting that a dynamic lead-lag quantile analysis can handle the endogeneity in data.

[12] According to German Emission Trading Authority (2019), the rate of traded volumes of EUA in spot, futures, and OTC markets in 2018 are 15.6%, 81.1%, and 3.3%, respectively.

[13] For simplicity, we refer energy/carbon prices to futures price returns in energy/carbon markets. Both terms are used interchangeably throughout the paper.

Our work contributes to the existing literature on the subject in the following aspects. First, we extend the sparse research regarding energy price impacts on carbon prices in Phase III, a phase which is largely different from the previous two phases. Second, we quantify the marginal impacts of energy prices at different locations of both carbon and energy price distributions. For this purpose, we apply the QQ method as it can adequately identify the heterogeneity and full-distributional characterization of carbon and energy price dynamics, providing statistically robust results (Lin and Nelson, 2019).[14] In fact, compared to the traditional quantile regression, the QQ method provides a complete picture on carbon price determinations by energy prices under different quantiles or economic conditions. Moreover, the asymmetric and non-linear impacts of energy prices captured by the QQ method tend to be more policy-informative against the mean-based estimations obtained by the OLS method because a differentiated, rather than a uniform policy, would produce allocative efficiency.

Third, we examine how carbon prices at different quantiles are causally affected by energy prices using a nonparametric causality-in-quantiles method. In contrast to the mean-based strategy that would incur serious information loss due to non-treatment of effects at various parts of the distribution, the causality-in-quantiles method characterizes Granger causality from energy to carbon prices in the entire distribution and produces robust results even in the presence of fat tails and outliers in the real data. Fourth, rather than solely relying on the well-known *fuel-switching effect* (i.e., the shift of fuel inputs between high-carbon coal and low-carbon gas in the power sector to achieve the abatement while maintaining the profitability), the paper identifies a new effect-transmission channel, *the aggregated carbon demand effect*, to describe how a change in energy prices can influence the carbon demand and then drive carbon prices given a fixed carbon supply. The two channels together offer the theoretical explanation in our paper, through which empirical results of the marginal energy price impacts on carbon prices can be well interpreted.

Consistent with our theoretical expectations, several important results emerge from our empirical analyses. First, while energy price impacts on carbon prices are found to be overall negative, the impacts are asymmetric at different quantiles of the carbon price distribution: higher at low carbon-price quantiles compared to that at high quantiles (in absolute values). Second, the impact patterns of prices of different energy sources (i.e., oil, natural gas, and coal) are distinct thanks to the differences in their market characteristics and carbon emission volumes. The causal relationship between energy and carbon prices is found to be significant except for a small range of extreme carbon quantiles, demonstrating the predictive power of energy prices on carbon prices. Our conclusions survive a battery of robustness checks. Our findings possess significant policy implications for policymakers and market practitioners in different market conditions (e.g., different locations of carbon-energy price distributions).

[14] Discussions about the technical strengths of the QQ method are detailed in Section 3.1.1.

The remainder of the paper proceeds as follows. Section 2 presents a succinct review of key literature. Section 3 describes employed estimation techniques and data. Section 4 discusses our empirical results and corresponding theoretical explanations. Section 5 concludes with a discussion of results in the context of policy.

2. Literature Review

In Table 3 we have summarized key literature related to energy price impacts on carbon prices in different phases of EU ETS. Specifically, we find a robust body of research for Phase I of EU ETS (Convery et al., 2008). Phase I is considered as a 'pilot period' during 2005-2007 where the regulatory and monitoring authority were put online. To investigate the dynamics of carbon prices in the first phase, with an argument regarding the carbon abatement cost, extant literature devotes attention to the determination of carbon prices driven by energy prices (see, e.g., Mansanet-Bataller et al., 2007; Alberola et al., 2008; Hintermann, 2010; Alberola et al., 2009), or alternatively, the prediction of future movements of carbon prices (see, e.g., Benz and Trück, 2009; Daskalakis et al., 2009; Paolella and Taschini, 2008; Seifert et al., 2008). Specifically, Mansanet-Bataller et al. (2007) highlight the important role of energy prices, i.e., oil, natural gas, coal and electricity, in determining carbon prices. As discussed in Christiansen et al. (2005), Alberola et al. (2008, 2009) and Hintermann (2010) further claim that institutional factors hold equally important role as energy prices in driving carbon prices. They find that in Phase I policy proxies are the main driver of carbon prices before the collapse of carbon spot prices (compliance break) during June 2005-April 2006, while energy prices dominate the carbon price dynamics henceforth during May 2006-April 2007.

Moreover, the compliance break that occurred in Phase I can be largely attributed to its underlying flaws in the institutional setting. These flaws result in a high exposure and risk of dramatic drop of carbon spot prices, which has experienced a significant price plunge in April 2006, falling from 29.5 euros to less than 12 euros only in a rather short period, when the National Allocation Plans for Phase I were proved to be too generous. In particular, one of its weaknesses regarding the restriction of 'banking' credits (e.g., carbon allowances) to subsequent phases makes EU ETS a self-contained market, leading to a lack of connection with following phases (Koch, 2014). Thus, through the aspects of information processing and market efficiency, EU ETS is immature in Phase I in contrast to the subsequent phases (Montagnoli and De Vries, 2010).

Accordingly, EU ETS in Phase II has made substantial improvements to ameliorate weaknesses in Phase I (Egenhofer et al., 2011), and is set to represent as a fundamental regulatory instrument to allow member states to comply with their commitment in the Kyoto Protocol (Creti et al., 2012). Having recognized significant difference between two phases of EU ETS, relevant literature has further contributed to the investigation of carbon price dynamics and its driven forces from energy markets in 2008-2012 (Phase II) (see, e.g., Aatola et al., 2013; Bredin and Muckley, 2011; Creti et al., 2012; Keppler and Mansanet-Bataller, 2010; Lutz et al., 2013; Schandl et al., 2016).[15]

Specifically, by employing a cointegration method, Creti et al. (2012) discusses carbon price determination pattern in the first and second phases of EU ETS, and find that the long-run relationship between the carbon price and its drivers is distinct in these two phases. They further evaluate that impacts of carbon price drivers including energy prices and equity price index on equilibrium carbon price determinations, are all significant and greater in Phase II compared with that in Phase I. Zhang and Sun (2016) analyze both return and volatility spillovers between carbon and energy markets using the DCC threshold GARCH (DCC-TGARCH) model and the full BEKK-GARCH model. They find significant and unidirectional volatility spillovers from the coal market to the carbon market, and from the carbon market to the natural gas market, whereas no spillover between carbon and oil markets were discerned. Using a DCC-TGARCH model, they further find that coal price returns exert negative and significant impacts on carbon price returns, while the impacts of both natural gas and oil price returns are also negative but insignificant.

Recent years have experienced frequent structural changes in economic and institutional functionalities across the globe. As a result, both sign and magnitude of impacts of market fundamentals involving energy prices on carbon price movements have also been subject to volatilities as well (Lutz et al., 2013; Ji et al., 2018; Tan and Wang, 2017). In view of the differences between Phase III and previous two phases, existing conclusions on the factors driving carbon price determination in Phases I and II may no longer be valid in Phase III. In the case of the US, Hammoudeh et al. (2014b) measure negative impacts of oil, natural gas, and coal on carbon prices and find that the intensity of negative impacts of oil prices increases with a rise in carbon price levels. The negative impacts of natural gas prices are found to be much stronger when carbon prices are at the higher quantiles. Hammoudeh et al. (2015) focus on CO_2 price determinations in the US and find negative impacts of fossil energy (i.e., oil, natural gas, and coal) on carbon emission allowance prices. The impacts of oil and coal are asymmetric while natural gas price impacts tend to be relatively symmetric. Tan and Wang (2017) employ a quantile regression approach and show that impacts of coal and oil prices are overall negative, while gas price impacts are negative at lower carbon quantiles and turn to become positive at higher quantiles.

A different strand of literature has emerged recently that indirectly investigates the impact of energy prices on carbon prices by focusing on the linkages between carbon and energy prices. For instance, Yu et al. (2015b) use a dataset from both Phases II and III and find no Granger causality between carbon and oil prices. By employing a multi-scale approach, they also find distinct relations between carbon and oil markets on decomposed time-scales, viz. no correlation on small time-scale; significant and bidirectional relationship on medium time-scale; the strong and linear relationship

[15] Comparisons between Phases I and II have been documented in Koch (2014).

between trend terms of the two markets on a long time-scale. In the same vein, Zhu et al. (2019) also find different impacts of energy prices on carbon price dynamics in EU ETS. Ji et al. (2018) investigate dynamic linkages and spillover effects, respectively in price returns and volatility between energy and carbon markets in Europe. Prices of fossil energy, viz. oil, natural gas, and coal, exert important impacts on the formation of carbon prices, while oil prices reserve the largest contribution to determining both carbon returns and volatility. Using a conditional vine copula approach with a dataset covering both Phases II and III, Chevallier et al. (2019) find that carbon prices in Europe display a weak negative association with both oil and natural gas prices.

Due to the reliance on the conventional mean-based estimations such as OLS, most studies fail to capture the heterogeneity in the marginal energy price impacts at different quantiles of carbon and energy prices. Eventually, extant studies report mixed results. For example, the impact of oil prices is found to be either positive (see, e.g., Chevallier, 2009; Creti et al., 2012; Reboredo and Ugolini, 2018), or negative/insignificant (see, e.g., Bredin and Muckley, 2011; Reboredo, 2014; Hammoudeh et al., 2014b, 2015; Yu et al., 2015b). Regarding the impact of natural gas, Hammoudeh et al. (2014b) show that it is negative when carbon prices are low, but positive when carbon prices are high. Lutz et al. (2013) point out a positive impact of natural gas prices regardless of whether carbon price volatility is high or low. Regarding the impact of coal, Lutz et al. (2013) find it tends to be positive in a high volatility regime, and negative in a low volatility regime of carbon prices. Hammoudeh et al. (2014b) find negative impacts of coal prices on carbon prices, while Creti et al. (2012) demonstrate that coal price impacts are negative in Phase I and positive in Phase II in equilibrium conditions.

Moreover, traditional quantile regression has also been applied, despitely sparsely, in recent studies. For instance, Hammoudeh et al. (2014b) find distinct impacts of energy prices involving oil, natural gas, and electricity on different quantiles of carbon prices in the US. Reboredo and Ugolini (2018) measure the impacts of price dynamics in energy markets on different quantiles of clean energy stock returns, and find that both oil and electricity prices contribute to the majority of stock return fluctuations. Nevertheless, this method fails to account for the potentially distinct impacts of quantiles of a given explanatory variable on the distribution of the dependent variable. Thus, to mitigate the weaknesses encountered by the conventional methods, Sim and Zhou (2015) propose an innovative quantile-on-quantile (QQ) approach to gauge the heterogeneous impacts of different quantiles of explanatory variables on quantiles of the dependent variable. Overall, our paper fills a gap in the literature by investigating the energy price impacts in Phase III, while accounting for the asymmetry in the impacts by using the QQ method.

3. Methodology and data

3.1. Methodology

3.1.1. The quantile-on-quantile approach

As briefly mentioned in Section 1, we use the recently developed quantile-on-quantile (QQ) approach (Sim and Zhou, 2015) to investigate the impact of crude oil, natural gas, and coal futures markets on the carbon futures market. The QQ method combines traditional quantile regression (Koenker and Bassett Jr, 1978) and nonparametric estimation, which can be used to empirically investigate how the quantiles of the explanatory variables affect the conditional quantiles of the dependent variable. Technically, the strengths of the QQ method are detailed summarized as follows. First, compared with the mean-based method such as OLS and the traditional quantile regression method, the QQ approach can fully capture the potential asymmetric response of dependent variable across distributions of both explanatory and dependent variables. At the same time, the QQ method can be robust to outliers and non-normality in the real data. Thus, it could provide a more comprehensive and precise understanding of the relationship between the variables under different market conditions. Second, as a nonparametric local linear regression method, the QQ approach can consistently estimate the smooth changing parameters and uncover underlying structural breaks in the real data (Stone, 1977; Sim and Zhou, 2015).[16] Thus, compared with the traditional quantile regression, the QQ method captures the local effects of each quantile of a given independent variable on the dependent variable. In addition, rather than assuming that the timing of the structural break is known, the QQ method endogenizes inherent structural changes in the real data.

