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Drivers of price formation and predictive properties of the forward curve, geographical distance, trade flow, and currency markets for global commodity trading

by

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Declaration of Original Authorship

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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Abstract

This thesis examines various drivers of commodity trade flows and it quantifies their predictability and impact on the prices of key industrial commodities.

The first empirical chapter discusses how short-term change in the position and gradient of the crude oil market forward curve can contribute to the formation of speculative supply shock. The conditions for causality between the forward curve position, its slope steepness, and oil supply are examined. Evidence of causality and, therefore, of a speculative supply shock is detected, resulting in the development of a structural model of the global crude oil market that allows for a speculative supply shock as a result of a forward curve shift and steepness.

The second empirical chapter investigates the dynamics between price and cross-border trade flows of the EU electricity market. First, I study the impact of the relative strength of economic activity and distance between two countries on their net cross-border electricity flow. The effect from changes of electricity flow between two markets on flows between another pair of markets is also examined. Lastly, I investigate the relationship between cross-border electricity flows and electricity prices. Evidence of causality between flow and price, flow and flow and the gravity of the trade coefficient and flow, is also documented. VAR/VEC model framework is employed to identify and trace the shocks introduced to the system of inter-connected markets, a short-term electricity trading model is proposed.

The third empirical chapter of the thesis examines the role of global foreign exchange markets in the formation of supply and demand shocks for key energy, metal, grain, and shipping commodity markets. Difference in the predictive power of the currencies of exporters and importers is investigated and an S&D model based exclusively on foreign exchange signals is proposed. The results provide evidence that currencies of importers have higher explanatory power than the currencies of exporters - a major departure from the established consensus in the literature. Additionally, the currency-based S&D model is found to possess a stronger predictive power over the price of commodity compared to the predictive power of each of its constituents, which improves the explanatory power of the proposed VEC model.

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Part I

Introduction

1. Motivation

Commodity market price formation is a notoriously complex process that depends not only on the traditional forces of supply and demand, but also on exogenous factors, market structure, and product-specific characteristics (Valiante 2013). This thesis examines important drivers of commodity trade flow, such as the shape and steepness of the forward curve, the geographical distance between trading partners, the size and direction of cross-border trade flow, and currency markets and attempts to quantify their predictability and impact on the prices of key industrial commodities.

The first empirical chapter discusses how the crude oil forward curve is affected by the information processed by all market participants, since producers tend to use the forward curve position and shape to guide their future market behaviour (Sockin and Xiong 2013). Therefore, unlike medium- to long-term shifts in production in response to changes in geopolitical conditions, underlying structural demand, or technological developments, any short-term change in the position or gradient of the forward curve can contribute to potential speculative supply shocks, which can, in turn, have an effect on price formation.

Other elements that prompt close examination of the link between the forward curve's shape and steepness and the reaction of supply are the high concentration of pricing power in the crude oil market, the transformation of global crude oil supply chains, the diminished role of inventory as a market balancing mechanism, the steady increase in the elasticity of supply over the last 10 years, and simply the improved agility of producers in their desire to maximize returns. Any combination of these factors suggests that producers are likely to respond to changes in the forward price environment not only by accumulating or liquidating inventory, but, more recently, also by adjusting their output and direct sales on the spot physical market.

The second empirical chapter examines the price versus cross-border trade flow dynamics of the European electricity market, which exhibits significant differences from other commodity markets because of its inherent inability to accumulate inventory, as well as the nature of instantaneous transactions of electric current invalidating the balancing mechanism between supply and demand.

Furthermore, structural changes in the architecture of the electricity market imposed by the European Union (EU) Energy Markets Initiative encourages investigation of the impact on trade flows across Europe, as well as the positive feedback between cross-border trade flows and prices. The material lack of industrial-scale storage capacity in the electricity market, instantaneous transactions of electrical current, and Kirchhoff's first law indicate that changes in cross-border electricity flows have the potential to influence the domestic supply and demand balance for a particular market. The lack of electricity storage removes the balancing mechanism between supply and demand, which means that the supply needs to equal the demand at any point in time. The need for instantaneous balancing, propagated by increasing connectivity between more and more markets, raises questions about the reaction of multiple interconnected markets. Moreover, increases in cross-border transmission capacity and the intermittent nature of electricity production in certain regions of this closely connected system suggest the need for a detailed examination of how electricity flows can affect prices. The chapter also infers that the link between geographical distance and economic activity, first established by Tinbergen (1962), is responsible for supply shocks in the pan-European electricity market network.

The third empirical chapter of the thesis examines the reasons behind supply and demand shocks in key energy, metal, grain, and shipping commodity markets, utilizing the foreign exchange rates of the major importers and exporters of these commodities. With the US dollar at the centre of global commodity trading in terms of commodity pricing and credit (Boz, Gopinath, and Plagborg-Møller 2017), the global currency market has the potential to accumulate unique information about producers' incentives to supply the market with a commodity and consumers' incentives to purchase the required amount of material on the international market. The size of the global currency market and its ability to efficiently gather and channel forward-looking information (Van Foreest and De Vries 2003) is a prerequisite for more efficient price discovery (Belke, Bordon, and Voltz 2013), which is also attracting attention as a potential tool for predicting future commodity markets price moves.

Contrary to the dominant research theme in the literature, evidence of a structural shift in global commodity supply chains from supply-push to demand-pull systems (Christopher and Towill 2001, and Christopher 2011) suggests that an exclusive focus on the relation between the prices and currencies of exporters is too simplistic and that valuable information can also be extracted from the currency values of the exporters, who dictate the direction and strength of the demand pull.

2. Thesis structure, findings, implications, and contribution

This thesis consists of three key parts. Part I introduces the topics, discusses the motivation behind the research of each topic, identifies the gaps in the literature, and reveals the results, implications, and contributions. Part II consists of three empirical chapters, each addressing a specific driver of commodity market price formation. Part III offers concluding thoughts.

The research hypotheses examined in the empirical part are contained in three separate essays, Chapters 3 to 5, because market specifics do not allow for a direct comparison of the selected price drivers across different commodities in a single essay. For instance, prerequisites for examining the hypothetical impact of the forward curve shape and its steepness on supply are that the markets have an efficient mechanism of forward price discovery, an option for physical storage in terms of geographical location and speed of recharge/discharge, as well as the producers' technological ability to alter supply in the short term. Under such conditions, the crude oil market qualifies for testing the hypothesis in Chapter 3, but the electricity, freight, metal, and agricultural commodities discussed in Chapters 4 and 5 do not. These markets are hardly suitable examples due to the material lack of storage, liquidity restrictions on their physical markets, high cross-border trade frictions, and the insufficient geographical distribution of origination and storage.

On the other hand, it is precisely these restrictions that, in Chapter 4, raise important research questions for the price formation within such constraints for markets such as electricity while excluding others, such as crude oil, metals, and agricultural commodities. Furthermore, the geographical distance between trading partners and its influence on price formation is a well-researched subject for crude oil, agricultural, and metals (Tinbergen 1962, Bergstrand and Egger 2010), but not electricity. The above arguments explain the focus on European electricity markets in Chapter 4.

Lastly, crude oil is included in the hypothesis testing in Chapter 5, but electricity is not, because the electricity market trades in a single currency unit, eliminating variations in the exchange rate from the price and cross-border trade flow formation.

The central hypothesis tests of the first empirical chapter is that commodity producers can deliberately alter the amount of output on the spot physical market by changing price structure, thus creating conditions for a short-term speculative supply shock. This means that the supply needs to increase simultaneously or briefly after the forward curve shifts into backwardation. The idea that supply is influenced by the shape of the forward curve also challenges the established theory of storage, and it therefore deserves further scrutiny.

The results not only suggest a speculative supply shock, contradicting Baumeister and Peersman (2013), and Kilian and Murphy (2014), but also, uniquely for the literature, identify a link between forward curve's steepness and the short-term crude oil supply. The implications for the market of changes in the forward curve can be significant. Forward prices rising above the current spot price level can potentially alter the speed at which producers extract oil, which, in turn, can trigger a reaction throughout the entire supply chain, affecting numerous related physical and financial markets and activities.

The second empirical chapter investigates the impact of the relative strength of the economic activity and distance between two countries on their net cross-border electricity flow. The effect from changes of electricity flow between two markets on the flow between another pair of markets and their market prices is also examined. The inherent need for instantaneous balance on the physical electricity market, as well as the increased connectivity between markets within the EU's Energy Union, raises important questions about the behaviour of the entire interconnected system.

I theorize that the application of Tinbergen's gravity theory of trade to the integrated EU electricity market enables better modelling of the forces behind changes in flows and prices. The results suggest that, with the exception of the French market, the reaction of the price to flow in all the markets in the study has become less pronounced over time and that the Italian, Swiss, and French electricity prices are the most responsive to changes in electricity flow. Furthermore, the outcome from the proposed cross-border arbitrage model is unambiguous, since the algorithm, which is guided exclusively by changes in cross-border electricity flows, delivers a Return on Investment (ROI) of 129.1% after adjustments for transaction costs for the sample period, or an annualized ROI of 26.3%. Further evidence is found that the ROI peaked in 2017 and started to contract since, in line with another finding of the study, that the reaction of price to flow has become less pronounced over time in numerous European electricity markets. Additionally, evidence of consistent interactions between Swiss/French and German/French cross-border electricity flows, and positive feedback between the Swiss/Italy and France/Italy flows, are documented.

I hypothesize in the third empirical chapter that the currency market is a suitable predictor of commodity price movements across different time frames because of their potential to accumulate unique information about the producers' incentives to supply the market with a commodity and consumers' incentives to purchase the required amount of material on the international market. The ability of currency markets to gather and channel forward-looking information (Van Foreest and De Vries 2003) is also acknowledged.

The results provide evidence that the currency market possesses predictive power over the price of commodities. Furthermore, the evidence suggests that the currencies of importers have higher explanatory power than the currencies of exporters, which is a major departure from the established consensus in the academic literature. Additionally, all commodity markets in the study are found to respond strongly to the proposed synthetic currency-based supply and demand model, which, in turn, significantly improves the explanatory power of the vector error correction model.

The contribution of the first empirical chapter is threefold. First, it establishes a causal link and constructive interference between the forward curve position and the event of a speculative supply shock. Second and, to the best of my knowledge, uniquely in the literature, it demonstrates that the responsiveness of short-term supply rises with an increase of the steepness of the forward curve slope. Third, the chapter proposes a general equilibrium model for the global crude oil market that exhibits significantly stronger explanatory power for the price of crude oil than the model that does not contain the forward curve gradient. Such findings not only increase theoretical knowledge about the way short-term supply reacts to changes in spot and forward prices, but also offer an analytical tool for market practitioners in the face of a general equilibrium model with characteristics unique to the literature.

By focusing the research on how one cross-border electricity flow impacts other flows, the second empirical chapter broadens understanding of the forces that form the supply in interconnected markets. The price of electricity is found to influence, as well as lag, cross-border electricity flow. This finding allows practitioners to exploit temporal mispricing more successfully and helps regulators address potential abuse of market positions (Gebhardt and Hoffler 2013). Furthermore, the successful application of the gravity theory of trade to the electricity market in Europe is unique in the academic and industry literature, and it paves the way for future research into how the macroeconomic data of one country are priced by the electricity market in another country within an energy union. Any mispricing identified by the proposed gravity model of electricity trade is likely to attract the attention of regulators and market participants alike.

The third empirical chapter of this thesis contributes to the literature not only by identifying the direction of causality between currency markets and commodity prices, but also by documenting the important role of exporters' currencies in commodity market price formation. The increasing complexity and variety of trade flows (Krugman 1995) in the world of global commodity trading dictate the need for a sample of currency pairs that is likely to capture more information about the forces driving these flows, which is what this study offers. Moreover, combining currency pairs of exporters and importers of commodities and thus extracting information from their joint relationships is an idea that, as far as I am aware, has not been considered in the literature. This study also offers a different perspective from the use of higher-frequency data in comparison to the relatively low-frequency monthly (Prokopczuk, Tharann, and Simen 2021), quarterly (Zhang, Dufour, and Galbraith 2014), and annual (Gargano and Timmermann 2014) data in the current literature.

Just as importantly and to the best of my knowledge, the literature lacks analysis on the difference in impacts currency markets can have on spot and forward commodity prices. To fill this gap, the study measures the differences in the reactions of spot and forward commodity prices to information contained in foreign exchange markets, which is an important empirical contribution. From practitioners' point of view, any divergence between spot and forward prices creates trading opportunities in the face of cash and carry arbitrage, as defined by Kawaller and Koch (1984) and Lien and Quirk (1984), amongst others. On the other hand, the interest of regulators is likely to be on the impact that spot prices can have on end-user prices and demand.

Part II

Empirical Analysis

3. The role of the forward curve in the formation of a speculative supply shock on the crude oil market

3.1. Introduction

Prices along the forward curve are affected by the information processed by all market participants. It is plausible to assume that many of them use the forward curve to guide their future market behaviour (e.g. Sockin and Xiong, 2013).

This chapter examines the role played by the shape and gradient of the crude oil market forward curve in the formation of a speculative short-term supply shock on the physical market.[1] Established microeconomic theory identifies the key drivers of individual producers' decisions to affect the market supply when the price dynamics for a given product provide incentives to do so. Such behaviour is based on the notion that producers are rational economic agents and their main purpose is to maximize revenue. For example and according to Leland (1972), who distinguishes between risk-neutral and risk-averse firms, the output of a quantity-setting firm tends to decline as uncertainty in demand increases. Such demand uncertainty on the physical commodity market is exhibited through the relationship between spot and forward prices.[2] This relation is in line with the conclusions of Litzenberger and Rabinowitz (1995) that expose the positive relationship between output on the oil market and backwardation. Their results suggest that producers are guided by the shape of the forward curve, make rational decisions to maximize revenue, and, therefore, adjust supply accordingly. Such action meets the definition of a speculative supply shock, as used by Kilian (2008a, 2008b). However, in spite of the numerous occasions of forward market shifting between contango and backwardation within the investigated period, Kilian does not find evidence of such shocks on the oil market.

Unlike medium- to long-term shifts in production in response to deterioration in geopolitical conditions underlying structural demand or technological developments, any short-term (e.g.

[1] In this paper, the gradient is defined as the quantity that defines the inclination, or slope, of a line or curve with respect to another line or curve. For a line defined as $y = mx + b$ in the x–y plane with angle θ, the slope m is the slope intercept of the line y, where $m = \Delta y/\Delta x = \tan\theta$.

[2] For the purpose of this paper, the terms *future price* and *forward price* are used synonymously, denoting the price of a commodity in the period t + n.

intra-monthly) changes in supply can constitute a speculative supply shock.[3] However, due to the difficulties associated with the implementation of short-term speculative supply shocks, the contemporary academic literature does not offer evidence of their existence. Such difficulties include the long investment horizon of the upstream crude oil extraction business and associated financial planning, the technological process of drilling and extracting oil, as well as the level of access to the forward market.[4] Therefore, the question put forward by this study is twofold.

First, the study examines the hypothesis that commodity producers deliberately alter the amount of output on the spot physical market due to changing price structure, thus creating conditions for a short-term speculative supply shock. This means that supply needs to increase simultaneously or briefly after the forward curve shifts into backwardation. The opposite will also be the case, that is, the supply is expected to drop with the curve moving into contango. The crude oil market is chosen under the assumption that it exhibits the necessary characteristics for the hypothesis investigation, namely, the size of the underlying physical and forward markets, storability, and the availability of reliable and comprehensive data.[5]

Second, the study explores the impact on supply of varying the gradient of the forward curve. Slope steepness is an important source of information for market expectations. The steeper the slope, the stronger the perception of spot and future market value amongst the participants, which relates to the producers' intention to alter supply in the short term. To the best of my knowledge, there has not been a study that examines the link between short-term supply and the shape of the curve and its slope steepness.

[3] Examples of medium-/long-term structural shocks include armed conflicts, reduced energy intensity, and fracking. Examples of short-term supply shocks include daily or weekly variations of production and/or inventory balance that affect the crude oil supply chain.

[4] Changes in upstream supply are difficult to achieve. First, the process of crude oil extraction is a long-term business; the investment horizon is usually measured in years or decades. Such long-term investments require predictability of cash flow. This is the reason why, historically, the majority of the crude oil production had been committed to long-term contracts. Such contracts allow for limited flexibility in terms of output. Second, a factor in the output that cannot change rapidly is the technological process of drilling, which is both a capital- and time-intensive operation. Third, easy access to the forward market could also be a reason for producers not to deliberately alter supply in the short term. In the event of prices higher than the spot market forward, a condition also known as contango, they will have the option to sell their production forward, thus locking in a favourable selling price for their product. Such selling along the forward curve, if aggressive enough, suppresses the price, and the curve returns to its 'normal state' of backwardation.

[5] Market size is considered on liquidity/price discovery grounds. Storability is an important element for price discovery. Sufficiently long time series are needed to capture different seasonal and economic cycles.

The idea that supply is influenced by the shape of the forward curve confronts the established framework of the theory of storage. One challenge to inventory theory is the increased ability and incentive of the producers to control a bigger share of the supply chain, combined with more frequent abrupt changes in supply at the origin. This is due to the fact that the theory of storage regards inventory as the main market balancing mechanism. Another challenge is successful establishment of the direction of the interaction between the forward curve and the oil supply reaction. Cause and effect are not trivial to establish in such a dynamic system. Forward curve changes on the back of many factors, not only supply. For example, increased influence of speculative money flow possesses the ability to distort the forward curve in the short-term, thus contributing to abrupt changes in the curve. Furthermore, commercials-hedging, plus hedging from financial institutions managing risk, may also affect the curve shape in specific maturities.

Therefore, positive feedback is likely to be present, since a shift in supply not only directly affects the forward pricing, but also indirectly, that is, through other price formation drivers, such as inventory, shipping, and refinery utilization. This is why evidence of bivariate causality is required before the study can advance to the next level. Furthermore, since changes in forward prices can occur as a result of other drivers, exogenous to supply, I hypothesize that the shift in the curve could cause a reaction by the producers to adjust the supply according to the new information priced by the curve. Such information is presented as four variables that are endogenous to price and exogenous to supply: the forward curve slope gradient, short-term (weekly) supply and demand, and the inventory change for the period.[6]

In my view, it is important that the proposed model include supply, demand, and inventory changes, because, even if production does not bypass inventory, only a fraction of it is recorded as such. The rest is committed contractual oil flow, which is not static and fluctuates according to contract terms and market conditions. Both the volume purchased and price can vary, since floating, or index-linked, prices are common on the market.[7] If the effort is focused only on inventory, most of the market information is lost.

[6] Weekly refinery capacity utilization is used as a proxy for short-term demand, because it represents the forces of downstream demand pull. Refineries are forced to respond quickly to changes in downstream demand because of the limited storage capacity for refined products.

[7] As of Q4 2017, the production of Organization of the Petroleum exporting Countries (OPEC) was 33,000 barrels daily (i.e. 33 mbd), with commercial stocks of 2.8 billion barrels and an annualized stock-to-output ratio of 22%. The global stock-to-output ratio was even lower. For example, the US ratio was about 3%. If the effort focuses only on inventory, most of the market information is lost. Source: International Energy Agency (IEA), US Department of Energy (DOE), BP Research.

Clearly, this is no longer bivariate relationship, and different methodology is required to examine the cause and effect signals. Therefore, a short-term vector autoregressive (VAR) model for the global crude oil market is proposed. The VAR model is used to investigate the complex interaction between all five variables (price plus four variables endogenous to price) through the introduction of a one-off structural shock to each variable and measures the reaction in terms of the magnitude, time, and duration of the dependent variables. This is why this paper spends considerable attention to examining the VAR impulse responses.

In building the argumentation to support or reject the hypothesis, I carry out three preliminary statistical diagnostic tests. The mechanical lead–lag relationship between the elasticity of supply (*Es*) and the price of oil is examined first. Furthermore, the conditions for bivariate causality between the forward curve and oil supply are investigated with the help of a lagged return (LR) test, followed by a Granger test and a test of cross-correlation on the forward curve slope. It is trivial to infer, based on the fundamental principles of economic theory that price reacts to changes in supply across all time frames. Transmission of the signal in the opposite direction, that is, price driving supply, represents a considerably more important event, particularly within the shorter, that is, intraday to intra-month time frames. Therefore, establishing the direction of causation is an important element in building the hypothesis of the study. Evidence of causality and, therefore, of a speculative supply shock is detected in all of the preliminary tests, resulting in the development of a structural model of the global crude oil market that, for the first time, allows for a speculative supply shock as a result of a forward curve shift.

Another unique proposition of the model is the weekly frequency of the time series used in the study. The econometric model employed is a vector error correction (VEC) model (VECM) that captures the joint dynamics of a set of variables, namely, the BFOE[8] physical spot price, the forward curve slope, the crude oil supply, inventories, and refinery capacity utilization. The sub-hypothesis of the study examines supply behaviour not only in relation to the binary shape of the curve, that is, contango or backwardation, but also according to its steepness.

Another trivial assumption is that the average oil producer is a rational economic agent aiming at maximizing profit. However, there are two important points to be made. First, such

[8] The term *BFOE* stands for Brent, Forties, Oseberg, and Ekofisk crude oil blends that comprise the physical Brent price.

a reaction is justified fundamentally and by OPEC only if the spot price falls below the cost of extraction, because it is difficult to alter production too often.[9] The forward curve moves from contango to backwardation multiple times within a long-term industrial cycle. This study is able to detect a speculative element in the formation of the supply shock, even if the spot price is well above the extraction cost. Second, the majority of previous studies do not find evidence of such a speculative supply shock. Their focus is on the influence of demand and macroeconomic drivers.

The results obtained from this study's preliminary diagnostic tests and the proposed VECM appear to support the main hypothesis. The results of testing the sub-hypothesis that short-term supply (*S*) impacts not only the sign of the slope of the forward curve (*X*), but also its gradient (*gradX*), confirms the key assumption of the study.

The initial argumentation behind the proposed hypothesis is based on observations of rising *Es* from 2007 to 2017. An LR test on the relationship between *Es* and the oil price reveals that the *Es* reaction is strongest four weeks after the price of oil changes. Furthermore, all three preliminary diagnostic tests imply a causal relationship between the two variables, with *X*, or *gradX*, leading *S*.

The proposed VECM for the global crude oil market examines the interactions between all five variables through the introduction of a one-off structural shock to each variable. The reaction in terms of magnitude, time, and duration of the dependent variables are measured by five sets of impulse response diagrams, which indicate that a positive shock to *gradX* results in a subsequent decline in S about three to four weeks after the shock is introduced. That said, a shock to the supply does not seem to deliver the same outcome for *gradX*. This finding is in line with evidence from the preliminary lead–lag relationship tests, which exhibited the same result. More importantly, such behaviour signals causality in the relationship between the two variables, with the forward curve leading the reaction of the supply by about four weeks.

The sub-hypothesis examines the reaction of supply to various gradients of the forward curve slope. The four-week lead time observation is consistent with previous data. More importantly, calculation of the gradient of each forcing (test in which the slope is forced to

[9] The reasons are FXelained in some detail in the Introduction. Price drops below the extraction cost are rare and usually associated with the bottom of the industrial cycle.

increase by 0.1) reveals that it steepens with the curve. Therefore, it is plausible to conclude that the supply reaction becomes stronger as the gradient of the curve increases. The direction of the response to shocks and the coefficient strength from the impulse response functions (IRFs) of the VEC test are also considered.

The results of this study suggest the existence of a speculative supply shock. Baumeister and Peersman (2013) and Kilian and Murphy (2014) however, do not find any evidence of such a shock, which is a major contradiction. The discrepancy in the results can be explained by the different frequencies and lengths of the time series used in both studies.[10] A speculative supply shock, if it arises, is more likely to be registered on a shorter time frame, which precisely is the focus of this paper. This is because a change in the forward pricing on the market requires the swift and short-lived reaction of supply adjustment by the market participants who are able to engage in such activity. Kilian and Murphy (2014) consider the existence of a speculative supply shock only in the context of producers leaving oil below ground or an inventory build-up by traders as part of an effort to speculate in anticipation of a forthcoming price increase. Furthermore, the authors do not discuss the actions of producers/traders who are able to control the supply chain to such an extent as to influence supply on short notice. Finally, the authors state that a negative flow supply shock has little to no impact on the real oil price.

This paper contributes to the literature in five ways. *First*, to the best of my knowledge, there has been no study on the interaction between the position of the forward curve (contango vs. backwardation) and direct short-term supply. The academic literature, with the important exception of Litzenberger and Rabinowitz (1995), appears to agree that such an interaction arises between the forward curve and inventory, and not between the direct supply and forward curve. It is important for market practitioners, academics, and policy makers to be able to identify the reasons for and measure the impact from a deliberate attempt to alter the supply of crude oil in the short term. The implications from changes in the forward curve in the short term on the entire commodity supply chain can be significant. Forward prices *(Pf)* rising above the current spot price *(Ps)* level can potentially change the speed at which producers extract the commodity, in this case crude oil, from the ground. This triggers a reaction throughout the entire production and the supply chain that the affects numerous

[10] The dataset used in this study is based on weekly data points, whereas the other researchers use monthly data. Furthermore, the period investigated in this study is from January 2007 to January 2017, as opposed to 2003 to 2008 in the case of Killian and Murphy (2014).

related physical and financial markets and activities. For example, hedging and borrowing become costlier when uncertainty increases. Storage costs rise as companies scramble to secure supply and increase inventory. Shipping, as one of the best examples of derived demand in the academic literature, is directly affected when the supply of oil in the physical market fluctuates. Due to the central role of crude oil and its derivatives in the manufacturing process, a higher unit cost could not only put producers in a difficult financial situation, but also cause inflationary pressure in the broader economy. Kilian (2008a) finds evidence that the Consumer Price Index peaks three to four quarters after a supply shock.

Second, an important contribution is the inclusion of the forward curve gradient in the research process. I quantify not only the binary position of the curve (contango vs. backwardation), but also its slope steepness, and I study the sensitivity of direct supply to it. I believe that this is the first such approach described in the academic and professional commodity market research literature. Evidence that the slope steepness is linked to the intensity of oil supply on the market adds to understanding the drivers behind the mechanism of short-term oil price formation. This relationship appears to be neither static nor stable. Two of the tests, namely, the lagged and cross-correlation tests, display a pattern of long periods of positive causality followed by periods of weak or non-existent causality.

Third, this is the first study examining short-term, that is, daily or weekly, supply shocks, as opposed to longer-term (monthly, quarterly, or annual) ones. Therefore, a weekly dataset is utilized that, to the best of my knowledge, is unique. All studies focusing on crude oil supply shocks use monthly or quarterly data. Higher-frequency data are significantly noisier, but, when handled properly from a statistical perspective, the weekly dataset yields valuable information on the changes in short-term direct supply on the physical oil market. Higher-frequency data points allow for the construction of models that capture shorter-term price fluctuations. The market practitioners are the direct beneficiaries of the improved visibility and new trading opportunities.

Fourth, through the development and introduction of a global short-term crude oil market VECM, I examine and document the dynamic interaction between supply, demand, inventory, spot prices, forward prices, and the slope of the forward curve. To achieve this in the particular time frame, higher-frequency (weekly) data are used compared to all other models, which use monthly or quarterly data points. The selection of the variables and data frequency makes the model proposed in this paper a unique specification in the academic literature.

Fifth, following the derivation of the VECM, identifying assumptions, and taking into account the first through third contributions listed above, I propose a form of short-term general equilibrium model for the global crude oil market that, to the best of my knowledge, has not been previously documented in the literature. The proposed model, of the form $P_t = gradX_t(S_t/D_t + dI_t)$, exhibits significantly stronger explanatory power for the price of crude oil compared to the model without the forward curve gradient.[11]

The remainder of this paper is organized as follows: Section 3.2 discusses the literature and attempts to identify some of the gaps and weaknesses. Section 3.3 describes the data samples, sources, and time frame selection criteria. Section 3.4 presents the methodological framework of the hypothesis and defines the hypothesis. Section 3.5 describes the results. Section 3.6 discusses the robustness of the proposed VECM of the global crude oil market. Section 3.7 concludes the paper.

3.2. Literature review

The main hypothesis of the study, discussed in the previous section, stipulates that change in the forward curve for crude oil influences the decisions of many producers and traders to not only accumulate or liquidate inventory, but, more recently, also extract oil from the ground and export it. This part of the study reviews the relevance of academic publications to the hypotheses of the study and highlights the flaws or gaps in these works.

The academic literature covers in detail the relationship between the forward curve and inventory. For example, the founding papers of Kaldor (1939), Working (1948), Telser (1958), Brennan (1958), and Johnson (1960) and more recent work by Pindyck (2001, 2004) and Routledge, Seppi, and Spatt (2002) have all revealed a great deal about the characteristics of the forward curve and the interactions between physical and forward markets. These papers all regard inventory fluctuations as the main expression of volatility. This is based on

[11] In this equation, p is the price of oil, S is the supply, D is the demand, $gradX$ is the gradient of the forward curve, and dI is the change in inventory levels

the premise that readily available stocks allow the holder of inventory to respond quickly to changes in supply and demand and thus avoid disruptions in the manufacturing process.

Kaldor (1939), Working (1948, 1949), and Telser (1958) stipulate that, during normal conditions (i.e. the market in equilibrium), the carry cost defines the relationship between spot and forward prices. However, in times of scarcity, the forward curve shifts into backwardation, and the yield on inventory should substitute for the cost of carry in the relationship. These authors have also established the link between volatility, inventory, production, consumption, and the price of commodities. Kaldor (1939), in particular, has suggested that the spot pricing of a commodity with a perfectly elastic storage supply is a function only of speculation. The author goes further to state that speculation has no impact on the spot price of commodities with no storage ability. Working (1949), on the other hand, suggests that, as inventory rises, volatility declines and the price increases. Therefore, as the price rises, volatility must decline.

More recently, Deaton and Laroque (1992), Ng and Pirrong (1994), Pindyck (2001), Geman and Ohana (2009), and Gorton, Hayashi, Rouwenhorst (2013) have contributed to understanding the dynamics between spot and forward pricing, the shape of the forward curve, volatility, and inventory changes. They have established that the implied return of the inventory, also known as the convenience yield, is a measure of the future scarcity of the commodity and, therefore, links the inventory level to the future spot price. All these studies consider volatility to be an inverse function of inventory, if the inventory level is below its long-term mean. If the inventory is above its long-term mean, the relationship becomes positive. Therefore, volatility is believed to impact the market variables through inventory changes. Pindyck (2001) goes further, stating that price volatility is positively correlated with the volatility of consumption and production. This result, in turn, puts upward pressure on the price of the commodity itself. The convenience yield should then also rise, which leads to further accumulation of inventory and continuous upward price pressure.

This result is not what has been observed on the global crude oil market in the last seven years. The market conditions observed are displayed in Figures A2 to A4 of the Appendix. Demand continued to rise at a steady rate of about +2% per year, but the volatility of price declined (see Figure A2 of the Appendix). Furthermore, contrary to the theoretical framework described above, the price of oil peaked in 2008 and has only declined since. Initially, the decline was gradual, but the momentum accelerated mid-2014 onwards. This led to a drop in the convenience yield, which was also supposed to increase with the price. A higher convenience yield theoretically leads to stronger incentives to accumulate inventory. In practice, as the convenience yield declined, inventories increased (in nominal terms, not as a share of production). This result is displayed in Figure A4 in the Appendix. Therefore, the diminished role of inventory as a market balancing mechanism represents a weakness in the methodology that appears to be overly reliant on the theory of storage. Furthermore, this reduced influence of inventory has the potential to amplify the impact that any short-term change in upstream supply could have on the overall price discovery and volatility.

Numerous studies, beginning with a founding paper on the topic by Keynes (1930), followed by more recent works by Kolb (1992) and Litzenberger and Rabinowitz (1995), assume that backwardation is the normal condition for forward commodity markets. The term *normal* was even introduced by Keynes in his book *A Treatise on Money*. In essence, theory suggests that, first, the future price at time t (P_{ft}) is less than the expected future price (EP_{ft}) and second, P_{ft} should increase to match EP_{ft} at the time of explanation. This idea, also known as convergence, is based on the premises that, to exclude a risk-free trading opportunity in a risk-neutral economy, futures price needs to equal the spot price upon maturity of the contract. Backwardation, in turn, is linked by the theory of storage to low levels of inventory. For example, Symeonidis, Prokopczuk, Brooks, and Lazar (2012) study the prices of 21 commodities from 1997 to 2011 and analyse their volatilities as predicted by the theory of storage. Their findings confirm that the relationship between the shape of the forward curve and the level of inventory is indeed as predicted by theory; that is, backwardation implies low inventory levels. The opposite condition, contango and high inventory, also holds.

The academic literature is in agreement that an important price formation interaction occurs between the forward curve and inventory. However, the interaction between the forward curve and direct supply – the key hypothesis of this study – is discussed significantly less frequently in academic publications. One particular study, by Litzenberger and Rabinowitz (1995), addresses the link between backwardation and oil supply. One of their findings, namely, that production occurs only if the forward curve is in backwardation, is tested in this paper. Although the results largely confirm their statement to the extent that production is adjusted when the forward curve position shifts, no evidence is found that production and, therefore, short-term direct supply to the market stop during periods of contango. Furthermore, their statement contradicts Hotelling's (1931) theory and data from recent surges in the US supply that occurred during prolonged periods of contango. Hotelling's theory states that the net price (price minus the extraction cost per unit) of an exhaustible resource will rise over time at the rate of interest. This result implies that the oil curve should not be in a form of weak backwardation, unless extraction costs increase more slowly than the interest rate. Strong backwardation is therefore possible only if extraction costs decline consistently over time. Evidence suggests that extraction costs did indeed decline over time, which can explain to some extent why production continued to increase, regardless of the state of the curve, that is, weak/strong backwardation or contango.

Interaction between the forward curve and production levels, and hence supply, is discussed by Lutz Kilian. In a paper discussing the impact from supply shocks on price, Kilian (2008a) focuses on exogenous (due to wars, civil unrest, and regional political instability) shocks to supply. More recently, Alquist and Kilian and (2010) have studied the response of production and price to changes in speculative and flow demand. Their findings suggest not only that change in speculative demand is a function of the forward supply and demand, but also that positive demand change results in increases in inventory holdings. In a later, key paper on the role of inventory and crude oil market speculation, Kilian and Murphy (2014) propose a model that allows for shocks of speculative demand for oil. They also account for the impact of such shocks on flow demand and flow supply. Their model allows for a speculative supply shock in terms of producers leaving oil below the ground, which, as they suggest, is a less common view. The authors express the speculative element of the real price of oil through changes in inventories, in line with earlier literature on the subject, discussed previously, which establishes the link between inventory and the price of the commodity.

Yet again, Kilian and Murphy (2014) do not find any evidence of a speculative supply shock for the period of their study, from 1973 to 2009. Since they dismiss the existence of a speculative supply shock, their focus appears to be on the interaction between changes in demand, both flow and speculative, with production and price. The authors conclude that the sharp price increase from 2003 to 2008 was due to a positive change in demand. This result is in line with the findings of Prokopczuk, Brooks, and Wu (2015), who argue that it was most likely that the fundamentals, such as changing expected demand for commodities or temporary supply shocks, that caused the significant price rises and falls between 1967 and 2011. Prokopczuk, Brooks, and Wu (2015) do not discuss in detail the origins of these temporary supply shocks. It is precisely these shocks on the crude oil market and one of their possible causes that I investigate with this paper.

Another paper, by Hamilton (2009), states the result that speculation can move the price on the physical market, even if there is no change in inventory. The author also suggests that certain oil producers, namely, members of the OPEC cartel, could hold back production and effectively use their oil below ground as inventory (Hamilton 2009).

Following the line of thought for the interaction between future prices and demand, Sockin and Xiong (2013) suggest that the impact of future prices on the demand flow is more important than the impact on speculative demand, as expressed by the inventory. More specifically, the authors build on the premise that, in the presence of information friction and assumed production complementarity, an increase in forward prices indicates strong underlying flow demand, which, in turn, has the potential to induce even stronger demand. The authors also caution against putting too much emphasis on the role of inventory as a metric for speculative demand.

Relevant to my hypothesis, Baumeister and Peersman (2013) examine the reasons for the systematic increase in the volatility of price at the time of a decrease in the volatility of the supply of crude oil. Their key argument is that the short-term price elasticity of both supply and demand has decreased since the mid-late 1980s. One reason for the apparent lack of confirmation of the reality of speculative supply in the crude oil market, in spite of the apparent conflict with the *Es* (which has been rising for the last eight to 10 years) could be the time frame selection of the studies and possibly the frequency of the data observations. All the works discussed above investigate market behaviour in the previous two to three decades and use monthly data points for supply. Speculative supply shocks, if they exist, are more likely to be evident in shorter time frames. Speculative buying, or speculative demand, is described in the literature as entities buying crude oil not for current consumption but in anticipation of a price increase (Kilian and Murphy 2014). The arbitrage opportunity window is therefore short-lived, since speculative purchases increase inventory holdings, which, as a market balancing mechanism, causes the price to correct, and close the window.

Furthermore, differences in the results so far can be explained by the different methodologies. Kilian and Murphy use a structural VAR model to explain the interaction between different variables affecting price formation on the crude oil market. They use a dry bulk freight market index as a proxy for global economic activity, inventory, demand, and supply. Their aim is to propose a model that accounts for all possible variables affecting price formation on the crude oil physical market. In contrast, I employ three different tests, each of which examines from a different angle the lead–lag relationship between two variables, namely, the short-term supply of crude oil and the position and gradient of the forward curve.

Another reason for the different results could be that the academic studies I identify are built around the concept of product push. In brief, product push is a supply chain behaviour based on the forecast producer demand for the commodity. Product pull, on the other hand, is based on the actual consumer demand. In the last 10 to 15 years, globalization, combined with improved infrastructure in key exporting and importing regions and pressure on suppliers and traders to optimize and reduce the cost of delivering goods to the end user, has resulted in supply chains stretched for raw materials. According to Christopher (2011), one of the biggest challenges for producers today is the need to respond to ever-increasing levels of volatility in demand. The concept of product push (products manufactured in anticipation of demand) versus demand pull (demand driving product towards the market) is also discussed in detail in the above-mentioned papers.

The concept of product pull has been prevalent in recent years, as discussed by Christopher and Towill 2001. This is not a static condition, and there are, of course, times when producers return to the old product-push system. This can be observed particularly during periods of price/market share wars or prices holding above their long-term averages. One example is OPEC's decision to continue increasing production in its attempt to drive shale oil producers out of the market when the global crude oil market was already oversupplied (2014–2015). Another example is the cartel's decision to reduce supply to stabilize the price in November 2016. Both occasions can be described as product-push interventions.