Third, by employing QQ method, we are able to relax the conventionally assumed linear model setting in traditional quantile regression (Koenker and Bassett Jr, 1978), and accommodate potentially existing non-linearity between explanatory and dependent variables. Indeed, it has been documented that the determinations of carbon prices tend to be non-linear (Paolella and Taschini, 2008; Benz and Trück, 2009). Fourth, since we consider the impacts of temporal-lag in the independent variable on the contemporaneous dependent variable, the QQ method ameliorates the endogeneity problem regarding the simultaneity, thanks to the nature of its model specification. Finally, using a *cross-validation method*, we further improve the original version of the QQ approach proposed by Sim and Zhou (2015) to find a suitable bandwidth, which provides the much required balance between the bias and the variance during the estimation. Thus, the QQ method enables us to uncover the real marginal impacts of energy prices on carbon prices over the carbon-energy price distributions, and can provide more informative

[16] The QQ estimator is built based on the local linear regression approach (Stone, 1977), which is a generalization of moving average and can determine a linear regression locally around the neighborhood of each data point in the sample.

results in contrast to both OLS and traditional quantile regression.

To explicate further, first consider the following nonparametric quantile regression equation for the θ-quantile of the carbon futures price return (C_t) as a function of another energy futures return shocks (E_{t-1}) as:[17]

$$C_t = \beta^\theta(E_{t-1}) + \alpha^\theta C_{t-1} + \epsilon_t^\theta \tag{3.1}$$

where E_{t-1} represents crude oil, natural gas or coal futures price return in following empirical research at time $t-1$, the residual term ϵ_t^θ has a zero θ-quantile; θ stands for the θ-quantile of the carbon futures price return; α^θ describes the impacts of the θ-quantile of the first-order temporal-lag of carbon futures price return (C_{t-1}) on its contemporaneous term (C_t); and $\beta^\theta(\cdot)$ represents the impact of energy price return on carbon futures price return. Due to the lack of prior information on the relationship, $\beta^\theta(\cdot)$ is assumed to be an unknown function.

To examine the impact of the τ-quantile of the energy futures price shocks (E^τ) on θ-quantile of the carbon futures price return, we expand the unknown function $\beta^\theta(\cdot)$ by taking a first order Taylor expansion around E^τ, where τ stands for the τ-quantile of the energy futures price return.

$$\beta^\theta(E_{t-1}) \approx \beta^\theta(E^\tau) + \dot{\beta}^\theta(E^\tau)(E_{t-1} - E^\tau) \equiv b_0(\theta,\tau) + b_1^{'}(\theta,\tau)(E_{t-1} - E^\tau). \tag{3.2}$$

By substituting Eq. (3.2) into Eq. (3.1), we can obtain

$$C_t = \beta^\theta(E^\tau) + \dot{\beta}^\theta(E^\tau)(E_{t-1} - E^\tau) + \alpha^\theta C_{t-1} + \epsilon_t^\theta. \tag{3.3}$$

Then, we solve Eq. (3.3) by considering

$$\begin{pmatrix} \widehat{b_0}(\theta,\tau) \\ \widehat{b_1}(\theta,\tau) \\ \widehat{\alpha^\theta}(\tau) \end{pmatrix} = \arg\min_{b_0,b_1,\alpha^\theta} \sum_{t=1}^{T} \rho_\theta \left[C_t - b_0 - b_1\left(E_{t-1} - E^\tau\right) - \alpha^\theta C_{t-1}\right] K\left(\frac{F\left(E_{t-1}\right) - \tau}{h}\right), \tag{3.4}$$

where $\rho_\theta(y) = y(\theta - I_{\{y<0\}})$ and I_A is the indicator function of set A. K is a Gaussian kernel function on $\mathbb{R}$, and $h > 0$ is the bandwidth. The empirical distribution function

[17]For the three energy prices, the first-order lag is selected as the optimal lag based on the Akaike information criterion (AIC) in the context of quantile estimation. While the selection results are not reported due to limited space in the paper, they are available from the authors upon request.

is defined as $F\left(E_{t-1}\right)=\frac{1}{T}\sum_{k=1}^{T} I\left(E_k<E_{t-1}\right)$. To obtain the optimal α^{θ}, we use the following average method:

$$\tilde{\alpha}^{\theta}=\frac{1}{n}\sum_{i=1}^{n}\hat{\alpha^{\theta}}(\tau_i). \tag{3.5}$$

The choice of bandwidth is important for a nonparametric estimation, because the bandwidth decides the size of variance and bias in the estimation. Therefore, a suitable bandwidth can provide a balance between the bias and the variance. To choose an optimal bandwidth, a commonly used method is rules of thumb (Jones et al., 1996). The rule-of-thumb bandwidth is easy to compute and able to select the optimal bandwidth based on an assumption that the underlying estimated density is Gaussian. Thus, the optimal selection of the bandwidth (h) is

$$h=\left(\frac{4\hat{\sigma}^5}{3n}\right)^{\frac{1}{5}}\approx 1.06\hat{\sigma}n^{-1/5} \tag{3.6}$$

However, as the accuracy of the rule-of-thumb bandwidth relies heavily on the density distribution, this bandwidth selection could be inaccurate when the density function is not normally distributed (Hall et al., 1991; Heidenreich et al., 2013). Given that the energy price impacts are characterized by asymmetry over the carbon-energy price distributions, applying the rule-of-thumb bandwidth selection is inappropriate for the QQ estimation and may lead to biased results. Moreover, the estimated bandwidth based on the rule-of-thumb method tends to be over-smoothed and may fail to approximate reality (Hall et al., 1991), further indicating its inappropriateness in our empirical analysis. Concerning the fix-bandwidth setting, particularly in the QQ estimation, existing literature (see, e.g. Sim and Zhou, 2015) arbitrarily chooses a constant bandwidth, $h=0.05$, which may not be suitable for different empirical data and would lead to biased and unreliable results.

Due to the weaknesses of existing strategies, we use cross-validation (CV) method for the optimal bandwidth selection following Stone (1984); Li and Racine (2004). Rather than imposing a normal distribution assumption, the CV method can account for asymmetric data characteristics and accordingly select the optimal bandwidth by minimizing the Integrated Estimation Error (IEE).

$$\mathrm{IEE}=\int\rho_{\theta}\{\mathrm{m(x)}-\hat{\mathrm{m}}\mathrm{(x)}\}\mathrm{dx} \tag{3.7}$$

where $\hat{m}_h(\cdot)$ is any proposed estimator, containing a smoothing parameter h, of the regression function $m(\cdot)$. For each given k, we use our sample data to construct a regression function $\hat{m}_{h,-k}(\cdot)$ and then validate the model by examining the prediction error $y_k - \hat{m}_{-k}(x_k)$. Therefore, the cross-validation method measures the effectiveness of the estimation and help us select an optimal bandwidth. The leave-one-out cross-validation estimator of Eq. (3.3) can be written as follows:

$$M(h) = \sum_{k=1}^{T} \rho_\theta \left(C_k - \hat{b}_{0,-k} - \hat{b}_{1,-k} E_{k-1} - \tilde{\alpha}_{-k}^{\theta} C_{k-1} \right), \tag{3.8}$$

where $\hat{b}_{0,-k}$, $\hat{b}_{1,-k}$ and $\tilde{\alpha}_{-k}^{\theta}$ are the local linear estimators obtained from Eq. (3.4) and Eq. (3.5) after removing kth observation. Then we use the grid search method to find the optimal bandwidth parameter and obtain the optimal bandwidth h_{CV}, which is shown in Eq. (3.9). Thus, the CV method appears to be more robust to bandwidth selection, and ensure reliable results from the nonparametric QQ estimation with less bias. This is in contrast to the conventional bandwidth method, such as the rule-of-thumb method and the fix bandwidth-setting.

$$h_{CV} = \arg\min_{h} M(h) \tag{3.9}$$

3.1.2. **The causality-in-quantiles approach**

To shed light on the nature of nonlinear and asymmetric causality between carbon and main energy prices, as a continuous analysis beyond the QQ estimations, we further use a nonparametric quantile causality method from Jeong et al. (2012). This approach models a causal relationship between any given two variables nonparametrically (a model-free approach), recovering thus a possible nonlinearity in the causal relationship. In other words, possible non-linear causality is not seen as an outcome of a prior defined theoretical construct, but a broad representation of multitudinous factors, which a researcher can ostensibly model to lend credence to a confounded theory. Denote carbon futures price return as y_t and uncertainty index as x_t^n, where $n = 1, 2, 3$ denoting crude oil, natural gas and coal futures price return, respectively. Then the quantile causality is defined as follows: x_t^n does not cause y_t in the θ-th quantile with regard to the lag vector of $\left\{y_{t-1}, \ldots, y_{t-p}, x_{t-1}^n, \ldots, x_{t-p}^n\right\}$ if:

$$Q_\theta\left(y_t | y_{t-1}, \ldots, y_{t-p}, x_{t-1}^n, \ldots, x_{t-p}^n\right) = Q_\theta\left(y_t | y_{t-1}, \ldots, y_{t-p}\right), \tag{3.10}$$

where $Q_\theta(y_t|)$ is the θth quantile of y_t depending on t and $0 < \theta < 1$. Let $Y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})$, $X_{t-1}^n \equiv (x_{t-1}, \ldots, x_{t-p})$, $Z_t = (X_t^n, Y_t)$, and $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1}. The hypotheses are:

$$H_0 = P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} = 1 \tag{3.11}$$
$$H_1 = P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} < 1. \tag{3.12}$$

Then Jeong et al. (2012) consider the following distance measure:

$$J = E\left[\left\{F_{y_t}|Z_{t-1}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} - \theta\right\}^2 f_Z\left(Z_{t-1}\right)\right], \tag{3.13}$$

where $f_Z\left(Z_{t-1}\right)$ is the marginal density function of Z_{t-1}. Note that $J \geq 0$, if and only if, H_0 is true. Therefore, we can use J to test H_0 consistently. The kernel-based test statistic for J is:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K_{ts}\hat{\varepsilon}_t\hat{\varepsilon}_s, \tag{3.14}$$
$$= \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K_{ts}\left[1\left\{y_t \leq \hat{Q}_\theta\left(x_t\right)\right\} - \theta\right]\left[1\left\{y_s \leq \hat{Q}_\theta\left(x_s\right)\right\} - \theta\right], \tag{3.15}$$

where $K_{ts} = K\left(\frac{Z_{t-1}-Z_{s-1}}{h}\right)$ is the kernel function, h is a bandwidth , T is the sample size, p is the lag order, and $\hat{\varepsilon}_t$ is the estimate of the regression error.

3.2. Data

Using Intercontinental Exchange (ICE) as the main source of data, we collect daily data of Brent crude oil futures prices, ECX EUA carbon futures prices, UK natural gas futures prices, and Rotterdam coal futures prices, from Jan 07, 2013 to Mar 30, 2019. The data are the price series based on spot-month continuous contract calculations. Figure 1 presents time series plots of carbon and energy price series, depicting the growth pattern of the series over the duration of our sample. Table 1 summarises descriptive statistics for the returns series. The positive kurtosis values in Table 1 characterise fat-tailed distributions of all series. The Jarque-Bera test shows that all series depart from normality. Additionally, the density plots of the daily price returns in Figure 2 confirm our conclusion that the price return series are non-normal. Finally, it is necessary to test whether the series are non-stationary as non-treatment of the latter might bias our inference of causal relationship - dynamically or otherwise. Indeed, a conventional ADF test indicates that the null hypothesis of a unit root is comfortably rejected at the 1% statistical significance level, indicating that our series are stationary.

[Figure 1 about here.]

[Figure 2 about here.]

[Table 1 about here.]

4. Empirical results

From the descriptive statistics, we have confirmed that our series are stationary and non-normal possessing heavy tails. Therefore, quantile regression framework is best suited for our purpose as it can model asymmetric effects of the independent variable on different quantiles of the dependent variable. It is necessary to model 'causality' between energy and carbon prices by moving away from the methods that assume 'unimodal' distribution. Motivated by this, in this section, we present two sets of results: estimates from the QQ regression depicting variable patterns of 'dynamic association' across the entire price distribution in carbon and energy markets. Second, we also present directions of causality, within the architecture quantile estimation. Our idea, thus is to recover 'heterogeneous correlation with an asymmetric pattern' and variable direction of causality over the price distributions. As we will see shortly, our results are consistent with established theoretical arguments.

4.1. Quantile-on-quantile (QQ) estimates

We present and discuss in this section the results from QQ estimation of the impacts of three main energy futures price returns on the carbon futures price return in Phase III.[18] Figure 3 summarises estimates of two coefficients, viz., $b_0(\theta, \tau)$ (that represents a constant) and $b_1(\theta, \tau)$ (that shows impact of the τth quantile of crude oil futures price return on the θth quantile of carbon futures price return), Likewise, Figures 4 and 5 display the estimation results for the impact of τth quantile of futures price return of natural gas and coal on the θth quantile of carbon futures price return, respectively. To graphically present the above results, Figure 6 displays the heat map of the estimated $b_1(\theta, \tau)$, indicating impacts of oil, natural gas and coal futures price return on the carbon futures price return, respectively. Thus, Figures 6(a) - 6(c) are the 2-D reproduction of the same results reported in Figures 3(b), 4(b), and 5(b) in the 3-D format, respectively.

[18] As discussed in Section 1, the variable carbon-energy price relationship can be largely induced by differences between phases through five aspect-lenses, i.e., allocation mechanism, cap-setting, banking limitations, market role, market liquidity and expertise. While micro-level data representing these aspects are not available (to the best of our knowledge), given that they demonstrate institutional conditions that are distinct over phases and in the spirit of Creti et al. (2012); Lutz et al. (2013), we control for their impacts by dividing the data sample. That is, we estimate energy price impacts on carbon prices in Phase III, and then compare the results with that in early phases. Through this, the role of the five aspects in driving the variation of energy price impacts over phases is captured.

The QQ estimation results reported in Figures 3, 4, 5 and 6 can be summarized as follows. First, for crude oil, we find its negative impact at all quantiles of the carbon price distribution, with increasingly higher negative effects at greater quantiles (from -0.034 to -0.425). The implication is that the impact magnitudes are the greatest at higher carbon price quantiles, becoming weaker around the median quantiles, declining further at the lower quantile levels. Thus, an increase in oil prices has an asymmetric and negative impact on carbon prices over the carbon price distribution. Second, concerning the impact of natural gas prices, while the effects are negative across quantiles of carbon prices, there is visible stability of trend and changes with a waveform. Specifically, we observe greater negative effect at the high and median carbon quantiles, experiencing a gradual decline at the middle to lower quantiles. Third, with respect to coal prices, its impacts on carbon prices are also negative over the entire distribution, while depicting a monotonic increase in weight as we move from low to high carbon quantiles. In absolute terms, the impact is much weaker at higher quantiles of carbon prices compared to that at the lower quantiles.

[Figure 3 about here.]

[Figure 4 about here.]

[Figure 5 about here.]

[Figure 6 about here.]

Overall, in Phase III of EU ETS, we note that the impacts of energy prices on carbon prices are overall negative and asymmetric at different carbon price quantiles. In absolute terms, price impacts of different energy sources (i.e., oil, gas, and coal) tend to inflate at low carbon quantiles in contrast to that at high quantiles. At the same time, prices of different energy sources on carbon price formation show distinct impact patterns, governed by forces from the two effect-transmission channels, i.e. *the fuel-switching effect* and *the aggregated carbon demand effect*.[19] Specifically, oil price impacts on carbon prices tend to be larger when carbon price quantiles become lower (in absolute terms). Gas prices present a relatively flat impact pattern over the carbon price distribution, while the impacts are smaller than that of oil and coal (in absolute terms). Similar to both oil and coal prices, impacts of different gas price quantiles on carbon prices appear to be broadly symmetric, while magnitudes of the impacts are still different although slightly over the gas price distribution. In terms of the coal price, its impact pattern is highly similar to that of the oil price and depicts a quasi-monotonic

[19] Theoretical explanations of our empirical results regarding the energy price impacts on carbon prices through the two channels will be discussed in Section 4.2.

growth with increases in carbon price quantiles, although magnitudes of both their impacts are different over the carbon price distribution.

To further compare our QQ-estimated results with that from the conventional approach, we estimate the price impacts of each energy source on carbon prices by using both the OLS method and the traditional quantile regression. The results are summarised in Table 2. In line with the QQ estimation and our expectations, the results from both the OLS method and the traditional quantile regression confirm the overall negative impact of energy prices on carbon prices. As shown in Table 2, oil prices exert a more negative and significant impact at lower carbon price quantiles compared with that at higher quantiles. The negative impact of natural gas prices on carbon prices behaves a relatively flat pattern although its impact at both lower and higher carbon price quantiles is greater than that at the middle quantile. In terms of the coal price, it also demonstrates a negative impact although the impact is less significant at lower carbon price quantiles. While the asymmetric energy price impacts at different carbon price quantiles are explored by employing the traditional quantile regression, the latter fails to fully capture the potential asymmetry, particularly over the energy price distribution. At the same time, OLS method is known to neglect the distributional asymmetry and thus paints only an incomplete picture about the true impacts of energy prices. These limitations are fully accounted for in our QQ method.

[Table 2 about here.]

4.1.1. **Contextualization of results**

In this subsection, we discuss our results vis-a-vis results from the previous studies. The first question is what inferences can be drawn when comparing existing results from early phases and ours from Phase III? In Table 3 we have summarized findings from the extant research. Then our strategy will be to draw upon these results to lend a detailed comparison with ours, be it with regard to the market period under consideration, the estimation method and the theoretical explanation, in a threefold manner. The corresponding significance and enlightenment are summarized in the comparative discussion.

[Table 3 about here.]

First, we observe that price impacts of each energy source (i.e., oil, gas, and coal) on carbon prices vary over time and are sensitive to the choice of sample periods, i.e., the specific phase of the EU ETS under consideration. For instance, the impacts of oil prices on carbon prices can be insignificant in Phase I and positive in Phase II (Alberola et al., 2008; Bredin and Muckley, 2011), while it can be negative after the initial periods based on a sample covering both Phases II and III (Hammoudeh et al., 2014a). For gas prices, its impacts could be insignificant in Phase I and negative in Phase II (Bredin and Muckley, 2011). They further find that the impacts of coal prices tend to be insignificant in Phase I, positive in Phase II and negative when considering both Phase I and II. Contextualized with our empirical results in Phase III, we find the overall negative impacts of prices of different energy sources on carbon price determination. Having compared our results in Phase III with the ones in previous phases, we demonstrate the evolutionary pattern of impacts of energy prices following the maturity of the market from Phases I to III. This confirms the argument of the existing research (see, e.g. Aatola et al., 2013; Creti et al., 2012; Tan and Wang, 2017) and our theoretical expectations. Thus, the evolutionary energy price impacts on carbon prices over phases, along with a better capture of the nature of carbon price formation in a more mature market (Lutz et al., 2013; Montagnoli and De Vries, 2010), motivate us greatly to extend the existing findings to the latest Phase III.

Second, energy prices can exert asymmetric and non-linear impacts at different locations of the carbon-energy price distributions, little attention has yet been laid on an in-depth study. Regarding the existing limited research, Hammoudeh et al. (2014b) employ the quantile regression and show that oil price impacts are overall negative and larger at lower carbon price quantiles; the negative impacts of gas prices turn to become positive from low to high carbon price quantiles; the coal price impacts are overall negative and among the lowest at mid carbon quantiles. Using a Markov-switching VAR model, Chevallier (2011) demonstrates that energy prices exert varied impacts on carbon prices when energy prices are respectively at high and low price levels implied by a strong and weak economy. When comparing our results with the existing studies, it is evident that the marginal effects of energy prices on carbon prices could be asymmetric over carbon-energy price distributions. This is consistent with the literature (see, e.g., Hammoudeh et al., 2014b; Tan and Wang, 2017). However, concerning the currently-employed method, its encountered weaknesses, such as the endogeneity issue and a failure to fully capture the asymmetry and nonlinearity across carbon-energy price quantiles, would result in a potential estimation bias. In contrast, our employed Quantile-on-Quantile (QQ) method can improve the aforementioned weaknesses and contribute to a robust estimation procedure, through which the true marginal impacts of energy prices on carbon prices over carbon-energy price distributions are uncovered.

Third, the theoretical explanation related to impacts of energy prices on carbon prices could be further elevated. Indeed, *the fuel switching mechanism* has been widely embraced in the existing literature to explain the relationship between carbon and energy prices (see, e.g., Alberola et al., 2008; Creti et al., 2012; Lutz et al., 2013). However, an increasing number of studies have recently pointed out that solely relying on this argument is inappropriate and insufficient due to the reasons, including a failure to directly explain the role of oil prices and a dampened effectiveness of the mechanism typically in Phase III (see, e.g., Hammoudeh et al., 2014b; Chevallier et al., 2019). Hence, the importance of our research also lies in establishing a solid and comprehensive theoretical explanation regarding the energy price impacts. In addition to *the fuel-switching mechanism*, our paper elaborates a naturally-existing but typically-ignored effect-transmission channel, i.e., *the aggregated carbon demand effect*, that clearly identifies how price changes in different energy sources impact carbon prices by altering the carbon demand given that the carbon supply is fixed. Thus, our empirical results can be well interpreted through our theoretical explanations that identify the two channels.

Although some studies have covered Phase III, their primary focus is on the analysis of previous phases, and only include very limited data for Phase III to invoke a reference. For example, the results of Hammoudeh et al. (2014a,b); Zhang and Sun (2016) (see Table 3) are with regard to a part of Phase I and the whole of Phase II, while considering only very initial periods of Phase III. Therefore, insights into energy price impacts on carbon prices drawn on extensive data in Phase III are still nascent despite the crucial differences between phases. From Table 3, although we find that results of the existing limited research in Phase III are broadly consistent with ours and demonstrate overall negative impacts of energy prices (see, e.g. Zhang and Sun, 2016; Zhu et al., 2019), the efforts that exploit the median-based estimation instead of the mean-based one are still sparse. While some recent studies investigate the dynamic distributional patterns of marginal energy price impacts on carbon price quantiles in Phase III (see, e.g. Hammoudeh et al., 2014b; Tan and Wang, 2017), their results are different from ours.

Specifically, the authors use traditional quantile regression and consider simultaneous terms of both carbon and energy prices, neglecting the potential existence of a bidirectional relationship between them. In other words, the previous research suffers from endogeneity issues arising out of the simultaneity of predictor and predicted variables. In line with Coglianese et al. (2017); Aldy and Pizer (2015); Duan et al. (2019), our model uses the time-lagged item of energy prices and then estimates its impacts on carbon prices by treating energy prices as predetermined variables of carbon prices. By doing so, we control for reverse causality from carbon to energy prices. Moreover, the traditional quantile regression only considers asymmetric carbon price response at different carbon quantiles when energy price changes. It fails to identify a potential source of asymmetry in energy price impacts at different quantiles of the energy price distribution. Hence, we employ a novel QQ approach, that not only fully models the asymmetry across carbon-energy price distributions, but also can be subject to reverse/bi-directional causality treatment.

In addition, there are similarities between our research and the existing studies from different phases as shown in Table 3. Specifically, they generally share a common research purpose (viz. the investigation of carbon price formation driven by energy prices); moreover, given the importance of the EU ETS as the largest carbon emission market worldwide, carbon credits traded in the EU ETS, i.e., EUA, have received a widespread focus in the existing literature alike that in our paper. Overall, as the energy price impacts on carbon prices vary over phases, our research contributes to the existing literature by extending its conclusions to the latest Phase III and provides new empirical evidence of the asymmetric marginal price impacts of different energy sources (i.e., oil, gas, and coal) on carbon prices over carbon-energy price distributions. The empirical results are consistent with our theoretical explanations that consider the two influencing paths to be elaborated in the next subsection.

4.2. Theoretical discussions

Do our results conform to an established theory? To shed light, we first revisit the currently popular theoretical argument, *the fuel-switching effect/mechanism*, and understand its potential weaknesses. The inappropriateness of solely relying on the fuel-switching mechanism to interpret energy price impacts on carbon prices in Phase III is discussed, considering the unique features of Phase III. Then, we introduce another effect-transmission channel, viz. *the aggregated carbon demand effect* (involving the energy demand effect and production restraint effect), and provide theoretical explanations regarding energy price impacts by identifying these two channels. We latter show that the framework provides a sensible theoretical interpretation of effect-transmissions from prices of different energy sources (i.e., oil, natural gas, and coal) to carbon prices at different locations of carbon-energy price distribution in Phase III. Given that the supply of carbon allowance allocation in EU ETS is fixed and available in advance to all market participants (Ellerman and Buchner, 2008), aggregate levels of carbon emissions and carbon price dynamics are determined by a shift of the carbon demand following shocks notably from energy price fluctuations (Chevallier et al., 2019; Lutz et al., 2013; Tan and Wang, 2017).