More importantly, commodity supply chains appear to switch from one mode to the other under a pricing pressure. According to Simchi-Levi (2011), supply chains evolve with market cycles. The author argues that, as the price of oil increases, supply chains shift from just-in-time delivery to systems with better use of transportation capacity through economies of scale. This shift, in turn, leads to the accumulation of greater inventory along the supply chain as both safety stocks and transported lot sizes increase. The author concludes that the greater importance of economies of scale in trading the commodity leads to a higher value of aggregating demand, which, in turn, increases the importance of managing the supply based on long-term forecasts. This scenario represents a push-based strategy. The opposite will also be the case, since a low oil price is likely to reset the supply chain into product-pull systems, implying agility in the response to a challenging price environment.

As a result of the progress of globalization in recent years, the shipping industry is now more closely linked to the global commodity supply chain than ever (Ekawan, Duchêne, and Goetz 2006). Any market that trades based on cost, insurance, and freight (CIF) indicates that shipping is already closely integrated within the supply chain. However, similar to other approaches linking forward prices to changes in inventory, shipping market research has been predominantly focused on the shipping market's reaction, both physical and financial (Stopford 2008, Beenstock and Vergottis 1989, Kavussanos and Visvikis 2011). A gap in the literature therefore becomes obvious that relates specifically to the lack of understanding of how producers adjust output and sales from the origin based on signals from the forward curve, regardless of changes in inventory at the origin or the seaborne shipping market.

In addition, such findings would open the road to studying in greater detail new developments in global commodity trading, namely, changing patterns in price formation and volatility, as well as positive feedback between "Free on Board" (FOB) and "Cost, insurance, Freight" (CIF) pricing points.

3.3. Hypothesis development

Academic research is focused mainly on the key role of inventory in the market pricing mechanism and largely ignores the possibility of deliberate changes by producers in short-term supply due to changes in price. For example, the implied return of inventory, that is, the convenience yield, is a common measure of the future scarcity of a commodity that links the inventory level to the future spot price. A carry trade is another example of how inventory is seen to play a key role in the balancing mechanism between supply and demand.[12]

Such overreliance on the theory of storage to explain the price has a weakness, since evidence of a diminished role of inventory as a market balancing factor has been found in recent years.[13] It is plausible that, as the share of stored oil from the total volume consumed globally declines, a larger change in inventory is required to have the same impact on price. Since the academic literature regards inventory as the key market balancing mechanism and the main expression of price uncertainty—see the work of Kaldor (1939) and Working (1948, 1949), or, more recently, Deaton and Laroque (1992), Ng and Pirrong (1994), Pindyck (2001), and

[12] A carry trade for commodities is defined by the following relationship between the return and carry: $R_c = C_s/Q*P_s) - C_o$, where C_s is the cost of storage, Q is the quantity stored, P_s is the spot price, and C_o, is the opportunity costs (risk-free return).

[13] See Figure A1 in the Appendix.

Gorton, Hayashi, Rouwenhorst (2013), amongst others—this is a development that can directly affect the price formation of crude oil. Furthermore, the reduced importance of inventory has the potential to amplify the impact that any short-term change of upstream supply could have on the process of price discovery and volatility. In addition, I consider overreliance on inventory to be a weakness in the market equilibrium framework, because of the low stock-to-output ratio of both OPEC and key non-OPEC oil producers discussed earlier. Such numbers suggest that overreliance on inventory fluctuations leaves a significant portion of trade flows unexamined.

Anecdotal evidence[14] suggests that sudden changes in the forward pricing structure of crude oil lead to subsequent changes in production, inventory, and exports and, therefore, shipping patterns. Attempts of crude oil producers to expand supply during times of high spot prices and reduce it when forward prices are higher can be considered to be logical, market-based behaviour. Such variations in supply should theoretically optimize the producer's revenue, since the aim is to sell as much volume as possible at the highest available price. Furthermore, a high market share controlled by relatively few producers makes the crude oil market prone to attempts to profit from changes in output.[15]

Another reason to attempt to adjust the supply based on a changed price environment can be the interaction between the price of the commodity and the supply chain itself. Global crude oil supply chains vary in type from product push, where the supply is based on that forecast by producer demand, to product pull, where the supply is based on actual consumer demand. However, according to Simchi-Levi (2011), supply chains are not static but evolve under crude oil price pressure. The author argues that, as the price of oil increases, supply chains shift from just-in-time delivery to systems with better use of transportation capacity through economies of scale and higher safety stock levels, and hence an increase in inventory. Simchi-Levi concludes that a stronger accent on economies of scale in trading leads to greater value in aggregate demand, which, in turn, increases the importance of managing the supply based on long-term forecasts. This represents a push-based strategy. The opposite will also be

[14] The idea that some oil producers might be able and willing to adjust output in the short term in reaction to changes in the forward curve came through my work as head of research for an energy trading firm in London. I observed such efforts on numerous occasions. Using lead–lag tests, I attempted to quantify the frequency of the changes and the effect on the overall supply chain for crude oil, which were all pointing towards deliberate attempts to adjust supply in the short term.

[15] According to the DOE, as of January 2017, the market share of the OPEC cartel was 34% of the total global oil output. The concentration of market share was also high amongst non-OPEC members, where, according to BP Plc, Russia and the United States hold a combined market share of 25% of the total global crude oil output.

true, since a low oil price is likely to reset the supply chain to product-pull systems, implying agility in response to a challenging price environment.

Last but not least, there is evidence that the *Es* – the traditional metric for the responsiveness of supply to changes in price – has been rising steadily since 2008–2009. The *Es* for crude oil is believed to be low in the short to medium term, due to difficulties in adjusting production levels at short notice. Numerous studies have been published over the years confirming this. For example, in a CEPS–ECMI Task Force paper, Valiante (2013) discusses the influence of the financial markets on the price formation of the physical markets[16]. The author argues that the *Es* on the oil market is usually low due to long authorization procedures, seismic exploration, and building the required infrastructure for oil extraction. Valiante concludes that, in the short-term, the *Es* and the elasticity of demand (*Ed*) are very rigid and that the crude oil market is supply-side inelastic. In addition, Cavallo, Caldara, and Iacoviello (2019) argue that the short-term *Es* for crude oil is around 0.1, that is, very low. A similar view is expressed by Krichene (2002) who proposes a global model for the crude oil and natural gas markets. Data from the last 10 years suggest that the trend is changing. The *Es* and *Ed* for crude oil based on IEA supply data and BFOE spot prices reveal that the short-term *Es* does not decline within the observed period (January 2007 to February 2017; see Figure A11 and Tables A1a&Ab in the Appendix). Instead, the *Es* increases steadily from 0.03 in 2007 to as high as 0.23 in 2017, which represents a significant departure from the long-term mean.

Bearing in mind the above arguments – namely, the high concentration of pricing power on the crude oil market, the transformation of global crude oil supply chains between product pull and product push under price pressure, the diminished role of inventory as a market balancing mechanism, the steady increase in *Es* over the last 10 years, and simply the improved agility of producers and their desire to maximize returns – I hypothesize that some producers are likely to respond to changes in the forward price environment not only by accumulating or liquidating inventory but, more recently, also by adjusting in the *short term* their output and sales on the spot physical market. Such a reaction is described in the academic literature by Kilian and Murphy (2014) and Baumeister and Peersman (2013) as a speculative supply shock, but these authors do not find any evidence of such shock, which is a major contradiction with the main hypothesis of this study.

[16] CEPS stands for Center for European Policy Studies. ECMI stands for European Capital Markets Institute.

In a study relevant to the hypothesis developed in this paper, Litzenberger and Rabinowitz (1995) argue that crude oil is produced only if the discounted futures price is lower than the spot price, a condition also known as backwardation. Their statement contradicts Hotelling's (1931) theory and data from the recent surges in the US supply that occurred during periods of contango. This paper demonstrates that the volume of supply is influenced by the switch in direction of the forward curve. Furthermore, the paper reveals that the strength of the forward curve slope, as measured by the slope gradient, matters for the crude oil made available to the market. However, there is no evidence to support the claim of Litzenberger and Rabinowitz (1995) that the supply of oil increases only if the backwardation is strong enough. It is plausible to assume that production will occur regardless of the forward curve condition (backwardation vs. contango) and that it will depend on the economics of extraction, that is, whether the spot price is above the break-even price of extraction.

Furthermore, a series of papers by Kilian in 2008, 2010, and 2014 investigates the impact from supply shocks on price. The author focuses on exogenous (due to wars, civil unrest, regional political instability) shocks to supply, as opposed to deliberate – also known as speculative – supply shocks. More recent work by Alquist and Kilian (2010) studies the response of production and price to changes in speculative and flow demand. One of the findings establishes a link between changes positive demand and increases in inventory. Furthermore, in a key paper on the role of inventory and crude oil market speculation, Kilian and Murphy (2014) propose a model that allows for shocks of speculative demand for oil. Their model allows for a speculative supply shock in the form of producers leaving oil below ground. The authors express the speculative element of the real price for oil through changes in inventory, which is in line with the literature.

None of the papers discussed above offers evidence of a speculative supply shock, which contradicts the main hypothesis of this study. A speculative short-term supply shock in response to a shift in the forward curve represents a major challenge to the physical and financial sectors of the oil industry.[17] The physical market is likely to become more volatile

[17] The paper focuses on the crude oil market because it is the largest commodity market in the world, in terms of both physical metric tonnes moved and financial derivatives traded on/off exchanges (see *Resources & Energy Quarterly*, March 2017, Department of Industry, Science, Energy and Resources, Office of the Chief Economist, Australian Government). Crude oil plays a vital role in the manufacturing process and the price formation of myriad finished goods. The share of crude oil and oil products in terms of the US dollar value of the global gross domestic product has remained stable at around 7% for the last 10 years. This share is by far

as crude oil availability changes more rapidly and at short notice along the supply chain. The supply chain includes both inventory and shipping markets, which are well placed to detect such stress, in a first-order reaction. It is reasonable to assume that, as a result of the stress on the physical market, the financial market will also attempt to price in the new underlying conditions. This, in turn, creates not only trading opportunities, but also a positive feedback loop involving the crude oil forward curve.

3.4. Data, sources, and time frame selection criteria

This study aims to examine the link between the direct supply of crude oil on the physical spot market *(S)*, the shape *(X)*, and gradient of the forward curve (*gradX)*. I hypothesize that a lead–lag relationship between the short-term direct supply and forward prices, as defined by the market forward curve, can be detected and quantified. The detection of a lead signal for *X* over *S* would imply producers' deliberate attempt to adjust the supply, that is, the introduction of a speculative supply shock to the market.

3.4.1. Data sample

The study is performed using just over 10 years of data, with 2,719 physical crude oil market orders to sell specified amounts of barrels of oil, also known as tenders, converted into 517 weekly data points. Tender on any physical commodity market is defined as an invitation to submit an offer for the purchase of a certain volume of the commodity. It involves a physical transaction, usually carried out under the terms of the International Chamber of Commerce (Incoterms), where the producer offers to sell a certain volume of crude oil to a buyer. The tender normally specifies the volume, origin, and date of the transaction, the date of loading, and the price. Therefore, the oil supply time series used in this study comprise tenders submitted to the physical markets by crude oil producers. For the purpose of the study, I define supply as the number of barrels in the daily crude oil tenders of 147 crude oil producers over 10 years, from 1 January 2007 to 28 February 2017. The sample of 147 different producers represents 82% of all sellers (180) of crude oil who appeared on the physical spot market in the last 10 years.

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the largest amongst all other commodities. Oil is also unique in terms of its applications in the real economy. No other commodity has more diverse applications. It is used to produce numerous types of fuels for the transportation sector, as a fuel to produce electricity, and as a key ingredient of plastic materials.

It is important to clarify that the data sample I work with is not the entire supply of crude oil available on the physical market. As noted in the Annual Statistical Review of World Energy of BP Research (2016), cross-border oil exports (seaborne plus pipeline) in 2015 amounted to 61.22 mbd, or 67% of the total production of 91.67 mbd. However, cross-border exports do not necessarily mean that all this volume is traded on the spot market. The majority of the crude oil transacted on the physical spot market is committed volume, under some form of contract. Such oil will be produced and exported, regardless of market conditions. My hypothesis, however, is built around the reaction of the marginal volume in the market when conditions incentivize it to do so.

According to the same BP annual report, the total annual trade movement in 2010 was 54.37 mbd. The sample I work with for this particular year is about 1.44 mbd, which represents 2.65% of total oil shipments. Such a sample could appear small, but it compares well with the share of the spot physical trade flow published by Fattouh (2011) includes information about the key crude oil benchmark production volume, the spot traded volume per benchmark, total oil exported, and my sample.

Table 1: Production and spot-traded volume of major crude oil benchmark baskets

This table compares the volume of crude oil production, the volume traded on the spot market, and the sample of major crude oil benchmark baskets used in the study. Source: Fattouh (2011), BP Research (2016).

Unit: ×1,000 bpd	ASCI[18]	WTI	BFOE	Dubai	Total (benchmarks)	Total (global)
Spot-traded volume (2010)	579	939	1,149	332	2,999	2,999
Sample of this study						1,436
Sample as the share spot traded						47.88%

3.4.2. Data sources

A number of data sources have been used in the hypothesis development process, including third-party data and data proprietary to Marex Spectron Research. For example, the *Es* and *Ed* were calculated with IEA data for the global crude oil demand and supply. The price time series comprise the spot *(Ps)* Brent price and weekly averages of the end-of-day closing prices of the Brent forward curve. The source for the Ps is Bloomberg (code EUCRBRDT Index). The source for the forward prices is ICE.[19] The spot market crude oil supply data comprise 2,719 physical crude oil market tenders by 147 oil producers. The dataset is a mix between tender data compiled by Bloomberg (function OTEN) and forward crude oil loading

[18] ASCI stands for Argus Sour Crude Index, WTI is West Texas Intermediate
[19] ICE stands for Intercontinental Exchange

schedules data proprietary to Marex Spectron Research. The crude oil inventory data are from Satellite Automated Identification System (AIS) and the US Department of Energy, and the units are in barrels. The source of the refinery capacity utilization data is the DOE, as the percentage of operating capacity from the total installed.

3.4.3. Time frame selection criteria

The duration of the period investigated in the paper (week 2 in 2007 to week 8 in 2017) ensures that different periods in the long-term investment cycle of the crude oil market are taken into account. For example, the crude oil market was well balanced from 2010 to the first half of 2014 and has been strongly out of balance (oversupplied) since mid-2014. See Figure A5 in the Appendix for a direct illustration of the historical supply and demand balance conditions. This finding is important, because market participants, including producers, change production and trading patterns according to the market cycle. The literature review section already mentioned that OPEC occasionally attempts to control the global prices of crude oil by adjusting output. This normally happens when the price drops below the break-even oil price required for OPEC's budgets (the so called fiscal budget oil prices published by the International Monetary Fund for each oil producer). The selected time frame also includes the problematic 2008–2009 period of abnormally high price volatility and contraction of production and trade due to trade finance issues, rather than a structural shift in demand.

Last but not least, the nature of speculative activity was taken into account when choosing the weekly frequency of the data sample. It is argued in the literature review section that speculation is likely to be a short-term/short-lived activity. Therefore, evidence is likely to be found with higher-frequency data points, not with the monthly – let alone quarterly or annual – data points used in the academic literature.

3.5. Methodological framework

The forward curve is the term structure of the forward market. It displays at a glance the value of each contract as it changes in time. Valuable information can be derived from the shape of the curve *(X)*, that is, contango versus vs. backwardation, and, regardless of the slope steepness *(gradX*), in relation to the production and exports of crude oil *(S)*. Since the slope is defined as the inclination of a line with respect to another line, for a Cartesian plane curve specified as y(x), the slope is $gradX = (dY)/(dX)$, where dX and dY are the changes in the two coordinates, x and y, respectively. The slope intercept form of a line in the Cartesian plane is given by $y = mx + b$, where b is the y-intercept and m is the slope. The reaction of producers linked to X or $gradX$ would imply that they adjust the exported volume S according to the forward price they are likely to receive for their product. Such a relationship between the forward curve and export flows, if confirmed by rigorous statistical testing, would imply a speculative supply shock, which forms the main hypothesis developed further in this chapter. Temporal precedence, covariance, and a lack of plausible explanation for the relationship between X and S, as discussed at the end of the literature review, are all conditions necessary for causality.

In constructing my argumentation in support (or rejection) of the study's hypothesis, I carry out three preliminary statistical tests. Each test aims to establish a possible lead–lag relationship (causality) between the oil production/supply and change in the forward curve. The hypothesis is further tested by the proposed econometric model in the form of a structural VAR model that studies the joint dynamics of a set of variables. The variables used in the models are as follows:

1. The BFOE physical spot price *(Ps)*, representing the temporal equilibrium between supply and demand;
2. The forward curve slope, or gradient ($gradX$), which is the variable tested by the study's hypothesis;
3. The weekly crude oil supply *(S)*, which represents the short-term physical market supply of oil;
4. The weekly change in inventories *(dI)*, regarded here as an important market balancing mechanism and therefore expression of the price; and
5. The weekly refinery capacity utilization, used as an expression of oil demand *(D)*.[20]

While it is known that the price is a function of the balance between the weekly supply *(S)* and the weekly demand *(D)* and the inventory *(dI)* is the balancing mechanism between the two, I test how inclusion of the form (contango/backwardation) and the slope of the forward curve interact, first, with the supply and, then, with the remainder of the variables in the dynamic system. This is done with the help of the forward curve gradient, or $gradX$.

[20] The weekly refinery capacity utilization is used as a proxy for short-term demand, because it represents the forces of downstream demand pull. Refineries are forced to respond quickly to changes in downstream demand because of the limited storage capacity for refined products.

The vast majority of academic papers involving the crude oil forward curve apply the exchange-traded forward curve; that is, Ps is not included in the forward curve formation. I consider this to be a weakness in the approach, because the difference between the spot physical price and the first forward contract can sometimes be significant. This means that, if Ps is not taken into account, the forward curve slope steepness will be different. In the case of this particular study, the inclusion of the spot Brent price is even more important, because the focus of the investigation is on the relationship between physical oil flows and the forward curve, and not between financial flows and the curve.

Furthermore, the forward curve price formation mechanism is a function of the spot, forward, and future crude oil prices. The methodology of the calculation of the price of crude oil (Brent) requires clarification, because, as mentioned above, the spot (dated) and forward Brent prices include layers of physical, forward, and future prices. The contract that links the futures Brent and the forward Brent is the exchange of futures for physical. Price reporting agencies rely on the exchange of futures for physical to derive the forward Brent price (Fattouh 2011).

The Brent futures prices and exchange for physical prices (P_{ext}) for a particular month allow the identification of the forward Brent price for that month, as follows:

$$P_{fwt} = P_{ft} + P_{ext} \qquad (1)$$

Where: P_{fwt} is the forward Brent at time t, P_{ft} is the futures price at time t, and P_{ext} is the exchange for physical at time t.[21]

Once the forward Brent price is calculated, the dated Brent price can be calculated. The dated Brent price is important to the overall process of price discovery, because it is considered to be the spot price for the commodity. It is therefore required, in order to reflect as closely as possible the conditions on the physical market. In this study, the dated *(Ps)* Brent price is important because it is inseparable from the forward curve. The price of the forward dated Brent *(Pf)* is calculated with the help of another layer, the over-the-counter market of contracts for differences, as follows:

[21] The standard unit of time t is one month.

$$P_{fw(db)} = CFD_t + P_{ft+2} \tag{2}$$

Where: $P_{fw(db)}$ is the forward dated Brent price, CFD_t is the contract for difference at time t, and P_{ft+2} is the forward Brent price in period $t+2$.

With the spot oil price information now available, I compile the remainder of the forward curve time series based on daily observations of the ICE Brent crude oil contract. The dataset consists of daily values for the entire curve for the period from January 2007 February 2017. Since the trade data consist of weekly data points, I convert the daily forward curve time series into weekly average values. I work with averaged values, as opposed to a value in a random day of the week, to avoid distortions in the data from potential strong intraweek movements of the curve. Averaging into weekly data points also mitigates the impact on the signal of potential distortion from convergence to physical and contract expiration.

The hypothesis development process consists of four stages: data transformation, testing the mechanical causality properties between *gradX* and *S*, development, and testing and interpretation of the VAR model of the global short-term crude oil physical market and robustness checks.

3.5.1. First hypothesis development stage: Data transformation

Transformation is often necessary to stabilize the variance of the time series. This study is based on weekly data points, which will be inherently noisier, compared to lower-frequency (monthly or quarterly) data. Noise is particularly problematic for the *S* time series. The use of log-transformed data for *S* is justified by the results of the probability density function (PDF), also known as kernel density estimator, as explained by Rosenblatt (1956) and shown below:

$$f_h(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x-xi}{h}\right) \tag{3}$$

The PDF is calculated on the original time series of the weekly crude oil supply and it is displayed in Figure A6 in the Appendix. The shape of the curve is exponential, a sign of the time series being skewed towards a small number of high-value observations. The PDF calculated on the log-transformed time series produces a completely different shape, where a normal distribution/Gaussian curve can be fitted.

Furthermore, I consider only a six-week lead–lag period for the required technological reaction to potentially adjust the production and related upstream supply chain. I call this time span the impact period. Another manipulation of the data involves the removal of the first week from each year. This is done to protect the consistency of the time series. The first week is inconsistent in terms of the number of days. It is also notoriously volatile when it comes to the reporting and registration of trade data.

3.5.2. Second hypothesis development stage: Testing for bivariate causality between the oil price *P* and the oil supply *S*

The next stage of the hypothesis build-up consists of three different tests, namely, a test for Es LRs, a test for forward curve LRs, and the signal processing Sliding Dot (Scalar) Product (SDP, or SSP) test. All tests involve bivariate descriptive statistical analysis. Their aim is to examine from different angles the lead–lag relationship between two variables and substantiate the research claim of causal relationship between the direction and steepness of the forward curve and the speculative supply of crude oil. The reason these tests are proposed in the paper is because long sampling periods can potentially conceal causality. This is logical, because causality is not a static process. Therefore, and to detect and isolate any potential causal period within the entire period of the study, I propose tests that are able to measure the evolution of causal relationship between two variables.

Establishing cause and effect between two events/variables (forward curve and direct supply) is not an easy task. True causality is a debated concept in the academic literature. According to Bryman (2012), three criteria, if met, potentially signal causality. First, there needs to be temporal precedence. This is why I consider using LR tests as a preliminary procedure in building the hypothesis. The second condition is of the cause X ($gradX$) and effect, or S. Initial tests reveal such covariation with a negative sign; that is, when the forward curve slope is positive (contango) and it steepens, the supply of oil declines. The opposite will also be true. Third, there should not be a plausible alternative explanation for the relationship between the two variables. There is sound economic logic behind the decision of each individual producer to change the supply of crude oil on the spot market if the market itself incentivizes the producers to do so. Oil producers are economic entities whose main purpose is to maximize revenue. According to established microeconomic theory, a competitive and rational profit-maximizing firm will have an output where the marginal revenue equals the marginal cost. It is also established that such a firm will have a flat marginal revenue curve equal to the market price. This implies that the output of a competitive firm will have a marginal cost equal to the market price. Therefore, acting otherwise would contradict this basic microeconomic relationship. According to Leland (1972), the introduction of uncertainty in the short term does not affect the decision of a price-setting risk-neutral firm with a constant marginal cost.

It is possible for some entities to act against their own interests, but this is likely to be temporary development, rather than a consistent effort. In other words, I am not able to propose any other plausible explanation for what appears to be truly free market behaviour, where producers are incentivized to alter the supply if forward market conditions dictate that this is in their best interests.

3.5.2.1. *Es* LR test

In building the argumentation of this study, I calculate and analyse the price Es and price Ed. These measures are based on the following well-established (e.g. Samuelson and Nordhaus 2001) relationships:

$$E_s = \frac{\left[\frac{(Qst2 - Qst1)}{|Qst1|}\right]}{\left[\frac{(Pst2 - Pst1)}{|Pst1|}\right]} * 100\% \tag{4}$$

$$E_d = \frac{\left[\frac{(Qdt2 - Qdt1)}{|Qdt1|}\right]}{\left[\frac{(Pst2 - Pst1)}{|Pst1|}\right]} * 100\% \tag{5}$$

Where: Q_s is the quantity supplied, Q_d is the quantity demanded, and P_{st} is the spot price of oil at time t.

The LR test carried out for E_s and the oil supply (S) is performed by shifting the two time series by one period at a time:

$$Es_t = \frac{dS}{P(_t)}, \ldots, Es_{(t,n)} = \frac{dS}{P(_{t-n})} \tag{6}$$

Where: for $n = 1, \ldots, 6;\ t = 1, \ldots, T,\ T$ is the length of the time series; E_{st} is the Es return for period t lagged by n; the change in oil supply between two periods $dS = S_t - S_{t-1}$; and P_t is the price of crude oil at time t.

The results of this initial test raise an important question about the sensitivity of the crude oil supply to its price, and more detailed research is required to determine the role of the price of crude oil in the reaction of supply.

3.5.2.2. Test of the forward curve versus supply LRs

This second test (Test 2) aims to establish a link between the forward curve position, contango or backwardation, and crude oil availability on the physical market. The economic logic behind the decision of each individual producer dictates that the supply should rise if the forward curve indicates that future prices will fall (forward curve in a state of backwardation), and decline if the curve is in contango (price indicated as being higher in the future than today). This test is carried out in four steps, as described below.

First, the binary conditions +1 and -1 are used to define the prevailing state of the forward curve for each particular week. These preset conditions are as follows:

If $P_s < P_f 1, \dots, 6, \text{then } +1 \text{ (contango)}$

If $P_s > P_f 1, \dots, 6, \text{ then } -1 \text{ (backwardation)}$

where Ps is the spot price and Pf1, …, 6 are the prices for six term contracts

This approach allows me to quantify and standardize 18,900 data points (5 days × 7 contracts along the curve × 540 weeks). It also provides the opportunity to introduce conditional formatting later in the study. The result is a continuous time series that indicates the position of the forward curve for each week.

Second, using the oil supply data, I calculate the week-on-week difference in the crude oil supply on the physical market:

$$\Delta S_t = S_t - S_{t-1} \qquad (7)$$

Where: S is the oil supply, t = (1,..., 513), and ΔS_t is the week-on-week difference in the oil supply.

Third, I introduce a conditional function that allows a comparison of the change in supply (Δ) and the change of the forward curve. The function covers six periods forward that is, six weeks, shifting the periods at each step. The pre-set rule searches for periods when the forward curve in week x is in contango and the availability of crude oil that particular week declines.

For i = (1,…, 6), then

$$Xt(i) = \begin{cases} \frac{Xt-i}{\Delta St} > 0 \rightarrow Zt = 1 \\ \frac{Xt-i}{\Delta St} < 0 \rightarrow Zt = 0 \end{cases} \tag{8}$$

Where: X represents either contango, or backwardation, ΔS_t is the change in supply, and Z is a binary test variable.

The data are simultaneously tested for the opposite conditions, where the market is in backwardation and the shipments increase. If any of the two conditions are met, the formula returns the value of one. If the two variables move in different directions, the formula returns the value of zero. This step is vital for the final outcome, since it reveals coincidental moves between the two variables.

Fourth, the statistic of the derived outcomes is calculated. The aim of this step is to detect how many positive and negative matches between the change in the forward curve and the change in production are obtained in total, as follows:

$$Pft = \frac{1}{n}\sum_{i=1}^{6} Pfi \tag{9}$$

The success rate represents the share of positive matches, which should confirm the validity of the argument. The logical threshold here is 50%, since any result equal to, or lower than 50% indicates a random occurrence. In other words, a threshold is necessary to differentiate between chance and a deliberate reaction.

3.5.3. Sliding Dot Product (SDP) test

The SDP test (Test 3) employs elements from the methodology of the test described in 3.5.2.2 (Test 2). I again reinvestigate the interaction between the binary positions of the forward curve (contango vs. backwardation) with oil production, but I also include a condition for the steepness of the slope of the forward curve.

To the best of my knowledge, there are no academic papers discussing the steepness of the slope of the forward curve in the context of a deliberate short-term change of production. Measuring the steepness of the forward curve and translating it into a possible short-term supply reaction is an important part of this study. I expect the slope steepness to potentially disclose valuable information about the urgency at which producers adjust the supply on the spot physical market. The key assumption here is that the steeper the slope of the curve, the stronger the incentive of producers to react.

At the start, I expand on the dataset created for Test 2 and I calculate the slope of the curve with ranges $P_{s\,t+1}$, $P_{f\,t+1}$, ...,$P_{f\,t+6}$, where $P_{s\,t}$ is the Brent spot, $P_{f\,t+1}$ is the Brent first-month future contract, and so on, until P_{t+6}, the Brent sixth-month future contract.

The methodology used in Test 2 cannot be applied directly in this case, since binary outcomes are required from both variables, namely, the forward curve *X* and the oil supply *S*. The weekly change in supply remains a binary outcome, since it either increases or decreases, but the slope steepness cannot be simplified in the same way as the position of the forward curve. This statement is based on the fact that the position of the forward curve is in either contango or backwardation. The steepness of the slope, on the other hand, has infinite positions, since it can go from infinitely positive, through the special case of neutrality (zero), to infinitely negative slope.

Test 3, instead, involves a bivariate descriptive statistical analysis of the evolution of the cross-correlation between *X*, or *gradX*, and *S*. By measuring the cross-correlation in different time frames, I attempt to quantify the lead–lag effect between *gradX* and *S*.

The SDP test is implemented using readily available time series for *gradX* and *S* from the previous tests, followed by calculation of the cross-correlation for the six lead and lagged periods, where each period represents one weekly observation.

Define $P[x, y]$ as the Pearson correlation of two time series x and y, where x is *gradX* and y is *S*. The cross-correlation times series consists of three different functions, *CCp*, as the positive correlation coefficient; *CCc*, as the coincidental correlation coefficient, and *CCn*, the negative correlation coefficient. Therefore,

$$CCn_{(t,\tau)} = P[x_{(t-\tau)}, y_{(t)}] \tag{10}$$

$$CCc_{(t)} = P[x_{(t)}, y_{(t)}] \tag{11a}$$

$$CCp_{(t,\tau)} = P[x_{(t)}, y_{(t-\tau)}] \tag{11b}$$

Where: $\tau = 1, \dots, 6$ =is the time step by which the time series are shifted, with $t = (1, \dots, 513)$ as the length of the time series.

The final correlation coefficient, on which the conclusions of the analysis are based, is the smoothed average of the first dimension t of the entire time series, namely,

$$CC_\tau = [CC_{n(t,\tau)}, CC_{c(t)}, CC_{p(t,\tau)}] \tag{12a}$$

which can be also written as

$$CC_\tau = [\sum_{t=1}^{T} CCn(\tau), \sum_{t=1}^{T} CCc(t), \sum_{t=1}^{T} CCp(\tau)] \tag{12b}$$

Where: *T = 513*.

The advantages of the SDP test approach can be summarized as follows. First, it allows for precise (up to the time unit chosen for the study; in this case, the minimum time unit is one week) identification of the lead–lag periods between the *gradX* and *S* variables. This is important for building trading strategies, since this approach accounts for better timing of the entry and exit of a position.

Second, SDP test data can be plotted in a coordinate system, for better visualization of the *gradX–S* relationship. The ideal outcome would be to record observations of lead periods clustered in the bottom left corner of the scatter plot chart. In the case of a line chart, this would involve lines starting from the bottom left corner, with negative values, trending upwards towards zero and then into positive territory. This result would suggest that *gradX* and *S* are negatively cross-correlated (forward curve with a positive slope, and lower exports) and *gradX* leads S by the number of periods observed (where each single period is one week). The advantage of such visualization is in the ability to quickly measure not only the lead–lag periods between the two variables along the x-axis, but also the strength of their lead–lag signal on the y-axis.

Third, there are periods in the data sample when the *gradX* lead property is clearly detected and displayed. However, there are also periods involving a lag in the *gradX* reaction. This result does not clash with the main hypothesis of the study, which allows for changes in lead–lag regimes. It is important to establish the existence of any long-term pattern in the *gradX–S* relationship. For example, higher conviction trades can be established when *X* exhibits clear leading properties.

To establish the timing of these switches, in step 6, I calculate the weekly average of the lead and lag observations. The result is a single weekly average number that is negative if *X* leads *S* (preferred state, according to the main hypothesis) and positive if *X* lags behind *S*. Since I am interested only in the lead characteristics of *X*, I calculate only the average of the lead periods. The next stage of the test is focused only on the periods when *X* leads *S*. I separate the periods of negative from positive observations and I plot the negative observations (those showing that *X* leads *S* by a number of weeks). This is done to isolate the exact timing of the lead reaction. The outcome for the last six months of the sample (16 September to 17 February) is displayed for the SDP test in Figure A7 in the Appendix. The exact number of lead periods is indicated on the x-axis. The value of the SDP test is indicated on the y-axis. Further information can be extracted through isolating the extreme results of the SDP test. I expect this approach to provide data on the strength of the test for each of the 513 observed periods.

The final step in the test aims to consolidate the results derived from all 513 weeks of cross-correlation returns. The outcome discussed in the previous step and displayed in Figure 6 is based on a relatively small sample of the entire dataset. More precisely, it represents 5% of the entire period. Therefore, if I want to plot the evolution of the cross-correlation for the entire period, I need to apply some generalization/averaging. The result is displayed in Fig. 8.

3.5.4. Third stage of hypothesis development: Introduction of the VAR model for the global crude oil market.

Establishing bivariate causality between the forward curve gradient X and the short-term oil supply S is an important element of the hypothesis, but the price formation is too complex to be successfully captured by such a simple relationship. More variables are necessary to explain the process; otherwise, important forces risk being omitted in the interaction between other variables related to X and S, hence the need to develop an econometric model for the global crude oil market that will test the relationship between five variables to represent the short-term supply and demand conditions on the market as described in Section 3.4 on the data. The proposed models use weekly fundamental data for the specified variables. To my knowledge, there is no study that discusses a crude oil econometric market model with such variables or time series frequency.

To avoid potentially spurious regression results, the time series of all five variables are tested for stationarity with the augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests. The initial results on levels reveal a lack of stationarity, which represents a potential flaw in the output of the VAR model. Non-stationarity is removed with the help of differencing, and the order of integration is obtained.

Stationarity is necessary, but it is not the only preliminary condition required by the VAR model. The results from VAR models are likely to be skewed if the time series exhibits cyclicality, both seasonal and non-seasonal. I test for cyclicality using a Fourier transform (FT). An FT (Lyon 2010) converts a signal from the time domain to the frequency domain. This is accomplished by the decomposition of any periodic function f(x) into a sum of sinusoidal (sine and cosine) functions, which, in turn, is represented as a complex exponential function of frequency. The noise is thus separated, and periodicity is uncovered. The FT of a function g(t) is a generalization of the complex Fourier series defined by a forward FT[22]:

$$F\{g(t)\} = G(f) = \int_{-\infty}^{\infty} g(t)e^{-2\pi ift}\,\mathrm{dt} \qquad (13)$$

Where: *F* is a forward FT, *g(t)* is the function, and *G(f)* is the spectrum (power) of the frequency *f*.

The original function *g(t)* can be obtained from *G(f)* via an inverse FT:

$$F^{-1}\{G(f)\} = G(f) = \int_{-\infty}^{\infty} G(f)e^{2\pi ift}dt = g(t) \qquad (14)$$

The process of obtaining an inverse FT is useful in reconstructing the original time series. I employ a forward FT to detect and isolate cycles of any possible length. In the event a strong and persistent enough cycle is detected, it will need to be isolated and removed, and the original signal reconstructed. The key advantage of the FT methodology in studying cycles of commodity markets is that numerous cycles can be simultaneously detected. As suggested earlier, time is transformed into frequency, which allows a detailed analysis of the cycle.

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Such an analysis involves the timing of the cycle's appearance, duration, and strength. The aim of the FT cyclicality test is to establish the length and strength of a cycle.

The bivariate Granger causality test, also known as the G-test, is applied as well, using differenced data. True causality is a debated concept in academia, and the G-test claims to find only predictive causality (Granger 1969). This is done with the help of *T*- and *F*-tests on lagged data points of *X/gradX* and the *S* variable, thus obtaining statistically significant information about the future values of *S*:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_i y_{t-i} + \beta_1\, x_{t-1} + \cdots + \beta_i\, x_{t-i} + \varepsilon_t \qquad (15a)$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_i x_{t-i} + \beta_1\, y_{t-1} + \cdots + \beta_i\, y_{t-i} + u_t \qquad (15b)$$

Where: for lag period $i = 1, \ldots, 6,$ the variables x_t and y_t are studied at time t, α_0 is the intercept, ε_t and $u_t$are the residual errors, and t = $(1, \ldots, 513)$ is the length of the time series.

When the specific variables of the test are substituted in equations (12a) and (12b), the result is:

$$St = \alpha_0 + \sum_{t=1}^{513} \alpha_i S_{t-i} + \sum_{t=1}^{513} \beta_i\; gradX_{t-i} + \varepsilon_t \qquad (16a)$$

$$gradX_t = \alpha_0 + \sum_{t=1}^{513} \alpha_i\, gradX_{t-i} + \sum_{t=1}^{513} \beta_i\; S_{t-i} + u_t \qquad (16b)$$

According to Sørensen (2005), Granger causality tests appear to be most successful in two-dimensional systems, or for a bivariate causal relationship. The author also suggests that caution should be applied when selecting the length of the sampling period. For example, a long sampling period tends to hide causality. This is logical, since causality is not likely to be a static process. This is precisely why the three preliminary tests discussed in Sections 3.2.1 to 3.2.3 are included in the study.

Since the set of variables each has unit root, ordinary regression analysis is not appropriate, because there could be one or more equilibrium (cointegrated) relationships, that is, they can have a common stochastic trend. Therefore, the time series are further tested for cointegration with the Johansen cointegration procedure. Unlike the Engle–Granger (1987) test, the Johansen test allows for testing the hypotheses of an equilibrium relationship between sets of variables.

The VAR models, first introduced in 1980 by Sims (1980), advanced the concept of modelling all endogenous variables in a system together, rather than one equation at a time. There are clear advantages to the VAR methodology over structural equation models when studying the dynamics of the relationships between numerous variables. For example, there is no need for extreme model constraints or any need to separate endogenous from exogenous variables, since all variables are considered endogenous. Furthermore, VARs are considered more flexible than univariate autoregressive models, because the values of the variables are allowed to depend on their own lag or white noise. This allows them to capture more aspects of the data. However, there appear to be doubts about the ability of VAR models to differentiate between correlation and causality (e.g. Lütkepohl 2005). These models also use little theoretical information for the underlying relationships in the data. Another downside of the methodology is that it can be hard to interpret in certain cases.

Regardless, the VAR model is useful in identifying and tracing shocks introduced to a system. This is done with the help of impulse response analysis and plots, by imposing restrictions on the model matrices. Kilian and Murphy (2014) introduce such a VAR model based on changes in oil production, the freight market (as a measure of global economic activity), the price of oil, and oil inventory, working with monthly data points for all the variables. In contrast, I use a weekly frequency time series that imposes restrictions on the nature of the dependent variables that can be used. For example, my proxy for the short-term demand for crude oil is the weekly refinery capacity utilization. Additionally, I work with the spot physical price of Brent crude oil (discussed in Section 3.1), and not with the US import price, which is used by Kilian and Murphy. My metric for short-term supply has already been discussed in Section 3.1.

The generic VAR model can be written as follows:

$$y_t = b_1 y_{t-1} + \cdots + b_k y_{t-k} + u_t \qquad (17)$$

However, for Johansen's method to be used, the model requires the following VEC form:

$$\Delta y_t = \Pi y_{t-k} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} \ldots + \Gamma_{k-1} \Delta y_{t-(k-1)} u_t \qquad (18)$$

Where: the long-run coefficient matrix $\Pi = \left(\sum_{i=1}^{k} \beta i\right) - I_g$, and $\Gamma_i = \left(\sum_{j=1}^{i} \beta j\right) - I_g, i = 1, \ldots, k-1$.

Cointegration is established by the rank of the matrix Π via the number of its characteristic roots/eigenvalues. The two tests are λ_{trace} and λ_{max}. According to the literature (Brooks 2019), differencing all the variables of the model to force them into stationarity is the correct approach for univariate models. However, if there are important relationships between the variables in the long run, such forced stationarity is seen as a weakness in the methodology. This study employs five variables; therefore, the elements of the matrix can be written as follows:

$$\Pi = \begin{bmatrix} \pi 11 & \cdots & \pi 15 \\ \vdots & \ddots & \vdots \\ \pi 51 & \cdots & \pi 55 \end{bmatrix} \tag{19}$$

Following the literature (e.g. Brooks 2015), if a cointegration relationship is established, that would imply a stationary linear combination of some of the variables. A VECM, and not a standard VAR model for first differences, is the most suitable approach for non-stationary and cointegrated time series, since it allows for both long- and short-run relationships to be captured.

In this study, the cointegration relationship, described by three cointegrating equations, is detected by the Johansen test. Therefore, since the matrix Π is defined as the product of the matrices $\boldsymbol{\alpha}$ and β`, the matrix has the following form:

$$\Pi = \boldsymbol{\alpha}\beta` \tag{20}$$

or, in the case of this study with five variables,

$$\Pi = \begin{bmatrix} \alpha 11 & \cdots & \alpha 31 \\ \vdots & \ddots & \vdots \\ \alpha 15 & \cdots & \alpha 35 \end{bmatrix} \begin{bmatrix} \beta 11 & \cdots & \beta 15 \\ \vdots & \ddots & \vdots \\ \beta 31 & \cdots & \beta 35 \end{bmatrix}$$

Once the number of cointegration relationships between all five variables (*P, gradX, S, D, dI*) in the system is established, the VECM takes the following form:

$$\Delta P_t = b_1 \Delta gradX_t + b_2 \Delta S_t + b_3 \Delta D_t + b_4 \Delta dI_t + b_5 (P_{t-1} - \gamma_1 gradX_{t-1} - \gamma_2 S_{t-1} - \gamma_3 D_{t-1} - \gamma_4 dI_{t-1}) + u_t \tag{21}$$

The residuals of the model need to be tested for stationarity, because they will be non-stationary if the variables are not cointegrated. This is accomplished with the help of ADF and KPSS tests with the null hypothesis of a unit root in the cointegrating regression residuals, or null hypothesis $H_0 : u_t \sim I(1)$.

According to Lütkepohl (2005), the optimal lag order of the model is estimated with the help of the Akaike information criterion (AIC), the Schwarz/Bayesian information criterion (BIC), the Hannan–Quinn information criterion (HQIC), as well as the final prediction error (FPE). The definitions of these criteria are as follows:

$$AIC(n) = \log det\,(\sum\nolimits^{\sim} u\,(n)) + \quad \tfrac{2}{T} n\ K^2 \tag{22a}$$

$$HQIC(n) = \log det\,(\sum\nolimits^{\sim} u\,(n)) + \quad \tfrac{2loglogT}{T} n\ K^2 \tag{22b}$$

$$BIC(n) = \log det\,(\sum\nolimits^{\sim} u\,(n)) + \quad \tfrac{logT}{T} n\ K^2 \tag{22c}$$

$$FPE(n) = \left(\tfrac{T+n*}{T-n*}\right) \det \sum\nolimits^{\sim} u(n)) \tag{22d}$$

Where: $\sum^{\sim} \boldsymbol{u(n)})$ is the total number of parameters in each equation of the model, $\boldsymbol{K}$ is the number of the model’s dimensions/degrees of freedom, and $\boldsymbol{n}$ is the lag order of the endogenous variables.

The most important difference between the criteria is the severity with which they penalize an increase in the model’s order. The motivation behind strong penalties for high model orders is to reduce over-fitting, which has an impact on the model’s forecasting ability. I employ a VAR model for reasons different from forecasting: it investigates the interaction between selected endogenous variables. More specifically, the aim is to investigate the causal relationship between the forward curve gradient and the supply of crude oil. This means that I prefer an information criterion that does not impose too strong of a penalty on the model order. According to Lütkepohl (2005), the HQIC penalizes a high model order more than the AIC, but less than the BIC. I work with the HQIC when selecting the optimal number of lags of the VAR model, also based on the size of the data sample. The consensus in the literature (e.g. Lütkepohl 2005) is that the AIC/FPE outperforms the HQIC for small samples, but the HQIC is better for bigger samples. A sign that the variables in the model are jointly meaningful is when the information criterion is different from zero.

The model developed in this paper also includes the gradient of the forward curve. It was already mentioned that valuable information can be derived in relation to the production and export of crude oil, not only from the overall position of the curve, such as contango versus backwardation, but also from the slope's steepness. By including the forward curve slope as a dependent variable in the econometric model, I aim to study not only the interaction between the different variables, but also potential causality between the slope and the short-term supply of crude oil. In the absence of an exogenous variable, which is the case proposed in this paper, the variance–covariance matrix contains the relevant information about the coincidental correlations between each of the variables.

Let $P = f(gradX, S, D, dI)$ and let *gradX* be a positive number when the curve is in contango and a negative one during periods of backwardation. The academic literature is in agreement on the role of inventory as a market balancing mechanism between *S* and *D*, which is why *dI* is assigned a neutral (positive) sign.

Therefore, the proposed relationship between the variables can be expressed in the following generic form:

$$P = gradX(S/D + dI) \tag{23}$$

This relationship represents a general short-term equilibrium model of the crude oil market. It is tested against economic theory by substituting the signs of the forward curve gradient in the equation. The following identifying assumptions are derived.

In the event of a backwardated market (-),

$$P = (gradX)*(S)/(-gradX)*(D) + (-gradX)*(dI) \tag{24}$$

The 1st identifying assumption with forward price negative development implied by the term structure of the market is described with the following sequence in the signs of *gradX* in model (24): (+), (-), (-)

In the event of a market in contango (+),

$$P = (-gradX)*(S)/(gradX)*(D) + (gradX)*(dI) \tag{25}$$

The 2nd identifying assumption with forward price positive development implied by the term structure of the market is described with the following sequence in the signs of *gradX* in model (25): (-), (+), (+)

To check further if the above assumptions hold, the signs of equations (24) and (25) are used to restrict the beta coefficient of the VECM. In other words, should the proposed relationship of equation (23) hold, the cointegration coefficients of *D, S,* and *dI* must be one, -1, and -1, respectively. Based on this assumption, I restrict B(1,1) = 1, B(1,2) = -1, and B(1,3) = -1 in the VECM.

As part of the structural analysis of the model, causality tests are performed for both Granger and instantaneous causality. These tests do not always reveal the true extent of the interactions between the variables in the model. Conclusions on possible causal relationships can be drawn from studying the responses of one variable to an impulse/stock introduced to another variable in a multivariable system. This 'shock view' is derived by removing elements from the structural model that are expected at t - 1. The VAR models focus only on modelling the unexpected changes in y_t, which is a major difference with traditional modelling practice, where dynamic simultaneous equations models do not differentiate between expected and unexpected changes in y_t.
The outcomes from the shock are displayed in the form of IRF diagrams. To isolate such an effect, suppose that all the variables in the system assume their mean value before time t = 0, yt = μ, t < 0, and one of the variables increases by one unit in period t = 0. If no further shocks are introduced, the impact from this single shock on the first variable in period t = 0 can be traced, namely,

$$yt = \begin{bmatrix} y_{10} \\ \vdots \\ y_{50} \end{bmatrix} = \begin{bmatrix} \varepsilon_{10} \\ \vdots \\ \varepsilon_{50} \end{bmatrix} = \begin{bmatrix} 1 \\ \vdots \\ 0 \end{bmatrix} \tag{26}$$

Therefore, y1 = $\begin{bmatrix} y_{11} \\ \vdots \\ y_{51} \end{bmatrix}$ = $\Phi_1 y_0$, where Φ represents the effect of the shocks to the variables in the system after *i* periods. This process is repeated for all the variables in the model. If the variables have different scales, it is common practice to apply the innovation of one standard deviation as a shock, rather than a one-unit shock. In this case, the matter is irrelevant, because all the variables are standardized (z-scored) prior to their inclusion in the model.

It is plausible to assume IRF outcome sensitivity to the ordering assumptions. Monte Carlo simulation is applied to the variables of the proposed short-term VECM of the global crude oil market. The aim is to detect changes in the relationship between the model's variables, since their positions within the model equation randomly change. This process is also known as orthogonalization. Similar results will provide confidence that the conclusions drawn based on the IRFs are not sensitive to assumptions about contemporaneous causality. As part of the Monte Carlo simulation, I first randomly generate combinations with the variables in the model. If n is the number of variables selected and r is the total number of variables in the model, then

$$\binom{n}{r} = \frac{n!}{r!(n-r)!} \tag{27}$$

I run the VECM IRF test on each sample and record the direction and strength of the reaction, as well as the reaction time of the short-term speculative crude oil supply.

The model performance analysis is completed with forecast error variance (FEV) decomposition (FEVD). This process breaks down the FEV for a specific time horizon and measures the proportions of the forecast errors in each variable while accounting for the other variables. In essence, FEVD quantifies the importance of each shock in explaining the variation in the other variables.. If $w_{i,j}(t)$ is the FEV of variable I due to shock j at horizon t, then:

$$w_{i,j}(t) = \sum_{k=0}^{t} Ci, j\ (k)^2 \tag{28}$$

When divided by the total FEV, denoted as $\delta_i(t)$, the result for the fraction of the FEVD is:

$$\emptyset_{i,j}(t) = \frac{w_{i,j}(t)}{\delta_{i,j}(t)} \quad (29)$$

3.5.5. Sub-hypothesis: The reaction of supply to the steepness of the forward curve slope *(gradX)*

As an extension of the main hypothesis, I investigate the reaction of short-term supply to the steepness of the forward curve slope. As already mentioned, I am not aware of any study that discusses the impact of the steepness of the forward curve's slope on short-term supply.

A steeper slope, positive or negative, implies greater difference between the spot and forward prices along the curve. I force the slope to become steeper by steps of 0.1 with the help of a conditional function that adds 0.1 if the slope is positive and subtracts 0.1 if the slope is negative. The test that best reveals the evolution of the relationship between short-term supply and the forward curve slope over time appears to be the SDP test, discussed in section 3.5.3. This is because the test in section 3.5.2.2. does not take into account slope steepness, only the position of the curve in a binary mode, that is, contango or backwardated. The Granger causality test (section 3.5.4.) is also inappropriate in this particular case, because it measures the static causality for the entire time series; that is, the test does not reveal the evolution of causality with time. The results are displayed in Figures A9 and A10 in the Appendix. The implications are discussed in the results in Section 3.6, next.

3.6. Results

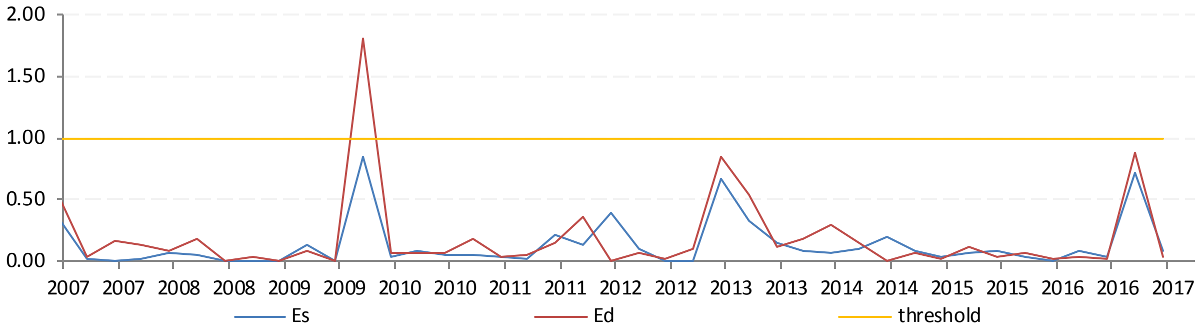
I find the results obtained with the help of the four preliminary tests described in the methodology in Section 3.5 support the main hypothesis. Elements of the proposed general equilibrium and VECMs relevant to the causal relationship investigated between the forward curve slope and the short-term crude oil supply also confirm the hypothesis. Last but not least, the test of the sub-hypothesis reveals a link between the steepness of the forward curve and the short-term crude oil supply.

3.6.1. Preliminary tests results

Quarterly values from the *Es* test since 1996 returns an average value of 0.18 for the *Es*, which indicates an environment with a low price *Es*. The same calculation for the Ed returns a higher value of 0.32. This is displayed in Figure 7.

Figure 7: Crude oil market *Es* and *Ed*

The chart compares the *Es* with the *Ed* in the global crude oil market. A threshold of one is used in economic theory to separate elastic from inelastic supply or demand market conditions (e.g. Case and Fair 1999). Source: IEA, Bloomberg.



The short-term price *Es* does not decline within the observed period from January 2007 to December 2016. The *Es* value increases steadily from 0.03 in 2007 to as high as 0.23 in 2017. Such a change represents a significant departure from the time series mean, further supported by the low values for the skewness and kurtosis of the dataset.

Therefore, neither the *Es* nor *Ed* stays too long above the threshold of one that is used in economic theory to separate elastic from inelastic supply or demand market conditions (Case and Fair 1999). There is only one year since 1996 when the *Ed* and the *Es* meet the definition of being elastic, as in 2003. It appears that the *Ed* is greater than one on five occasions, while the *Es* is observed to be greater than one on only two occasions (see Figure 7).

An LR test carried out for the *Es* and the crude oil supply reveals that the average *Es* for the last 20 years was highest one month after the price of crude oil changed (see Table 2, value in bold).

Table 2: LR test of the Es versus the oil supply

This table shows the lagged correlation coefficient in terms of the number of months between *Es* and the actual crude oil supply. Source: IEA, Bloomberg.

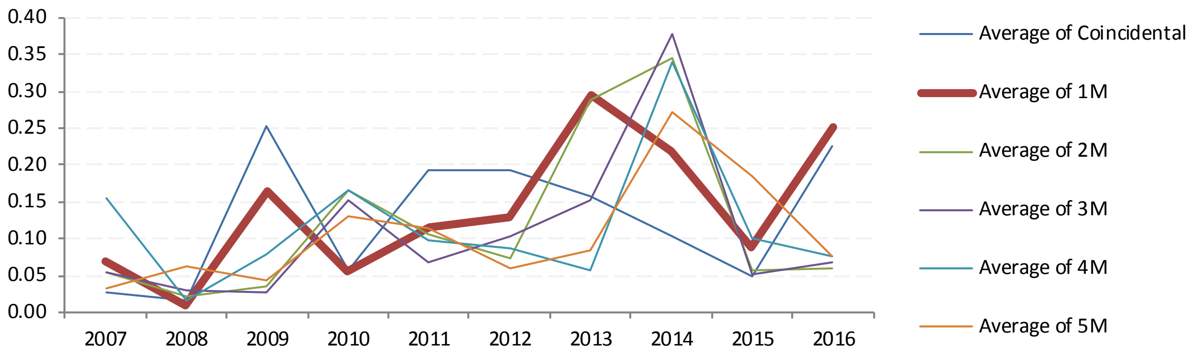
Es coefficient	Coincidental	1-month lag	2-month lag	3-month lag	4-month lag	5-month lag
Average	0.13	**0.14**	0.12	0.11	0.12	0.11

This results of this test are important, because, as shown late, the tests carried out with weekly supply data point towards very similar reaction times between two and four weeks.

The results from the LR test between the forward curve position and the short-term crude oil supply, displayed in Figure 8, show periods of positive lagged correlation occurrences.

Figure 8: LR test of the oil curve versus the crude oil supply

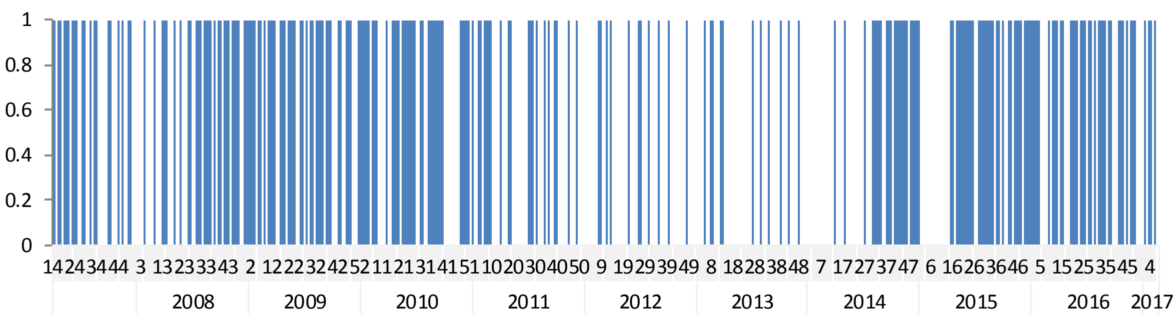
This chart displays the evolution of the results from the LR test on the relationship between the forward curve and the short-term crude oil supply, where coincidental and 1M to 5M indicate the lagged periods in terms of the number of months. Source: IEA, Bloomberg.



These periods are when the crude oil supply is likely to respond to a shift in the forward curve. It is evident from the data that the intensity of these reactions has increased (trending upwards with time). This result is documented by overlaying all he lagged periods of the *Es* reaction to price in Figure 8, where the thick red line represents the annual values of the one-month lag, as discussed above. In addition, Figure 9 shows a histogram of the frequency for periods of lead occurrences.

Figure 9: Lead frequency of occurrences

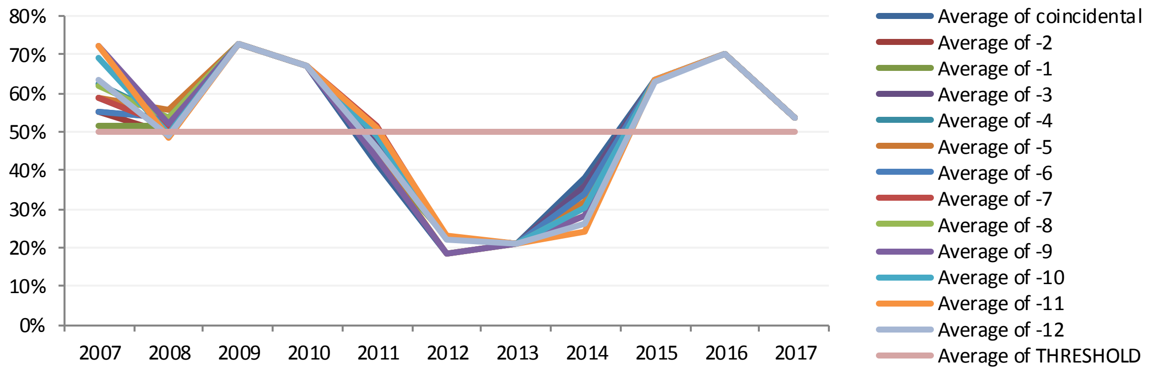
This chart illustrates the moments in time when the shape of the forward curve (contango vs. backwardation) and the change in weekly crude oil supply on the physical market reacted in the same direction and at the same time. The x-axis of the chart indicates time in years and the number of weeks within a year. The y-axis indicates each entry in the histogram, with one denoting a positive occurrence and zero denoting the lack of occurrence. Source: IEA, Bloomberg.



The histogram in Figure 9 displays the positive occurrences in the relationship between the shape of the forward curve (contango vs. backwardation) and changes in the weekly crude oil supply on the physical market. The initial result measured by the frequency of lead occurrences, points towards an increased tendency to change the supply as the shape of the forward curve changes. It is evident from Figure 9 that the occasions when producers increase the supply of crude oil when the forward curve moves into backwardation tends to cluster in time. The same is valid for the opposite reaction, namely, that the curve moving into contango tends to reduce supply. Such reactions are economically justified, since producers attempt to maximize their revenue. Another output from this test, namely, the annual averages for each of the periods for the last 10 years, is displayed in Figure 10.

Figure 10: Dispersion of results

The chart demonstrates the dispersion and cyclicality of the results of the LR test on an annual basis. The coefficient on the y-axis represents the ratio between all the observations in the sample and the number of events when the shape of the forward curve and the change in the weekly crude oil supply on the physical market react in the same direction and at the same time. Source: IEA, Bloomberg.

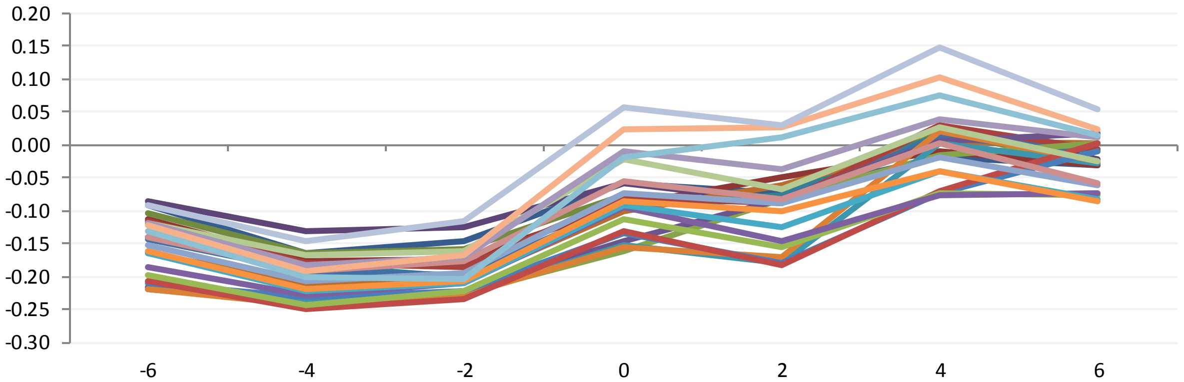


The degree of dispersion of the results between the different periods is low, but more important is that the periods of the relationship investigated between the forward curve and the supply of oil have a convincingly high ratio of +65% that persists for many months, sometimes for entire years. Periods of no reactions to changes in the curve can also be pronounced. For example, there is no evidence to suggest that the availability of crude oil was influenced by the position of the curve from 2011 to 2014. There appears to be cyclicality in the result that is not seasonal. Analysing the existence of such cyclicality is not the aim of this paper, but the topic deserves further investigation. The findings from the test are in line with the trend of the *Es* for the same period (10 years), but further investigation into the validity of the argument behind the speculative supply shock is needed.

The outcome of the SDP test, displayed in Figure 11, where the exact number of lead periods is indicated on the x-axis and the value of the rolling cross-correlation (RCC) is found on the y-axis, confirms that the gradient of the forward curve *(gradX)* does have a predictive value for supply *(S)*, that is, *gradX* leads *S* by a number of periods. This result is suggested by the shape of the RCC for each period.

Figure 11: SDP test results

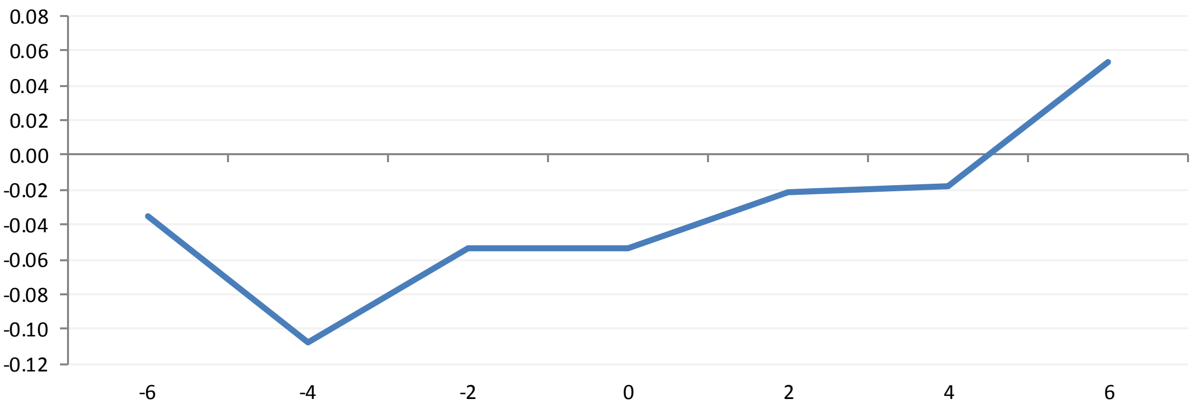
This chart shows the results from the cross-correlation between the oil supply S and the gradient of the forward curve *gradX*. Each line represents one sample period, while the lead–lag period is indicated on the x-axis, from -6 (*gradX* leading the oil supply) to +6 (*gradX* lagging behind the oil supply). The correlation coefficient is displayed on the y-axis; Source: IEA, Bloomberg.



A logical extension of this test is to consolidate the RCC for the entire sample. This is done to better visualize the evolution of the RCC relationship for all lead periods. The results displayed in Figure 12 are equally encouraging, since they confirm a cross-correlation with the longest average leading period of *gradX* over *S* of four weeks.

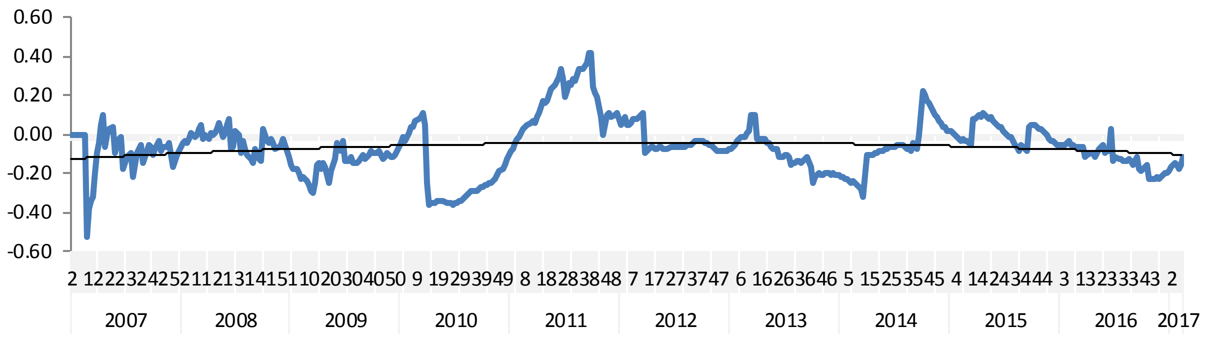
Figure 12: Average SDP test results

This chart shows the average cross-correlations between the oil supply S and the forward curve gradient *gradX* from January 2007 to February 2017 on the y-axis. The lead–lag period is indicated on the x-axis, from -6 (*gradX* leading the oil supply) to +6 (*gradX* lagging behind the oil supply) Source: IEA, Bloomberg



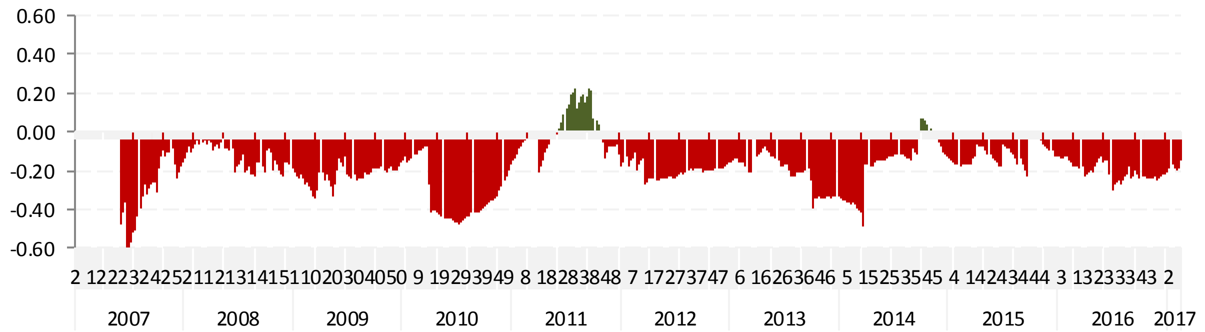
The results show that, since January 2007, on average, the oil supply reacts to changes in the forward curve and the steepness of its slope four weeks in advance. There are also periods when *gradX* loses its predictive power. There are long periods when it lags substantially. These are all periods with positive values, as displayed in Figure 13a.

Figure 13a: Evolution of SDP test results over time
The chart displays the evolution of the average cross-correlation values with a six-week lag . The x-axis shows the time span in years and weeks. The y-axis shows the correlation coefficient. Source: IEA, Bloomberg.



The long-term trend, described by a second-order polynomial function, shows the predictive value of *gradX* diminishing in the first half of the observed period (2007–2011), followed by a steady increase in predictive power (2011–2017). Results from the Fisher test assign a p-value significantly lower than 0.05, rejecting the null hypothesis. Skewness is positive, at 0.60, with a kurtosis of 1.34. Further analysis of the solely negative RCC returns suggests that the long-term mean of the time series is negative, as shown in Figure 13b.

Figure 13b: Average negative cross-correlation values
This diagram demonstrates the average negative cross-correlation values between *S* and *gradX* for all lead periods (X_t, ..., X_{t-20}). The coefficient is displayed on the y-axis. The x-axis shows the time span in years and weeks. Source: IEA, Bloomberg.



The results of the Fisher test reject the null hypothesis, with a value of 0.000329. Skewness is negative, at -0.1541, and kurtosis is 1.5585. In this case, I again use only periods of negative RCC values.

3.6.2. Results from the VECM

This paper employs the VAR methodology to investigate the reactions of the model variables to a one-off structural shock introduced to the system. The stationarity of the time series used in the model is determined by ADF and KPSS tests, and the results are displayed in Table 3.

Table 3: ADF and KPSS test results

This table displays the results of ADF and KPSS tests with levels and first differences, with a null hypothesis of non-stationarity for the ADF test and a null hypothesis of stationarity for the KPSS test, where [x] denotes the 5% critical value and (x) denotes the t-statistic. The test variables are as follows: P is the oil price, $gradX$ is the gradient of the forward oil curve, dI is the change in inventory, and D is the oil demand.

Test result / Variable	P	gradX	S	dI	D
Critical value	[-2.87]	[-2.87]	[-2.87]	[-2.87]	[-2.87]
at level	(-0.99)	(-2.90)	(-7.19)	(-1.56)	(-4.17)
at 1st difference	-14.03	-15.7	-16.5	-20.1	-14.4

The ADF test with levels fails to reject the null hypothesis (H_0) for P and dI, since their t-statistics appear to be above the critical level, within a 5% confidence interval. The test is repeated for first differences, and the null hypothesis is comfortably rejected, with t-statistics for all the variables under the 5% critical value. Therefore, the order of integration is one, or I(1). The KPSS tests for all the variables fail to reject the null hypothesis with first differences; therefore, the time series are stationary with order of integration one, or I(1).

Seasonality is tested with a FT. The aim of the FT cyclicality test is to establish the length and strength of a cycle. The explained frequency component (EFC) is then compared to the 'ideal EFC' (IEFC) of an ideal sinusoidal function. A threshold of 33% from the ideal cycle is applied, which is the test's the null hypothesis. If a cycle with a stronger EFC than 33% is detected, the time series are seasonally adjusted.

The results displayed in Table A4 and in Figures A14a to A14e in the Appendix suggest that a weak seasonality cycle is detected only in the inventory data (the real EFC, or REFC, denotes the maximum inventory). However, the test fails to reject the null hypothesis. Therefore, no attempt is made to remove seasonality from the time series.

Table 4: FT cyclicality test results

This table displays the results of the FT test with H_0: REFC < 33%, where P is the oil price, $gradX$ is the gradient of the forward oil curve, dI is the change in inventory, D is the oil demand, * denotes the IEFC, and ** denote the REFC.

	P	gradX	S	dI	D
IEFC*	4.54%	3.80%	2.06%	7.26%	6.14%
Cycles in number weeks	43	23	13	51	26
REFC**	13.76%	11.53%	6.24%	21.99%	18.60%

The lag order selection criteria for the VAR model are based on the premise of minimizing their value. Both the BIC and HQIC return the lowest lag order of one, or VAR(1).

Table 5: VAR lag order selection criteria

This table shows the results of the VAR lag order selection criteria process, with the following endogenous variables*:* P is the oil price, $gradX$ is the gradient of the forward oil curve, dI is the change in inventory, and D is the oil demand. The sample comprises 348 observations. Furthermore, * denotes the lag order selected for the criterion and LR is the sequential modified LR test statistic (at the 5% level).

Lag	LogLag	LR	FPE	AIC	BIC	HQIC
0	196.8760	NA	2.28e-07	-1.10	-1.05	-1.08
1	2042.668	3627.936	6.52e-12	-11.57	-11.23497*	-11.43485*
2	2086.687	85.25387	5.84e-12*	-11.67636*	-11.07	-11.43
3	2102.474	30.12234	6.16e-12	-11.62	-10.74	-11.27
4	2132.285	56.02591	6.00e-12	-11.65	-10.49	-11.19
5	2142.892	19.62807	6.52e-12	-11.57	-10.13	-11.00
6	2152.412	17.34468	7.13e-12	-11.48	-9.76	-10.80
7	2171.796	34.75651	7.38e-12	-11.45	-9.45	-10.65
8	2186.480	25.90841	7.84e-12	-11.39	-9.12	-10.48
9	2213.187	46.35259*	7.78e-12	-11.40	-8.85	-10.38
10	2230.818	30.09572	8.14e-12	-11.36	-8.53	-10.23

As discussed in the methodology in Section 3.5, since the set of variables all have a unit root I(1), ordinary regression analysis is not appropriate for the estimation, because there could be one or more equilibrium (cointegrated) relationships. Following the lag selection procedure discussed above, a Johansen cointegration test is performed (see Table 6).

Table 6: Johansen cointegration test results

This table shows the results from a Johansen unrestricted cointegration rank test on the non-stationary daily time series of P, gradX, S, D, and dI. The size sample consists of 355 data points after adjustments, spanning from 15.03.2010 to 20.02.2017. A linear deterministic trend is assumed, with one to two lag intervals for first differences. The notation Prob.** corresponds to a statistical significance level of 5%. Trace test statistics at the 0.05 level indicate three cointegration equations as indicated by "*".

Hypothesized no. of cointegration Equations	Eigenvalue	Trade statistic	Critical value = 0.05	Prob.**
None*	0.283041	179.3759	69.81889	0.0000
At most 1*	0.075478	61.25428	47.85613	0.0017
At most 2*	0.059341	33.39461	29.79707	0.0185
At most 3	0.031901	11.67778	15.49471	0.1731
At most 4	0.000474	0.168322	3.841466	0.6816

The trace statistic is lower for the three test levels, suggesting three cointegration equations within a 5% confidence interval. The maximum eigenvalue of the unrestricted cointegration rank test rejects the null hypothesis of no cointegration at the third test level, indicating three cointegrating equations Additionally the normalized cointegration coefficient estimates represent the long-term relationships between the variables in the system. Short-term relationships are displayed as the adjustment coefficients.

Table 7 displays the complete VECM results, including standard deviations, p-values, and t-values of the lagged endogenous and deterministic terms. As discussed in the methodology in Section 3.5.4. and following equation (23), the signs of equations (24) and (25) are used to restrict the beta coefficient of the VECM. In other words, should the proposed relationship of equation (24) hold, the cointegrating coefficients of *D*, *S*, and *dI* need to be one, -1, and -1, respectively. Based on this assumption, the VECM is restricted to B(1,1) = 1, B(1,2) = -1, and B(1,3) = -1. Should equation (25) hold, the coefficients of D, S, and dI will be -1, one, and one, respectively, and the VECM will be restricted to B(1,1) = -1, B(1,2) = 1, and B(1,3) = 1.

Table 7: Complete VECM results

This table displays the results from the VECM for five endogenous variables (P, gradX, S, D, dI). The cointegration restrictions of the model are as follows: B(1,1) = 1, B(1,2) = 1, B(1,3) = 1, B(1,4) = -1, and B(1,5) = 1, with chi-squared = 15.41114 and probability 0.000450.The results represent the summary statistics for the VECM system as a whole. These statistics include the determinant of the residual covariance, the log-likelihood, the associated information criteria (AIC, BIC), and the number of coefficients. The sample size is 355, after adjustment.

VECM summary statistics	P	gradX	S	D	dI
R-squared	0.095715	0.174136	0.473106	0.118404	0.058147
Adj. R-squared	0.061241	0.142651	0.453019	0.084795	0.022241
Sum sq. resids	0.409893	26.94849	416.7401	0.005113	1.204896
S.E. equation	0.034670	0.281119	1.105492	0.003872	0.059443
F-statistic	2.776433	5.530829	23.55302	3.522955	1.619407
Log likelihood	696.8826	-46.09436	-532.1844	1475.065	505.4929
Akaike AIC	-3.847226	0.338560	3.077095	-8.231354	-2.768974
Schwarz SC	-3.694523	0.491263	3.229799	-8.078651	-2.616271
Mean dependent	-0.000944	-0.00064	0.001088	0.000135	0.001744
S.D. dependent	0.035783	0.303607	1.494753	0.004048	0.060115

The results, given the standard errors and t-statistics, provide evidence of a relationship between the variables of the model. The standard OLS regression summary statistic of the model for each equation is also displayed. The R-squared and adjusted R-squared coefficients reveal that the variable with the strongest explanatory power in the model is the supply, followed by the gradient of the forward curve and demand. The number of determinant residual covariance statistics suggests that the model is stable.