4.2.1. **Weaknesses of the fuel-switching effect**

Conventional studies normally attribute the impacts of energy prices on carbon prices to the existence of fuel switching mechanism: the switch of energy consumption tendency between high- and low-carbon energy resources used in power production (see detail descriptions in, e.g. Mansanet-Bataller et al., 2007; Alberola et al., 2008; Hammoudeh et al., 2014a). For instance, a rise in gas prices can push carbon-intensive plants to turn to coal, leading to an increase in both carbon emissions/demand and prices. While this explanation about the energy price impact on the carbon price has been widely embraced in extant literature, it nevertheless suffers from a number of weaknesses. First, although it links carbon allowance prices with energy prices, the switching mechanism only considers shifting fuel inputs of power generators between natural gas and coal in the power and heat sector. However, it cannot directly explain oil price impacts on carbon prices as oil is normally not used in the power generation (Hammoudeh et al., 2014b).[20] Moreover, the argument fails to account for the impacts of other regulated carbon-intensive sectors, such as fuel combustion by energy users, transportation, and oil refineries, etc. (Eurostat, 2019), on the carbon price formation driven by energy

[20]Instead, oil impacts can be only indirectly discussed through natural gas prices, which could be driven by oil price changes and are interacted with carbon prices (Kanen, 2006).

prices.[21]

Second, recent research, such as Chevallier et al. (2019), admit the possible 'failure of fuel switching mechanism' in the power generation. The implication is that the switching from high-carbon coal to low-carbon natural gas has not yet occurred when carbon abatement costs have been considered in the measurement of the relative price levels of energy fuel inputs. This failure can be attributed to the current higher costs of the switching mechanism compared with that of the carbon abatement. Moreover, a failure of the fuel switching mechanism can also be attributed to the high production costs driven by high levels of energy prices (Tan and Wang, 2017). For example, given an increase in gas price, the fuel switching from gas to coal could be weakened when the coal price is exceptionally high, leading to an inflation in power production costs and then a drop in both the carbon demand and prices.

Hence, solely relying on the fuel-switching mechanism cannot well explain the price impacts of different energy sources on carbon prices in Phase III, because the impacts of oil prices cannot be directly considered in the mechanism. Likewise, given the rising maturity of the EU ETS over phases, the relationship between carbon and energy prices tends to be closer in Phase III, indicating that information about carbon emission costs can be more reflective on the expectation of energy price dynamics, leading to a weakened effectiveness of the mechanism in Phase III. In addition, the effectiveness of the mechanism also tends to be unstable and highly depends on the price levels of energy (i.e., coal and gas).

4.2.2. **The aggregate carbon demand effect**

In addition to *the fuel-switching mechanism*, we introduce another effect-transmission channel, i.e., *the aggregated carbon demand effect* (involving the energy demand effect and production restraint effect) to explain our empirical results. While exploiting aggregate carbon demand effect, the influencing path from energy prices to carbon prices can be explained jointly by the dynamics of energy demand and industrial production restraint of carbon-intensive installations in the aggregate level (Tan and Wang, 2017). Specifically, a positive/negative price change in carbon-intensive resources (i.e., oil, natural gas, and coal), due to either a strong/weak demand or weak/strong supply, can inflate/deflate marginal production costs of installations using such energy as an input. It results in a smaller/larger expectation of future production outputs, before depressing/amplifying their future energy demand. Eventually, it might lead to a bearish/bullish market expectation of future carbon emissions and prices. We therefore, conclude that current energy price fluctuations are expected to exert negative impacts

[21] Although the power generating sector is ranked as the first among all sectors in terms of the carbon emissions, it only accounts for 38% and 39% of total energy-related carbon emissions worldwide (International Energy Agency, 2019) and in EU (Creti et al., 2012), respectively. See a full list of regulated carbon-intensive sectors from the website of EU Emissions Trading System (EU ETS) (https://ec.europa.eu/clima/policies/ets_enfor).

on future carbon prices, while the impact intensity on this market expectation could be asymmetric at different locations of carbon-energy price distribution (Hammoudeh et al., 2014b; Tan and Wang, 2017).

In a situation when current carbon prices are at high quantiles (such as in a booming economy), in response to an initial positive shock in energy prices, the installations could also face strong concurrent demand for their outputs. As a result, they would still keep their production levels and the energy demand at a relatively high level, hence a sustained high CO_2 emissions. This may dampen the expectation of a decrease in future carbon emissions and prices, indicating that during a boom with high carbon prices, a positive shock in current energy prices can exert (small and negligible) negative impacts on the movement of future carbon price levels. Contrarily, when current carbon prices are at low quantiles (i.e., the economy is in the bust period), production costs of the installations will accelerate given an increase in energy prices, while the market demand of their production outputs would be considerably tightened. This leads to a significant drop in the future expectation of the energy demand and carbon emissions as well as carbon prices. Hence, the expectation tends to become more intense during bust with low carbon prices compared with that in the boom periods with high carbon prices. Our theoretical explanations concerning the channel of the aggregated carbon demand effect are also supported by the extant literature (see, e.g., Chevallier, 2011; Hammoudeh et al., 2014b; Tan and Wang, 2017).

4.2.3. **Theoretical explanations of energy price impacts in Phase III**

Given that the market characteristics and carbon emission intensity of different energy sources (i.e., oil, gas, and coal) are largely dissimilar, therefore, they demonstrate differential impact paths on carbon price variations (Hammoudeh et al., 2014a,b). We now discuss how the impacts of each energy prices can be transmitted to carbon prices in Phase III by combining both the channels of *the aggregate carbon demand effect* and *the fuel-switching mechanism*. Through this mechanism, our theoretical explanations can mitigate potential weaknesses of solely relying on the fuel-switching strategy, while considering unique characteristics of Phase III, such as a close carbon-energy price relationship. Thus, we provide a comprehensive framework to explain price impacts of each of the three energy resources on carbon prices over carbon-energy price distributions in Phase III.

With regard to oil, as it is typically not used in electricity production, there is negligible substitution of coal and gas for oil. Eventually, its impacts are dominated by aggregate carbon demand effect in that an increase in current oil price could depress economic activities and raise production costs (Hamilton, 1983; Kilian, 2008; Lardic and Mignon, 2008). This, in turn, can lead to depression of future expectation of production outputs and energy (i.e., oil) demand. The process leads to a fall in future carbon emissions and prices. In the case of Phase III, this negative impact tends to be stronger when the carbon price is low or the economy is weak, while being less intense when carbon prices are at high quantiles or the economy is strong (in absolute terms). The explanations are consistent with our obtained results shown in Figure 3(b).

With regard to gas, its impacts on carbon price determinations are governed by the aforementioned two channels, while the impacts from different channels appear opposite. Through the channel of aggregated carbon demand effect, similar to the oil price impacts, the impacts of gas prices are generally negative and tend to be stronger at low carbon price quantiles compared with that of at high carbon price quantiles (in absolute terms). At the same time, through the channel of fuel-switching mechanism, given that gas is a cleaner energy source that only contains around half of the CO_2 in coal (Hammoudeh et al., 2014a), a rise in gas prices can increase the demand for coal from the plants, subsequently leading to a heightened carbon demand and prices in the future. Our findings of the overall negative impacts of gas prices shown in Figure 4(b) suggest that the negative impact from the aggregated carbon demand effect channel outweighs the positive impact from the fuel switching mechanism in Phase III. Moreover, given that the fuel-switching mechanism tends to be weak especially in Phase III as previously discussed in this section, it further indicates that the theoretically positive effects from this mechanism are negligible. In addition, the offset of opposite forces from the two channels leads to smaller negative impacts of gas prices with a relatively flat pattern compared to the impacts of both oil and coal prices.

Finally, as for coal, despite the well-known environmental hazards, its consumption still accounts for one-third of the total inputs for power generation in the EU; therefore, its changes can greatly affect carbon price levels (Aatola et al., 2013). Exploiting the logic of the two *channels*, both of them predict negative impacts of coal prices on carbon prices (see Figure 5(b)). Coal prices tend to manifest greater impacts than oil prices, which impacts are only driven by one channel (i.e., the aggregated demand effects), especially at high carbon quantiles (in absolute terms). In addition, effects of coal prices demonstrate a quasi-monotonic increase with increases in carbon price levels. We conclude that in Phase III the price impacts of different energy sources (i.e., oil, gas, and coal) on carbon prices are overall negative. Different energy price impacts are distinct and governed by dual forces from the two effect-transmission channels, while their impacts exert a similar asymmetric pattern over the carbon price distribution: smaller at high carbon quantiles and larger at low carbon quantiles (in absolute values). Our theoretical explanations are in line with the obtained empirical results.

4.3. Causality-in-quantiles test

We now present the result from the causality-in-quantile test, which identifies the causal effects of energy prices on carbon prices. It considers the dynamics of the causality on different market conditions represented by different carbon quantile levels. In Figures 7(a), 7(b), and 7(c) we have presented the nonparametric and asymmetric price impacts of different energy sources (i.e., oil, natural gas, and coal). Specifically, Figure 7(a) shows that the null hypothesis of no Granger causality-in-quantile from oil prices to carbon prices is rejected at the most quantile levels of carbon prices. The hump-shaped curve shows that the causality is non-linear and asymmetric, indicating a strong predictive power of oil prices around the median quantile (normal market conditions). In this case, the power decreases at upper and lower quantiles, eventually becoming insignificant at the extremely high and low quantiles. Overall, we find that the oil price is a significant predictor of the carbon price across carbon quantiles except when the quantiles are extremely low or high.

As for natural gas prices, the causality is statistically significant at most quantiles (approximately from 0.1- to 0.9-quantile level) (see Figure 7(b)). It indicates that gas prices can consistently Granger cause carbon prices on the normal market conditions. The inverted U-shaped trajectory of causality presents evidence of a significant causality from lower to upper quantile levels, implying a sound predictive power of natural gas prices at most market conditions except at the extreme market states. Moreover, as presented in Figure 7(c), the range of significant area of the Granger causality-in-quantile from coal prices to carbon prices is a bit smaller than that of oil and natural gas prices. The ridge-shaped curve implies the existence of strong predictability around normal market conditions; the magnitude declines quickly as we move to extreme quantiles. On the whole, causality-in-quantiles test enriches our understanding of the causal impacts of energy prices on carbon prices under different carbon market states. Inferences obtained through the causality-in-quantiles test further confirm our findings from QQ estimates and are consistent with our theoretical explanations.

[Figure 7 about here.]

4.4. Robustness

How robust are our results to alternate estimation strategy, sample choice and alternative measure of energy price series? We present results for each of these cases to reassure the robustness of our benchmark results.

4.4.1. **Alternative estimation strategy: The τ-averaged QQ estimation**

Although the QQ method can capture specific impacts of the explanatory variable at different quantile levels, this can be viewed as a decomposition of tradition quantile regression (Sim and Zhou, 2015). In this context, a simple way to check the validity of the QQ approach is to compare the estimated quantile regression parameters with the τ-averaged QQ parameters. In particular,

$$\gamma_0(\theta) \equiv \overline{\hat{b}_0}(\theta) = \frac{1}{S}\sum_{\tau} \hat{b}_0(\theta, \tau), \tag{4.1}$$

$$\gamma_1(\theta) \equiv \overline{\hat{b}_1}(\theta) = \frac{1}{S}\sum_{\tau} \hat{b}_1(\theta, \tau), \tag{4.2}$$

where S is the number of points of the grid of τ. Figure 8 presents results of quantile regression and the averaged QQ parameters that measure the impacts of the three main energy prices on carbon prices, respectively. We find that the averaged QQ parameters are qualitatively similar to the quantile regression estimators.

These figures provide a simple validation of the QQ method employed in the preceding section by showing that the main features of the traditional quantile regression model can be recovered by summarizing the more disaggregated information contained in the QQ estimations. The results estimated by using the quantile regression are consistent with the ones obtained using QQ estimates.

[Figure 8 about here.]

4.4.2. **Application to earlier phases**

The literature has investigated the energy price impacts on carbon prices in Phases I and II of the EU ETS (see, e.g., Mansanet-Bataller et al., 2007; Alberola et al., 2008; Creti et al., 2012; Zhang and Sun, 2016). To compare with our main results in Phase III, we employ the QQ method to the data in Phases I & II, and estimate the price impacts of main energy sources (i.e., oil, natural gas, and coal). The results are presented in Figure 9. Due to the data limitation for coal prices, our sample ranges from 2006-09-05 to 2012-12-31. Once again, we find that the impacts of energy prices on carbon prices in Phases I and II are different from that in Phase III, and this is consistent with our theoretical expectation and related literature regarding the variable carbon-energy price relationship over phases.

Notably, the impact of oil prices on carbon prices (shown in Figure 9(a)) is observed to rise from -0.3979 to 0.1047 with a rise in the carbon quantile level. The increase at very low carbon quantiles is different from a relatively steady increase pattern as in Phase III (see Figure 3(b)). The impact of natural gas prices in Phases I and II depicts a basin shape as shown in Figure 9(b). This is different from the waveform in Phase III (Figure 4(b)). Furthermore, as for the impact of coal prices in Phases I and II (see Figure 9(c)), it tends to fluctuate with a smooth pattern at high and middle carbon quantile levels before dropping dramatically at lower quantiles. The results stand in contrast to a consistently declining trend from high to low quantiles in Phase III (shown in Figure 5(b)). Thus, our baseline results are robust to the change of the sample period.

[Figure 9 about here.]