Causality within the model is tested with Wald tests of Granger causality/block exogeneity. The results from Table 8 display a strong lead–lag relationship between one particular pair of variables in the model. More specifically, causality appears to be running from *gradX* to supply, significant at the 5% level. The results provide further evidence supporting the hypothesis of the study.

Table 8: VEC Granger causality/block exogeneity Wald tests

This table displays the results of the VEC Granger causality/block exogeneity Wald tests (at the 5% level of significance), in five panels. The table displays the results from the causal testing with price as the dependent variable and *gradX*, the supply, the demand, and inventory as the excluded variables.

Dependent variable	Excluded variable	Chi-sq	df	Prob.
Price	gradX	0.015863	1	0.8998
	Supply	0.016574	1	0.8976
	Demand	0.015276	1	0.9016
	Inventory	0.056382	1	0.8123
	All	0.102762	4	0.9987
gradX	Price	1.634212	1	0.2011
	Supply	0.263001	1	0.6081
	Demand	0.099872	1	0.7520
	Inventory	0.011909	1	0.9131
	All	1.999199	4	0.7359
Supply	Price	1.839296	1	0.1750
	gradX	4.448680	1	0.0349
	Demand	0.223264	1	0.6366
	Inventory	3.621967	1	0.0570
	All	8.086330	4	0.0885
Demand	Price	0.675502	1	0.4111
	gradX	0.035147	1	0.8513
	Supply	0.540565	1	0.4622
	Inventory	0.640715	1	0.4235
	All	1.963500	4	0.7425
Inventory	Price	4.059281	1	0.0439
	gradX	0.527115	1	0.4678
	Supply	0.166412	1	0.6833
	Demand	0.746432	1	0.3876
	All	5.122077	4	0.2750

To study the spillover between the variables in the model, the IRFs are calculated. The graphical interpretation of the results is shown in Figure 14. There are 20 IRF outcomes, because there are as many shocks as there are variables (five variables × the shocks on each of the remaining four variables). The values on the x-axis represent the number of weeks. The values on the y-axis represent changes in the dependent variable due to a structural shock introduced to the independent variable. When it comes to the model's validation, one of the first signs of model robustness is the shape of the impulse response curves. Most impulse

responses tend to die down after the introduction of the initial shock, which is a sign of a model's stability.
Shocks to each of the variables in the model tend to inspire strong reactions from them. The remainder of the outcomes appear to be in line with economic theory. For example, a positive shock to *gradX* tends to decrease *P*. The opposite is also true, since a shock to *P* appears to reduce *gradX*. This is also true for a shock applied to *S* that reduces the value of *gradX*. In turn, if the shock is applied to *gradX, S* initially rises in periods 1 and 2, before declining in periods 3 and 4, after the event. This particular result is inconclusive and further investigation on the causal relationship between *gradX* and *S* is warranted.

The forward curve tends to flatten as demand increases. This is logical, since growing demand pushes up nearby/prompt prices and flattens the curve. The opposite reaction is also investigated, with the shock applied to *gradX* and recording the response of *D*. In this case, an increase in the slope's steepness signals an increase in demand, which is explained by the incentive created by lower prompt prices. However, the coefficient of the outcome is significantly weaker when compared to the *D–gradX* pair, which suggests a potential direction for causality.

Higher inventories suppress the forward curve slope. A sufficiently steep contango incentivizes inventory accumulation, but, as the stocks are replenished, the prompt price is likely to come under pressure, which flattens the curve. Other meaningful reactions recorded by the model and displayed in Figure 14 include the reduction of the supply with rising demand and inventory, as well as a reduction in demand due to higher prices.
The last chart within Figure 14 group of charts displays diverse set of reactions, all of which follow the logic of market fundamentals. Let us begin with the reaction of inventory to a positive price shock. Stocks tend to increase with an increase in price, because a higher price for a commodity triggers a restocking effort. Inventory also rises with the curve moving into contango, which is explained by the cash and carry arbitrage condition (the steeper the contango, the stronger the incentive to accumulate stocks). The effect reverses later. A positive shock to the supply appears to help build up inventory. Finally, as demand rises, inventory declines. This result is likely due to the drawdown on stocks following the demand shock.
Variance decomposition reveals that most of the variations in returns are explained by each of the variables' own shocks. The asymmetry of the explained variability in the returns of the

price and the slope of the forward curve can be explained by the fact that spot is inseparable from the forward curve formation. Another observation is that even if more than 95% of the variability of the supply is explained by the supply itself, the second most influential factor is the gradient of the curve, which is evidence, albeit weak, in support of the hypothesis of this study.

Figure 14: IRF diagrams – Responses to Cholesky one standard deviation of innovation

The five panels below represent the outcomes of the introduction of a positive shock to the system of equations within the proposed VAR model. The x-axis indicates time, as the number of weeks, from the moment of the introduction of the shock at t = 0. The y-axis displays the coefficient strength, which measures the reaction of each variable to the introduced shock. The endogenous variables in the VAR system are as follows: P is the oil price, gradX is the gradient of the forward oil curve, dI is the change in inventory, and D is the oil demand.

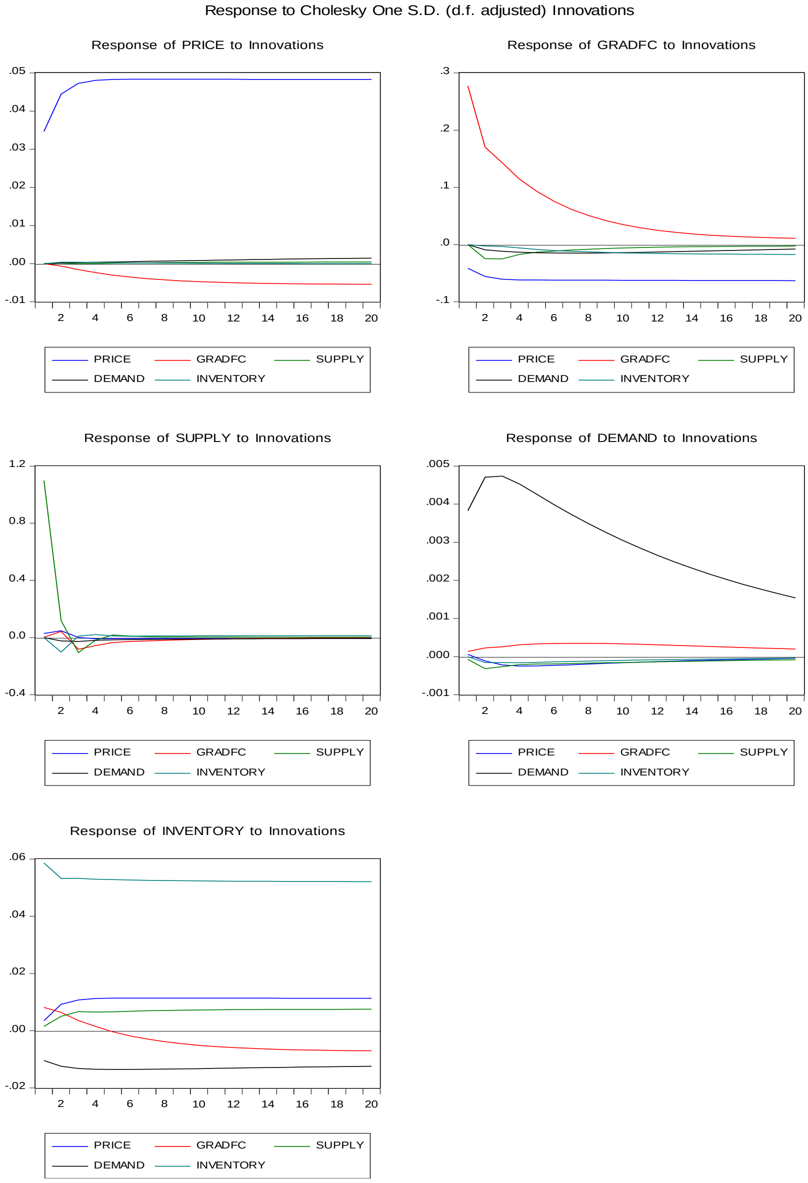
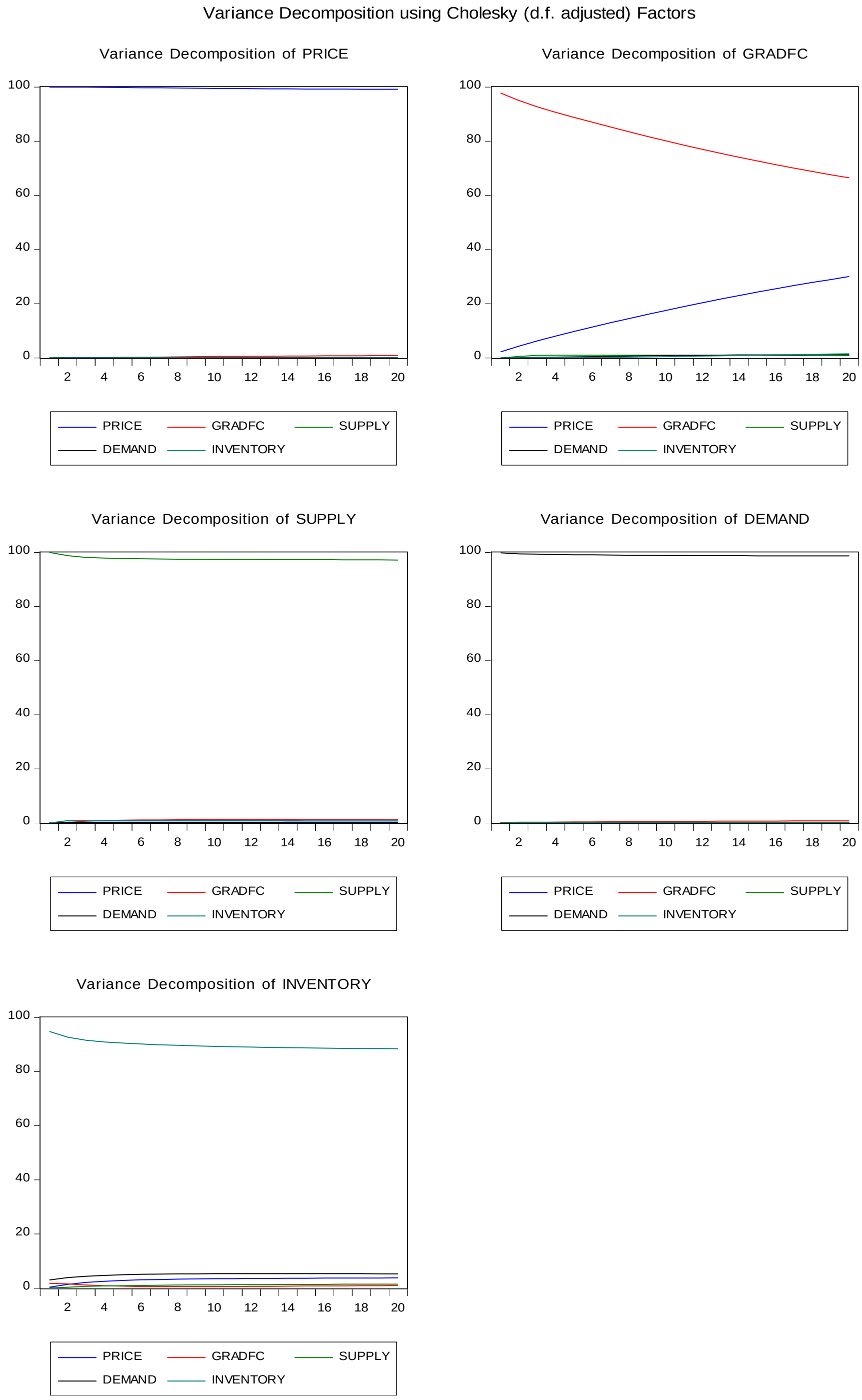


Figure 15: Variance decomposition with Cholesky factors

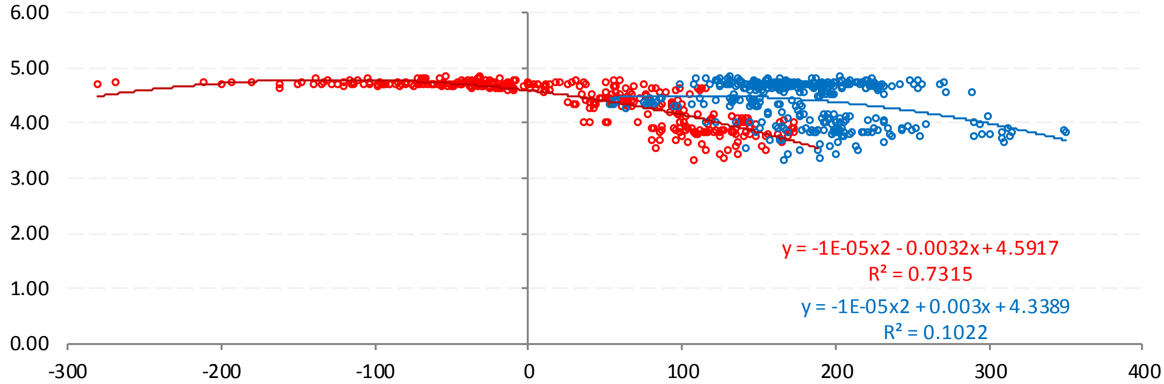
This figure shows the five VECM variance decomposition plots describing the evolution of the balance between each model variable, as expected in reaction to Cholesky factors. The x-axis indicates time as the number of weeks from the moment of the introduction of the shock at t = 0. The y-axis displays the coefficient strength, which measures the reaction of each variable to the introduced shock. The endogenous variables in the VAR system are as follows: P is the oil price, gradX is the gradient of the forward oil curve, dI is the change in inventory, and D is the oil demand.



By determining the VECM identifying assumptions, I construct and propose a general short-term equilibrium model for the global crude oil market as defined in equation (23). To the best of my knowledge, models of this form are not discussed in the literature. The model exhibits significantly stronger explanatory power for the price of crude oil (R-squared = 0.7315, correlation coefficient = -0.79) compared to the form without the forward curve gradient (R-squared = 0.1022, correlation coefficient = -0.28). This is evident from the scatter plots in Figure 16. The trend of the relationship is described by a second-order polynomial function with the regression equation displayed in the figure.

Figure 16: Scatter plot with results

This scatter plot describes the relationship between the proposed short-term equilibrium model values, on the x-axis, and the price of crude oil, on the y-axis. The gradient of the forward curve, *gradX*, is one of the independent variables of the model, with the results in red. The blue values represent the results without *gradX*.



3.6.3. Results of the SDP tests on the sub-hypothesis

The sub-hypothesis of the study investigates the reaction of short-term supply to the steepness of the forward curve slope. The steepness is understood to be a direct measure of the difference between spot and forward prices along the time curve. Therefore, by artificially pushing the curve into different modes of steepness, I test the supply's response over time. I do so by forcing the slope to become steeper by steps of 0.1, with the help of a conditional function that adds 0.1 if the slope is positive and subtracts 0.1 if the slope is negative. The results from the test in Table 9 reveal the correlation coefficients of the actual and forced slopes of the Brent crude oil market forward curve versus the short-term supply. More negative coefficients occurring in negative periods suggest that the forward curve leads the supply. This argument is also illustrated in Figures 17 and 18.

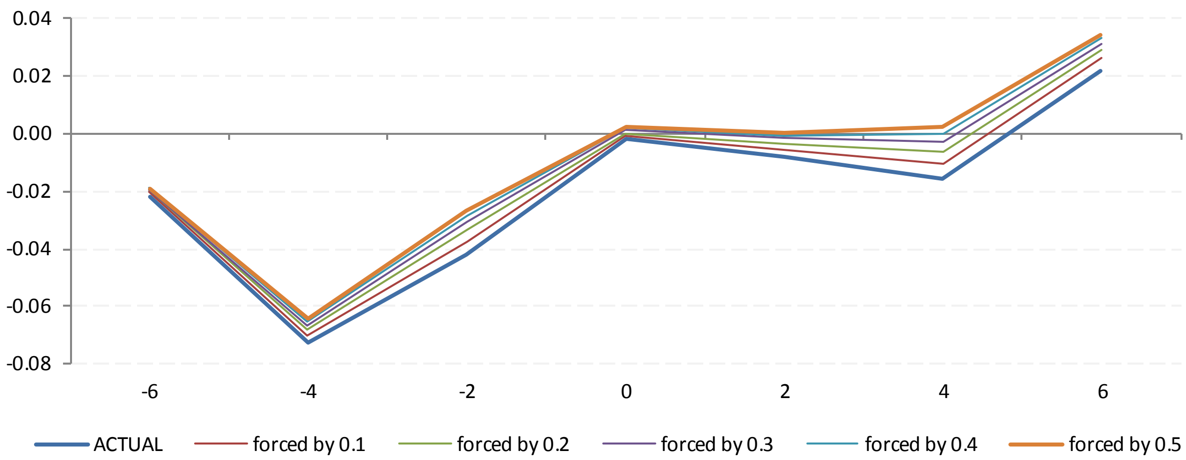
Table 9: SDP test results, forcing the curve slope

The table demonstrates actual versus forced SDP test values between the oil supply *S* and the gradient of the forward curve *gradX*. Each row represents the test results after forcing the slope to become steeper by adding 0.1 if the slope is positive and subtracting 0.1 if the slope is negative. The lead–lag period runs from t - 6 (*gradX* leading the oil supply) to t + 6 (*gradX* lagging behind the oil supply). The numbers in the slope column represent the slope steepness coefficient for each position, that is, from actual to forced, by increments of 0.5. Source: IEA, Bloomberg ICE, Marex Spectron Research.

	Leading			Coincidental	Lagging			
Position	-6	-4	-2	0	2	4	6	Slope
Actual	-0.0220	-0.0726	-0.0424	-0.0016	-0.0081	-0.0158	0.0218	0.0100
Forced by 0.1	-0.0203	-0.0699	-0.0374	-0.0008	-0.0054	-0.0103	0.0261	0.0104
Forced by 0.2	-0.0195	-0.0679	-0.0337	0.0001	-0.0033	-0.0060	0.0291	0.0107
Forced by 0.3	-0.0192	-0.0664	-0.0309	0.0011	-0.0018	-0.0025	0.0314	0.0110
Forced by 0.4	-0.0191	-0.0652	-0.0287	0.0019	-0.0005	0.0003	0.0332	0.0113
Forced by 0.5	-0.0191	-0.0642	-0.0270	0.0027	0.0005	0.0026	0.0345	0.0115

Figure 17: Actual versus forced SDP test results

This chart demonstrates the actual versus forced SDP test values between the oil supply S and the gradient of the forward curve *gradX*. Each line represents the test result after forcing the slope into further steepness by adding 0.1 if the slope is positive and subtracting 0.1 if the slope is negative. The lead–lag period is displayed on the x-axis and it runs from t - 6 (*gradX* leading the oil supply) to *t + 6* (*gradX* lagging behind the oil supply). The test result coefficient is on the y-axis. Source: IEA, Bloomberg ICE, Marex Spectron Research.



The lowest 10-year average score of the SDP test coefficient is achieved in period *t - 4*, with a reading of -0.0726. This means that, on average, change in the slope of the forward curve leads to a change in the short-term supply of four weeks. This observation was already discussed in Section 3.2.3, as well as in Section 3.6, on the results. The new information obtained here is from the comparison between the actual market data (denoted as actual in Table 9), used for all previous causality studies, and the different positions of the forced curve. The actual record appears to possess the highest negative SDP test score. This means that the gradient coefficient of the actual forward curve slope data (with no forcing) possesses the strongest mechanical lead properties over the short-term supply. However, once the slopes of the results are calculated, the outcome changes. The numbers in the slope column in Table 9 represent the slope steepness coefficient for each position, that is, from actual to forced, by increments of 0.5. It is evident that the curve steepens with the steepness of the slope of the forward curve. This means that the responsiveness of supply increases as the curve steepens, which, in turn, confirms the sub-hypothesis that the reaction of the short-term supply intensifies with the steepness of the forward curve.

3.7. Conclusions

The first test (for the *Es*) reveals that a change in the oil price leads to a change in the *Es*, and the most common reaction time is four weeks, which suggests that further investigation into the subject is worthwhile. The increase in the *Es* detected is the first, albeit weak evidence in support of the hypothesis of a speculative supply shock after 2008–2009. After all, the *Es* is nothing more than a ratio of the proportionate change in the quantity of supply to the proportionate change of price. Evidence collected from the second (LR) test implies that there is indeed a link between the forward curve position, contango or backwardation, and crude oil availability on the physical market. The direction of the relationship investigated involves a backwardated forward curve causing a positive speculative supply shock. Test results also reveal that the intensity of the response of the short-term supply to change in the steepness of the forward curve slope has risen consistently in recent years. Oil producers are more likely to engage in speculative supply-side operations, leading to speculative supply shocks. The events appear to cluster in time, which suggests cyclicality in the relationship investigated between the forward curve and the spot oil supply.

It is worth mentioning also, that the reaction of producers' supply to change in the steepness of the forward curve within such a short time frame (weekly) would be a necessary but not the only condition for a speculative supply shock on the crude oil market. Bivariate statistical analysis performed on the forward curve gradient and the short-term supply with the help of an SDP test also offers evidence of predictive properties; that is, the analysis confirms a causal condition where $S = f(gradX)$. The events where *gradX* is influencing S are found to tend to cluster in time. When such events arise, they persist for long periods (months and even years) and are followed by periods of a weak or no relationship. The sub-hypothesis developed investigates the reaction of the short-term supply to the steepness of the forward curve slope by artificially pushing the curve into different modes of steepness. The results confirm that the responsiveness of the short-term supply rises with increases in the steepness of the forward curve slope.

The proposed general equilibrium and VECMs for the global crude oil market play an important role in the argumentation of the hypothesis. The result from the VEC Granger causality test rejects the null hypothesis at the 5% confidence level, with a p-value of 0.0349, and confirms the existence of predictive causality between the slope of the Brent oil curve and the short-term oil supply. The reverse test hypothesis, that is, *S* causing *gradX*, fails to reject the null hypothesis, which defines the direction of the causal relationship in each pair of variables.

Further conclusions can be drawn from the VECM IRF results. The evidence collected from the IRF outcomes suggests that the short-term supply is reduced as a positive shock is introduced to the slope of the forward curve. This result is in line with evidence from earlier tests. More importantly, such behaviour signals causality in the relationship whereby the forward curve leads the supply reaction by about two weeks. The same reaction is detected in the opposite direction, that is, a shock introduced to the supply decreases the steepness of the slope of the curve. This feedback relationship is studied as a robustness test in Section 3.6 and reveals positive feedback, also known as constructive interference, between *gradX* and *S*. The proposed short-term general equilibrium model for the global crude oil market provides further evidence in support of the hypothesis. The model has strong explanatory power for price, as measured by the fit of the second-order polynomial function (R squared = 0.7315) and the time series correlation coefficient (-0.79). A robustness check is performed by removing the forward curve slope from the model equation. The result is markedly weaker; that is, the fit/explanatory power of the model deteriorates on both occasions (R-squared = 0.1022 and the correlation coefficient = -0.28 providing further support for the hypothesis of this paper.

3.7.1. Implications

The impacts from the findings of this study are relevant to crude oil market practitioners and can be categorized according to the nature of their business, namely, involving the physical or derivative market. The effect on the physical market is related to the short-term alteration of crude oil availability and the subsequent supply shock. Any short-term stress along the industrial supply chains due to a short-term speculative supply shock is likely to affect price formation, in terms of both price value and price volatility. This can have a direct impact on the real economy. On one hand, overstretching supply chains of raw materials can lead to disruptions in the production process downstream, which affects the financial performance of the companies involved. The logical reaction is to accumulate excessive amounts of inventory, which also negatively affects the results of the firm, because working capital is locked up in idle inventory. On the other hand, given that global oil inventories have stayed above the long-term average for the last five years and, as stated by Deaton and Laroque (1992), Pindyck (2001), Geman and Ohana (2009), and Gorton et al. (2013), price volatility and inventory have a positive relationship in times of above-average long-term inventory levels. Such higher price volatility increases the uncertainty of the cost of production. Therefore, there can be two economic impacts, at the micro and the macro levels.

At the microeconomic level, companies are forced to increase their hedging ratio, which comes at a cost and leads to higher costs of production and higher unit costs. At the macroeconomic level, inflationary pressure could emerge, since producers typically attempt to pass on higher costs to the end user/consumer. In other words, due to the very high level of oil and oil product usage in the economy of any developed country, higher unit costs could not only put producers in a difficult financial situation, but also create inflationary pressure in the broader economy (Gisser and Goodwin, 1986). The derivative markets also react to short-term supply changes, creating trading opportunities for the entities and individuals involved in crude oil derivatives market operations. Therefore, my findings offer additional insight into how to improve further the short-term trading analytics and risk management for crude oil.

The implications, from an academic perspective, could also be significant. The hypothesis proposed in this paper increases understanding of the way the short-term supply reacts to changes in the spot and forward prices. This is because the use of a dataset of weekly observations for the supply is unique in the literature. Furthermore, to my knowledge, no study has been carried out on the relationship between the weekly spot physical oil supply and the position of the forward curve. Equally important, no study appears to have been conducted on the relationship between the weekly oil supply and the steepness of the slope of the forward curve.

Last but not least, the proposed short-term general equilibrium and VECMs for the global crude oil market aim to test the relationships between five variables representing the short-term supply and demand conditions on the crude oil physical spot market. To the best of my knowledge, no study discusses a crude oil econometric market model with such variables or time series frequency.

The findings are also likely to attract the attention of key policy makers. For example, a European Energy Union initiative is a priority project for the European Commission. The role of Directorate General for Competition is to ensure that the energy markets function properly and deliver reliable energy supplies at reasonable prices for businesses and consumers. Evidence of deliberately introduced price volatility, as well as of higher energy prices for the end user, is likely to attract the attention of regulators. Another concern of policy makers is likely to be inflationary pressure, as noted in the discussion above.

3.7.2 Areas for further research

Throughout this paper, I have identified the following areas as suitable for further research.

First, any change in short-term crude oil availability on the Ps physical market due to a shift in the forward curve is likely to affect not only the short-term supply and demand balance on the oil market, but also the demand for shipping capacity. An opportunity for further research involves the acquisition of deeper understanding of the origins of the short-term demand shocks for crude oil tanker freight. Shipping is derived demand, and, therefore, changes in the crude oil supply directly affect the freight market. Unlike dry bulk shipping, crude oil has no substitutes as a shipping capacity demand driver. Therefore, any change in short-term crude oil availability on the spot physical market is likely to affect freight rates.

Second, a transformation of the dynamics of FOB–CIF price formation on the back of deliberate short-term supply changes on the physical market, combined with traders' increased ability to purchase oil at different points along the supply chain, can potentially create a positive feedback loop of volatility between FOB and CIF pricing points.

Third, one of the preliminary tests of causality identifies multi-year cyclicality in the lead–lag relationship between the forward curve and the reaction of supply. Periods of strong regime reaction have a convincingly high ratio of +65% that persists for many months and sometimes entire years. Periods of no reaction to changes in the curve can also be pronounced. For example, this particular test offers no evidence to suggest that crude oil availability was influenced by the position of the curve from 2011 to 2014. Analysing the existence of such cyclicality is not the aim of this paper, but the topic deserves further investigation.

Fourth, the results from the proposed models reveal that, after the introduction of a positive structural shock on the crude oil's short-term supply, demand, and inventory, no meaningful reaction of the spot price of crude oil is recorded within the observed period. This finding clearly contradicts economic theory, cannot be easily explained, and therefore demands further and more detailed investigation.

Fifth, it is not immediately obvious why stocks should fall steadily after the initial increase when the curve slope steepens. A contango market should theoretically create an incentive for steady inventory accumulation, as dictated by cash and carry arbitrage. Therefore, the reaction of inventory to a steepening forward curve also deserves further investigation.

Appendix of Chapter 3

Figure A1: Crude oil inventory share of total production

This chart displays the global crude oil inventory share of total global production on the y-axis, and the time line on the x-axis. The long-term trend is described by second-order polynomial regression trend line. Source: DOE.

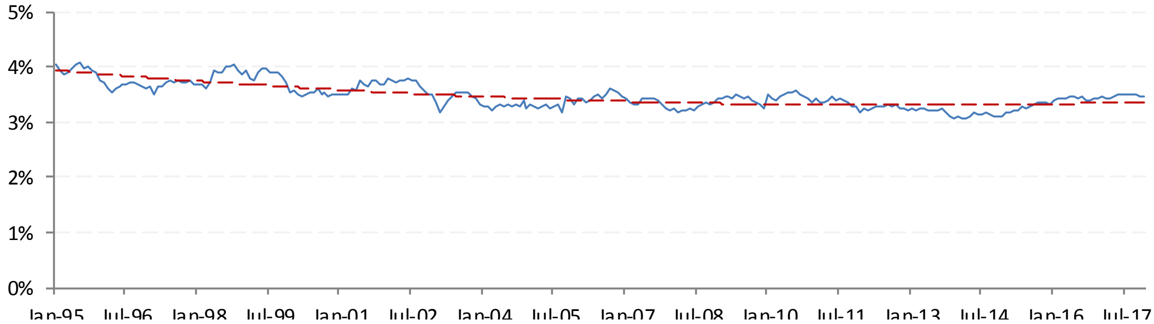


Figure A2: Global crude oil demand versus Brent price volatility

This chart demonstrates the logarithm of the term (seven years) trend in global oil demand and physical crude oil market volatility. The trend line for the relevant variable is a linear regression line. Source: DOE.

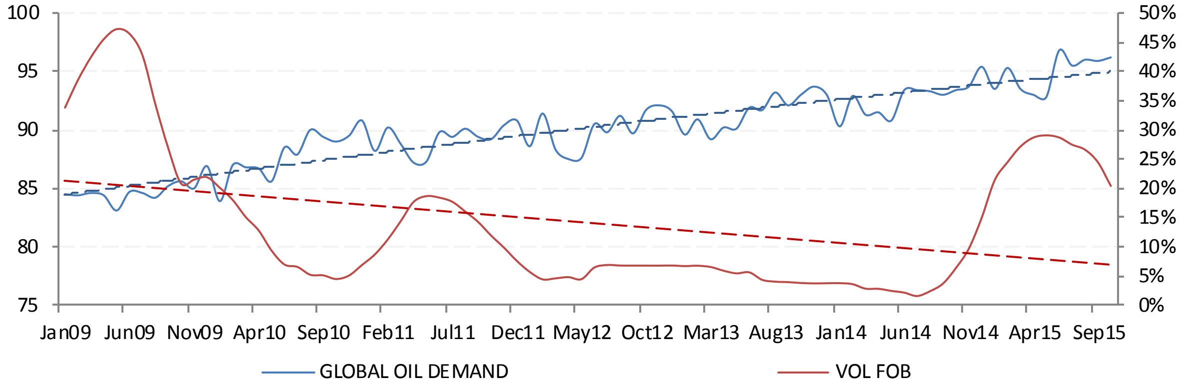


Figure A3: Brent price versus volatility

This chart presents the relationship between the (Brent) crude oil price and volatility. The long-term trend is described by the second-order polynomial regression trend line. Source: DOE.

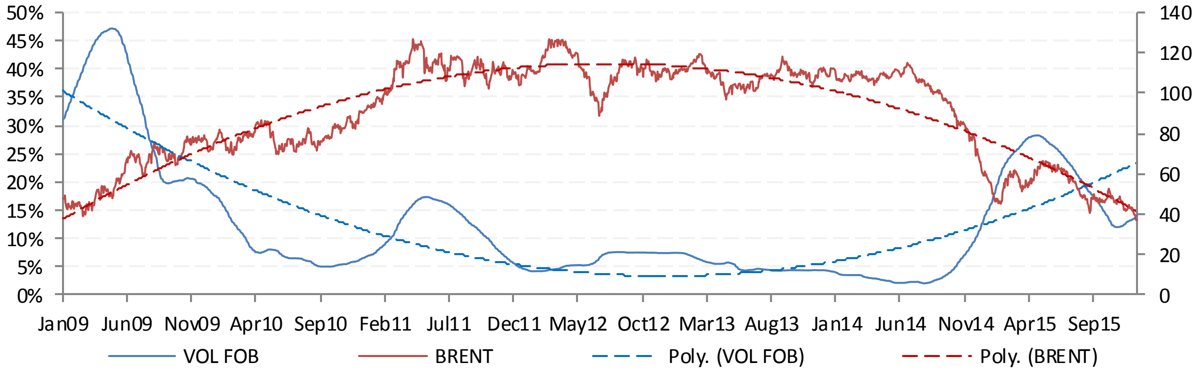


Figure A4: Organisation for Economic Co-operation and Development (OECD) oil inventory versus the Brent convenience yield

The chart presents the relationship between the OECD crude oil inventory and the Brent market convenience yield. The long-term trend is described by the second-order polynomial regression trend line. Source: OECD, DOE, Bloomberg.

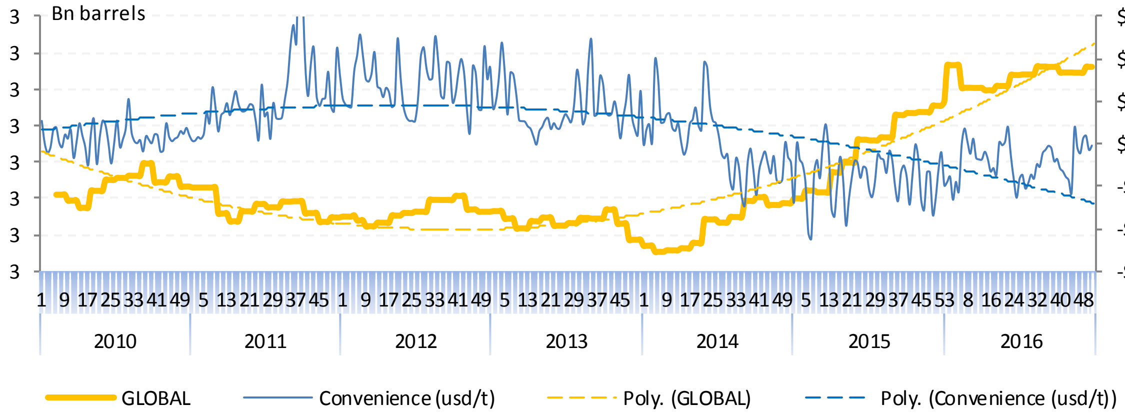


Figure A5: Global crude oil supply and demand balance

This chart presents the relationship between the global crude oil market's supply and demand balance (bar chart, dashed line is the 3-month simple moving average) and the Brent spot price (line). The Source: IEA, Bloomberg, Marex Spectron Research.

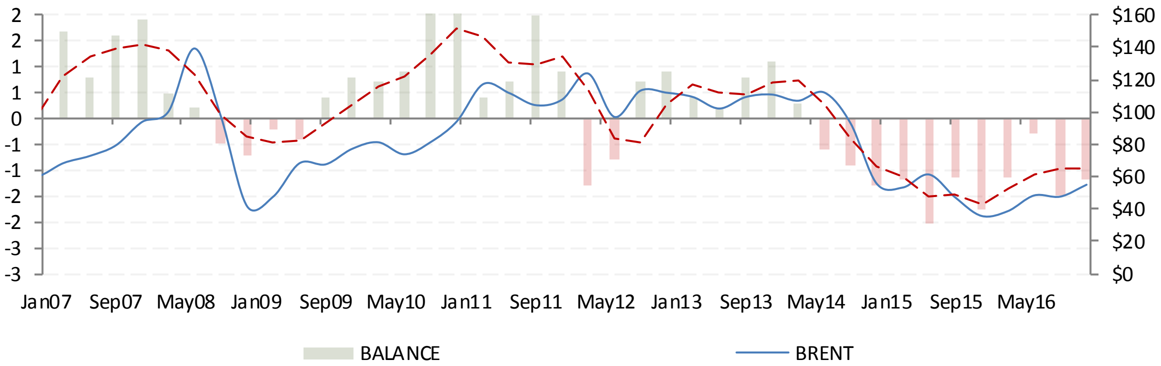
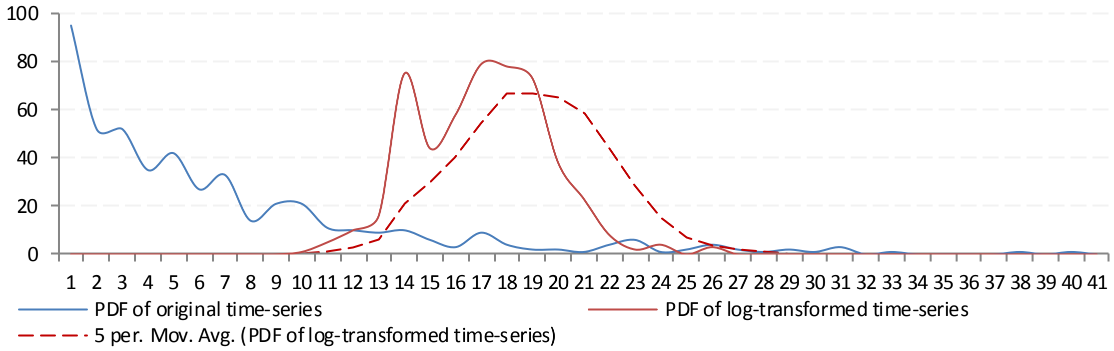


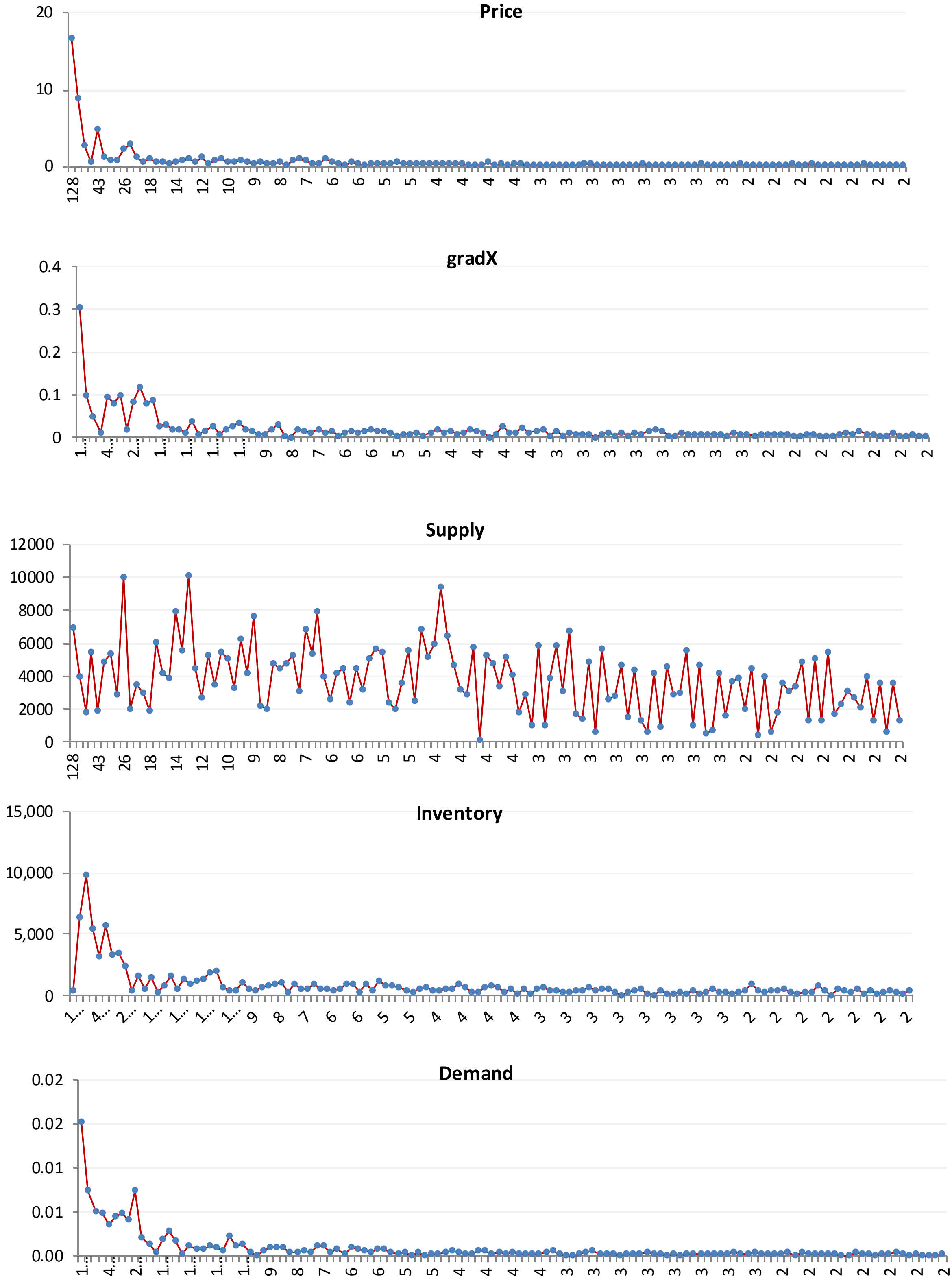
Figure A6: PDF function of the supply

This chart presents the PDF of the crude oil supply time series. The blue line represents the PDF of the original time series. The red line represents the PDF on the log-transformed series. The dashed red line is the five-period moving average on the log-transformed series. Source: DOE.



Figures A14a-14Ae: FT cyclicality

The following charts display the results from the FT cyclicality test for all five model variables, namely, the oil price, gradX, inventory, supply, and demand. The value on the x-axis on each chart represents the time component of the Fourier function in number of weeks. The value on the y-axis is the unit of the variable tested.



4. Optimal cross-border electricity trading in the context of the gravity model of international trade and the flow–price relationship

4.1. Introduction

In this paper, I first examine the impact of the relative strength of economic activity and distance between two countries on their net cross-border electricity flow. The effect from changes of electricity flow between two markets on flows between another pair of markets is also examined. Lastly, I investigate the relationship between cross-border electricity flows and electricity prices.

The electricity market is different from any other commodity market, since the technological inability to accumulate inventory and the instantaneous nature of the transactions of electrical current remove the balancing mechanism between supply and demand. The resulting need for instantaneous balance and increased connectivity between markets that is part of the European Union (EU) Energy Union Initiative pose important questions about the behaviour of the entire interconnected system.[23]

Microeconomic theory postulates that the demand for electricity from rational end users increases up to the point where the marginal benefit for the consumer is equal to the price of the units of electricity consumed (e.g. Kirschen 2003). This makes the end user demand response susceptible to prevailing economic conditions. One theoretical framework that could provide a direct link between commodity demand, supply as measured by cross-border flow, and the relative economic activity between different markets is the gravity model of international trade, following Tinbergen (1962). Tinbergen, who identifies a similarity between Newton's law of gravitation and bilateral trade flows between countries, has proposed that trade between any two markets can be expressed as a function of their economic size and the distance between the two countries. I conjecture that the application of Tinbergen's gravity theory of trade to the integrated EU electricity market enables better modelling of the forces behind changes in flows and prices.

[23] European Commission (EC) MEMO/15/4486, 'Connecting power markets to deliver security of supply, market integration and the large-scale uptake of renewables'.

Following the hypothetical link between the gravity theory of trade and cross-border electricity trade, I also examine the influence of one cross-border flow on another. Improved connectivity between markets in recent years makes it credible to hypothesize that trade flow between two neighbouring countries can be affected by trade flow between another pair. Furthermore, it is plausible to assume that, once the supply of electricity in any given market is altered by the forces discussed, the price will respond. Therefore, I aim to identify such electricity flow changes and quantify their impact on the electricity price. Consequently, the importance of cross-border trade flow in the overall price formation mechanism for the electricity market in Europe is articulated by investigating the links between economic activity and trade flow, trade flow and other flows, and trade flow and electricity prices.
It is important to address the absence of the use of the gravity theory of trade proposed by Tinbergen (1962) in the literature as an analytical tool capable of explaining certain electricity market price and volume movements. This paper not only offers confirmation of the explanatory power of the gravity theory over changes in trade flow direction and size, but also ascertains evidence that the theory can be successfully employed for predicting electricity flows and prices.

The lack of research on the flow-on-flow impact on the electricity market is also identified. Poor connectivity between various national grids in the past and, therefore, a lack of significant cross-border electricity flows can be one explanation for this gap. However, the EU market coupling regulation has significantly changed the flow across borders.[24] The strand of research on international trade (e.g. Krugman 1979) helps one identify the potential link between different trade flows, but further research is warranted, specifically into the topic of the short-term flow-on-flow impact on electricity markets.

Furthermore, the available academic research documents the relationship between price and volume but offers no evidence in favour of a causal relationship that runs from the market volume to the market price (e.g. Granger and Mortgenstern 1963, Jennings, Starks, and Fellingham 1981). The sequential arrival and noise trader models of Copeland (1976) and DeLong, Shleifer, Summers, and Waldmann (1990), respectively, attest to a bidirectional causal link, but they stop short of identifying and confirming directional causality from volume to price. Their work has been exclusively focused on equity markets, not

[24] See the European Council for an Energy Efficient Economy (ECEEE), https://www.eceee.org/policy-areas/energy-union/.

commodities, which is an important distinction from the hypotheses tested in this paper. To the best of my knowledge, in terms of commodity markets, evidence of causality from volume in the direction of price is practically non-existent. Kiesel and Kustermann (2016) conclude that it is the *price* differential between two electricity markets that dictates the cross-border electricity flow. In contrast, the findings of this study point towards a persistent causal link in the direction from volume (flow) to price. Once causality is identified and quantified, it is also proposed as a powerful addition to any trading strategy.

The methodological framework employed in this paper that is used to identify cross-border trading opportunities is also worth documenting. As far as I can ascertain, the academic literature omits any methodology that records a cross-border arbitrage trading strategy for electricity markets based on trade flow signals. Differently, this study utilizes the findings from a rigorous causality testing process, proposes a trading model that uses the cross-border electricity flow/volume as the prime input to generate the entry signal into a long/short position on the forward electricity market, and documents the results.

Gebhardt and Hoffler (2013), who investigate the relationship between spot and interconnector capacity prices, claim that well-informed traders do not engage in cross-border trading. The authors even postulate that an incumbent could buy interconnector capacity only to block international competitors. While their findings do not contradict the results of this paper, the evidence gathered here suggests that well-informed, rational market participants can and should engage in cross-border electricity trading.

Differences from the available literature in the methodology employed to investigate the hypotheses are also reported. Key published works on the topic of the price–volume relationship on the financial markets address the research problem of employing traditional bivariate Granger causality and correlation techniques following Granger and Mortgenstern (1963), Grossman and Stiglitz (1980), and Hiemstra and Jones (1994). In contrast, this paper uses customized coincidental response (CR) and sliding scalar product (SSP) tests, as well as a multivariate vector autoregressive (VAR)/vector error correction (VEC) model (VECM) framework. The assertion here is that these techniques are superior to the one traditionally used to study the price–volume relationship on the electricity market.

The EC market coupling regulation aims at integrating European wholesale electricity markets into a single liberalized electricity market. The initiative is part of the EC's Energy

Union project (see the ECEEE policy guidelines, as well as Meeus et al. 2005). One of the pillars of this project is the motion to remove barriers to physical electricity trading and coordinated grid operations through the construction of new interconnecting facilities, known as bidirectional transmission lines, connecting the grids of two adjacent countries. This policy effectively pools together all member state markets for the same-day delivery of electricity, and it is designed to facilitate and prompt cross-border flows between member states. The goal is for stronger cross-border trading flows to increase competition on the marketplace and to lower price volatility and transmission costs.[25] It is, therefore, in the interest of the stability of the entire system to study the factors affecting these flows. One such potential factor affecting the behaviour of the cross-border flow of electricity between any two countries, adjacent or non-adjacent but still connected by the grid of a third country in the middle, is the relative size of their economic activity. According to the original gravity model for international trade proposed by Tinbergen (1962), and the work of Bergstrand and Egger (2010) and Brakman and Bergeijk 2010, who argue that the gravity theory of trade can be applied universally to any good, I conjecture that application of the first null hypothesis H_0^1 to the European electricity market allows better understanding of the forces behind electricity price formation and to model and predict trade flow changes using macroeconomic input.

Anecdotal evidence suggests that the change to the market architecture imposed by the EU Energy Market Initiative is already having an impact on the way electricity flows across Europe.[26] The material lack of storage on an industrial scale on the electricity market, the instantaneous transaction of electrical current, and Kirchhoff's first law indicate that changes in cross-border electricity flows have the potential to influence the domestic supply and demand balance for a particular market.[27] The lack of industrial-scale storage for electricity removes the balancing mechanism between supply and demand, which means that supply needs to equate demand at any time. Such need for instantaneous balancing, propagated by increasing connectivity between more and more markets, raises questions about the reactions of multiple interconnected markets. Hypothetically, as market connectivity continues to improve, one electricity trade flow will have an even stronger impact on the electricity flow of another market that is one or even two borders away in the interconnected system. It is therefore credible to hypothesize under the second null hypothesis H_0^2 that trade flow between

[25] See the ECEEE, https://www.eceee.org/policy-areas/energy-union/.
[26] EC Quarterly Report on EU Electricity Markets, DG Energy, Vol. 11, Q1 2018.
[27] See https://isaacphysics.org/concepts/cp_kirchhoffs_laws.

a pair of neighbouring countries can be affected by trade flow between another pair. In this context, I examine the cases of countries with a common border, as well as those without. One particular strand in the academic literature addresses international trade and it represents the theory of market connectivity and trade flow interaction. For example, the work of Krugman (1979) is related to this hypothesis, since it demonstrates not only clear welfare gains from cross-border trade, with zero assumed transport costs, but also economies of scale increasing cross-border trade. Krugman's ideas can be considered pivotal for the continuous European electricity market coupling process and the development of the hypotheses described in this paper.

Research on how one cross-border flow impacts other flows broadens understanding of the forces that form the supply in interconnected markets. It also allows practitioners to exploit temporary mispricing more successfully, and regulators to address situations of possible abuse of market position (e.g. Gebhardt and Hoffler 2013). It is also plausible to assume that changes in electricity flow patterns across borders can lead to distortions in the price formation on the affected electricity market, with subsequent temporary mispricing. This study addresses such situations by selecting pairs of countries with and without a common border, which allows for the testing of the impact between both direct neighbours, that is, cross-border, and other countries, that is, beyond neighbouring countries. The aim is to investigate the influence that direct and indirect cross-border electricity trade flows can have on the price formation for each of the markets in the study.[28]

The third null hypothesis H_0^3 stipulates that change in the electricity price is a function of the change in cross-border trade flow. Price distortions from changes in trade flows are identified, and an optimal trading strategy is proposed for market participants with access to all the financial electricity markets included in the study. Theoretically, such price distortions should not exist under the assumption of free market forces and the flow-based market coupling mechanism.[29] The flow-based market coupling mechanism represents the cross-

[28] Direct electricity flow is defined as cross-border flow between two countries that share a common border with the tested market. For example, market A is tested against flow between countries A and B or A and C. Indirect flow is defined as flow between two countries with no common border with the tested market. For example, market A is tested against flow between countries C and D or D and E.

[29] The term *arbitrage* in this case and throughout the paper is used to describe buying and/or selling of the same asset (electricity) triggered by simultaneous changes in volume in connected markets. This should not be confused with the strict definition of arbitrage, which involves taking advantage of price differences by buying or selling the same asset in a different market.

border capacity allocation of Central and Western European day-ahead electricity markets, which have superseded the available transfer capacity methodology (Van den Bergh, Boury, Delarue 2016, Tennet 2015).[30] On one hand, early evidence from the equity markets provided by Copeland (1976) and Jennings, Starks, and Fellingham (1981) suggests a bidirectional positive causal link between price and trading volumes. DeLong, Shleifer, Summers, and Waldmann (1990) even find that short-term trading activity on the equity markets can cause changes in price direction. On the other hand, in a study directly relevant to the EU electricity markets, Kiesel and Kustermann (2016) conclude that cross-border electricity flow is *dictated by the price differential* between two markets.

This study utilizes daily pricing of day-ahead forward contracts and daily net cross-border trade flow data to examine the impact on price of changes in cross-border trade volume between Germany, France, the United Kingdom (UK), Spain, Italy, and Switzerland. Such a frequency of the time series and the selection of the countries in the sample represent important differences from the work of Cartea, Flora, Slavov, and Vargiolu (2019), who use not only intraday data, but also a different selection of countries.

There are 1,237 daily data points in the time series for both prices and trade flow from February 2015 to June 2018. The countries included in the study represent the electricity markets responsible for 64% of the overall European electricity physical market volume and constitute the most liquid spot and forward electricity markets in Europe.[31] The same sample with daily trade flow data is employed in the analysis of the impact that one particular cross-border flow has on another flow under H_0^2. Hypothesis H_0^3 is examined using 41 monthly data points for the average monthly electricity price and the distances between 10 pairs of countries with and without a common border, namely, Germany–Switzerland, Switzerland–Italy, Switzerland–France, Germany–France, France–UK, France–Spain, France–Italy, Germany–UK, Germany–Spain and Germany–Italy. Purchasing managers' index (PMI) data are utilized as a proxy for gross national product (GNP)/gross domestic product (GDP) data, which are published less frequently.

[30] See https://www.tennet.eu.

[31] According to Eurostat September 2018 data release, and the London Energy Brokers' Association monthly transaction reports.

The proposed hypotheses are first tested with the help of the customized CR and SSP tests. Further evidence of a causal link between flow and price, flow and flow, and the gravity of the trade coefficient and flow is obtained from Granger causality and Wald tests. The VECM framework is also employed to identify and trace the shocks introduced to a system. More specifically, these are accomplished with the help of impulse responses and variance decomposition analysis by imposing restrictions on the model matrices. Drawing on the findings from the test of H_0^1, a short-term electricity trading model for the day-ahead market is proposed.

The results from examining the first hypothesis H_0^1 suggest that, with the exception of the French market, the reaction of price to flow in all the markets in the study has become less pronounced over time. Regardless, the results also confirm that the Italian, Swiss, and French electricity prices are the most responsive to electricity flow changes. Furthermore, the outcome from the cross-border arbitrage model advanced by this study is unambiguous. The proposed trading algorithm, which is guided exclusively by changes in cross-border electricity flows, has a 71.8% success rate. This amounts to an accumulated return on investment (ROI) of 129.1% when adjusted for transaction costs, or an annualized return of 26.3%. Studying the evolution of the ROI reveals another finding, namely, that the ROI peaked in 2017 and has contracted since. This result is in line with an earlier finding, that the reaction of price to flow has become less pronounced in a number of European electricity markets. It is plausible to assume that such result will attract the attention of market participants active in the physical and financial electricity markets. In addition, regulators are likely to take note from the findings regarding the diminishing sensitivity of prices to changes in the trade flows discussed.

Analysis of cross-border flow versus another cross-border flow performed under H_0^2 reveals evidence of a consistent interaction between the Switzerland–France and Germany–France cross-border electricity flows. There is also evidence of positive feedback between the Switzerland–Italy and France–Italy flows. Similar to one of the outcomes recorded under H_0^1, the number of occurrences in which flow impacts another flow is also showing signs of a decline. One reason for this trend could be that suggested by Fuss, Mahringer, and Prokopczuk (2017), who estimate that, under the ongoing process of market coupling, cross-border flows into economically inefficient directions can be avoided.

While the strongest impact on flow from another flow is documented for a number of adjacent countries, such as Germany–France and France–Switzerland or France–Italy and Switzerland–Italy, there is evidence of an impact between two flows with no common border. The flow between France and Spain appears to be the most likely to be affected by other flows, such as the Switzerland–Italy and Germany–Switzerland flows. Overall, the French power market is found to have the strongest cross-border impact on other markets, which provides insight into the price formation mechanism affecting the European power market at its core.

Analysis of the impact of the gravity of trade on electricity prices under the third hypothesis (H_0^3) reveals the reaction in 18 gravity–electricity flow pairs, only six of which have no common border, which represents 5.7% of the total of 105 pairs tested for H_0^3. Such results make it plausible to reject the hypothesis of non-applicability, H_0^3; that is, the trade gravity equation also applies to the electricity market. In other words, distance does matter when it comes to cross-border electricity trading. This conclusion is reached independently of any consideration, based on the cost of transportation of electricity in the face of transmission losses. Apart from the academic value of testing for the first time the gravity theory of international trade on the European electricity market, H_0^3 paves the way for future research into the topic of how the macroeconomic data of one country is priced by the electricity market in another country within the environment of an energy union. Any mispricing is likely to attract the attention of regulators and market participants alike.

This paper's first contribution is to identify and quantify causal processes between cross-border electricity trade flow and electricity prices that lead to price lagging behind the flow. Contrary to the established literature, which considers trade flow to be the dependent variable (e.g. Kiesel and Kustermann 2016), this paper finds that changes in cross-border electricity flow anticipate changes in prices. The collected evidence corroborates the finding that the Italian, Swiss, and French markets are the three most responsive countries in the sample to cross-border trade flow markets.

Still under the first hypothesis, the second contribution is the attestation of the strong incentive for participation in cross-border trading in the European power market. This finding, which contradicts the claims of Gebhardt and Hoffler (2013), is documented with the help of the results from the introduced trading model, whose algorithm is based on the identification of causal relationships between electricity flow and price, where flow leads the price. Since the tradable instrument is the electricity price, not the flow, the algorithm searches for a causal signal only when the volume leads the price. The evidence collected in this study shows an annualized return of 129.10% for the sample period,[32] with a Sharpe ratio of 2.15 for the risk-adjusted return.

As the EU power market continues its process of integration, this paper's third contribution is revealed, namely, that the proposed methodology under H_0^1 can be extended to examine the reaction of one cross-border electricity trade flow to changes in another trade flow, also called the flow-on-flow reaction. This contribution represents the second hypothesis, H_0^2. The importance of quantifying the flow-on-flow reaction is encapsulated in the process of European electricity market integration. The lack of price convergence between adjacent markets included in this study, as displayed in Figure A1 in the Appendix, allows one to infer that this integration is far from over. This makes the results from the econometric flow-on-flow tests and models developed under H_0^2 very topical. First, the results expand understanding of the electricity flow within the entire system. Second, it allows one to forecast electricity flows between two countries based on flows between two other countries that sometimes do not even share a common border. The outcomes and sensitivities identified are likely to attract the interest of regulators involved in Europe's energy market design, academics, grid operators, and market participants who are interested in profiting from the temporary distortions identified under H_0^2.

The fourth contribution of this paper is the analysis of the influence of economic activity and geographical distance between two electricity markets, applying Tinbergen's (1962) gravity model to international trade. To the best of my knowledge, this study represents the first attempt in both the academic and practical literature to explain electricity flow formation and direction with the help of the trade gravity equation. Successful application of the gravity model of international trade to the electricity market in Europe also confirms the claim of Bergstrand and Egger (2010), that the model is applicable to any commodity market.

[32] The return is net of transaction costs and annualized based on 252 trading days per year.

The remainder of this paper is organized as follows: Section 2 discusses the available literature and attempts to identify gaps and weaknesses in the academic work. Section 3 explains the data, samples, sources, and time frame selection criteria. Section 4 describes the methodological framework of the various hypotheses. Section 5 describes the results and Section 6 concludes the paper.

4.2. Literature review

The first hypothesis is based on the application of the gravity model to international trade. Following the seminal work of Tinbergen (1962), who draws an analogy with Newton's law of gravitation to explain statistically bilateral trade flows between large numbers of countries, the sub-hypothesis studies the impact the gravity of trade is likely to have on cross-border electricity flows. Tinbergen, who was also awarded the first Nobel Prize in Economics for his work on the topic, expressed the coefficient of gravity of trade between two countries as the relationship between their economic size, as measured by the GNP in US dollars, and the geographic distance between the two markets. In the original version of the model, trade flows are measured in terms of both imports and exports, and the distance between countries with a common border is assumed to be one. The original equation also takes into account trade frictions, such as the preferential treatment of one exporter over another on political grounds.

Later work by Anderson (1979) contributes to the theoretical framework of the topic. Even though the gravity model has found wide use in also explaining the behaviour of foreign direct investment and migration flows, its core value applies in international trade. Cross-border trade flows consist of a huge variety of goods, in both their finished and intermediate states. The gravity theory of trade is believed to apply universally to any such goods (Bergstrand and Egger, 2010, Brakman and Bergeijk 2010). Electricity is one of the most important commodities in an intermediary state, and I hypothesize that the laws of gravity of trade apply to this market as well. To the best of my knowledge, there is no academic or practitioner work on the behaviour of the pan-European electricity market and the gravity of trade flows.

One strand in the academic literature that draws a connection between all three hypotheses discussed in this paper is work on international trade. For example, Stern (1976) claims that price elasticity is necessary to estimate the response of imports and exports. Such an assertion explicitly defines the causal relationship between trade and price. Furthermore, Krugman (1979) has introduced a model that stipulates that trade between two countries is caused by economies of scale, as opposed to factor endowments or technology. The author demonstrates not only clear welfare gains from cross-border trade (assuming zero transport costs), but also that economies of scale increase cross-border trade. Krugman's ideas are fundamental for the success of the ongoing European electricity market coupling process, which is considered to increase economic efficiency (see also Weber, Graeber, and Semmig 2010). Last but not least, Bahmani and Oskooee (1986) studies the reaction of trade flows to changes in exchange rates and price levels as two determinants of trade flows. The author also FXilicitly defines the direction of causality as prices and exchange rates causing changes in trade flows.

The interaction between trading volume (cross-border trade flow) and price is not a novel research subject. Academic research on the price–volume relationship can be traced back to Osborne (1962), who represents the stock price change as a diffusion process whose variance depends on the number of transactions. The author implies a positive correlation between volume and changes in prices. Another early attempt to describe the price–volume relationship is that of Granger and Mortgenstern (1963), who conduct the spectral analysis of weekly stock market data from 1939 to 1961 but find no evidence of a positive link between price and volume. In a subsequent study, Godfrey, Granger, and Morgenstern (1964) present evidence of a lack of correlation between prices and volume. Instead, they find that the daily volume is positively correlated with the difference between the daily high and daily low of the particular market. The authors consider this correlation to be the result of trading-specific factors, such as stop-loss orders and orders to buy above the market that increase the volume when the price deviates from its current mean. Both studies of Granger and Mortgenstern (1963), and Godfrey, Granger, and Morgenstern (1964), work with data on stock market aggregates and two to three common stocks.

Later works by Epps and Epps (1976) on both stocks and bonds suggest that the market volume changes with intraday price variability. The authors find evidence that the distribution of the change in transaction price is a function of volume. The topic is further developed by Tauchen and Pitts (1983), who establish the form of the joint probability distribution of the change in price and trading volume. These authors also establish that a strong increase in the trading volume/number of traders in the market can conceal most of the relationship between the squared price change and the trading volume. Evidence of a positive correlation between price and volume does not appear to be limited to the fixed income and equity markets.

To the best of my knowledge, the first study focusing on a commodity market is that of Clark (1973), who finds a positive relation between the price change (squared) and the aggregate volume, using daily data from the cotton futures market. The topic of the price–volume relationship on the commodity markets gained further ground in the early-mid 1980s, with the paper of Grossman and Stiglitz (1980) suggesting that, given the market's growth in terms of number of participants and trading volumes, price has become a more accurate predictor, since it tends to average the forecasts of more participants. Rutledge (1979) finds strong correlations between daily volumes and daily price changes for 113 of 136 futures contracts analysed.

Academic research on the price–volume relationship during this early period (1963–1988) is largely focused on establishing a contemporaneous relationship (e.g. Karpoff 1987; see also Table A1 in the Appendix). The papers by Rogalski (1978) and Smirlock and Starks (1985) form one of the first groups of studies to investigate a statistically significant causal relationship between absolute stock price changes and volume. Smirlock and Stark (1985), for instance, detect such a relationship at the firm level and find it to be stronger around earnings announcements. Jain and Joh (1988) confirm bivariate causality between intra-day equity prices and trading volume, using exclusively linear Granger causality tests. The literature is in agreement that evidence of a causal relation between price and volume is down to the so-called sequential information arrival model, introduced by Copeland (1976) and developed by Jennings, Starks, and Fellingham (1981). The hypothesis of this model is built on a positive causal link between the price and trading volume in both directions and on the asymmetry of information dissemination. New information flows into the market and is distributed to the market participants, one unit at a time. This implies a sequence of momentary equilibria that comprise numerous short-lived price–volume combinations before the final information equilibrium is reached. Given this step-like sequence of information flow, the lagged trading volume can have predictive power for price, and lagged price returns can have predictive power for trading volumes.

Other evidence in support of the price–volume causality is the influence of short-term trading on price formation. This relation is summarized by the so-called noise trader model of DeLong, Shleifer, Summers, and Waldmann (1990). Any positive causal relation, in this case, will be in agreement with the assumptions made by this model, that the trading strategies pursued by short-term traders, that is, noise traders, cause changes in price direction. This particular group of market participants tends to not base their decisions on fundamental data; so, they impose temporary pressure on the price of the asset, which leads to short-term mispricing. This pressure dissipates in the long run, which leads to mean reversion in pricing. Therefore, a causal relation from price to volume is consistent with such a positive feedback trading strategy (see also Hiemstra and Jones 1994).

It is logical that the first academic research papers on the price–volume relationship, starting with Osborne (1962), as discussed above, all date back to the 1960s through 1980s (see also Table A15 in the Appendix for a summary of papers published in this period). Their focus is predominantly on the equity and fixed income markets, which can be explained by the fact that these are bigger and more mature markets, compared to commodities, which in turn implies longer and more consistent time series available for research. Commodities appear later in this strand of the literature: first in the mid to late 1970s and 1980s, and then more frequently in the 1990s, as the markets improved the quality of data.

To the best of my knowledge and with the notable exception of Cartea, Flora, Slavov, and Vargiolu (2019), there also appears to be no research on the interaction between two or more electricity flows in the European power market. Supply plays an important role in electricity price formation, and the technological inability to store this commodity on an industrial scale makes moments of potential stress in such a finely balanced system between two and more markets particularly appealing for arbitrage.

An important strand in the literature, however, discusses price formation in the European electricity market in the context of price convergence between two neighbouring markets and the impact of available interconnector capacity on the electricity price. For example, according to Kiesel and Kustermann (2016), it is the price differential between two markets that dictates the cross-border flow. Their findings also suggest that, due to the convexity in the market supply curve, an inverse relationship exists between interconnector capacity and the average base and peak load prices between two adjacent markets.

Contrary to Kiesel and Kustermann's (2016) findings, the results of this paper support the hypothesis that cross-border electricity flow can be a powerful stand-alone factor in the price formation mechanism of both adjacent markets and markets without a common border but part of the European electricity market. Another study, by Gebhardt and Hoffler (2013), investigates the relationship between spot and interconnector capacity prices and claims that well-informed traders do not engage in cross-border trading. The authors even postulate that incumbents could buy interconnector capacity only to block international competitors. Their findings do not necessarily contradict the results of this paper. It is plausible to assume that the strong arbitrage signal identified in this study is the result of market inefficiency, that is, insufficient numbers of market participants, and hence lower liquidity, in the cross-border electricity market.

There is another potential gap in the literature: the gravity theory of trade is largely omitted from explaining certain price and volume movements in power markets. A further gap in the literature is identified through the methodologies employed by researchers to study the link between price and volume. Most studies address the issue by employing traditional bivariate Granger causality and correlation techniques. In contrast with this paper, I did not find any evidence for application in the literature of VAR/Impulse response models. Last but not least, the literature lacks a cross-border arbitrage model in the day-ahead power market based exclusively on trade flow signals.

For the linear interdependencies of multivariate time series to be captured, this study utilizes a stochastic process model, also known as a VAR model, and the restricted form of a VECM. VAR models, first introduced in 1980 by Sims (1980), advanced the concept of modelling all the endogenous variables in a system together, and not one equation at a time. There are doubts about the ability of VAR models to differentiate between correlation and causality (e.g. Lütkepohl 2005). Additionally, VAR models use scant theoretical information for the underlying relationships in the data. However, the reasons for using a VAR system to study the relationships between electricity flow and price include its flexibility of VARs over univariate autoregressive (AR) models (since the variables are allowed to depend on their own lag or white noise) the lack of "incredible" restrictions in the model, and, very importantly, the treatment of all variables as endogenous.

Another common test for studying the interdependence between variables is the Granger (1969) causality test. According to Sørensen (2005), Granger causality tests appear to be most successful in two-dimensional systems, or bivariate causal relationships, which is where this test is applied in this study. Sørensen also suggests caution in selecting the length of the sampling period, since a long one will tend to hide causality. A major weakness of this test is its static nature, that is, it relies on a strictly defined sampling period; however, causality is not a static condition, since its properties evolve over time. The test does not offer a solution to this problem, which is why I apply a SSP test. A SSP is a form of cross-correlation function (CCF) between two variables. The cross-correlation of multivariate time series involves more than one process. It is thus a function of the relative time between signals. Von Storch and Xu (1990) describe cross-correlation in a principal signal oscillation processing analysis. They provide a detailed account of the measure of similarity of two waveforms as a function of a time lag applied to one of them, also defined as a sliding dot (scalar) product or a sliding inner product.

4.3. Data, sources, and time frame selection criteria

This paper utilizes three groups of data. The first group is the daily pricing data of day-ahead contracts for Germany, France, the UK, Spain, Switzerland, and Italy. The countries in the study are chosen based on trade flow reliability and the availability of financial electricity market data, as well as intraregional connectivity and common supply and demand patterns. For example, the Nord Pool market is deliberately excluded because it is relatively geographically detached and the price is strongly influenced by the utilization rate of the installed hydroelectric power generation capacity. This is in contrast to the group of countries chosen for this study, whose electricity generation systems are dominated by nuclear power, fossil fuels, and wind/solar generation.

The Austrian, Polish, and Czech electricity markets are also excluded, based on the following reasons. First, the trading model proposed in this paper relies on liquid financial electricity markets to execute entry/exit signals. The Polish and Czech markets do not satisfy the minimum required liquidity threshold.[33] Second, the German and Austrian power markets were effectively coupled between 2002 and 2018. This means that the markets were in price equilibrium, which, in turn, did not allow for arbitrage conditions to emerge, even if the recorded cross-border trade flows were significant. Third, due to excess renewable power generation capacity in the north, there is valid concern that electricity flow originating in Northern Germany will enter the Polish and/or Czech grid and exit in Southern Germany. Under the settings of my model, such flow has to be counted as a cross-border import/export. In reality, some of the electricity bypasses the congested grid of Central Germany. It is thus difficult, if not impossible, to quantify which flow is a genuine import and which one is simply bypassing the grid. Therefore, in the interest of accuracy, these markets are excluded. Fourth, following formal complaints by neighbouring grid operators, the European Agency for Cooperation of Energy Regulators (ACER) published an opinion in 2015. The opinion effectively agreed with the formal complaints filed in 2014 by Polish and Czech grid operators, who claimed that excessive renewable power generated in Northern Germany was forced to flow south, unlawfully disrupting the operations of the grids of neighbouring countries. ACER advised that the Germany–Austria interconnector flow should be subject to capacity allocations, which effectively laid the groundwork for splitting up these coupled markets, which took place in October 2018.

All adjacent countries in the sample have interconnector facilities in place, but the study does not focus on the limitations imposed by the existing interconnector capacity. What changes on a daily or intraday basis is the incentive to export/import electricity, not the maximum interconnector capacity. This incentive can be 1) price driven, under the conditions of cross-border price arbitrage; 2) economy driven, in the face of a demand shock, and 3) excess supply driven, since renewables displace fossil fuel power generation and traditional sources are not able to adjust immediately. Since any of these conditions will arise within the limitations of the existing (and static, in the short term) interconnector capacity, the hypotheses advanced by this paper are built on the assumption that market signals generated by price or electricity flows can be detected, regardless of the limitations imposed by cross-border connectivity.

[33] This threshold is based on internal Marex Spectron guidelines for speed and accuracy of execution in any given market.

The second group of data consists of the daily amounts of net cross-border electricity flow between Germany, Switzerland, Italy, France, Spain, and the UK. For the purpose of this paper, cross-border electricity flow is considered to be the trading volume of the cross-border market. The third group consists of PMI data from IHS Markit,[34] which are used for the calculation of the gravity of trade coefficient.

There are 1,237 daily data points in the time series for both prices and trade flow, 41 monthly data points for the PMI data, and 10 distances between countries with and without a common border. Following Tinbergen (1962) and De Benedictidis and Taglioni (2011), adjacent countries with a common border are assigned a dummy variable that equals one; these pairs of countries are Germany–Switzerland, Switzerland–Italy, Germany–France, France–UK, France–Spain, and France–Italy. Pairs with no common border are Germany–UK, Germany–Spain, and Germany–Italy.

The source of the day-ahead pricing data is the European Energy Exchange (EEX). The unit of the electricity contracts is the euro per megawatt–hour. The trade flow data are from the European Network of Transmission System Operators for Electricity (ENTSO), in units of megawatts (MW) per day. Both pricing and trade flow intraday data are provided by the EEX's European Power Exchange.

Distances, in kilometres, between the country border interconnectors of all the countries in the study are measured as a straight line. The distances between countries without a common border are calculated using Google Maps.

4.4. Methodological framework

This paper investigates the reaction of electricity prices and flows to changes in the cross-border flows between Germany, France, the UK, Spain, Italy, and Switzerland. These markets represent 64% from the total EU-28 electricity market.[35] The applicability of the gravity theory of trade to the European electricity market is also examined. The methodological framework of this paper evolves in six stages, as follows.

[34] IHS Markit is a global economic data provider firm.
[35] Source: Eurostat, September 2018. The data release on the Eurostat website is monthly.

Stage 1 defines the three hypotheses of the study. **Stage 2** explains the procedure of calculation of the gravity of trade coefficients. The first and preliminary evidence of the relationships between price and flow, flow and flow, and the gravity of trade and flow is gathered in **Stage 3,** with the help of the proposed CR test. **Stage 4** examines the same relationships described above, namely G–F, F–P, and F–F, using SSP analysis. **Stage 5** employs econometric VAR analysis to study the reaction of price to changes (shocks) in the gravity of trade and cross-border electricity trade. VAR models and VECMs are widely used for identifying and tracing shocks introduced to a system, with the help of impulse response analysis, imposing restrictions on the model matrices. The interaction between trade flows across adjacent and non-adjacent borders is also investigated. Finally, **Stage 6** proposes a short-term electricity trading model for the day-ahead market. The signal reflecting the trading decisions draws on the findings from the econometric tests and models discussed in the previous three stages. Short-term contracts (with a first rolling calendar month) are used to calculate the returns. Transaction costs per the market rate as of September 2018 are also taken into account.[36]

4.4.1. Stage 1

Under Stage 1, I specify the set of research questions tested against their respective null hypotheses, denoted as H_0. The first research question, H_0^1, calls into question the link between the gravity of trade (G) and the flow of electricity (F). Under this null hypothesis, it is assumed that the flow of electricity not only follows the economic activity in the pair of countries, but is also influenced by the distance between the two countries. The second research question, H_0^2, concerns the influence of one trade flow over the behaviour of another trade flow. The key third hypothesis , H_0^3, involves the relationship between the electricity trade flow and market price for a neighbouring market with a common border and for markets within the EU internal energy market but without a common border.

The three null hypotheses investigated in this paper can be summarized as follows.

1. H_0^1 : Trade flow (F) between two countries A and B is a function of the gravity of trade (G) between the two countries.

[36] The transaction cost information is obtained from the Marex Spectron EU power trading desk.

2. H_0^2 : Not only is the price (P) in countries A or B a function of the cross-border electricity flow between the countries, but also a causal link exists where flow causes changes in price..
3. H_0^3: Cross-border electricity trade flow (F) between countries A and B is a function of the trade flow between the countries B and C, D and E, or A and C. The cases of pairs of countries both with a common border (AB vs. BC) and without a common border (AB vs. DE or AB vs. AC) can thus examined.

4.4.2. Stage 2

Following the seminal work of Tinbergen (1962), the gravity of trade (G) between two countries A and B is expressed by the relationship between their economic size, measured by their GNP in US dollars, and the distance between the two markets. In the original version of the model, trade flows are measured in terms of both imports and exports, and the distance between countries with common border is assumed to be one. The original equation also takes into account trade frictions, such as the preferential treatment of one exporter over another on political grounds. A stochastic term e is also included, and the model adopts the following time series regression form:

$$\mathrm{lnG}_{AB} = lnC + a_1 lnGNP_A + a_2 lnGNP_B + a_3 d_{AB} + a_4 D_{AB} + a_5 P_{AB} + e_{AB} \tag{1}$$

Where: G is the gravity trade flow between countries A and B, C is a constant, the GNP is that of countries A and B, d is the geographical distance between countries A and B, D is a dummy variable with a value of one if the countries are adjacent, and P is a dummy variable for trade policy conditions between countries A and B. Trade policy conditions, in this case, imply preferential treatment through lower tariffs. There are no such barriers in intra-EU trade, which is why this dummy variable is zero.