4.4.3. **Alternative energy price series**

As another robustness test, we replace our applied energy price series in the main estimation by alternative measures. Specifically, in terms of oil prices, the early used Brent crude futures is replaced by the E-mini crude futures and WTI crude futures, respectively; for natural gas prices, the early used UK natural gas futures is replaced by the Henry Hub natural gas futures. Finally, we replace the coal price series (measured by the Rotterdam coal futures) by the Newcastle coal futures. All data are price series based on spot-month continuous contract calculations. The E-mini crude futures and Henry Hub futures are obtained from Chicago Mercantile Exchange (CME), whereas the WTI crude futures and Newcastle coal futures are collected from Intercontinental Exchange (ICE).

With these replaced series, our re-estimated QQ results are presented in Figure 10. For price series of E-mini and WTI crude futures, (Figures 10(a) and 10(b)), their impacts depict a quasi-monotonic increase pattern with increased carbon price quantiles, and are consistent with the impact pattern of the Brent crude futures demonstrated in Figure 3(b). As characterized by a similar feature in the original data, both E-mini and WTI crude futures present similar impact patterns on carbon prices. As for the Henry Hub gas price, its impacts (as shown in Figure 10(c)) demonstrate a flatter pattern and are relatively smaller than that of both oil and coal price series except when carbon quantiles are very low. Its estimated impacts are broadly consistent with the impacts of the UK natural gas prices reported in Figure 4(b). Moreover, similar to the impact pattern of the Rotterdam coal prices depicted in Figure 5(b), the Newcastle coal price overall exerts negative impacts and the impact intensity experiences a generally decreasing pattern with decreased carbon price quantiles. The impacts witness an amplification when carbon price quantiles drop to extremely low levels. Hence, the estimated impacts of the four alternative energy price series are broadly consistent with the results in our main estimation.

[Figure 10 about here.]

5. Conclusion

This paper studies how carbon prices are driven by energy prices in Phase III of EU ETS. Specifically, by using a novel Quantile on Quantile (QQ) and the causality-in-quantiles methods, we uncover the potential asymmetry of marginal price impacts of different energy sources (i.e., oil, natural gas, and coal) on carbon price variations over carbon-energy price distributions. The empirical results of the marginal energy price impacts are consistent with our theoretical explanations that identify the two potential effect-transmission channels from energy prices to carbon prices, i.e., *the aggregated carbon demand effect* and *the fuel switching mechanism*.

We find that energy price impacts on carbon prices are asymmetric and generally negative across carbon-energy price distributions. Our findings of the variable impact of energy prices across the price distributions can be explained by changing market conditions (high or low carbon price quantiles) and the nature of price shocks (e.g., oil, natural gas, and coal). When the economy is strong with high carbon price levels, the impacts of energy prices on carbon prices are less intense in comparison to a state when the economy is weak with low carbon price levels (in absolute terms). Specifically, the oil price impacts on carbon prices increase from low to high carbon price quantiles, and are governed by the channel of *the aggregated carbon demand effect*. In the coal market, the impacts of coal prices are jointly driven by both channels of *the aggregated carbon demand effect* and *the fuel switching mechanism* in the same direction. Its impact pattern is similar to that of oil prices and demonstrates a quasi-monotonic rise with increases in carbon price quantiles. Absolute values of coal price impacts are greater than that of oil price impacts, especially at high carbon quantiles. As for the natural gas price, its impacts are also led by the two channels but in opposite directions. Absolute values of the gas price impacts tend to be flatter and smaller compared with both oil and coal price impacts. Our interpretation on the carbon and energy price relationship is further enriched by the causality-in-quantiles test as we identify a significant causality from prices of the three energy sources to carbon prices except at a small range of extreme carbon quantiles.

Our findings possess useful implications for policymakers and practitioners (such as market investors and regulated installations). From the perspective of policymakers, a precise interpretation of the marginal energy price impacts on carbon price dynamics can help contribute to an effective environmental regulatory process for a significant control of carbon emissions and sensible policy guidance towards the healthy and prosperous market development in Phase III. Our results indicate that differential policy implementations across carbon-energy price distributions rather than a uniform policy can prove fruitful. Specifically, given that rises in both oil and coal prices lead to a substantial fall in carbon prices when they are low led by the two effect-transmission channels, it indicates that higher oil and coal price levels are effective in dampening carbon consumption at low carbon quantiles. The result suggests levying taxes on prices of the two energy sources and their related products in a bust carbon market as effective policies to reduce the fossil pollution and carbon emissions, through which a tendency to adopt clean-energy sources is further prompted. Moreover, while negative, the price impacts of natural gas on carbon prices are negligible compared to that of oil and coal in absolute terms. Thus, adding taxes to gas prices would not effectively decline carbon consumption and its prices potentially due to the substitution between gas and coal in the power generation driven by *the fuel-switching mechanism.*

From investors' standpoint, the asymmetric negative impact of energy prices on carbon prices is important for risk management. Assuming a constant carbon-energy price relationship may lead to an inappropriate financial decision making. Instead, an effective hedging strategy should account for the asymmetry of the relationship across the entire data distribution and its variations over time. Since carbon prices behave a strong negative linkage with oil and coal prices at low carbon quantiles, it offers an effective approach to diversify the risk of adverse price fluctuations associated with the investors' portfolios, especially in periods of economic turmoil. In addition, introducing the pricing mechanism of carbon allowances has changed the cost structure of regulated installations. Thus, an accurate interpretation of the variable energy price impacts on carbon prices over the data distribution can help the regulated sectors minimize carbon and energy-related production costs and meet their carbon reduction targets in the compliance period.

References

Aatola, P., Ollikainen, M., Toppinen, A., 2013. Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals. Energy Economics 36, 380–395.

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. P., Chèze, B., 2009. European carbon prices fundamentals in 2005-2007: The effects of energy markets, temperatures and sectorial production. Journal of Policy Model 31, 446–462.

Aldy, J. E., Pizer, W. A., 2015. The competitiveness impacts of climate change mitigation policies. Journal of the Association of Environmental and Resource Economists 2 (4), 565–595.

Balcılar, M., Demirer, R., Hammoudeh, S., Nguyen, D. K., 2016. Risk spillovers across the energy and carbon markets and hedging strategies for carbon risk. Energy Economics 54, 159–172.

Benz, E., Trück, S., 2009. Modeling the price dynamics of CO2 emission allowances. Energy Economics 31, 4–15.

Bredin, D., Muckley, C., 2011. An emerging equilibrium in the EU emissions trading scheme. Energy Economics 33, 353–362.

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

Chevallier, J., 2011. A model of carbon price interactions with macroeconomic and energy dynamics. Energy Economics 33 (6), 1295–1312.

Chevallier, J., 2012. Time-varying correlations in oil, gas and CO2 prices: an application using BEKK, CCC and DCC-MGARCH models. Applied Economics 44 (32), 4257–4274.

Chevallier, J., Nguyen, D. K., Reboredo, J. C., 2019. A conditional dependence approach to CO2-Energy price relationships. Energy Economics 81, 812–821.

Christiansen, A. C., Arvanitakis, A., Tangen, K., Hasselknippe, H., 2005. Price determinants in the EU emissions trading scheme. Climate Policy 5, 15–30.

Chung, D., Hrazdil, K., 2010. Liquidity and market efficiency: A large sample study. Journal of Banking & Finance 34 (10), 2346–2357.

Coglianese, J., Davis, L. W., Kilian, L., Stock, J. H., 2017. Anticipation, tax avoidance, and the price elasticity of gasoline demand. Journal of Applied Econometrics 32 (1), 1–15.

Convery, F. J., Ellerman, A. D., De Perthuis, C., 2008. The European carbon market in action: Lessons from the first trading period. Journal for European Environmental and Planning Law 5, 215–230.

Creti, A., Jouvet, P.-A., Mignon, V., 2012. Carbon price drivers: Phase I versus Phase II equilibrium? Energy Economics 34, 327–334.

Daskalakis, G., Psychoyios, D., Markellos, R. N., 2009. Modeling CO2 emission allowance prices and derivatives: Evidence from the European trading scheme. Journal of Banking & Finance 33, 1230–1241.

Duan, K., Mishra, T., Parhi, M., Wolfe, S., 2019. How effective are policy interventions in a spatially-embedded international real estate market? Journal of Real Estate Finance and Economics 58 (4), 596–637.

Egenhofer, C., Alessi, M., Georgiev, A., Fujiwara, N., 2011. The EU emissions trading system and climate policy towards 2050: Real incentives to reduce emissions and drive innovation? CEPS Special Reports.

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.

European Parliament and Council, 2009. Directive 2009/28/EC of the European Parliament and of the Council of 23 april 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC. Official Journal of the European Union 5, 2009.

Eurostat, 2019. Shedding light on energy in the eu.
URL https://ec.europa.eu/eurostat/cache/infographs/energy/images/pdf/pdf-energy-eurostat-2019.pdf

Fan, J. H., Akimov, A., Roca, E., 2013. Dynamic hedge ratio estimations in the European Union emissions offset credit market. Journal of Cleaner Production 42, 254–262.

German Emission Trading Authority, 2019. German auctioning of emission allowances periodical report: Annual report 2018. Tech. rep., the German Environment Agency.

Hall, P., Sheather, S. J., Jones, M., Marron, J. S., 1991. On optimal data-based bandwidth selection in kernel density estimation. Biometrika 78 (2), 263–269.

Hamilton, J. D., 1983. Oil and the macroeconomy since world war II. Journal of Political Economy 91 (2), 228–248.

Hammoudeh, S., Lahiani, A., Nguyen, D. K., Sousa, R. M., 2015. An empirical analysis of energy cost pass-through to CO2 emission prices. Energy Economics 49, 149–156.

Hammoudeh, S., Nguyen, D. K., Sousa, R. M., 2014a. What explain the short-term dynamics of the prices of CO2 emissions? Energy Economics 46, 122–135.

Hammoudeh, S., Nguyen, D. K., Sousa, R. M., 2014b. Energy prices and CO2 emission allowance prices: A quantile regression approach. Energy Policy 70, 201–206.

Heidenreich, N.-B., Schindler, A., Sperlich, S., 2013. Bandwidth selection for kernel density estimation: a review of fully automatic selectors. AStA Advances in Statistical Analysis 97 (4), 403–433.

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

Ibrahim, B. M., Kalaitzoglou, I. A., 2016. Why do carbon prices and price volatility change? Journal of Banking & Finance 63, 76–94.

International Energy Agency, 2019. Global energy and $CO2$ status report. URL https://webstore.iea.org/download/direct/2461?fileName=Global_Energy_and_CO2_Status_Report_2018.pdf

Jeong, K., Härdle, W. K., Song, S., 2012. A consistent nonparametric test for causality in quantile. Econometric Theory 28, 861–887.

Ji, Q., Zhang, D., Geng, J.-b., 2018. Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. Journal of Cleaner Production 198, 972–978.

Jones, M. C., Marron, J. S., Sheather, S. J., 1996. A brief survey of bandwidth selection for density estimation. Journal of the American Statistical Association 91 (433), 401–407.

Kanen, J. L., 2006. Carbon trading & pricing. Environmental Finance Publications.

Keppler, J. H., Mansanet-Bataller, M., 2010. Causalities between CO2, electricity, and other energy variables during Phase I and Phase II of the EU ETS. Energy Policy 38, 3329–3341.

Kilian, L., 2008. Exogenous oil supply shocks: how big are they and how much do they matter for the us economy? Review of Economics and Statistics 90 (2), 216–240.

Koch, N., 2014. Dynamic linkages among carbon, energy and financial markets: A smooth transition approach. Applied Economics 46, 715–729.

Koenker, R., Bassett Jr, G., 1978. Regression quantiles. Econometrica, 33–50.

Lardic, S., Mignon, V., 2008. Oil prices and economic activity: An asymmetric cointegration approach. Energy Economics 30 (3), 847–855.

Li, Q., Racine, J., 2004. Cross-validated local linear nonparametric regression. Statistica Sinica 14, 485–512.

Lin, B., Nelson, B. I., 2019. Determinants of industrial carbon dioxide emissions growth in Shanghai: A quantile analysis. Journal of Cleaner Production 217, 776–786.

Lutz, B. J., Pigorsch, U., Rotfuß, W., 2013. Nonlinearity in cap-and-trade systems: The EUA price and its fundamentals. Energy Economics 40, 222–232.

Mansanet-Bataller, M., Pardo, A., Valor, E., 2007. Co2 prices, energy and weather. Energy Journal 28, 73–92.

Mizrach, B., Otsubo, Y., 2014. The market microstructure of the European climate exchange. Journal of Banking & Finance 39, 107–116.

Montagnoli, A., De Vries, F. P., 2010. Carbon trading thickness and market efficiency. Energy Economics 32 (6), 1331–1336.

Paolella, M. S., Taschini, L., 2008. An econometric analysis of emission allowance prices. Journal of Banking & Finance 32, 2022–2032.