The interconnector capacity between each pair of adjacent countries is not taken into account. The capacity is considered to be static within the time frame (monthly) investigated. What changes within this time frame is the incentive to export/import, not the available interconnector capacity. This incentive can be 1) price driven, through cross-border price arbitrage; 2) economy driven in the face of a demand shock; or 3) excess supply driven (i.e., a supply shock) through renewables displacing other (fossil fuel) power generating capacity. Since traditional sources are not able to adjust immediately, the result is a supply shock.

Any of the three conditions will materialize within existing interconnector limitations.

For the purpose of this study, G is calculated as follows:

$$\mathrm{G}_{AB} = \frac{\mathrm{GDP}_A * \mathrm{GDP}_b}{(TL * d^2)} \tag{2}$$

Where: G_{AB} is the gravity of trade from country A to B, GDP_A is the GDP of country A, GDP_B is the GDP of country B, d is the distance between the countries, and TL represents transmission losses.

Due to the chosen data frequency periods, quarterly GDP data are substituted with monthly PMI numbers. Markit uses a standard methodology to calculate a specific country's PMI across the spectrum of countries it covers, which means that the data are comparable between countries. Another advantage is the leading property of the PMI. This result is due to 1) the methodology of the calculation that captures the forward sentiment amongst industry participants and 2) the publication schedule (the PMI is published on the last trading day of the month for the current month, as opposed to GDP or industrial production data, which are published for the previous month with a minimum of a two-week delay.

The distance between two countries A and C without a common border is calculated as a straight line between the two interconnectors on their borders.[37] Following Tinbergen (1962) and equation (1), the distance d is considered to be equal to one in the case of neighbouring countries A and B.

Transmission losses, which reduce the incentive to transport electricity over large distances, are also taken into account. Therefore, it is plausible to assume that countries with a common border will have the technological advantage of trading electricity more cheaply, compared to countries without a common border. Transmission losses depend on many factors, including the landscape, the elevation above sea level, climatic conditions, and the length of the transmission line.

[37] See ENTSO, https://www.entsoe.eu/data/map/.

4.4.3. Stage 3

A test for a coincidental link between two cross-border flows is performed with the help of the CR test, where binary conditions denoted by one and zero are used to define the coincidental response of cross-border trade flow F between locations A and B and between B and C within the chosen time frame. First, I calculate the period variation of F:

$$\Delta \mathrm{F}_{1t} = F_{ABt} - F_{ABt-1} \tag{3a}$$
$$\Delta \mathrm{F}_{2t} = F_{BCt} - F_{BCt-1} \tag{3b}$$

Where: ΔF_1 is the difference in cross-border trade flows between countries A and B between time t and time t - 1, and $\Delta \mathrm{F}_2$ is the difference in cross-border trade flows between countries B and C between time t and time t - 1.

A pre-set rule searches for CRs and assigns a one if it finds any, and a zero otherwise. In other words, if either of the two conditions is met, the test returns a value of one. If the two variables move in different directions, the formula returns a value of zero. Therefore, for the length of time series i = (1,…, n),

$$CRt(i) = \begin{cases} \frac{\Delta Ft1}{\Delta \mathrm{F}t2} > 0 \rightarrow Zt = 1 \\ \frac{\Delta \mathrm{F}t1}{\Delta Ft2} < 0 \rightarrow Zt = 0 \end{cases} \tag{4}$$

Where: $CRt(i)$ is the outcome from the CR test, $\Delta \mathrm{F}_1$ and $\Delta \mathrm{F}_2$ are as specified above, and Z is a binary test variable.

The CR test outcomes are displayed with a histogram and the statistics of the time series are calculated as follows:

$$CRTt(i) = \frac{1}{n}\sum_{i=1}^{n} CRTi \tag{5}$$

The test outcome is recorded as a one and zero, where the value of one indicates a positive slope of the linear regression line y = a*x + b as measured by the sign of the slope a. A positive slope of the regression line also indicates increasing numbers of occurrences, that is, where $\Delta \mathrm{F}_2$ at time t reacts to change in $\Delta \mathrm{F}_1$ at the same time t. In essence, in the case of the described flow-flow relationship, the test quantifies instances of coincidental reaction of the dependent variable on any change in the independent variable

The same procedure is repeated for the flow–price relationship. Positive outcomes are recorded when flow increases and P increases (marked by +1), or when flow decreases and price decreases (marked by -1). Either of the two outcomes satisfies the hypothesis of the relevant research question.

4.4.4. Research design procedure: Stage 4

The proposed SSP test involves a bivariate descriptive statistical analysis of the evolution of the cross-correlation between each pair of cross-border flow and price or two flows under the null hypotheses specified above. The cross-correlation of multivariate time series involves more than one process. It is therefore a function of the relative time between the signals. Von Storch and Xu (1990) describe cross-correlation in a principal signal oscillation processing analysis. They provide a detailed account of the measure of similarity of two waveforms as a function of a time lag applied to one of them, also defined as the sliding dot (scalar) product or sliding inner product.

I compute the cross-correlation time series $P_{t=}\,p_{0,\dots,}p_T$ from two input time series $Y_{t=}\,y_{0,\dots,}y_T$ and $X_{t=}\,x_{0,\dots,}x_T$ by computing Pearson's correlation coefficient $\rho(X,Y)$ over a rolling window, as follows:

$$\rho(X,Y) = \frac{cov(X,Y)}{\sigma X \sigma Y} \quad (6)$$

which is the usual Pearson coefficient, with $cov(X,Y)$ as the covariance and σX and σY as the standard deviations of the variables X and Y, respectively. The definition of the Pearson correlation $\rho(X,Y)$ requires further clarification, because the same SSP test is applied for three different hypotheses, each of which, in turn, requires different specifications of the variables X and Y, as follows.

- Under H_0^1, X is the gravity of trade coefficient G and Y is F.
- Under H_0^2, X is the cross-border flow F between any two countries with a common border and Y is F.
- Under H_0^3, X is the cross-border electricity trade flow F between any two countries with a common border and Y is the price of electricity P of the tested market.

For every time step t and lead–lag k in the constructed time series P_t, the correlation coefficient of a window of size n is computed. explicitly, to compute P_t with a window of size n with the lead–lag step k = 0,

$W_t := \{x_{t,\dots,}x_{t+n}\}$, for k = 0 (7)
$V_t := \{y_{t,\dots,}y_{t+n}\}$, for k = 0 (8)

$$P_t := \rho(X_{t,}Y_t) \quad (9)$$

Where: the lead–lag number of days k is between -10 and 10, and k = 0 indicates a coincidental correlation. A negative k value means that W_t lags k days behind V_t.

The cross-correlation time series $P_t = p_{0,\dots,}p_{T-n}$ is constructed by repeating this T - n time series for every p_t. Therefore,

$$P_0 := \rho(W_{0,}V_0) \quad (10a)$$

$$P_t := \rho(W_{t,}V_t) \quad (10b)$$

Using the outlined procedure, additional correlation time series are computed on the input pair, where the series V_t^k is time lagged against the series W_t. To define a lead–lag operator,

$$L^k X_t = X_{t-k} \quad (11)$$

which is then applied as follows:

$$W_t^k := L^k(W_t) = \{X_{t+k,\dots,}X_{t+n+k}\} \quad (12a)$$

$$V_t^k := L^k(V_t) = \{Y_{t+k,\dots,}Y_{t+n+k}\} \quad (12b)$$

where k > 0 denotes a lead and k < 0 denotes a lag.
The new correlation time series on the input pair is then computed as

$$\theta_t^k := \rho(W_t^k, V_t^k) \quad (13)$$

In the final step, the series of all lags' CCF using the means of the cross-correlation time series means that :

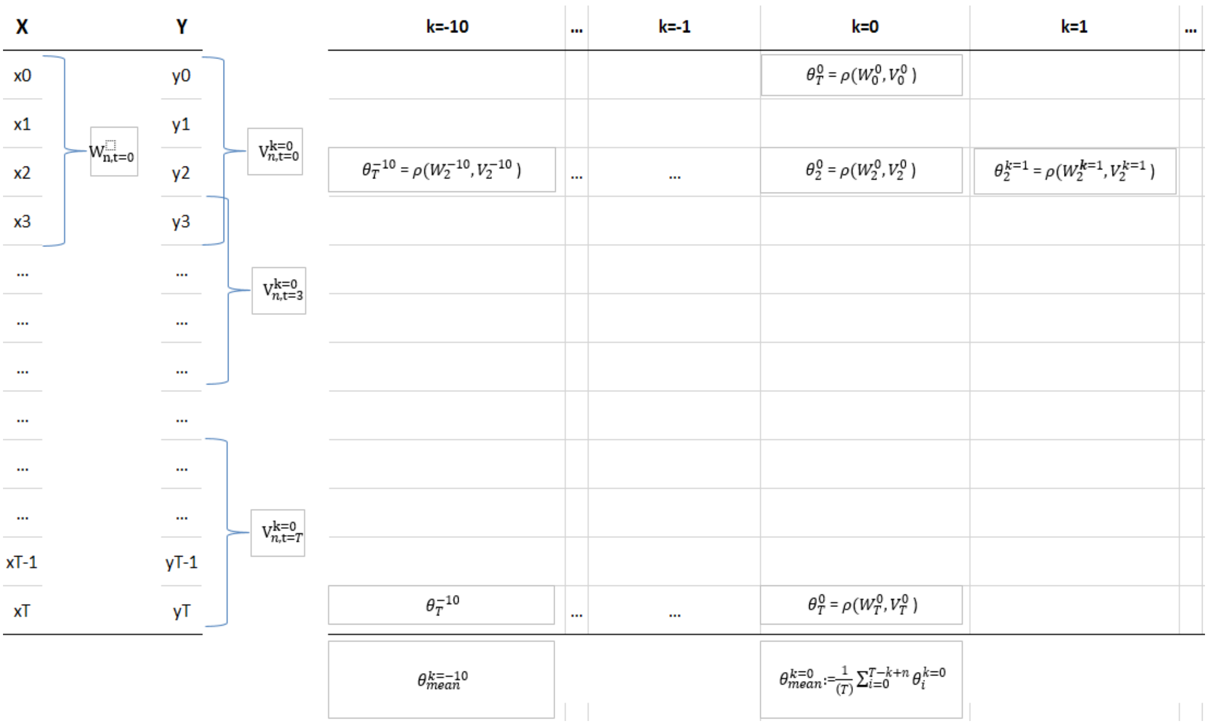
$$\theta_{mean}^{k} := \frac{1}{(T-|k|-n)} \sum_{i=0}^{T-|k|-n} \theta_i^k \tag{14}$$

$$\text{CCF(k)}: = \theta_{mean}^{-k}, \dots, \theta_{mean}^{o}, \dots, \theta_{mean}^{K} \tag{14a}$$

The schematic of the proposed test can be found in Figure 1.

Figure 1: Schematic of the SSP test

This figure displays the elements of the proposed SSP test, where X and Y are the time series variables, t is the time step, T is the total length of the time series, k is the lead–lag step, W_t and V_t are the lagged series, P_t is the cross-correlation time series of X and Y, n is the window size, θ_t^k is the new correlation series on the input pair, and θ_{mean}^k is the cross-correlation series mean.



When applying the analysis to a problem, the choices of window size and lags depend on the use case. For example, in tests using monthly data points, three lags will be considered (K = 3), because I assume that the impact from a change in the gravity of trade coefficient on the electricity price or the cross-border trade flow (the two input time series in this scenario) will have dissipated within three months. For daily data, the choice is K = 10. The total lengths (T) of the time series considered are 1,270 for daily data and 42 for monthly data, respectively.

The CCF(k) is positive when the correlation between the two variables is positive. The opposite is also true. Only lead occurrences are recorded, and they are assigned a score of one if the lead correlation is positive and a score of -1 if the lead correlation is negative. At this stage of building the trading algorithm, the sign of the correlation is ignored, since the purpose is to understand the lead–lag relationship between the two variables. The correlation sign is determined at a later stage, when the trading algorithm is designed, since it has an impact on the overall decision to go long or short in the specific market. The outcomes from the SSP test of each F–P pair are recorded within 10 days before or after the CR. In other words, the test measures the lead–lag properties of the pair for 10 leading days and 10 lagging days.

The advantages of the SSP test approach can be summarized as follows. First, it allows for the precise (up to the time unit chosen for the study) identification of the lead–lag periods between the X and Y variables. This is important for the process of building trading strategies, since it accounts for the better timing of a position entry and exit. Second, SSP test data can be plotted in a coordinate system for better visualization of the x–y relationship. Since the sign of the correlation does not matter (I examine the correlation strength, not the direction), the ideal outcome would be to record observations of lead periods clustered in the top-right or bottom-right corners of the scatter plot chart. In the case of a line chart, this would consist of lines starting from the top-right or bottom-right corners. The advantage of such a visualization is in the ability to quickly measure not only the lead–lag periods between the two variables along the x-axis, but also the strength of their lead–lag signal on the y-axis. Third, there are periods in the data sample when the lead property of the independent variable is clearly detected and displayed. However, there are also periods when its reaction lags. This finding does not clash with the null hypothesis of the test, which allows for changes in lead–lag regimes. It is important to be able to establish the existence of any long-term pattern in the X-Y relationship. For example, higher conviction trades can be established at times when X has clear lead properties.

4.4.5. Research design procedure: Stage 5

This stage involves a Granger causality test and a Johansen cointegration test, followed by a restricted VECM. Data are tested for a unit root with the augmented Dickey–Fuller (ADF) test, since bivariate and multivariate regression analysis in the form of VAR models requires stationarity. Non-stationary and cointegrated time series are then employed under the VECM framework.

True causality is a debated concept in academia, and the Granger (1969) test claims to find only predictive causality. This is done with the help of t-tests and f-tests on lagged data points of trade flow between countries A and B versus trade flow between countries B and C:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_i y_{t-i} + \beta_1 x_{t-1} + \cdots + \beta_i x_{t-i} + \varepsilon_t \tag{14a}$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_i x_{t-i} + \beta_1 y_{t-1} + \cdots + \beta_i y_{t-i} + u_t \tag{14b}$$

where i is the lag period of the AR model, x_t and y_t are the studied variables at time t, α_0 is the intercept, ε_t and u_t are the residual errors, and t $= (1, \dots, 1270)$ is the length of the time series.

When the specific variables of the test are substituted in equations (14a) and (14b), the result is

$$Fab_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i \, Fab_{t-i} + \sum_{i=1}^{2} \beta_i \, Fbc_{t-i} + \varepsilon_t \tag{15a}$$

$$Fbc_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i \, Fbc_{t-i} + \sum_{i=1}^{2} \beta_i \, Fab_{t-i} + u_t \tag{15b}$$

According to Sørensen (2005), Granger causality tests appear to be most successful in detecting causal links in two-dimensional systems, or bivariate causal relationships. This is an important reason why this paper focuses on pairwise Granger causality tests. Sørensen also suggests caution in selecting the length of the sampling period. For example, a long sampling period tends to hide causality. This is logical, since causality is not likely to be a static process. This is precisely why I run the preliminary tests discussed in Sections 4.2.1. to 4.2.3. One of the advantages of a Granger (1969) test is that an endogenous variable can be treated as exogenous.

The results in the face of p-values from the pairwise bivariate Granger test procedure are recorded, and if H_0: is rejected, the score is one, and zero otherwise. Since each of the set of variables has a unit root, ordinary regression analysis is not appropriate for the estimation, because there could be one or more equilibrium (cointegrated) relationships, that is, they can have a common stochastic trend. Therefore, the time series are further tested for cointegration under the Johansen cointegration procedure, which is based on an unrestricted VAR approach. Unlike the Engle–Granger (1987) test, Johansen's test allows one to test the hypotheses for an equilibrium relationship between sets of variables.

The generic VAR model can be written as follows:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_i y_{t-i} + \beta_1 x_{t-1} + \cdots + \beta_i x_{t-i} + \varepsilon_t \tag{16}$$

However, to use Johansen's method, the model requires the following VEC form:

$$\Delta y_t = \Pi y_{t-k} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} \ldots + \Gamma_{k-1} \Delta y_{t-(k-1)} + u_t \tag{17}$$

Where: the long-run coefficient matrix is

$$\Pi \quad = \left(\sum_{i=1}^{k} \beta i\right) - I_g;\ \Gamma_i = \left(\sum_{j=1}^{i} \beta j\right) - I_g, i = 1, \ldots, k-1 \tag{18}$$

Cointegration is established by the rank of matrix Π via the number of its characteristic roots/eigenvalues. The two tests are λ_{trace} and λ_{max}. According to the literature (e.g. Granger and Joyeux 1980), differencing all the variables of the model to force them into stationarity is the correct approach for univariate models. However, if there are important relationships between the variables in the long run, such forced stationarity is seen as a weakness in the methodology. If a cointegration relationship is established, this would imply the existence of a stationary linear combination of some of the variables. A VECM, and not a standard VAR model, in first differences is the most suitable approach for non-stationary and cointegrated time series, since it allows for both long- and short-run relationships to be captured.

In the F–P process, the Johansen test detects a cointegration relationship described by 12 cointegrating equations (CEs). Therefore, since matrix Π is defined as the product of matrices $\boldsymbol{\alpha}$ and β\`, the matrix has the form

$$\Pi = \boldsymbol{\alpha}\beta` \tag{19}$$

or, in the case of this study with seven variables,

$$\Pi = \begin{bmatrix} \alpha 11 & \cdots & \alpha 17 \\ \vdots & \ddots & \vdots \\ \alpha 71 & \cdots & \alpha 77 \end{bmatrix} \begin{bmatrix} \beta 11 & \cdots & \beta 17 \\ \vdots & \ddots & \vdots \\ \beta 71 & \cdots & \beta 77 \end{bmatrix} \tag{20}$$

Once the number of cointegration relationships between all seven variables in the system is established – namely, the cross-border flows from Germany to France (GERFR), from Germany to Switzerland (GERSWI), from France to the UK (FRUK), from France to Spain (FRSP), from France to Italy (FRITA), from Switzerland to Italy (SWIITA), and from Switzerland to France (SWIFR) – the VECM takes the following form:

$$\Delta P_t = b_1 \Delta GERFR_t + b_2 \Delta GERSWI_t + b_3 \Delta FRUK_t + b_4 \Delta FRSP_t + b_5 \Delta FRITA_t + b_6 \Delta SWIITA_t + b_7 (GERFR_{t-1} - \gamma_1 GERSWI_{t-1} - \gamma_2 FRUK_{t-1} - \gamma_3 FRSP_{t-1} - \gamma_4 FRITA_{t-1} - \gamma_5 SWIITA_{t-1} - \gamma_4 SWIFR_{t-1}) + u_t \tag{21}$$

The same methodology is followed when testing the H_0: of the processes G–F (monthly), P–F (daily), and F–F (daily). The residuals of the model need to be tested for stationarity because they will be non-stationary if the variables are not cointegrated. This is done with the help of the ADF test with the null hypothesis of a unit root in the cointegrating regression residuals, or $H_0\colon u_t \sim I(1)$

According to Lütkepohl (2005), the optimal lag order of the model is estimated with the help of the Akaike information criterion (AIC), the Schwartz/Bayesian information criterion (BIC), the Hannan–Quinn information criterion (HQIC), as well as the final prediction error. The most important difference between the various criteria is the severity with which they penalize an increase in the model order. The motivation behind a strong penalty for high model orders is to reduce overfitting, which has an impact on the models' forecasting skill.

I employ VAR models/VECMs for reasons different from forecasting. The model investigates the interaction between selected endogenous variables. More specifically, the aim is to investigate the causal relationships in the processes described under equation (6). This means that I prefer to select an information criterion that does not impose too strong a penalty on the model order. According to Lütkepohl (2005), the HQIC penalizes high model orders more than the AIC, but less than the BIC. I choose to work with the HQIC when selecting the optimal number of lags of the VAR model, based on the size of the data sample as well. The consensus in the literature (Lütkepohl 2005) is that the AIC/final prediction error outperforms the HQIC for small samples, but the HQIC is better for bigger samples. An information criterion different from zero indicates that the variables in the model are jointly significant.

Conclusions on possible causal relationships are also drawn from studying the responses of one variable to an impulse/shock introduced to another variable in the same multivariable system. This view is derived by removing elements from the structural model that are expected at t - 1. The VAR models focus only on modelling unexpected changes in a variable y at time t, which is a major difference with the traditional modelling practice, where dynamic simultaneous equations models do not make a difference between expected and unexpected changes in y_t.

The outcome from the shock is displayed in the form of impulse response functions (IRFs). To isolate the effect from the shock, suppose that all the variables in the system assume their mean value before time t = 0, yt = μ, t < 0, and one of the variables increases by one unit at t = 0. If no further shocks are introduced, one can trace the impact from this single shock on the first variable at t = 0, which can be represented as follows:

$$\text{yt} = \begin{bmatrix} y_{10} \\ \vdots \\ y_{50} \end{bmatrix} = \begin{bmatrix} \varepsilon_{10} \\ \vdots \\ \varepsilon_{50} \end{bmatrix} = \begin{bmatrix} 1 \\ \vdots \\ 0 \end{bmatrix} \qquad (22)$$

Therefore, y1 = $\begin{bmatrix} y_{11} \\ \vdots \\ y_{51} \end{bmatrix} = \Phi_1 y_0$, where Φ represents the effect of the shocks to the variables in the system after i periods. This procedure is repeated for all the variables in the model. If the variables have different scales, it is common practice to apply a shock of one standard deviation, rather than a one-unit shock. The trend of the reaction of the dependent variable is recorded within 10 days of the shock's introduction. The observed value of the IRF is equal to one if the reaction to the shock is positive – that is, the dependent variable increases after the shock is introduced to the independent variable – and equal to -1 if the reaction is negative.

The last test is a block exogeneity Wald test based on the VECM results. The block exogeneity Wald test is a bilateral test of whether the lags of an exogenous variable affect an endogenous variable. The test probes for joint significance between each of the variables for each VAR equation. A variable is block exogenous if it does not Granger-cause any of the other variables in the VAR model. Similar to the pairwise Granger test discussed above, the results are recorded in the form of p-values, and, if H_0: for non-causality is rejected with a 5% level of confidence, the score equals one, and zero otherwise. If H_0: is rejected both ways, the direction of causality is determined by the smallest p-value, and this is the pair that receives a score of one.

4.4.6. Research design procedure: Stage 6

The results from all five tests discussed above, namely, the CR test, the SSP test, the VAR pairwise Granger causality test (i.e., G-test), the VECM IRF test, and the VEC block exogeneity Wald test (or just Wald test), are summarized in tables (see Table 6 in Section 4.5) and aggregated in a single outcome table Π (see Table 7a in Section 4.5). These results indicate the strongest causal relationships to be between the independent variable (trade flow) and the dependent variable:

$$\Pi = A_{CR} + B_{SSP} + C_{IRF} + D_{GRANGER} + E_{WALD} \tag{23}$$

A summary of the scores for each dependent variable in Π reveals the strength of the conviction behind each market signal of the trading model, discussed later, in Stage 7. The probability of occurrence is also calculated with the help of

$$P(x) = \frac{n}{N} \tag{24}$$

Where: $P(x)$ is the probability of an occurrence, n is the number of causal relationships detected, and N is the total number of potential outcomes. The results are displayed in Table 9b in Section 4.5, on the results).

4.4.7. Research design procedure: Stage 7

The design of the trading model relies upon the output displayed in Π. The higher the score of each pair of results recorded in the table, the stronger the conviction of the trade on that pair. The sign of each coefficient indicates the direction of the relationship, that is, whether the correlation is positive or negative. The timing for the execution signal is denoted by the change in the independent variable. The exit timing is predefined at five days after entry, because the combined results from the VECM IRF and SSP tests clearly indicate that the price reaction to changes in trade flow, if any, dissipates, on average, 5.83 days after the shock is introduced. The first derivatives of the price and flow time series are calculated, respectively, as

$$\Delta P_t^A = P_t^A - P_{t+5}^A \qquad (25a)$$

$$\Delta F_t^{AB} = F_t^{AB} - F_{t-1}^{AB} \qquad (25b)$$

Where: F_{t-1}^{AB} is the electricity flow at times t and t - 1 between countries A and B and P_{t+5}^A is the price of electricity at times t and t + 5, where t + 5 reflects the holding period, as discussed above.

The direction of electricity flow is estimated with the help of a filter, where a rolling window of the standard deviation over the last five trading days is subtracted from the last observation. The sign of the numerical outcome with this filter defines the direction of the signal. A positive (negative) sign indicates that the electricity flow is rising above (falling below) the standard deviation of the last five trading days, which, in turn, dictates the direction of the trade:

$$F_{St}^{AB} = P_t^{AB} - \sigma_F \qquad (26)$$

Where: σ_F is the standard deviation of the flow sample and F_{St}^{AB} is the standardized flow between countries A and B.

To avoid contract roll skew between the last trading day of the first month and the first trading day of the second month, no trade is executed on the last trading day, to allow for a smooth contract roll. This case is handled with the following filter:

$$\begin{cases} M_t = 0 \rightarrow & \forall F_t \in S' \\ & F \oslash F_{ld} \end{cases} \qquad (27)$$

Where: M_t is the filter that differentiates in-month days versus end-of-month days, S' is the sample, and F_{ld} is the flow on the last trading day of month.

The filtered price is represented with the help of M_t as follows:

$$\begin{cases} P_{ft} = \varDelta P_t \;\rightarrow\; M_t = 0 \\ \qquad\qquad\quad \varDelta P_t \end{cases} \tag{28}$$

Where: P_{ft} is the final price at time t.

Long (short) positions are taken if the sign of the oscillator is positive (negative), provided that the correlation between the price and electricity flow for this particular market is found to be positive in the pre-selection process. Should the correlation be found to be negative, the opposite action is taken, that is, a long (short) position is entered when the sign of the flow oscillator is negative (positive):

$$\begin{cases} L = 1 \;\rightarrow\; F_{St}^{AB} > 0 \text{ and } \varDelta P_t > 0 \\ \qquad\qquad\qquad\qquad\qquad\quad 0 \end{cases} \tag{29a}$$

$$\begin{cases} S = 1 \;\rightarrow\; F_{St}^{AB} < 0 \text{ and } \varDelta P_t < 0 \\ \qquad\qquad\qquad\qquad\qquad\quad 0 \end{cases} \tag{29b}$$

Where: L is a long position and S is a short position.

The first combined result is calculated by adding successful long and short positions, which are matched with the corresponding first derivative of the price, as follows:

$$I = L + S \tag{30}$$

Where: the signal I is a combination of long and short signals.

The final result X_t is derived after applying a filter for a contract roll, as follows:

$$\begin{cases} X_t = 1 \;\rightarrow\; M_t = 0 \\ \qquad\qquad\qquad I_t \end{cases} \tag{31}$$

Finally, the accumulated result is calculated by adding each day's positive or negative result to that achieved the previous day, and only pairs with a success ratio of 70% and above are included in the model:

$$\begin{cases} K_t = Pf_t \text{ if } X_t = 1 \; \rightarrow |Pf_t| \\ \qquad\qquad\qquad\qquad\quad 0 \end{cases} \tag{32a}$$

$$\begin{cases} N_t = K_t \text{ if } K_t \oslash 0 \; \rightarrow K_t \\ \qquad\qquad\qquad\quad -|Pf_t| \end{cases} \tag{32b}$$

Where: K_t is the positive-only return from each trade and N_t is the positive or negative return for each trade.

Finally, the accrued return net of transaction costs is calculated:

$$W_t = N_t + W_{t-1} - C \tag{33}$$

Where: W_t is the accrued net return and C is transaction costs.

The results supporting the statistical output are discussed in the following section.

4.5. Results

4.5.1. Test results for H_0^1

Table 1a displays the descriptive statistics of all the time series involved in the analysis.

Table 1a: Descriptive statistics of electricity cross-border flows

This table displays the descriptive statistics of the non-stationary time series of the electricity trade flows , including the number of observations, mean, median, minimum and maximum, standard deviation, sum of squared standard deviations, skewness, kurtosis, Jarque–Bera test result, and probability. The cross-border trade flow between two countries is indicated with the country initials, namely, FRITA for France to Italy, FRSP for France to Spain, GERFR for Germany to France, GERSWI for Germany to Switzerland, SWIFR for Switzerland to France, and SWIITA for Switzerland to Italy

	FRITA	FRSP	FRUK	GERFR	GERSWI	SWIFR	SWIITA
Mean	1402.07	59.05375	1494.143	1188.179	1918.522	205.7204	2476.822
Median	1446.45	2.21	1575.5	987.95	1794.9	32.44	2527.3
Maximum	2717.9	2377.58	2048	4081.9	4769	3377.75	4490.5
Minimum	186.7	0	0	180.9	149.8	0	0
Std. Dev.	591.6074	257.3019	457.0666	695.7997	1071.97	564.8775	1017.522
Skewness	-0.144783	6.838233	-1.11301	1.016649	0.233916	3.481786	-0.368796
Kurtosis	2.144592	52.18803	3.820705	3.580155	1.93849	14.59328	2.591668
Jarque–Bera	42.06988	134452.3	290.3483	230.6229	69.41416	9434.359	36.66433
Probability	0	0	0	0	0	0	0
Sum	1735762	73108.54	1849749	1470966	2375130	254681.8	3066306
Sum Sq. Dev.	4.33E+08	81894667	2.58E+08	5.99E+08	1.42E+09	3.95E+08	1.28E+09
Observations	1238	1238	1238	1238	1238	1238	1238

Table 1b: Descriptive statistics of electricity price

The table displays the descriptive statistics of the non-stationary time series of the electricity day-ahead prices , including the number of observations, mean, median, minimum and maximum, standard deviation, sum of squared standard deviations, skewness, kurtosis, Jarque–Bera test result, and probability.

	France	Germany	Italy	Spain	Switzerland	UK
Mean	39.65208	32.55969	49.4409	47.41506	41.61387	45.3588
Median	37	32	49.34	48.575	37.09	44.5
Maximum	99.25	47.13	69.85	72.07	90.98	87.45
Minimum	20.5	20.28	31.39	23.21	22.22	29.4
Std. Dev.	13.36716	5.538541	8.106359	9.607562	12.66387	9.127706
Skewness	1.727116	0.332352	-0.00708	-0.48538	0.792411	1.289698
Kurtosis	7.221904	3.208686	2.842052	3.216617	3.02332	6.844928
Jarque–Bera	1534.923	25.03753	1.297219	51.03084	129.588	1105.779
Probability	0	0.000004	0.522772	0	0	0
Sum	49089.27	40308.9	61207.83	58699.85	51517.97	56154.19
Sum Sq. Dev.	221028.4	37945.51	81287.06	114181.6	198382	103060.7
Observations	1238	1238	1238	1238	1238	1238

Preliminary ADF test results on the pricing and trade flow data reveal a unit root in the time series at I(1), or stationarity in first differences. In the next step, all the time series are differenced and tested again for a unit root. In this case, the ADF test results reject the test's null hypothesis of non-stationarity.

The results from the CR test based on stationary data reveal that, even if the total cross-border trade flow increases within the sample period (January 2015 to August 2018), the number of coincidental cross-border transactions decreases. A positive slope of the linear regression line on the test observations signals the increasing occurrence of price reactions to changes in trade flow, denoted by +1, and a negative slope is denoted by -1. The results of all the pairs are displayed in Table 2 and Figure 1C. This means that the electricity flow transiting from country A through country B to country C has decreased, while the single cross-border transaction volume between A and B or B and C has increased. France is the only electricity market in the sample whose sensitivity to trade flows increases. All the other markets exhibit a reduction in sensitivity.

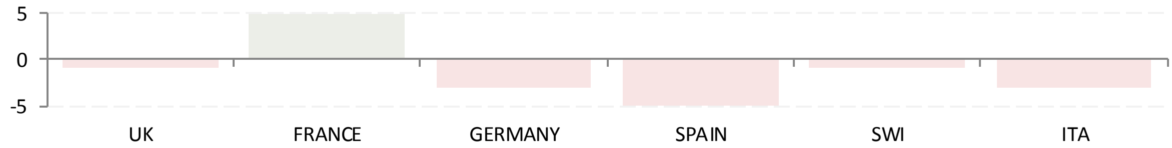
Table 2: CR test of the flow on price impact

This table shows the binary (+1 and -1) outcomes of the CR test on the reaction of prices (columns) to changes in electricity flow (rows). The frequency of the time series is daily. The sign (+/-) depends on the slope of the linear regression line y = ax + b applied to the CR test results. A positive slope for the linear regression line on the CR test observations signals increasing numbers of price reactions to changes in trade flow, and a negative slope signals decreasing numbers of price reactions to changes in trade flow.

		Dependent					
	Flow\Price	UK	FRANCE	GERMANY	SPAIN	SWI	ITA
Independent	GERFR	1	1	-1	-1	1	-1
	FRUK	-1	1	1	-1	1	-1
	FRSP	-1	1	-1	1	1	-1
	FRITA	-1	1	-1	-1	-1	-1
	GERSWI	-1	-1	-1	-1	-1	-1
	SWIITA	1	1	1	-1	-1	1
	SWIFR	1	1	-1	-1	-1	1
	Total score	-1	5	-3	-5	-1	-3

Figure 1C: CR test sensitivity to flow scores

This figure displays the sums of all the sensitivity values to cross-border electricity flow (y-axis) per market (x-axis), as in the total scores in Table 2. France stands out as the one market that increases its sensitivity to cross-border electricity trade flows.



Furthermore, the results from the SSP test based on the stationary dataset, which studies the evolution of the lagged CCF, suggest that the seven cross-border trade flows exhibit the strongest leading properties with the highest combined correlation coefficients in the Italian electricity market, followed by France and the UK. This result is displayed in Tables 3a (nominal values) and 3b (absolute values), as well as in Figure 2. The values for the combined cross-correlations are calculated with the help of the absolute values displayed in Table 3b. Absolute values are necessary, because some of the correlation coefficients are negative.

The Pearson correlation does not involve dependent and independent variables, since both sides are treated equally. However, since the SSP test is applied in both directions (see the methodology in Section 4.4) and the focus of this paper is to examine the leading properties of electricity flow over the price of electricity, I record the coefficients only in cases where price is the dependent variable and lagging, and flow is the independent variable and leading. Instances of price leading flow are indicated by empty cells in Table 3a or are indicated by a zero in Table 3b.

Even if the coefficients' strength is weak, the aim of this test is predominantly to establish the direction of the relationship and the lead–lag period. The results are later input into the proposed trading algorithm with equal weights of +1 and -1.

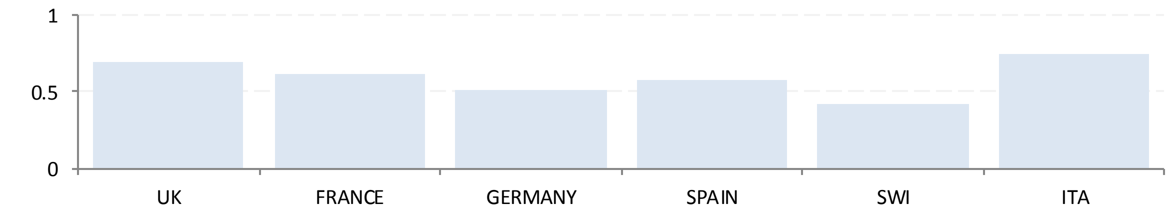
Table 3: SSP test of the flow on price, daily

The top panel of this table displays the average nominal values of the lagged CCF(k), which measures the price reaction to changes in cross-border electricity flow. The lower panel displays the absolute values from the test.

		Dependent					
	Flow\Price	UK	France	Germany	Spain	Switzerland	Italy
Independent	GERFR	-0.09	-0.07			-0.08	
	FRUK	-0.2	-0.15		-0.13		0.14
	FRSP	-0.16	-0.17	-0.18	0.15		-0.14
	FRITA	0.1		0.11		0.12	-0.13
	GERSWI	0.14	0.08	0.13	0.17	0.15	0.15
	SWIITA					0.07	0.06
	SWIFR		-0.15	0.09	-0.12		0.13
Independent	GERFR	0.09	0.07	0	0	0.08	0
	FRUK	0.2	0.15	0	0.13	0	0.14
	FRSP	0.16	0.17	0.18	0.15	0	0.14
	FRITA	0.1	0	0.11	0	0.12	0.13
	GERSWI	0.14	0.08	0.13	0.17	0.15	0.15
	SWIITA	0	0	0	0	0.07	0.06
	SWIFR	0	0.15	0.09	0.12	0	0.13
	Total score	0.69	0.62	0.51	0.57	0.42	0.75

Figure 2: SSP test total scores

This figure displays the sum, or combined score, of the absolute values of the lagged CCF(k) between the market price and cross-border electricity flows for each market, as presented with Table 3 under total score.



A bivariate Granger causality test applied to the electricity price and cross-border flow data reveals no evidence of causality running from flow in the direction of price. The two exceptions are the two pairs with cross-border flows, namely, the France–UK and France–Spain flows versus the Swiss electricity price. Both flows are found to Granger-cause changes in the Swiss power market, since the null is rejected within a 5% confidence interval. The results are summarized in Table 4a and, later, in Table 6.

Table 4a: Pairwise Granger causality test

This table displays the outcomes of a pairwise bivariate Granger causality test between all variables with the three tested conditions, namely: flow against price, flow againstflow, and price against price, at the 5% level of statistical significance. Flow data between countries is indicated as "FLOW_Country1Country2" where the country initials are used. Electricity price is indicated with the initials of the individual country. The frequency of the time series in the test is daily, with 1,237 data points. Only pairs with causality (p-value rejected at the 5% level of significance) that is taken into account by the trading algorithm are displayed in the table.

Null hypothesis	Prob.
ITA does not Granger-cause FLOW_FRSP	0.0478
FLOW_FRSP does not Granger-cause SWI	0.0356
FRANCE does not Granger-cause FLOW_FRUK	0.0031
FLOW_FRUK does not Granger-cause SWI	0.0078
FRANCE does not Granger-cause FLOW_GERSWI	0.0359
ITA does not Granger-cause FLOW_GERSWI	0.0388
SPAIN does not Granger-cause FLOW_GERSWI	0.0283
ITA does not Granger-cause FLOW_SWIFR	0.0325

All original (non-stationary) time series are tested for cointegration by applying Johansen's test. The test specifications are such that no deterministic trend in data is selected, and the lag intervals are equal to one and two. Strong cointegration is identified, since the test finds eight CEs. The test results are summarized in Table 4b.

Table 4b: Johansen cointegration test of the flow on price, daily

This table shows the results from a Johansen unrestricted cointegration rank test on the non-stationary daily time series. The original sample comprises 1,238 data points, and 1,233 after adjustments. A linear deterministic trend is assumed, and the lag intervals in first differences are from one to four. The notation "*" indicates CE. The notation Prob.** corresponds to statistical significance at the 5% level.

No. of CE(s)	Eigenvalue	Statistic	Critical value	Prob.**
None	0.094243	654.1686	NA	NA
At most 1 *	0.077896	532.1205	334.9837	0
At most 2 *	0.070315	432.1273	285.1425	0
At most 3 *	0.06005	342.2298	239.2354	0
At most 4 *	0.055269	265.8718	197.3709	0
At most 5 *	0.042617	195.7695	159.5297	0.0001
At most 6 *	0.033542	142.0696	125.6154	0.0034
At most 7 *	0.023689	100.0032	95.75366	0.0247
At most 8 *	0.021153	70.44347	69.81889	0.0445
At most 9	0.016123	44.08261	47.85613	0.1083
At most 10	0.013035	24.04123	29.79707	0.1987
At most 11	0.006096	7.86294	15.49471	0.4802
At most 12	0.000263	0.32407	3.841466	0.5692

Furthermore, I construct the error correction terms, also known as the cointegration of the estimated CEs, and I estimate the restricted VAR, or VECM, with the error correction term as the regressor. Since the data are stationary in first differences, the deterministic trend specification of the VECM involves no trend or intercept. Equal tothe number of CEs, the rank of the cointegrating matrix is eight. No further restrictions on the VECM are imposed; therefore the model uses default normalization to identify all cointegrating relations. The lag structure of the VAR model is calculated according to the methodology in Section 4.4 and Lütkepohl (2005). The HQIC returns the lowest lag length of two. The results from the VECM are displayed in Tables 5a and 5b.

Table 5a: VECM of cross-border electricity flow and the electricity market price
This table displays the ordinary least squares (OLS) regression summary statistics for the VECM system as a whole. These statistics include the determinant of the residual covariance, log-likelihood, the associated information criteria (AIC, BIC), and the number of coefficients. The original sample comprises 1,238 data points, and the adjusted sample is 1,235 points.

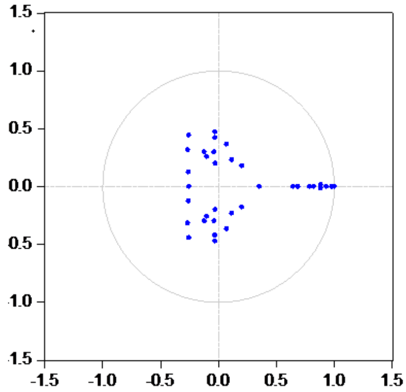
	Flows from … to …						
	FRITA	FRSP	FRUK	GERFR	GERSWI	SWIFR	SWIITA
R-Squared	0.196641	0.165999	0.338329	0.205275	0.174467	0.246055	0.188841
Adj. R-squared	0.173879	0.142369	0.319582	0.182758	0.151077	0.224693	0.165858
Sum sq. resids.	1.72E+08	24348023	1.33E+08	2.72E+08	1.95E+08	53783637	5.29E+08
S.E. equation	378.125	142.443	332.3085	475.8254	402.9666	211.7066	664.2483
F-Statistic	8.639041	7.024911	18.04679	9.116377	7.459008	11.51847	8.216601
Log-likelihood	-9064.639	-7858.93	-8905.125	-9348.474	-9143.221	-8348.31	-9760.476
AIC	14.73626	12.78369	14.47794	15.19591	14.86352	13.57621	15.86312
BIC	14.88133	12.92876	14.623	15.34098	15.00858	13.72128	16.00819
Mean dependent	-0.232874	0.046802	-0.136842	2.082348	-2.055142	2.592567	-1.397328
S.D. dependent	416.0193	153.8123	402.8595	526.3472	437.3557	240.435	727.2947

Table 5b: VECM of cross-border electricity flow and the electricity market price
This table shows the summary statistics for the VECM system as a whole. These statistics include the determinant of the residual covariance, log-likelihood, the associated information criteria (AIC, BIC), and the number of coefficients. The original sample comprises 1,238 data points, and the adjusted sample is 1,235 points.

	Electricity prices					
	France	Germany	Italy	Spain	Switzerland	UK
R-Squared	0.075136	0.03601	0.043141	0.054396	0.085558	0.112144
Adj. R-squared	0.048931	0.008697	0.01603	0.027604	0.059649	0.086988
Sum sq. resids.	2715.019	453.1658	1168.201	1539.67	2616.913	2060.522
S.E. equation	1.504166	0.614523	0.986662	1.132722	1.47674	1.310382
F-Statistic	2.867288	1.318419	1.591276	2.030301	3.302229	4.457973
Log-likelihood	-2238.811	-1133.303	-1718.052	-1888.546	-2216.085	-2068.48
AIC	3.682285	1.891989	2.838951	3.115054	3.645481	3.406446
BIC	3.827353	2.037057	2.984019	3.260122	3.790549	3.551514
Mean dependent	0.016721	0.013401	0.011951	0.012057	-0.004939	0.008826
S.D. dependent	1.542375	0.617213	0.994666	1.148687	1.522856	1.371387

Diagnostics are run on the VECM and the results are illustrated in Figure 3, showing the inverse roots of the AR characteristic polynomial (Lütkepohl 2005).

Figure 3: Output comprising the inverse roots of the AR characteristic polynomial
This figure shows the inverse roots of the AR characteristic polynomial resulting from the diagnostic test on the VECM.



The estimated VECM is stable (stationary) if all the roots have modulus less than one and lie inside the unit circle. If the model is not stable, certain results, such as impulse response standard errors, will be spurious. When the VECM is estimated with cointegrating relations, the roots should be equal to unity, such as the observations within the unit circle.

As discussed in the methodology in Section 4.4, the VECM is utilized for identifying and tracing shocks introduced to a system. This is done with the help of impulse responses (IRFs) and variance decomposition analysis by imposing restrictions on the model matrices.

4.5.1. Trading model based on H_0^1

Following the methodology described in the previous section, I combine the results of all five tests displayed in Table 6 into a single matrix, presented in Table 7a, whose coefficients report both the direction of and conviction behind each trade. In the case of pairwise Granger and Wald causality tests, only pairs that reject the null are reported in their relevant matrices D and E.

Table 6: Consolidated test results

This table summarizes the results for the five tests included in the model, namely, the CR, SSP, Granger, Wald, and VECM IRF tests. The outcome of each test is binary, that is, one or zero, where a value of one indicates a causal link detected from flow to price.

			Dependent					
		Flow\Price	UK	France	Germany	Spain	Switzerland	Italy
Granger test	Independent	GERFR						
		FRUK					1	
		FRSP					1	
		FRITA						
		GERSWI						
		SWIITA						
		SWIFR						
Granger test	Independent	GERFR	1	1			1	
		FRUK	1	1		1		1
		FRSP	1	1	1	1		1
		FRITA	1		1		1	1
		GERSWI	1	1	1	1	1	1
		SWIITA					1	1
		SWIFR		1	1	1		1
CRT test	Independent	GERFR	1	1			1	
		FRUK		1	1		1	
		FRSP		1		1	1	
		FRITA		1				
		GERSWI						
		SWIITA	1	1	1			1
		SWIFR	1	1				1
VECM IRF test	Independent	GERFR		1			1	1
		FRUK	1	1	1	1	1	1
		FRSP				1	1	
		FRITA		1			1	1
		GERSWI	1	1	1	1	1	1
		SWIITA	1	1	1	1	1	1
		SWIFR	1	1	1	1	1	1
VECM Wald test	Independent	GERFR						
		FRUK						1
		FRSP					1	
		FRITA						
		GERSWI						
		SWIITA						
		SWIFR	1			1		

Tables 7a and b: Sums of the coefficients from all five tests and the probability of an event

The top panel summarizes the results of all five causality tests employed in the model and displayed in Table 6. These results combine the binary results of one and zero from the CR, SSP, Granger, Wald, and VECM IRF tests for each cross-border flow–electricity market pair. The total score is the sum of the combined results per market. The lower panel displays the probability of occurrence, calculated as the score obtained divided by the maximum possible score of five.

		Dependent					
	Flow\Price	UK	France	Germany	Spain	Switzerland	Italy
Panel a Independent	GERFR	**2**	**3**	0	0	**3**	**1**
	FRUK	**2**	**3**	**2**	**2**	**3**	**3**
	FRSP	**1**	**2**	**1**	**3**	4	**1**
	FRITA	1	**2**	1	0	**2**	**2**
	GERSWI	2	2	2	2	2	2
	SWIITA	2	2	2	1	2	3
	SWIFR	3	**3**	2	3	1	3
	Total score	13	17	10	11	17	15
Panel b Independent	GERFR	40%	60%	0%	0%	60%	20%
	FRUK	40%	60%	40%	40%	60%	60%
	FRSP	20%	40%	20%	60%	80%	20%
	FRITA	20%	40%	20%	0%	40%	40%
	GERSWI	40%	40%	40%	40%	40%	40%
	SWIITA	40%	40%	40%	20%	40%	60%
	SWIFR	60%	60%	40%	60%	20%	60%
	Average	37%	49%	29%	31%	49%	43%

Figure 4: Sums of the coefficients from all five tests and the probability of an event

This figure summarizes the results from all five causality tests employed in the model and displayed in Table 7a. These results combine the binary results of one and zero from the CR, SSP, Granger, Wald, and VECM IRF tests for each cross-border flow–electricity market pair. The total score is the sum of the combined results per market.

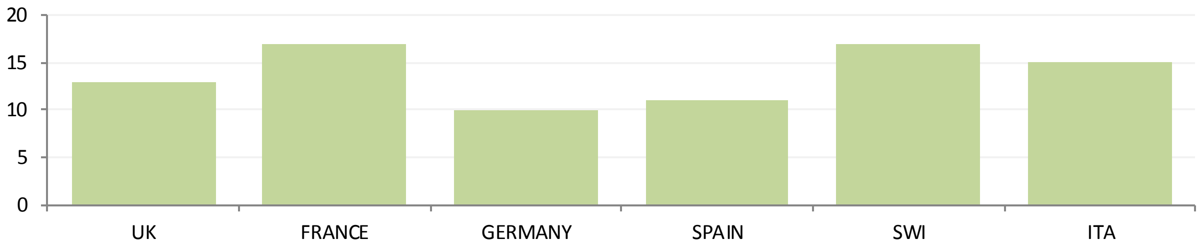
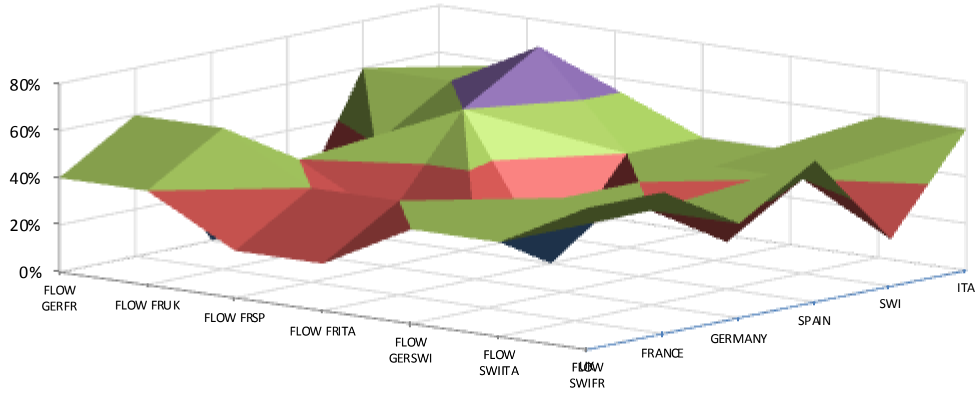


Figure 5: Probabilities of occurrence

This figure shows the three-dimensional distribution of the probability of occurrence as derived in Table 7b. The diagram demonstrates the link between flow, price, and the probability of occurrence.



The results, as displayed in Table 7a&b and Figures 4 and 5, show the market trading system with the strongest chance of reacting to a change in trade flow. Arbitrarily, only probability coefficients higher than 50% are taken into account. The numbers in bold represent the inverse / negative relationships. This is an important point, since the trading algorithm requires adjustments if the direction of the relationship is to be taken into account.

In this case, the Swiss and French markets are on top in terms of the probability of reaction, with average scores of 49%. Italy is third, with 43%. It is important to note that, on all three occasions when the French market reached a probability above 50%, the relationship with trade flow is actually negative; that is, as the trade flow increases, the price is more likely to decrease. Italy is on the other end of the spectrum, with two occasions when flow and price are strongly (>50% probability of reaction) and positively related.

As already discussed, the strengths of the coefficients and the probabilities of occurrence in Table 7 demonstrate which trade flows are most likely to provide a trading signal. To complete the trading strategy, the system also requires an exit signal. The combined results from the VECM IRF and SSP tests, which can be found in Table 8, indicate that price reactions to changes in trade flow dissipate, on average, 5.83 days after the shock is introduced. This result is used to inform the trading strategy of closing any open position on day 5.

Table 8: Number of days in which flow leads price

This table shows the number of days in which the cross-border electricity flow leads the electricity price. Empty cells indicate instances where the flow does not lead the price. The results are obtained from the VECM IRF and SSP tests. These are the two tests from the five included in the model that specify the duration of the lead–lag period.

		Dependent					
	Flow\Price	UK	France	Germany	Spain	Switzerland	Italy
Independent	GERFR		3.5			8.5	
	FRUK		6			7.5	8
	FRSP				6.5	3	
	FRITA						
	GERSWI						
	SWIITA						6
	SWIFR	3.5	7		4		6.5

The first results from the suggested trading system are displayed with Table 9. A total of 12 flow–price relationships are selected on the basis of the scoring system described earlier in the chapter. The success ratio is calculated as the number of occasions the model's predicted direction of price changes over the total number of observations. As expected, the Swiss and Italian markets register the highest success ratios once again, both averaging above 71.8%. This means that the proposed model of trading in the electricity market using the trade flow to signal changes is correct 71.8% of the time.

Table 9: Trading strategy success ratios

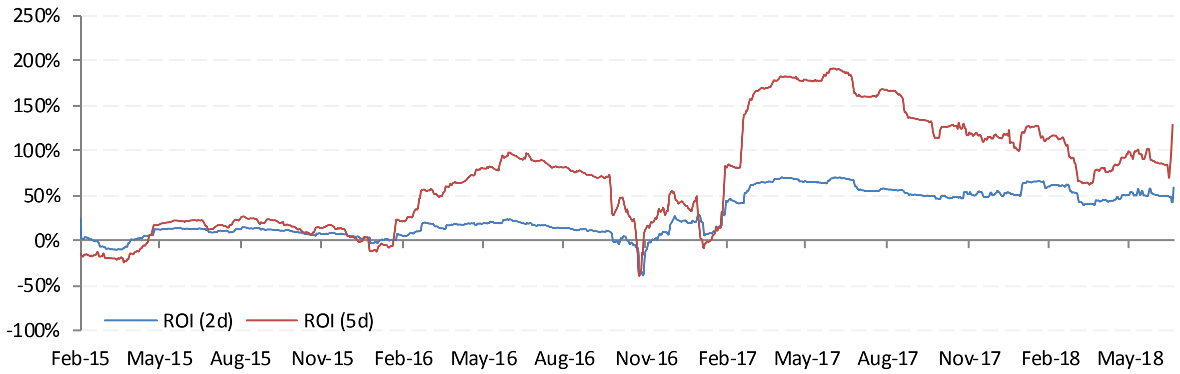
This table presents the ratios between the number of occasions the model predicted the direction of the price movement and the total number of possible predictions. Cross-border electricity flows are shown across the columns, and the electricity markets are shown as the rows.

		Dependent					
	Flow\Price	UK	France	Germany	Spain	Switzerland	Italy
Independent	GERFR		68.19%			73.67%	
	FRUK		68.90%			73.55%	72.88%
	FRSP				70.97%	74.37%	
	FRITA						
	GERSWI						
	SWIITA						74.01%
	SWIFR	72.48%	68.27%		70.11%		73.96%

The result suggests a strong probability of gains if the signals generated by the proposed arbitrage model are heeded. The evolution of the trading record, which is constructed according to the approach described in the methodology in Section 4.4, is displayed in Figure 6. Only pairs with a success ratio of 70% or above, as displayed in Table 9, are included in the model. The filter is arbitrary, but a high threshold of over 70% ensures that only pairs with a statistically strong ratio are considered by the algorithm. The ROI is calculated by applying holding period of five trading days, as recommended by tests and models mentioned earlier.[38] Figure 6 shows a cumulative return of 129.10% for the period.

Figure 6: Evolution of cumulative returns

This chart presents the evolution of accumulated returns based on a two-day and a five-day holding period. The return is net of transaction costs.



The results of the trading model have been positive during the sample period, with the exception of the short-lived drawdowns in March 2015, December 2015, and October 2016. Tests on risk-adjusted returns based on different holding periods are performed. The results, calculated with the help of the commonly used Sharpe (1966) ratio for the risk-adjusted returns, are displayed in Tables 10a and 10b and Figure 7.

Table 10a: ROI calculation variables

This table displays the data for the ROI calculation and total FXeosure, namely, the number of contract days, which is the duration of the traded front month contract; the price movement of the contract; the number of hours per month of the contract; the number of megawatts traded, which is the size of the contract; and the result, which is equal to the product of the price movement, number of hours per month of the contract, and the number of megawatts traded.

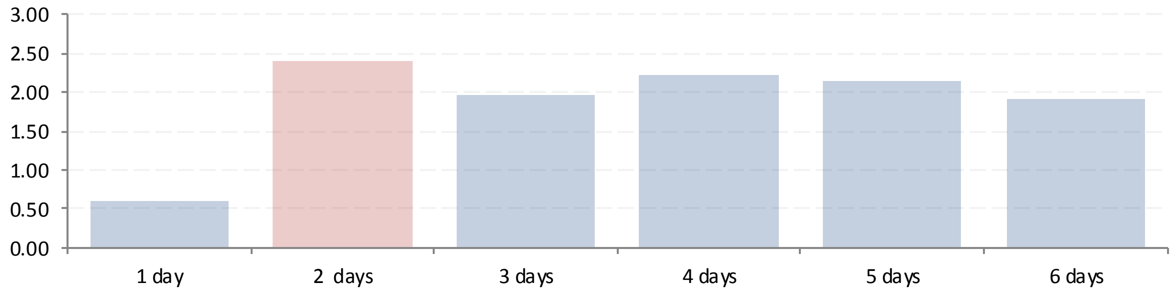
Contract days	Price move	Hrs/month	MW traded	Result
30	0.5	720	5	1,800

[38] Other assumptions in the ROI calculation are as follows. The size of each trade is 5 MW, which is standard for the EU electricity market, and trades are executed on the month-ahead market, which FXilies 720 hours per month. Therefore, the result equals the product of the price change dP, the number of hours per month, and the number of megawatts per trade size (see also Table 11a).

Table 10b: Sharpe ratios of the proposed trading strategy
This table shows the statistics of the trading strategy, based on different holding periods. The metrics listed are used in the calculation of the Sharpe ratio as described in the methodology in Section 4.4. The sample period is from 2 June 2015 to 25 June 2018.

Holding period	Cumulative return	Annualized return	St. dev.	Risk-free return	Sharpe ratio
1 day	10.60%	2.20%	16.10%	1.00%	0.6
2 days	59.30%	12.10%	24.20%	1.00%	2.41
3 days	61.20%	12.50%	30.60%	1.00%	1.97
4 days	97.30%	19.80%	43.30%	1.00%	2.22
5 days	129.10%	26.30%	59.50%	1.00%	2.15
6 days	113.20%	23.10%	58.90%	1.00%	1.91

Figure 7: Sharpe ratio results
This figure displays the Sharpe ratios calculated based on different holding periods, as presented in Table 10b. The sample period runs from 2 June 2015 to 25 June 2018. The higher the Sharpe ratio, the better the risk–reward trade-off will be for an investment.



The results demonstrate strong performance for the proposed methodology in terms of annualized returns, since a holding period of five days delivers an annualized ROI of 129.10%. However, tests for the risk-adjusted return using the Sharpe ratio reveal that the optimal holding period is two days, with an ROI of 59.27% and a Sharpe ratio of 2.41.

4.5.2 H_0^2 – Test results

The second hypothesis of this study, H_0^2, relates to the interaction between one trade flow and another trade flow. The results from the preliminary CR test reveal that, even if the amount of cross-border electricity volume has grown during the period, the number of positive flow reactions to changes in another flow is decreasing. A positive gradient of the linear regression line is assigned the value +1, and a negative slope is assigned a value of -1. The results are displayed in Table 11.

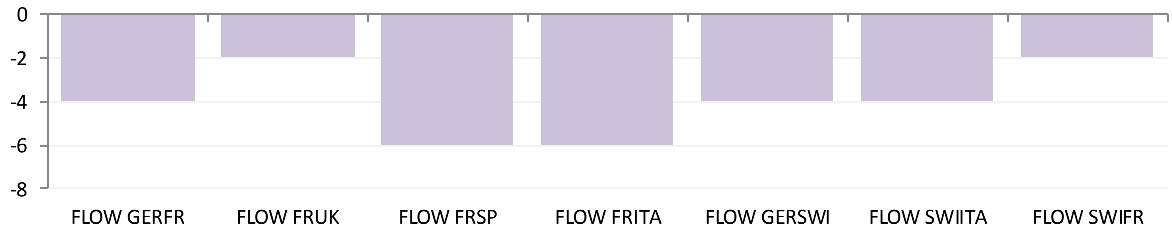
Table 11: CR test of flow on flow

This table shows the binary outcomes (+1 and -1) of the CR test on the reaction of cross-border electricity flow (columns) to changes in another cross-border flow (rows). The frequency of the time series is daily. The sign depends on the slope of the linear regression line y = ax + b applied to the CR test results. A positive slope of the linear regression line for the CR test observations signals the rising occurrence of price reactions to changes in the trade flow, and a negative slope signals the decreasing occurrence of price reactions to changes in trade flow.

		Dependent flow						
		GERFR	FRUK	FRSP	FRITA	GERSWI	SWIITA	SWIFR
Independent flow	GERFR	0	1	-1	-1	1	-1	-1
	FRUK	-1	0	-1	-1	-1	-1	1
	FRSP	-1	-1	0	-1	-1	-1	-1
	FRITA	-1	-1	-1	0	-1	-1	-1
	GERSWI	1	-1	-1	-1	0	-1	-1
	SWIITA	-1	-1	-1	-1	-1	0	1
	SWIFR	-1	1	-1	-1	-1	1	0
	Total score	-4	-2	-6	-6	-4	-4	-2

Figure 8: CR test total scores

This figure displays the sum of all the values of sensitivity to cross-border electricity flow per market, as presented in Table 11 as the total score. All the pairs in the study appear to have diminished sensitivity to other cross-border electricity trade flows (negative sign).



The results of the SSP test that studies the lead–lag dynamics between any two variables are shown in Table 14. This test evidently shows that some of the F–F pairs do not have sufficiently strong lead correlation coefficients. Some pairs, such as Germany–France and France–UK, do not have any significant relationship at all.

Switzerland–France exhibits the strongest evidence of a flow that is influenced by another flow. For example, compared to all the other flows, the flow from Germany to France appears to have an abnormally strong impact on that of Switzerland to France. The case of the flow from France to Italy flow is similar, in that it is strongly affected by movements in the flow from Switzerland to Italy.

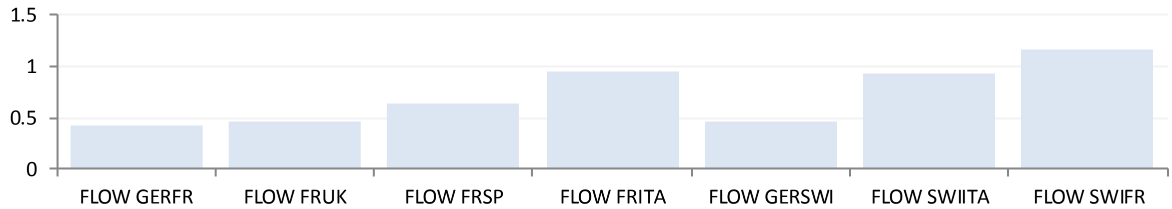
Table 12a: SSP test of flow on flow

This table displays the average nominal values of the lagged CCF(k), which measure the reactions of one cross-border trade flow to changes in another cross-border electricity flow.

		Dependent flow						
		GERFR	FRUK	FRSP	FRITA	GERSWI	SWIITA	SWIFR
Independent flow	GERFR	0		0.12	0.14		0.1	0.61
	FRUK	0.13	0				0.18	0.17
	FRSP		0.12	0				
	FRITA	0.15	0.15	0.16	0	0.13	0.65	0.24
	GERSWI	0.14	0.19	0.15		0		
	SWIITA			0.21	0.65	0.17	0	0.15
	SWIFR				0.16	0.17		0

Figure 9: SSP test of flow on flow

This figure displays the sums, or combined scores, of the absolute values of the lagged CCF(k) between one cross-border electricity flow and another.



While some of the interactions involve pairs of countries with a common border, others do not. Following the example above, trade flow between Germany and France affects the flow between Switzerland and France. This is to be expected if one considers the findings of Cartea, Flora, Slavov, and Vargiolu (2019), as well as the level of integration of the electrical grids and minimal transportation friction costs between these three countries. The strongest coefficients belong to pairs of trade flows with one country as a common denominator, for example, Germany–France and France–Switzerland or France–Italy and Switzerland–Italy.

What is more difficult to explain is the lead–lag relationship between countries without a common border. For example, the test results show that a change in the flow between Switzerland and Italy has a positive and leading impact on the flow between France and Spain. Another example is the impact of the flow between Germany and Switzerland on flows between France and the UK.

The bivariate Granger causality test results in Table 12 reveal strong causality from the Germany–Switzerland cross-border flow towards the France–Spain flow. Another pair that rejects the null hypothesis H_0 of non-causality is the Switzerland–France flow in the direction of France–Spain. The third pair is the France–UK flow towards Germany–Switzerland.

Table 12b: Pairwise Granger causality test

This table displays the outcomes of a pairwise bivariate Granger causality test between cross-border electricity flows at the 5% statistical significance with two lags.

Null hypothesis	Prob.
FLOW_GERSWI does not Granger-cause FLOW_FRSP	0.0194
FLOW_SWIFR does not Granger-cause FLOW_FRSP	5.00E-15
FLOW_FRUK does not Granger-cause FLOW_GERSWI	0.0491

The data are also tested for cointegration with the results of a Johansen cointegration test indicating the seven CEs (see Table 12a).

Table 12c: Johansen cointegration test

This table shows the results of a Johansen cointegration test for the number of cointegrated equations, which indicates the cointegration matrix rank on the non-stationary monthly time series of seven cross-border electricity flows. The original sample comprises 41 data points, and 39 after adjustments. A linear deterministic trend is assumed, and the lag intervals in first differences are from one to one. The notation Prob.** corresponds to a statistical significance level of 5%.

Hypothesized no. of CE(s)	Eigenvalue	Trace statistic	Critical value 0.05	Prob.**
None *	0.917796	262.0134	125.6154	0
At most 1 *	0.777717	164.5699	95.75366	0
At most 2 *	0.649141	105.9216	69.81889	0
At most 3 *	0.467079	65.07413	47.85613	0.0006
At most 4 *	0.454773	40.52825	29.79707	0.002
At most 5 *	0.26506	16.87272	15.49471	0.0308
At most 6 *	0.11721	4.862044	3.841466	0.0274

A VECM is employed also in this case, with the results in Table 12b. The relevant IRFs and variance decomposition are calculated and displayed in Figures 10a and 10b.

Table 12d: VECM output

This table displays the summary statistics for the VEC Model. These statistics include the determinant of the residual covariance, the log-likelihood, the associated information criteria (AIC, SIC), and the number of coefficients.

	Flows from … to …								
	FRITA	FRSP	FRUK	GERFR	GERSWI	SWIFR	SWIITA	Summary statistics of the VECM	Value
R-Squared	0.627381	0.995842	0.416497	0.580176	0.787939	0.826835	0.448	Determinant resid. covariance (df adj.)	6.78E+31
Adj. R-squared	0.325736	0.992477	-0.055862	0.240319	0.616271	0.686654	0.001142	Determinant resid. covariance	8.90E+29
Sum sq. resids.	2.42E+06	9993.006	1.86E+06	2.73E+06	3.61E+06	639472.6	9.67E+06	Log-likelihood	-1732.102
S.E. equation	339.7629	21.81416	297.2618	360.5531	414.4269	174.5024	678.7035	AIC	96.3642
F-Statistic	2.079868	295.8754	0.881739	1.707116	4.589898	5.898345	1.002556	BIC	102.6345
Log-likelihood	-270.569	-163.4871	-265.3573	-272.8853	-278.3163	-244.5829	-297.5545	Number of coefficients	147
AIC	14.79841	9.307033	14.53114	14.91719	15.19571	13.46579	16.18228		
BIC	15.56621	10.07483	15.29894	15.68499	15.96351	14.23359	16.95008		
Mean dependent	-8.82359	0.950769	-0.37	45.67769	-22.53179	57.45538	-30.49667		
S.D. dependent	413.7719	251.4955	289.2914	413.6695	669.0149	311.7379	679.0913		

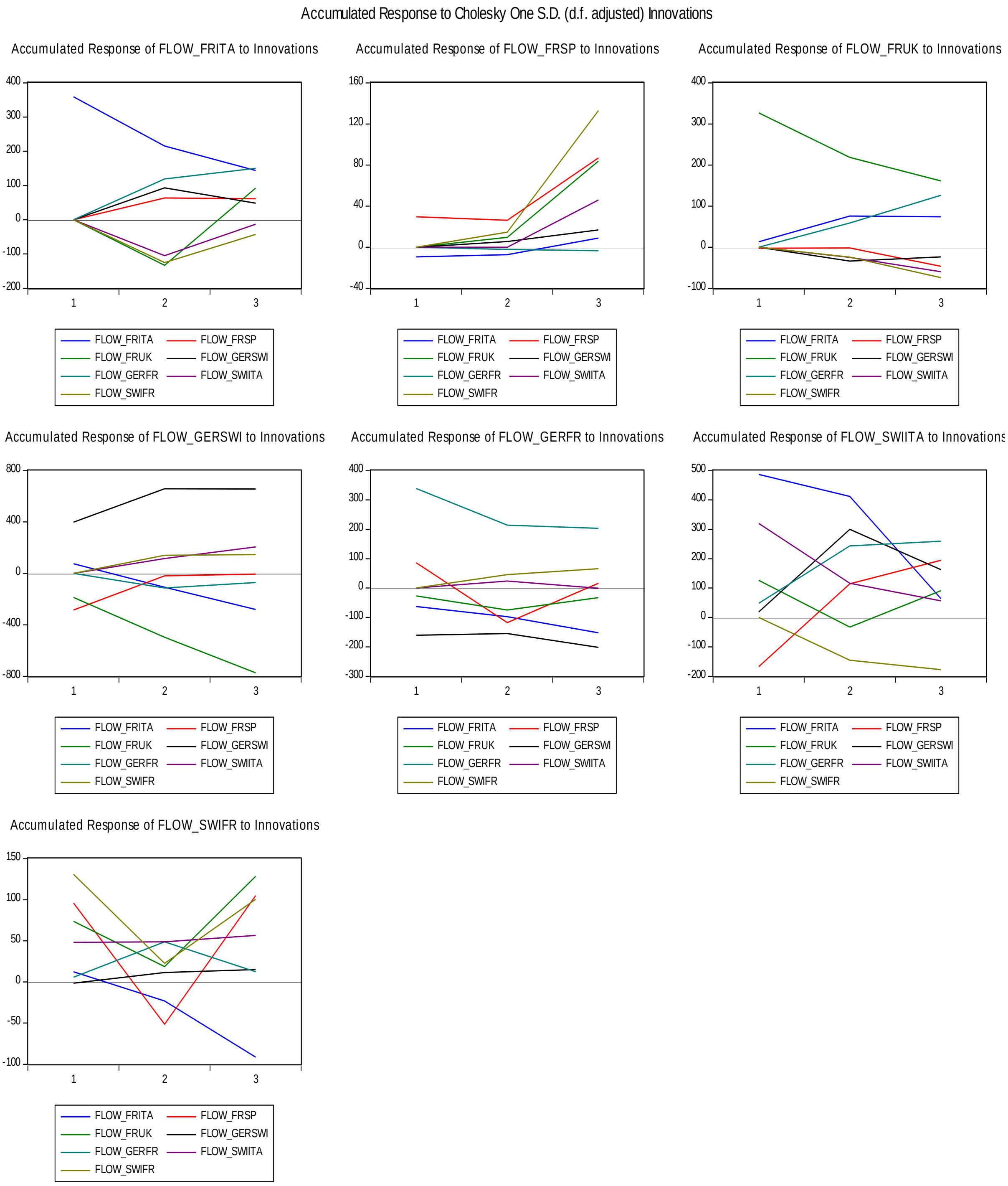
After the introduction of a positive shock to all 49 pairs (7 flows × 7 reactions), the French electricity market appears to have the strongest impact on the other cross-border flows. This finding is backed by Eurostat[39] data, which identifies France as a leading exporter in the EU. What is not clear from the official data – and which this study offers insight into – is how the French market influences not only neighbouring markets, but also flows beyond the country's immediate borders. The variance decomposition clearly indicates that France is on one side of the flows in six of all seven groups, as shown in Figure 8b. Most of the identified impact pairs (six in total) include a neighbouring market as the most likely receiver of the shock. For example, a shock to the France–UK flow has a positive impact on the flow between France and Italy. Interestingly, the impact grows with the time. Another example is the reaction of the flow between Switzerland–France to a shock to the flow between France–Spain, which is also identified as a causal pair by the Granger test.

There is one occasion when shock to the flow between France and the UK has an impact on a market that does not share a common border, namely, the Germany–Switzerland flow. This observation is also supported by the outcome of the Granger causality test discussed above. This finding represents an important piece of evidence that suggests that the flow of electricity between one pair of countries can potentially affect the flow between another pair of unrelated countries, that is, without a common border.

[39] Latest Eurostat data release on EU electricity generation, September 2018, available at https://ec.europa.eu/eurostat/web/energy/data/database.

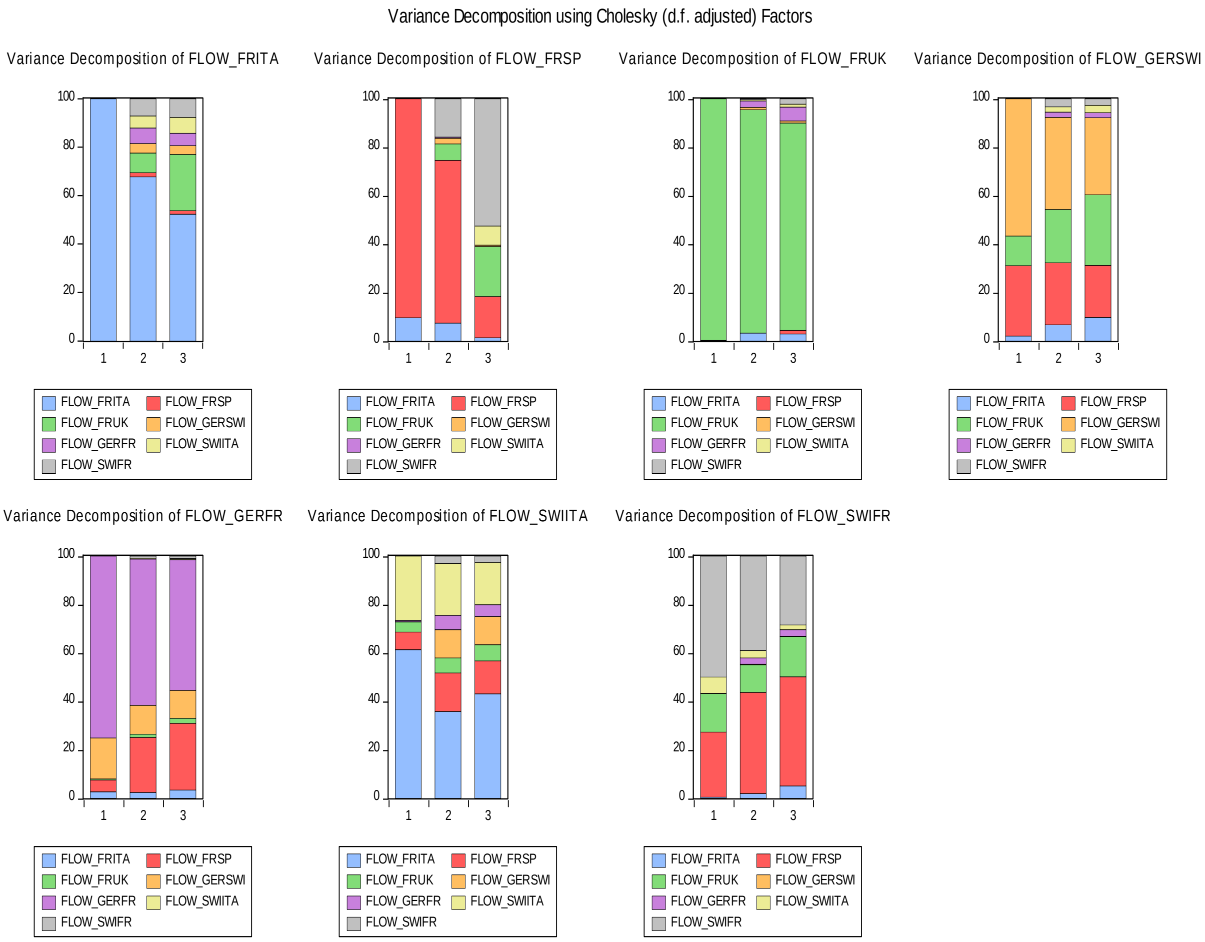
Figures 10a: IRF plots

This figureconsists of VECM IRF plots with projected accumulated responses based on a Cholesky one standard deviation innovation on the sample of cross-border electricity flows. The x-axis is time, and the coefficient on the y-axis is the IRF value of the reaction to a positive introduced shock of one standard deviation.



Figures 10b: Variance decomposition plots

This figure shows the VECM variance decomposition plots describing the evolution of the balance between each model variable, as it is expected to react, on Cholesky factors. The x-axis is time and the coefficient on the y-axis displays the decomposed balance between the different model variables.