Reboredo, J. C., 2014. Volatility spillovers between the oil market and the European Union carbon emission market. Economic Modelling 36, 229–234.

Reboredo, J. C., Ugolini, A., 2018. The impact of energy prices on clean energy stock prices. a multivariate quantile dependence approach. Energy Economics 76, 136–152.

Rickels, W., Duscha, V., Keller, A., Peterson, S., et al., 2007. The determinants of allowance prices in the european emissions trading scheme: Can we expect an efficient allowance market 2008? Tech. rep., Kiel Working Paper No. 1387.

Schandl, H., Hatfield-Dodds, S., Wiedmann, T., Geschke, A., Cai, Y., West, J., Newth, D., Baynes, T., Lenzen, M., Owen, A., 2016. Decoupling global environmental pressure and economic growth: Scenarios for energy use, materials use and carbon emissions. Journal of Cleaner Production 132, 45–56.

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

Sim, N., Zhou, H., 2015. Oil prices, US stock return, and the dependence between their quantiles. Journal of Banking & Finance 55, 1–8.

Stone, C. J., 1977. Consistent nonparametric regression. Annals of Statistics 5, 595–620.

Stone, C. J., 1984. An asymptotically optimal window selection rule for kernel density estimates. Annals of Statistics 12, 1285–1297.

Subramaniam, N., Wahyuni, D., Cooper, B. J., Leung, P., Wines, G., 2015. Integration of carbon risks and opportunities in enterprise risk management systems: Evidence from Australian firms. Journal of Cleaner Production 96, 407–417.

Tan, X.-P., Wang, X.-Y., 2017. Dependence changes between the carbon price and its fundamentals: A quantile regression approach. Applied Energy 190, 306–325.

Yu, L., Li, J., Tang, L., 2015a. Dynamic volatility spillover effect analysis between carbon market and crude oil market: A DCC-ICSS approach. International Journal of Global Energy Issues 38, 242–256.

Yu, L., Li, J., Tang, L., Wang, S., 2015b. Linear and nonlinear Granger causality investigation between carbon market and crude oil market: A multi-scale approach. Energy Economics 51, 300–311.

Zhang, Y.-J., Huang, Y.-S., 2015. The multi-frequency correlation between EUA and SCER futures prices: Evidence from the EMD approach. Fractals 23, 1550020.

Zhang, Y.-J., Sun, Y.-F., 2016. The dynamic volatility spillover between european carbon trading market and fossil energy market. Journal of Cleaner Production 112, 2654–2663.

Zhu, B., Ye, S., Han, D., Wang, P., He, K., Wei, Y.-M., Xie, R., 2019. A multiscale analysis for carbon price drivers. Energy Economics 78, 202–216.

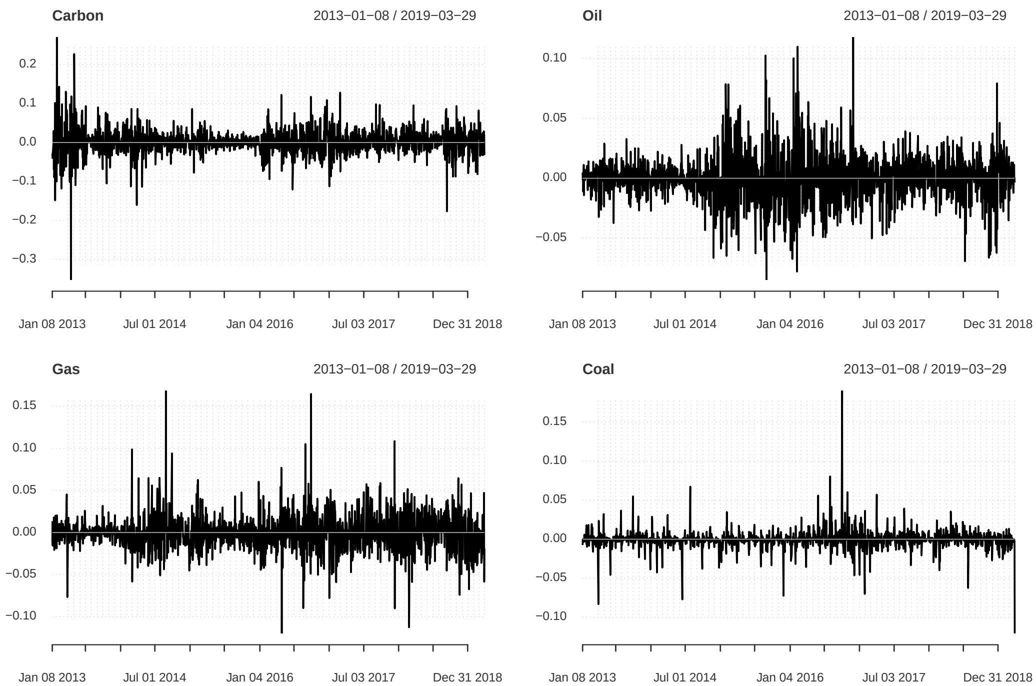


Figure 1: *Time series plots of the daily return of carbon futures prices, Brent crude oil futures prices, natural gas futures prices and coal futures price from 2013-01-07 to 2019-03-30.*

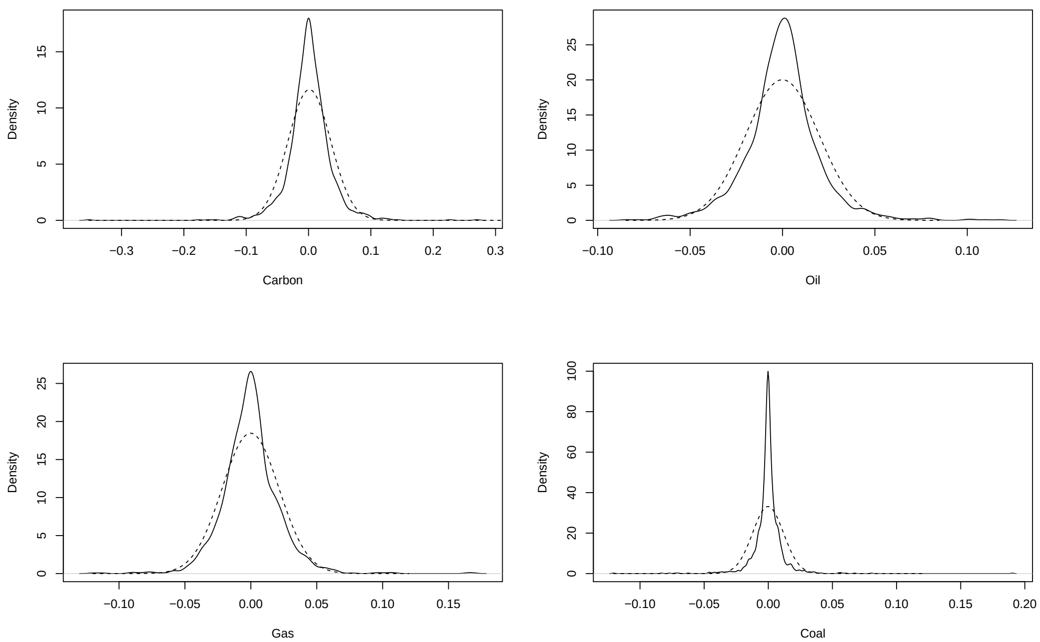
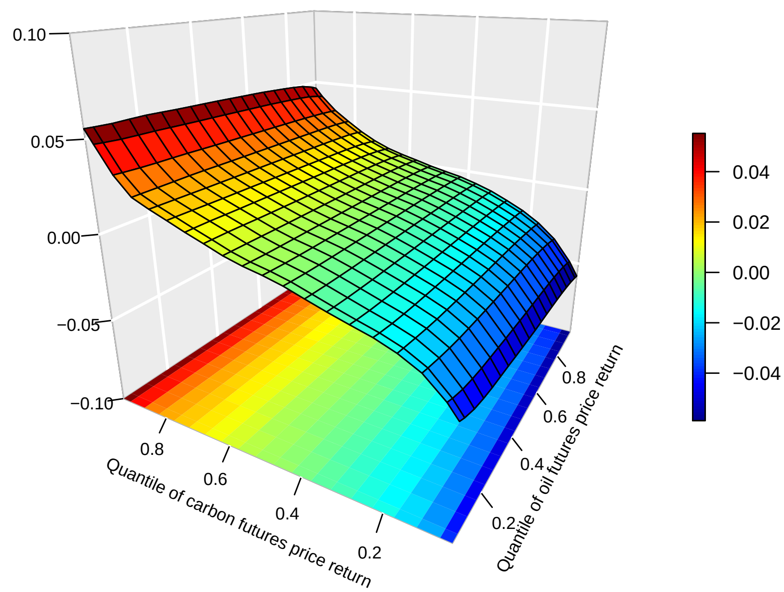
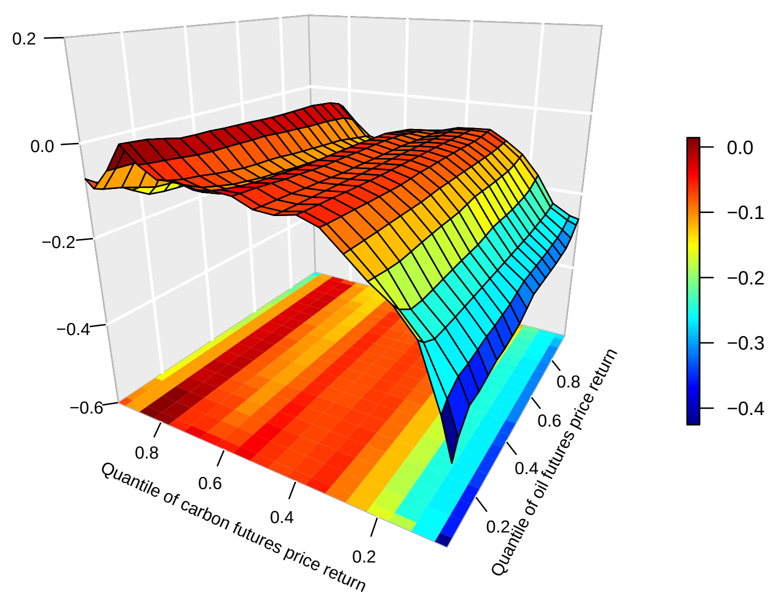


Figure 2: *Density plots of the daily return of carbon futures prices, Brent crude oil futures prices, natural gas futures prices and coal futures prices from 2013-01-07 to 2019-03-30.*

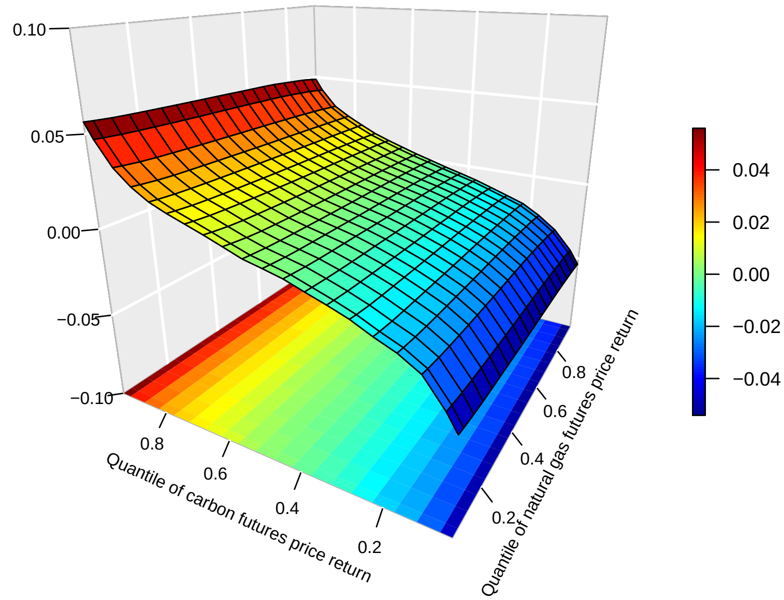


(a) $b_0(\theta, \tau)$

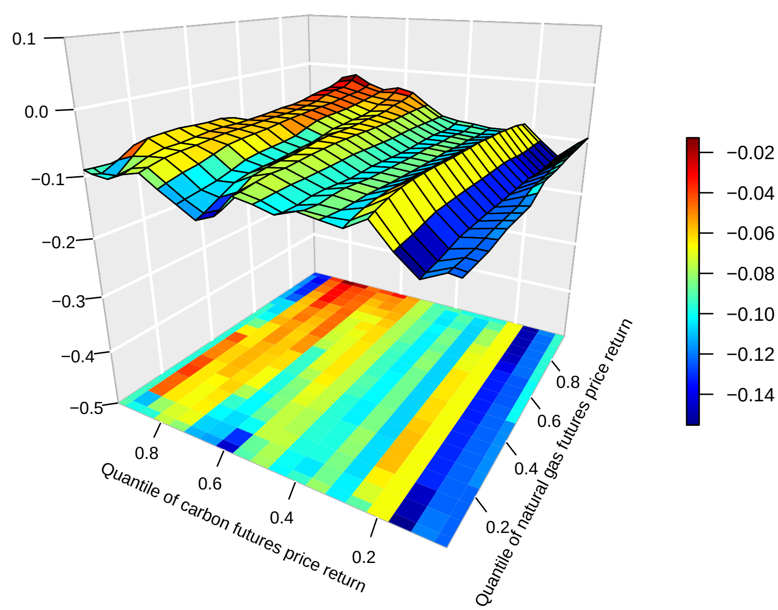


(b) $b_1(\theta, \tau)$

Figure 3: *QQ estimates for the impacts of oil futures returns on carbon futures returns*

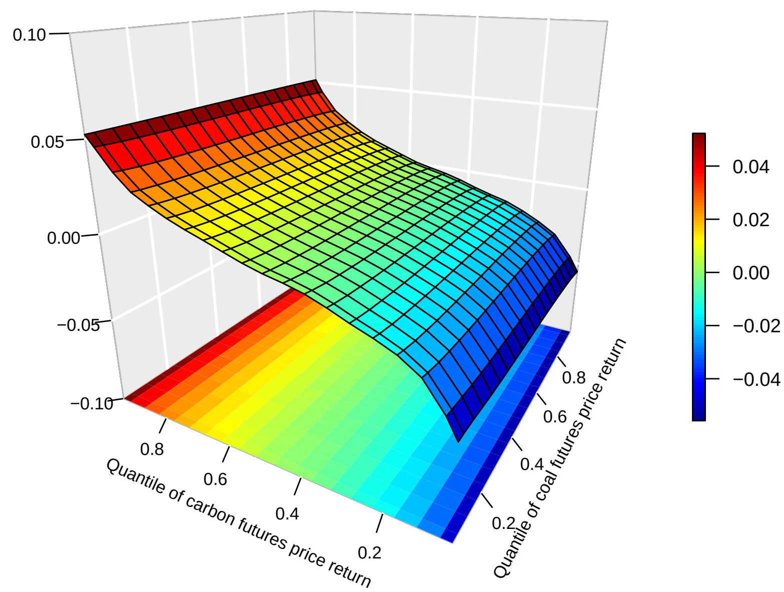


(a) $b_0(\theta, \tau)$

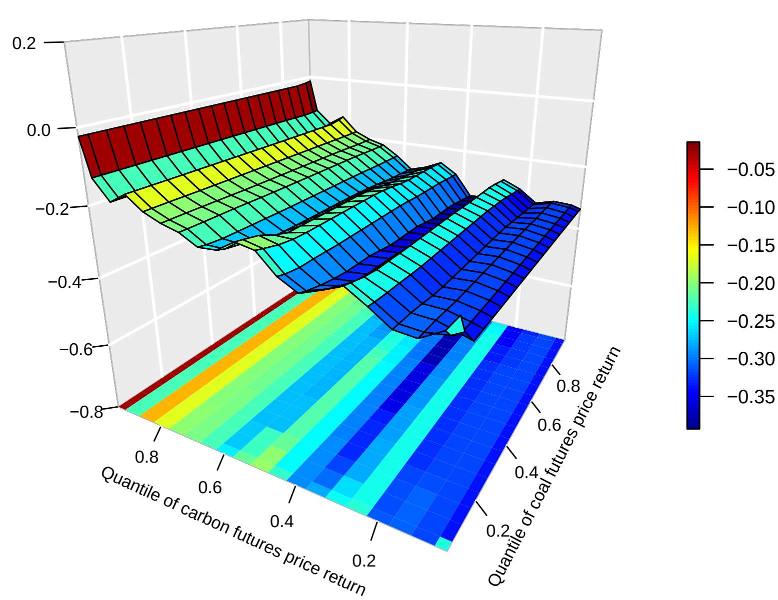


(b) $b_1(\theta, \tau)$

Figure 4: *QQ estimates for impacts of natural gas futures returns on carbon futures returns*

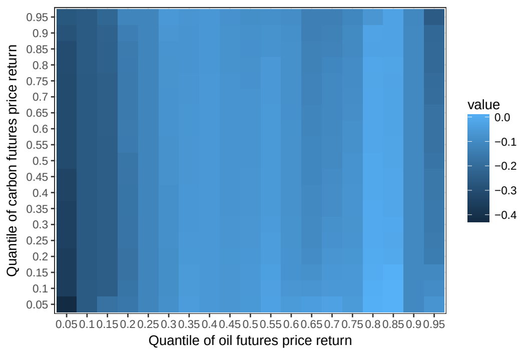


(a) $b_0(\theta, \tau)$

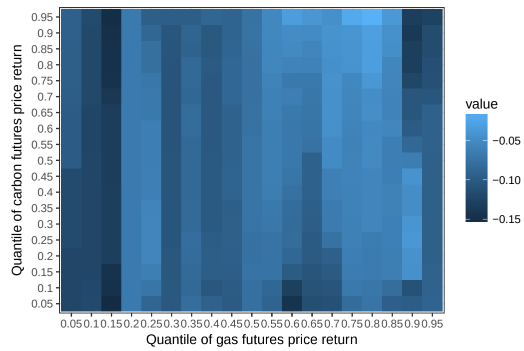


(b) $b_1(\theta, \tau)$

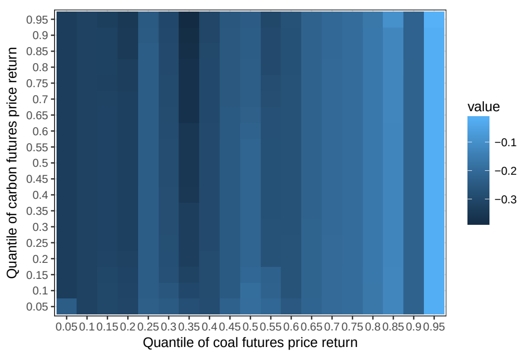
Figure 5: *QQ estimates for impacts of coal futures returns on carbon futures returns*



(a) The impacts of oil futures price returns

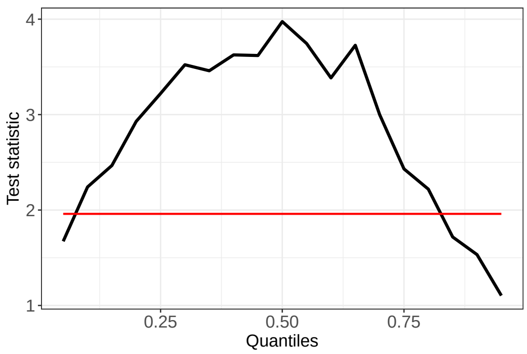


(b) The impacts of natural gas futures price returns

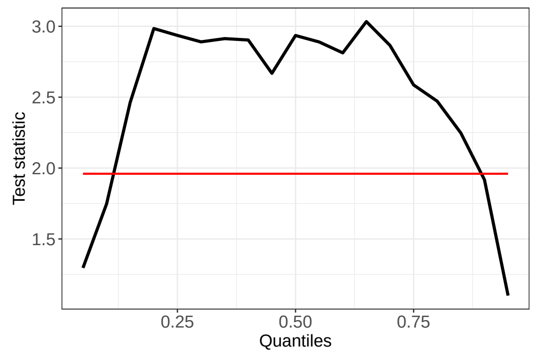


(c) The impacts of coal futures price returns

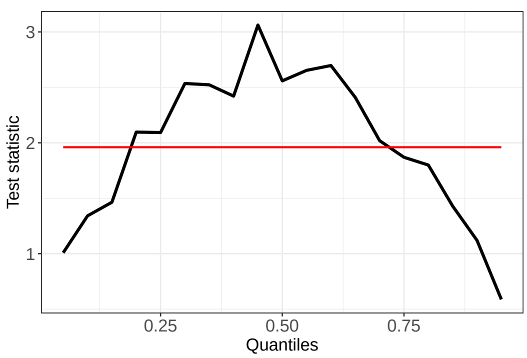
Figure 6: *The heat map of estimated coefficients $b_1(\theta, \tau)$ for the impacts of oil, natural gas and coal futures returns on carbon futures returns by the QQ method.*
Note: (i) The legend describes the extent of impacts of the energy price returns on carbon price returns. (ii) Figures 6(a) - 6(c) are the 2-D reproduction of the same results reported in Figures 3(b), 4(b), and 5(b) in the 3-D format, respectively. (iii) The vertical axis indicates 19 quantile levels (from q=0.05 to q=0.95) of oil, natural gas and coal futures returns, respectively. The horizontal axis denotes 19 quantile levels (from q=0.05 to q=0.95) of carbon futures returns.



(a) Oil futures to carbon futures



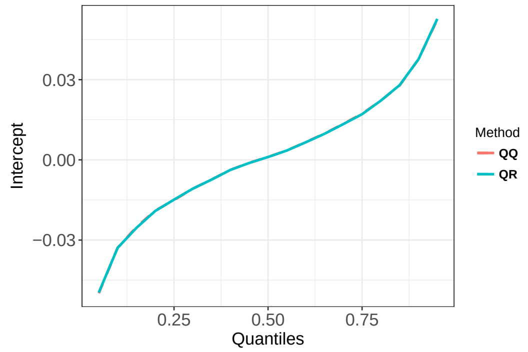
(b) Natural gas futures to carbon futures



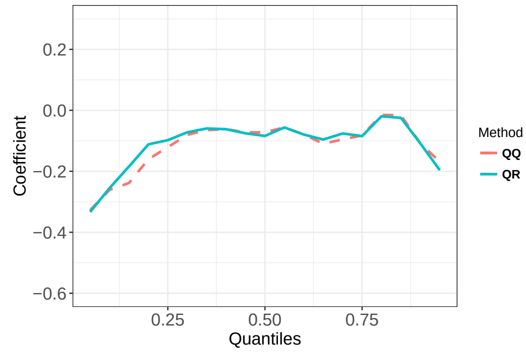
(c) Coal futures to carbon futures

Figure 7: *Causality-in-quantile test results*

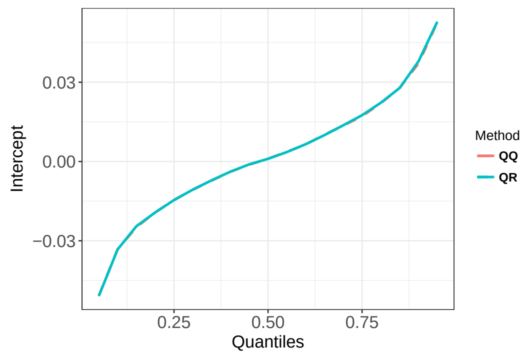
Note: (i) The figure plots results of the nonparametric causality-in-mean test from three energy futures price returns to different quantiles of the carbon futures return, as well as the opposite effect , and the corresponding estimate of the 5% critical value (CV) represented as the horizontal red solid line. (ii) The vertical axis reports test statistics of the null hypothesis of the test, and the horizontal axis indicates 19 quantile levels (from q=0.05 to q=0.95).



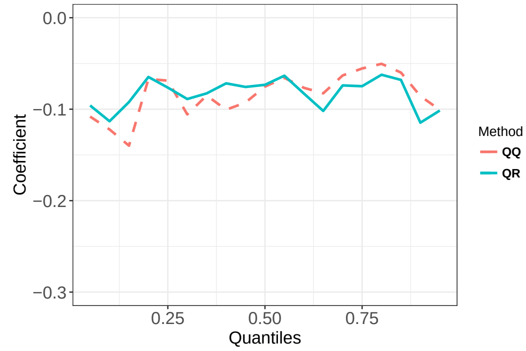
(a) Intercept of oil futures price return



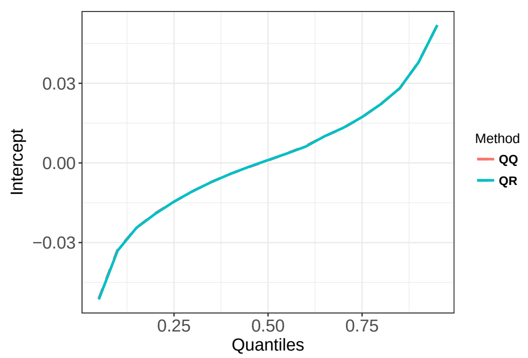
(b) Impact of oil futures price return on carbon futures price return



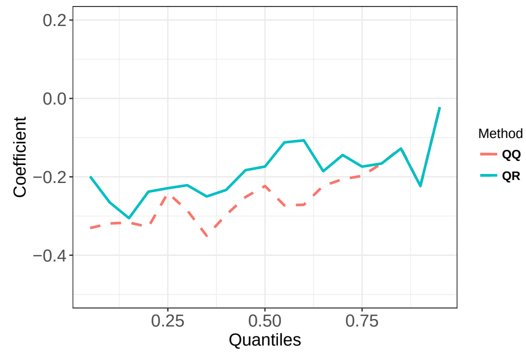
(c) Intercept of natural gas futures price return



(d) Impact of natural gas futures price return on carbon futures price return



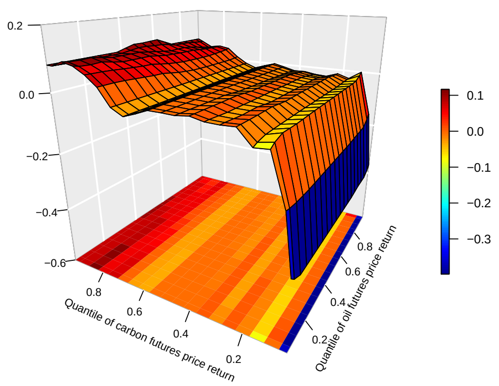
(e) Intercept of coal futures price return



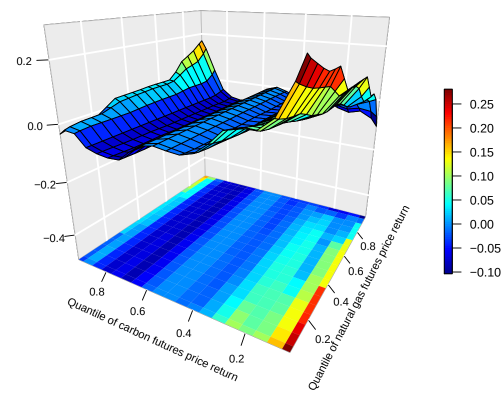
(f) Impact of coal futures price return on carbon futures price return

Figure 8: *The robustness check: Comparisons of the results from the quantile regression and the QQ estimate*

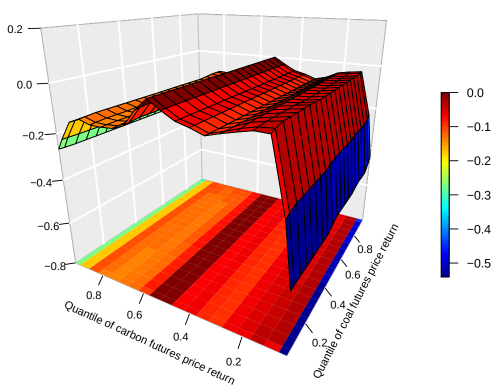
Note: The graph plots and compares the estimates of the traditional quantile regression parameters, denoted by QR (continuous green line), and the averaged QQ parameters regarding averaged impacts of the three energy futures price returns on different quantiles of the carbon futures price return.



(a) Impact of oil futures price returns

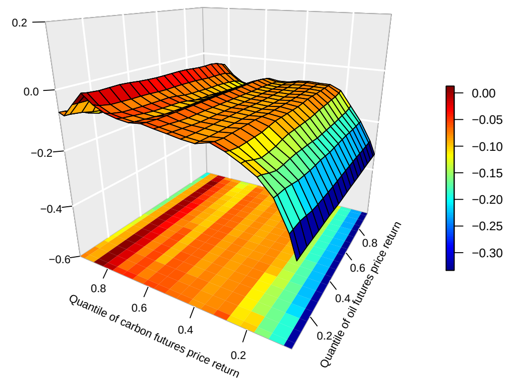


(b) Impact of natural gas futures price returns

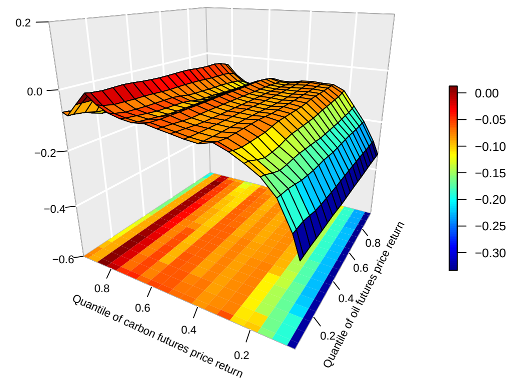


(c) Impact of coal futures price returns

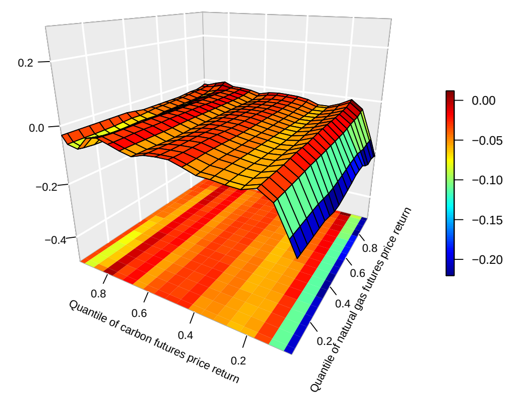
Figure 9: *The robustness check: QQ estimates for the impacts of main energy futures returns on carbon futures returns in Phase I&II*



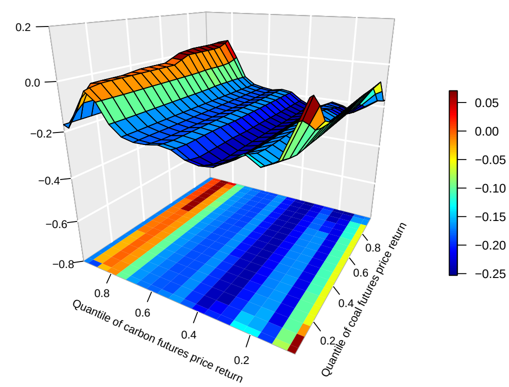
(a) Impact of E-mini crude oil futures price returns



(b) Impact of WTI oil futures price returns



(c) Impact of Henry Hub natural gas futures price returns



(d) Impact of Newcastle coal futures price returns

Figure 10: *The robustness check: QQ estimates for the impacts of four different main energy futures returns on carbon futures returns in Phase III*

Table 1: *Descriptive statistics*

	Carbon	Oil	Gas	Coal
Minimum	-0.353	-0.085	-0.120	-0.083
Maximum	0.270	0.118	0.169	0.190
25th Quartile	-0.014	-0.010	-0.012	-0.003
75th Quartile	0.017	0.009	0.010	0.003
Mean	0.001	-0.000	-0.000	-0.000
Stdev	0.034	0.020	0.022	0.012
Skewness	-0.336	0.347	0.612	2.364
Kurtosis	12.236	3.637	6.913	52.870
JB test	10035.841***	917.369***	3295.700***	188217.575***
ADF test	-12.135***	-11.440***	-10.242***	-10.295***

Note: (i) This table summarizes descriptive statistics of the futures price return of Brent crude oil, UK natural gas, Rotterdam coal, and ECX EUA (Carbon). (ii) The sample period is from Jan 07, 2013 to Mar 30, 2019. (iii) The Jarque-Bera (JB) statistics test for the null hypothesis of normality of target series. The Augmented Dickey-Fuller (ADF) test reports unit root test results with the null hypothesis of non-stationarity. (iv) * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.

Table 2: *OLS and quantile regression results*

	Variable	OLS	Quantile		
			0.1	0.5	0.9
Carbon	Constant	0.0013	-0.0329***	0.0011*	0.0376***
		(0.115)	(0.000)	(0.097)	(0.000)
	L.Oil	-0.1208***	-0.2551***	-0.0839**	-0.1088
		(0.005)	(0.000)	(0.011)	(0.101)
	L.Carbon	0.0039	0.0690	-0.0512*	-0.0421
		(0.878)	(0.213)	(0.084)	(0.355)
Carbon	Constant	0.0013	-0.0334***	0.0010*	0.0379***
		(0.119)	(0.000)	(0.095)	(0.000)
	L.Gas	-0.1024**	-0.1107*	-0.0746**	-0.1148**
		(0.011)	(0.090)	(0.014)	(0.043)
	L.Carbon	0.0064	0.0373	-0.0482	-0.0461
		(0.803)	(0.534)	(0.104)	(0.292)
Carbon	Constant	0.0013	-0.0334***	0.0011	0.0379***
		(0.121)	(0.000)	(0.102)	(0.000)
	L.Coal	-0.1522**	-0.2027	-0.1431**	-0.2235**
		(0.034)	(0.187)	(0.040)	(0.046)
	L.Carbon	0.0016	0.0573	-0.0554*	-0.0472
		(0.951)	(0.357)	(0.079)	(0.261)

Note: (i) This table reports estimations of the OLS and traditional quantile regression on different quantile levels (i.e. $\alpha = 0.1$, $\alpha = 0.5$ and $\alpha = 0.9$) regarding impacts of the futures price return of Brent crude oil (Oil), natural gas (Gas), and coal (Coal) on the ECX EUA (Carbon) futures price return, respectively. (ii) 'Constant' denotes estimations of the constant model intercept; the prefix 'L.' denotes the temporal lag of the variable. (iii) P values are in parentheses. * denotes the 10% significance level; ** denotes the 5% significance level; *** denotes the 1% significance level.

Table 3: *Summary of the key literature*

Authors	Method	Period	The Price Impacts of Energy Sources on EUA Prices		
			Oil	Gas	Coal
Mansanet-Bataller et al. (2007)	Multivariate linear regression model	2005.01.01-2005.11.30 (Phase I)	Positive	Positive	Insignificant
Alberola et al. (2008)	Multivariate linear regression model	2005.07.01-2007.04.30 (Phase I)	Insignificant in full sample; positive before and after the compliance break	Positive in full sample; insignificant before and after the compliance break	Negative in full sample; insignificant before and after the compliance break
Hintermann (2010)	A structural model in an ARCH form	2005.01-2007.06 (Phase I) 2005.01-2006.04 (Pre-crash) 2006.05-2007.06 (Post-crash)	Not included	Positive in full period, Pre-crash, and Post-crash	Insignificant in full period, Pre-crash, and Post-crash
Bredin and Muckley (2011)	VECM model	2005.07.01-2009.12.14 2005.07.01-2007.12.31 (Phase I) 2008.01.01-2009.12.14 (Phase II)	Insignificant in Phase I and full sample; positive in Phase II	Insignificant in Phase I; negative in Phase II; and positive in full sample	Insignificant in Phase I; positive in Phase II; and negative in full sample
Chevallier (2011)	Markov-switching VAR model with two states	2005.01-2010.07 (Phase I and II)	Positive in strong economy; negative in weak economy	Negative in strong economy; negative in weak economy	Positive in strong economy; negative in weak economy
Creti et al. (2012)	VECM model	2005.06.24-2007.12.24 (Phase I) 2008.01.01-2010.12.01 (Phase II)	Positive in Phases I and II	The effect of switching prices between gas and coal is positive but very small in Phase II, and are insignificant in Phase I	
Aatola et al. (2013)	Model of OLS, IV, and VAR	2005.01.03-2010.12.31 (Phases I and II)	Positive	Positive	Negative
Lutz et al. (2013)	Markov-switching model	2008.01.01-2012.12.31 (Phase II)	Positive in both high and low volatility regimes	Positive in both high and low volatility regimes	Positive in high volatility regime; Negative in low volatility regime
Hammoudeh et al. (2014a)	Bayesian Structural VAR	2006.08-2013.11 (Phases I, II, and III)	Positive at initial periods, then becomes negative	Negative	Positive; insignificant when the electricity price is considered
Hammoudeh et al. (2014b)	Quantile regression model	2006.08-2013.11 (Phases I, II, and III)	Overall negative and larger at high carbon quantiles (in absolute values)	Negative at low carbon quantiles; positive at high carbon quantiles	Negative and larger at med carbon quantiles (in absolute values)
Zhang and Sun (2016)	VAR-DCC-TGARCH	2008.01.04-2014.09.30 (Phases II and III)	Insignificant	Insignificant	Negative
Tan and Wang (2017)	Quantile regression model	2005.08.22-2016.01.06 (Phases I, II, and III)	Positive in Phase I; negative in Phases II and III	Negative in Phase I; positive in Phase II; Phase III: negative at lower carbon quantiles; positive at higher carbon quantiles	Negative in Phase I and III positive in Phase II
Chevallier et al. (2019)	Conditional vine copula model	2010.01.01-2016.05.19 (Phases II and III)	Weakly negative correlated	Carbon prices are weakly negative correlated with the gas price and the switching price from coal to gas fuels	
Zhu et al. (2019)	Multivariate empirical mode decomposition	2009.01.02-2016.06.30 (Phases II and III)	Insignificant in original level, short and medium timescales; negative in long timescales	Insignificant in original level, short and medium timescales; negative in long timescales	Negative in original level and Medium timescales; insignificant in short and long timescales