4.5.3. H_0^3 – Test results

The analysis of the third hypothesis, H_0^3, involves the familiar CR, SSP, and Granger causality tests on the relationship between the gravity of trade and cross-border electricity trade flows. An analysis with a VAR model/VECM with a subsequent IRF and variance decomposition is performed. The time series are monthly, with 41 data points. This is problematic for a multivariate regression analysis, since the model's degree of freedom is then too low. The solution would be to either increase T or decrease the number of variables. Since I am not able to increase T, the only option is to decrease the number of variables and run the VAR analysis on 15 gravity pairs and seven cross-border trade flows, not all at once, but groups. Some variability and important information on the interactions between all 22 variables can be lost. Therefore, the conclusions drawn from this section could be weak.

Nevertheless, I include this sub-hypothesis in the paper, because it provides the framework for future research on the trade gravity and electricity trading.

Table 13: CR test results

This table displays the results of the CR test on the coefficient of the gravity of trade (rows) versus cross-border electricity flow (columns). The time series frequency in the test is monthly. Only pairs that display a response are included and are denoted by a value of one. Values in bold indicate a negative correlation.

		Dependent: Flow				
		GERFR	SWIFR	FRUK	GERSWI	FRSP
Independent: Gravity	FRSWI					
	SPITA			**1**	**1**	
	GERSWI		1			
	GERFR		1			1
	GERSP					
	UKSP					
	FRSP			1		

The CR test results displayed in Table 13 reveal that only 6% of the 105 flow pairs in the study display coincidental reactions. In addition, 33% of pairs with such properties do not share a common border. This is the first, albeit inconclusive result in support of the gravity theory of trade.

The next test is the SSP test, whose results can be found in Table 14. The results are very similar the results of the CR test, with 6% of the trade flow showing some degree of causality for gravity pairs. Only two pairs without a common border are detected, and they are indicated in bold: the coefficient of the gravity of trade of Spain–Italy versus the France–UK trade flow and the coefficient of gravity of trade of Germany–Spain versus the France–Spain trade flow.

Table 14: SSP test results

This table shows the binary (one or zero) outcomes of the lagged CCF(k) that measures the reactions of electricity cross-border flows to changes in the coefficient of the gravity of trade. If such a causal process is detected, the ratio of gravity to flow is assigned a value of one. Coefficients in bold indicate a negative correlation. Only pairs that display a causal relationship are shown. The time series utilized in the test have monthly frequency.

		Dependent: Flow				
		GERFR	SWIFR	FRUK	GERSWI	FRSP
Independent: Gravity	FRSWI		1			
	SPITA			**1**		
	GERSWI		1			
	GERFR					1
	GERSP					**1**
	UKSP			1		
	FRSP			1		

The next test is a pairwise bivariate Granger causality test and the complete results are shown in Tables 15a and 15b. The test produces higher numbers of causal relationships than are detected by the SSP test above. There are 13 pairs, or 12.4% of the total, with p-values under 0.05, which is a sufficient threshold to reject the null hypothesis. Regardless, the share of pairs with no common border remains stable, at 31%.

Table 15a Pairwise Granger causality test results

This table displays the outcome of a pairwise bivariate Granger causality test between the coefficient of the gravity of trade and the flow time series with a 5% level of statistical significance and two lags.

Null hypothesis	Prob.
FLOW_FRSP does not Granger-cause G_FRITA	0.0499
G_FRSWI does not Granger-cause FLOW_FRSP	0.0191
FLOW_FRSP does not Granger-cause G_FRSWI	0.0019
G_GERFR does not Granger-cause FLOW_FRSP	0.0002
FLOW_FRSP does not Granger-cause G_GERFR	0.0471
G_GERSWI does not Granger-cause FLOW_FRSP	0.0101
FLOW_FRSP does not Granger-cause G_GERSWI	0.0209
FLOW_FRSP does not Granger-cause G_SWIITA	0.039
G__UKSP does not Granger-cause FLOW_FRUK	0.0257
G_SPITA does not Granger-cause FLOW_FRUK	0.0048
G_FRSWI does not Granger-cause FLOW_GERFR	0.0411
FLOW_GERFR does not Granger-cause G_FRUK	0.0043
G_GERFR does not Granger-cause FLOW_GERFR	0.0292
FLOW_GERFR does not Granger-cause G_GERUK	0.0276
G_SPITA does not Granger-cause FLOW_GERSWI	0.0232
G_FRSWI does not Granger-cause FLOW_SWIFR	0.0448
G_GERFR does not Granger-cause FLOW_SWIFR	0.0031
G_GERSWI does not Granger-cause FLOW_SWIFR	0.0407

Table 15b: Pairwise bivariate Granger causality test results

This table displays the outcome of a pairwise bivariate Granger causality test. The test outcome is binary, that is, one or zero, where a value of one indicates a causal link is detected (H_0 rejected at the 5% level of statistical significance) from gravity to flow. The coefficients in bold indicate possible causality, but a negative correlation between the variables.

		Dependent: Flow				
		GERFR	SWIFR	FRUK	GERSWI	FRSP
Independent: Gravity	FRSWI	1	1			
	SPITA			**1**	**1**	
	GERSWI	1	1			**1**
	GERFR	1	1			1
	GERSP					**1**
	UKSP			1		
	FRSP			1		

The data are tested for cointegration, and the results are displayed in Table 16. The test returns evidence of cointegration, with eight cointegrating equations.

Table 16: Johansen cointegration rank test results

This table shows the results from an unrestricted Johansen cointegration rank test on the non-stationary monthly time series of seven cross-border electricity flows and one gravity coefficient (UK–Spain). The original sample comprises 41 data points, with 39 after adjustments. A linear deterministic trend is assumed and the lag intervals in first differences are from one to one. The notation Prob.** corresponds to a statistical significance level of 5%.

Hypothesized no. of CE(s)	Eigenvalue	Trace statistic	Critical value 0.05	Prob.**
None *	0.933784	324.5242	159.5297	0.0000
At most 1 *	0.820898	218.6456	125.6154	0.0000
At most 2 *	0.672282	151.5735	95.75366	0.0000
At most 3 *	0.646409	108.0649	69.81889	0.0000
At most 4 *	0.462800	67.52003	47.85613	0.0003
At most 5 *	0.446298	43.28606	29.79707	0.0008
At most 6 *	0.317459	20.23206	15.49471	0.0089
At most 7 *	0.127888	5.336673	3.841466	0.0209

The application of a restricted VAR in the face of a VECM is therefore appropriate. Due to a small T value, I am forced to decrease the number of variables in the model. Therefore, the analysis is performed in clusters of one gravity pair versus seven flow pairs. I begin with the gravity of UK–Spain versus all seven flows. The VECM output is displayed in Table 17a, the IRF is shown in Figure 11a, and the variance decomposition plots are shown in Figure 11b. The results reveal no significant impact on any of the flows from a shock to the gravity of UK–Spain.

Table 17a: VECM output

The table displays the summary statistics for the VECM system as a whole. These statistics include the determinant of the residual covariance, log-likelihood, associated information criteria (AIC, SIC), and the number of coefficients..

Flows from … to …

	FRITA	FRSP	FRUK	GERFR	GERSWI	SWIFR	SWIITA	GRAVITY_FRITA
R-Squared	0.196641	0.165999	0.338329	0.205275	0.174467	0.246055	0.188841	0.075136
Adj. R-squared	0.173879	0.142369	0.319582	0.182758	0.151077	0.224693	0.165858	0.048931
Sum sq. resids.	1.72E+08	24348023	1.33E+08	2.72E+08	1.95E+08	53783637	5.29E+08	2715.019
S.E. equation	378.125	142.443	332.3085	475.8254	402.9666	211.7066	664.2483	1.504166
F-Statistic	8.639041	7.024911	18.04679	9.116377	7.459008	11.51847	8.216601	2.867288
Log-likelihood	-9064.639	-7858.93	-8905.125	-9348.474	-9143.221	-8348.31	-9760.476	-2238.811
AIC	14.73626	12.78369	14.47794	15.19591	14.86352	13.57621	15.86312	3.682285
BIC	14.88133	12.92876	14.623	15.34098	15.00858	13.72128	16.00819	3.827353
Mean dependent	-0.232874	0.046802	-0.136842	2.082348	-2.055142	2.592567	-1.397328	0.016721
S.D. dependent	416.0193	153.8123	402.8595	526.3472	437.3557	240.435	727.2947	1.542375

Summary statistics of the VECM	Value
Determinant resid. covariance (df adj.)	2.24E+35
Determinant resid. covariance	1.07E+33
Log-likelihood	-1925.744
AIC	107.3715
BIC	114.5376
Number of coefficients	168

Figure 11a: VECM IRF plots

This figure consists of the VECM IRF plots the coefficient of the trade gravity of UK–Spain versus cross-border trade flow pairs, with projected accumulated responses based on a Cholesky one standard deviation innovation. The data frequency is monthly, and there are 41 data points in the sample.

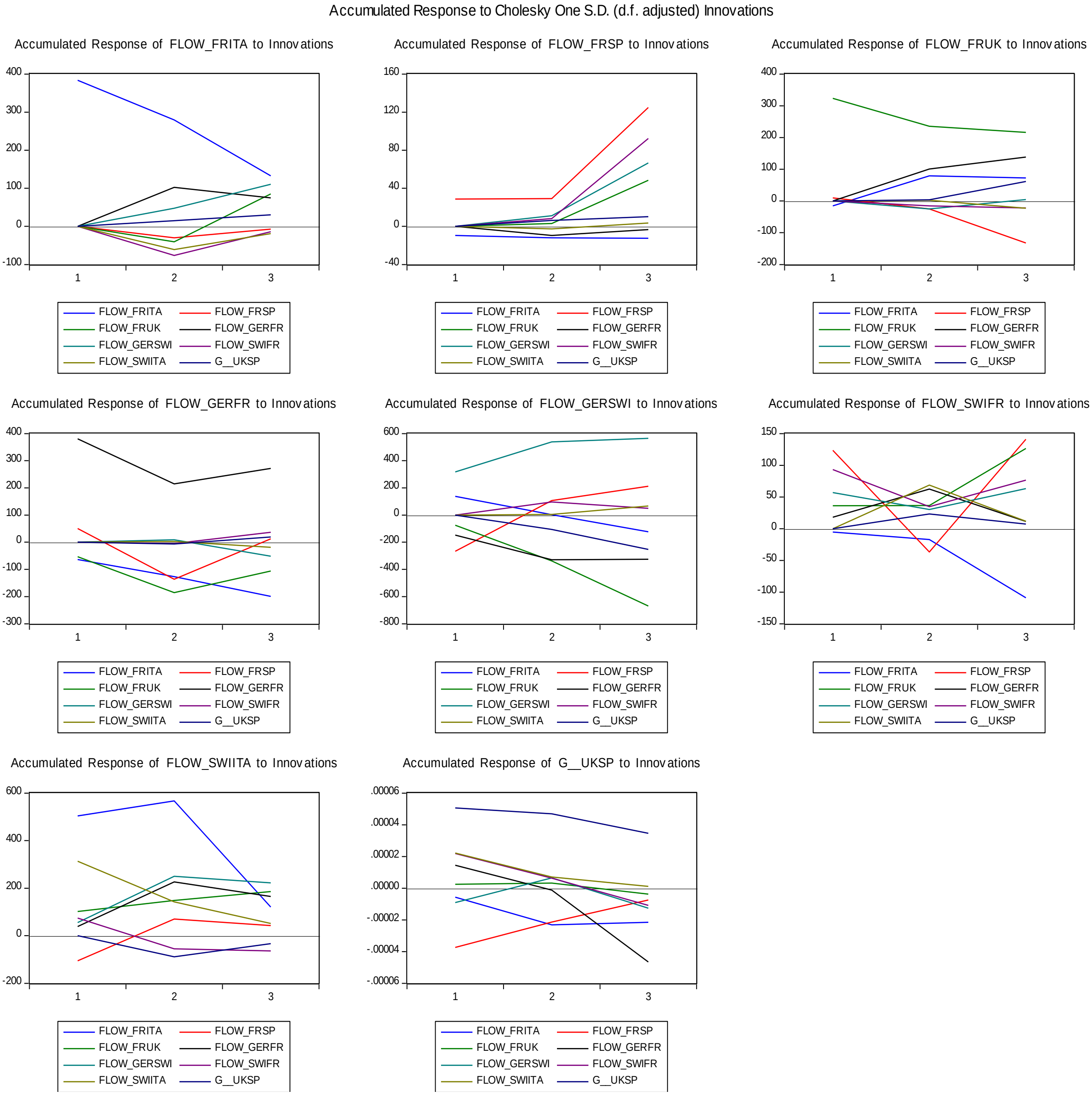
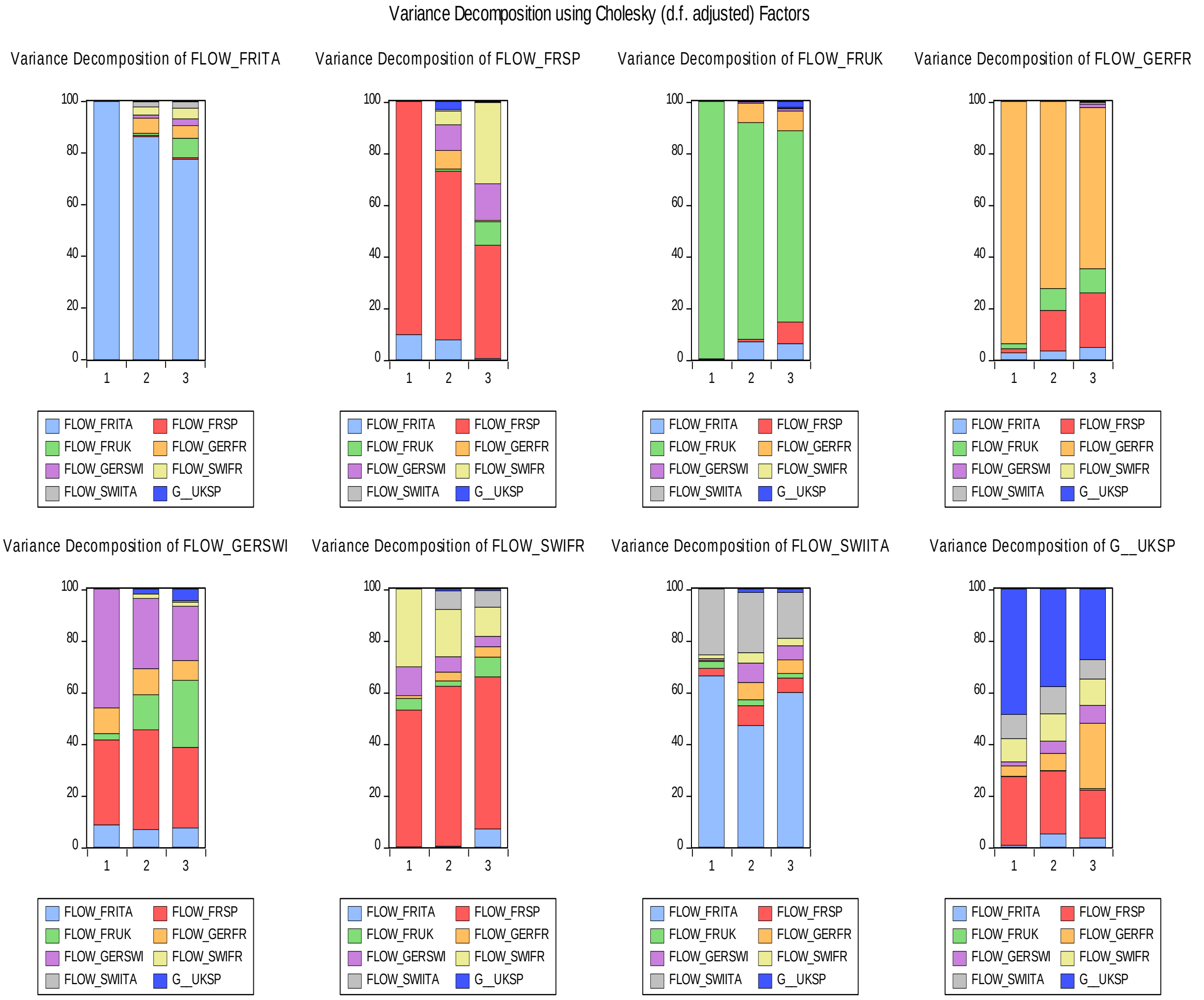


Figure 11b: VECM variance decomposition analysis

This figure shows VECM variance decomposition plots of the gravity coefficent of the UK–Spain pair against all seven cross-border electricity trade flows, describing the evolution of the balance between each model variable as it is expected to react on Cholesky factors. The frequency of the time series is monthly.



The identical analysis is performed on the other 14 gravity pairs, and the results are summarized in Table 17b, where only variance decomposition coefficients of over 10% of the total are taken into account and denoted by a value of one.

Table 17b: Summary of the VECM IRF results

This table summarize all 105 (15 gravity × 7 trade flow) variables tested within the VECM IRF framework. Each plot represents projected accumulated responses based on a Cholesky one standard deviation innovation. The recorded outcome after applying a positive one standard deviation shock is binary, that is, one or zero, where a value of "1" indicates a causal link of flow reacting to a shock to gravity.

		Dependent: Flow						
		GERFR	SWIFR	FRUK	GERSWI	FRSP	SWIITA	FRITA
Independent: Gravity	FRSWI					1	1	
	SPITA			**1**		1		
	GERSWI					**1**	1	
	GERFR							
	GERSP							
	UKSP							
	FRSP							
	UKITA							
	UKSWI	1	1			1		
	FRITA							
	FRUK	1						
	GERITA			1				
	GERUK							
	SPSWI				1	1	1	
	SWIITA		1			1	1	1

It is evident from the results that the gravity of trade has a significant impact on 17% of all 105 pairs. The VECM indicates that, of the 18 pairs with a variance decomposition coefficient above 10%, only six pairs (or 5.7%) do not have a common border, and they are gravity (Spain–Italy) versus flow (France–UK), gravity (Germany–Switzerland) versus flow(France–Spain), gravity(UK–Switzerland) versus flow (Germany–France) and flow (France–Spain), gravity (Germany–Italy) versus flow (France–UK), and gravity (Switzerland–Italy) versus flow (France–Spain). These results from the electricity market in Europe appear to support Tinbergen's gravity model of trade.

4.6. Conclusions

4.6.1. H_0^1 – The gravity theory of trade does not apply to the European electricity market

Under the first hypothesis, I apply the gravity theory of trade to the electricity market in Europe. The impact of the gravity of trade on electricity prices is detected in 18 gravity–electricity flow pairs, of which only six do not have a common border. This represents 5.7% of all 105 pairs tested with H_0^1. These results make it plausible to reject the hypothesis H_0^1 of non-applicability, that is, the gravity equation of trade also holds for the electricity market. In other words, distance does matter when it comes to electricity cross-border trading. This conclusion is reached independent of any consideration based on the cost of transportation of electricity in the face of transmission losses. Apart from the academic value of testing for the first time the gravity theory of international trade on the European electricity market, H_0^1 paves the way for future research into how the macroeconomic data of one country are priced by the electricity market in another country within the environment of an energy union. Any mispricing is likely to attract the attention of regulators and market participants alike.

4.6.2. H_0^2 – The cross-border flow between any pair of adjacent countries does not have any impact on the cross-border flow of other pairs of countries

The second null hypothesis is rejected on the grounds that analysis of the cross-border flow of one pair of countries versus another cross-border flow reveals evidence of consistent interactions between the Switzerland–France and Germany–France electricity cross-border flows. The results also suggest positive feedback between the flows of Switzerland–Italy and France–Italy. Furthermore, the number of instances that one flow impacts another flow shows signs of decreasing. While the strongest impact of a flow on another flow is documented for a number of pairs of adjacent countries, such as Germany–France versus France–Switzerland and France–Italy versus Switzerland–Italy, evidence of an impact between two flows with no common border is also detected. The France–Spain flow appears to be the most likely to be affected by other flows, such as the Switzerland–Italy and Germany–Switzerland flows. Overall, the French power market is shown to have the strongest cross-border impact on other markets, providing insight into the price formation mechanism affecting the European power market at its core.

4.6.3. H_0^3 – The electricity price in any two adjacent countries is not a function of the cross-border electricity trade flow

The results from examining the third hypothesis suggest that, with the exception of the French market, the reaction of price to flow in all the markets in this study has become less pronounced over time. The third null hypothesis is rejected on the grounds of numerous findings that the price of electricity is influenced and lags behind cross-border electricity flow. The Italian, Swiss, and French electricity prices appear to be the most responsive to electricity flow changes. The outcome of the cross-border trading model advanced in this study under H_0^3 is unambiguous. The proposed algorithm, which is guided exclusively by changes in cross-border electricity flows, has a 71.8% success rate, which reveals inefficiencies in the system. This rate equates to an accrued ROI (with a five- day holding period and a Sharpe ratio of 2.15) of 129.10% that is net of transaction costs for the test period from February 2015 to June 2018. A lower nominal return of 59.3% with a higher Sharpe ratio of 2.41 can also be considered.

With all three null hypotheses of the study rejected, important implications for academics, professionals, and regulators can be drawn. Academics are likely to benefit from the preliminary conclusions of the direct application of the gravity theory of trade, which begets further and more detailed investigation by employing a bigger data set. The results of the various econometric tests on the links of flows with other flows, and the links of flows with electricity prices are also significant and are likely to draw further academic research attention to the subject. Market participants can benefit from the proposed electricity trading model. The energy market integration process in the EU is far from over. This makes the results from the econometric flow on flow tests and models very topical. The outcomes and sensitivities identified are likely to attract the interest of regulators involved in the design of the European energy market.

Although the results from the arbitrage trading model under the main hypothesis of this paper are a formidable argument in favour of the proposed methodology, questions about market access can be raised. The intensity of the proposed trading activity is such that it favours incumbent market participants, that is, companies with an established infrastructure on the physical electricity market and the ability to trade in multiple markets at the same time. Missing trades from either the timing or geographical flow perspective will result in significant deviation from the model results. Another weakness of the model is the insufficient amount of data for the gravity of trade sub-hypothesis. All the results from the multivariate regression analysis need to be revisited, with a longer time series in the model.

Further research is needed to gain an even more detailed understanding of the EU-wide electricity market. Sizeable markets have been omitted from this study, which, if included, could alter some of the outcomes discussed. The issue here would be the length of the available pricing and trade flow time series. The number of degrees of freedom of the multivariate regression model drops too low as the number of variables n is increased. Therefore, significantly longer time series are required to study the rest of the EU power market.

The suggested trading model based on cross-border trade flow signals can benefit from further investigation into the ROI analysis. This is because a relatively high frequency of recommended transactions is likely to deliver a strong ROI only if the transaction costs are carefully considered.

Another topic worth investigating further is the gravity–flow CR test, which is currently based on the binary conditions +1 and -1, indicating the reaction of flow to changes in the gravity of trade. This model is worth testing with the actual coefficient of the intercept. It is plausible to assume that this test will reveal more information about the changing dynamics through the steepness of the regression line, which, in turn, indicates the higher or lower probability of the occurrence of the event.

Another potential theme for further research could include tests on the gravity–price and flow–price relationships, not only with an outright, that is, flat price, but also with price spreads. Spreads tend to behave differently from a flat price, since they are influenced by both statistical arbitrage trading flows and the diverging fundamental views in the two markets that constitute the spread. This scenario has the potential of delivering different end results for the proposed trading model.

Appendix of Chapter 4

Table A1: Empirical studies of the price–volume relationship

This table summarizes the first recorded empirical studies from which inferences can be drawn about the relationship between the market price and the trading volume. The information provided includes the authors, the year the study was published, a description of the sample data and period, the time interval, and the conclusion. Source: Karpoff (1987).

Author	Year of publication	Sample data	Sample period	Differencing interval	Support positive correlation?
Granger and Morgenstern	1963	Stock market aggregates, 2 common stocks	1939–1961	Weekly	No
Godfrey, Granger, and Morgenstein	1964	Stock market aggregates, 3 common stocks	1959–1962	Weekly, daily	No
Ying	1966	Stock market aggregates	1957–1962	Daily	Yes
Epps	1975	20 NYSE bonds	1971	Transactions	Yes
Morgan	1976	17 common stocks	1962–1965	4 days	Yes
Morgan	1976	44 common stocks	1926–1968	Monthly	Yes
Epps	1977	20 common stocks	1971	Transactions	Yes
Hanna	1978	20 NYSE bonds	1971	Transactions	Yes
Rogalski	1978	10 common stocks and 10 associated warrants	1968–1973	Monthly	Yes
James and Edmister	1983	500 common stocks	1975, 1977–1979	Daily	No
Comiskey, Walking, and Weeks	1984	211 common stocks	1976–1979	Daily	Yes
Harns	1984	50 common stocks	1981–1983	Daily	Yes
Smirlock and Starks	1985	131 common stocks	1981	Transactions	Yes
Wood, McInish, and Ord	1985	946 common stocks	1971–1972	Minutes	No
Harns	1986	479 common stocks	1976–1977	Daily	Yes
Jain and Joh	1986	Stock market aggregates	1979–1983	Hourly	Yes
Richardson, Sefcik, and Thompson	1987	106 common stocks	1973–1982	Weekly	Yes

5. The importance of currency in the process of commodity market price formation

5.1. Introduction

In this paper, I examine the predictability of key energy, metal, grain, and shipping commodity markets by the foreign exchange (FX) rates of the major exporters and importers of these commodities. With the US dollar (USD) at the centre of the global commodity trading in terms of commodity pricing and credit (Boz, Gopinath, and Plagborg- Møller 2017), the FX markets have the potential to accumulate unique information about the incentives of producers to supply the market with a commodity and of consumers to purchase the required amount of material on the international market. The FX markets are also significantly bigger than the commodity markets in terms of transactional value, which is a prerequisite for more efficient price discovery (for equity markets, see Chung and Hrazdel (2010); for commodity markets, see Belke, Bordon, and Voltz (2013)).[40] In addition, they can gather and channel forward-looking information (e.g. Van Foreest and De Vries 2003). It is this combination of properties that makes the currency markets a suitable candidate for predicting commodity price movements across different time frames.

Although there are studies on the interaction between FX and commodity markets, they have at least six limitations. *First*, only the currencies of *Exporters* are used in the relevant analysis. The possibility of utilizing the currencies of *Importers* is only briefly mentioned by Chen, Rossi, and Rogoff (2010), henceforth CRR (2010). The idea remains outside the scope of their discussion and, to the best of my knowledge, no other paper investigates the topic further. Many trade flows in the global supply chain are supply pull – that is, production is based on actual demand (e.g. Christopher 2011) – which means that important drivers of trade flows are not captured if only the currencies of commodity exporters are used in the analysis. According to international trade theory reasoning, the value of the exporters' currencies should be partly influenced by the value of sales generated on the international market, which captures directly the amount of commodity supplied (e.g. Chen and Rogoff 2003). Demand, on the other hand, is best captured by measuring the purchasing power of the

[40] According to the Bank for International Settlements, the sizes of the global currency and commodity markets in 2018 were 90.66 trillion USD and 1.90 trillion USD, respectively.

buyer (Devereux, Shi, and Xu 2007). An indirect demand component is included in the value of the currency, if one assumes that the supply chain for the commodity in question is demand pull, that is, a supply chain that is highly responsive to changes in demand.

Second, not only are other studies – for example, CRR (2010), Bork, Kaltwasser, and Sercu (2014; henceforth BKS), Ferraro, Rogoff, and Rossi (2015), henceforth FRR (2015), and Zhang, Dufour, and Galbraith (2014) – based just on exporter currencies, but also the samples of FX pairs selected are limited to six pairs of local currency against the USD, involving the Australian dollar (AUD), the Canadian dollar (CAD), the Chilean peso (CLP), the South African rand (ZAR), the New Zealand dollar (NZD), and the Norwegian krone (NOK). The increasing complexity and variety of trade flows (Krugman 1995) and the world of global commodity trading dictate the need for a significantly larger sample of currency pairs that can potentially capture more information about the forces driving these flows.

Third, the idea of combining currency pairs of importers and exporters of commodities and thus extracting information from their joint relationship has not been considered in the literature. Naturally, the currencies of exporters of commodities represent supply-side pressure to the market, since a stronger domestic currency is likely to limit incentives for producers to export. The opposite situation is also true, namely that weaker domestic currency incentivises the producers to export. Currencies of importers, on the other hand, represent the demand side through the purchasing power channel. Combining the two signals requires taking into account valuable information on the pressure from both the supply and demand (S&D) channels. The two signals combined represent a synthetic S&D balance based exclusively on the currencies of the main importers and exporters of the commodity in question. This balance is achieved by proposing a model, henceforth called the FX Impact Model (*FXIM*). Such explicitly designed importer and exporter trade-weighted currency indices that are specific to the commodity, direction, and size of the trade flow in question offer both theoretical and methodological contributions. The advantage of the proposed methodology lies in creating a significantly more relevant representation of the specific commodity market than the basket of only six currency pairs widely used in the literature.

Fourth, the academic literature employs relatively low-frequency data, such as monthly (Prokopczuk, Tharann, and Simen 2021), quarterly (Zhang, Dufour, and Galbraith 2014), and annual data (Gargano and Timmermann 2014). The use of higher-frequency data offers a different perspective. Although low-frequency data might be the norm in macroeconomic research, long-term investing, and policy decision making, where slower-moving and often more reliable data are used, trading and risk management require a higher data frequency, due to the speed and numbers of decisions made within limited amounts of time. Lower-frequency macroeconomic data are typically released with a delay of 10 to 30 days after the period described by the data (monthly, quarterly, or annual). The ability to remove this lag is invaluable from both trading and risk management perspectives. The solution is to work with higher-frequency (daily, weekly) data that allows for the modelling of processes developing during the period described by the data, and not afterward. The application of weekly time series is a significant departure from the lower data frequency used in research and comprises an important methodological contribution.

Fifth, the direction of causality between commodity prices and currency pairs stated in the literature is a point of contention. Chen (2004) and Zhang, Dufour, and Galbraith (2014) report evidence of stronger causality from commodity prices to the FX market. BKS (2014) argue in favour of a contemporaneous relationship between currency and price and find no evidence of predictive power of currency over price. The results in the current study, however, support the view that the FX market possesses predictive power over price (P), which is an important empirical contribution. Quantifying the direction in which causality flows between commodity prices and currency values is an important first step when studying predictability. Whether the aim is to construct a short-term trading model or inform policy makers about future changes in commodity prices and exchange rates, a causal link between the two variables needs to be established. This task is not trivial, since certain assumptions about the market properties in terms of efficiency and structure need to be made. For example, BKS (2014) assume that commodity prices, even physical spot prices, can be considered financial assets, since spot and future prices move in tandem (Fama and French 1988). Therefore, BKS also assume that the commodity markets are efficient, that is, prices are set efficiently by the relevant financial markets. Such a conjecture is in accordance with Fama’s Efficient Market Hypothesis, but contradicts the conclusions of De Bondt and Thaler (1989), who find no evidence that the market price represents an unbiased gauge of changes in stock market fundamentals. Moreover, directly relevant to the topic of this paper, Froot and Thaler (1990) find large and persistent anomalies on the global FX market, which they define as a condition of outright inefficiency within the price formation process of the largest financial market in the world.

Sixth, to the best of my knowledge, the literature lacks analysis on the differences in impact that currency markets can have on spot and forward commodity prices. This study measures the differences between the reactions of spot and forward commodity prices to the information contained in the FXmarkets, which is another empirical contribution. Understanding the differences in the reactions of spot and forward prices is valuable for market practitioners and regulators alike. From practitioners' point of view, any divergence between spot and forward prices creates trading opportunities in the face of cash and carry arbitrage, as defined by Kawaller and Koch (1984) and Lien and Quirk (1984), amongst others. On the other hand, the focus of regulators is likely to be on the impact that spot prices can have on end user prices and demand.

The relationship between commodity prices and the proposed baskets of currencies of importers and exporters does not appear to be homogeneous across markets or time frames. The initial results confirm the claims of CRR (2010, and BKS (2014), that commodity prices and the currencies of exporters are positively correlated. This result is observed through the consistently strong negative correlation between spot prices (*Ps*) and forward prices (*Pf)* and the currency indices of exporters (*FXe*) and importers (*FXi)*, relations that hold across all three time frames (daily, weekly, and monthly).[41] The evidence suggests that the correlation between *FXe* and *P* is the strongest one across all time frames, with a stronger correlation with *Ps*, and not *Pf*. The correlation between *FXe* and *P* is stronger than that between *FXi* and *P* for all commodities except freight. Furthermore, the strength of the correlation increases with decreasing frequency, that is, the correlation appears to be stronger for a monthly frequency compared to daily or weekly. Significant correlations are found throughout between *FXIM* and *P* and between *FXi* and *P* for the weekly frequency, whereas the correlation between *FXe* and *P* is strongest for the monthly frequency.

The results from a series of Granger causality tests reveal that the strength of the causal processes diminishes with decreasing data frequency. In other words, more causal processes are detected in the daily frequency dataset than in the monthly frequency dataset. Comparison across markets also reveals that, overall, the shipping, iron ore, and oil markets have more

[41] Since FXi and FXe consist of currency pairs with the USD in the numerator of the currency cross, any weakness in the currency index equates to strength in the currency of the FXeorter (or FXiorter), which is in the denominator of the currency cross.

causal links than copper and soybeans, but the evidence is weak, since the only causal link detected is between *FXIM* and *Ps* for the shipping market, where *FXIM* Granger-causes *Ps*.

The outcomes from one of the tests employed in the paper, namely, the coincidental response (CR) test, confirm that all markets respond strongly to changes in *FXi*. The reaction to *FXi* is significantly stronger than that to *FXe*, which is a rejection of the first hypothesis H_0^1. This is particularly the case for daily data frequency. Furthermore, all markets respond strongly to the proposed synthetic S&D, that is, *FXIM*, which confirms the second hypothesis H_0^2. The response is mainly concentrated within the weekly and monthly time domains. Furthermore and contrary to the results in the literature, *FXi* appears to play an important role in relation to both spot and forward prices *Ps* and *Pf*, respectively. Such results are significant because they cast doubt on the claims in the academic literature in relation to the importance of *FXe* for commodity markets' price formation.

Another test applied in this paper is the sliding scalar product (SSP) test. Its results indicate that *FXi* leads *Pf* for the shipping, crude oil, and soybean markets. The coefficients are stronger than for *FXe* versus *P*, which is an argument in favour of rejecting H_0^1. Signals of FXIM leading Ps for the soybean and iron ore markets are also detected when confirming H_0^2. The leading properties appear to be stronger for the daily data frequency; the signal is lost for the weekly frequency but reappears, albeit weakly, for the monthly frequency. The results of the SSP test are significant because the test not only addresses the two hypotheses of the study, but also provides guidance on the most suitable data frequency for the lead–lag relationship.

The final test applied to both hypotheses consists of running series of multivariate vector autoregressive (VAR) models and comparing how much of the variation each equation explains, using their *R-squared* values. Contrary to the established academic literature, the results point to evidence that the currencies of importers, *FXi*, have higher explanatory power than the currencies of exporters, *FXe*. Furthermore, and in line with H_0^2, the proposed synthetic S&D metric *FXIM* is found to significantly improve the explanatory power of the vector error correction model (VECM).

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 discusses the hypothesis development. Section 4 describes the data, samples, sources, and time frame selection criteria. Section 5 presents the methodological framework. Section 5 discusses the results and Section 6 concludes the paper.

5.2. Literature review

This paper analyses the relationship between the prices of selected commodities with the currency exchange rates of the most important exporters and importers of these commodities.[42] The paper draws insights from multiple branches of the literature that study the interaction between commodity prices and macroeconomic variables, including currency values. Four branches of academic research are relevant to this study.

The first branch of the literature revolves around the importance of international trade fundamentals in exchange rate price formation within the framework of established trade theory. For example, the claim that the value of national currency is linked to the USD amount of exports is supported by Amano and van Norden (1998a&b), who find a negative correlation between the CAD and the oil price, with causality running from the commodity price to the currency value. Further studies on the topic include those of Chen and Rogoff (2003), Cashin, Céspedes, and Sahay (2004), and Chen (2004), who argue that commodity prices play an important role in exchange rate fundamentals. All of these works explore the channel of rising commodity prices followed by an increase in revenue for the country selling on the international market in USD, which, in turn, appreciates the value of the domestic currency as demand for the commodity also increases. Therefore, according to the authors, changes in commodity prices should cause changes in the exchange rate values for those countries most exposed to the production and export of the commodity in question. The argument, in this case, is largely macroeconomic and supported by trade theory, and it states that an economy exposed to a disproportionately large value of commodity exports should see its currency value appreciate as demand for the currency increases.

More recently, published works in this branch of the literature also find evidence that commodity prices explain some of the movements in the FX values of those countries most

[42] The selection is based on the share of trade flow.

exposed to businesses exporting these commodities. FRR (2015), who study the daily data of five currency pairs and three commodity markets, ascertain a positive correlation and causality and demonstrate that the price of crude oil is positively correlated with the chosen currency values. The authors also detect a statistically significant causal process running from the price of oil to the currency values at the daily frequency. No such evidence is found for the monthly or quarterly frequency.

Another comprehensive study of the causality between exchange rates and commodity prices is that of Zhang, Dufour, and Galbraith (2014). They employ high-frequency data (daily and intra-day) for four commodity-exporting economies (Canada, Norway, Australia, and Chile) and the prices of their main export commodities (WTI crude oil, Brent crude oil, gold, and copper, respectively). The authors find that causality from commodity prices to exchange rates is stronger than in the opposite direction. They also conclude that the trade theory–related mechanism dictates the exchange rate dynamics.

The second branch of the literature considers the impact that currency values can have on the prices of commodities. This branch of the literature is also where this paper makes its main contribution. The links between commodities and currencies are fundamentally strong, as dictated by trade theory. The common denominator for all the commodity markets in the study is the USD, which sits at the centre of the global commodity trading in terms of commodity pricing and credit (Boz, Gopinath, and Plagborg- Møller 2017. Furthermore, FX markets are significantly more liquid compared to other commodity market in terms of transactional value, as evidenced by data from the Bank for International Settlements (2018), a state that requires more efficient price discovery (Garbade and Silver 1983). In turn, more efficient price discovery begets faster information flow and signal generation. Therefore, one way to explain the hypothetical causal link from currencies to commodity prices is the ability of the FX markets to gather and channel forward-looking information (Van Foreest and De Vries 2003).

Furthermore, Meese and Rogoff (1983), Cheung, Chinn, Pascual (2005), and Rogoff and Stavrakeva (2008) ascertain that exchange rates have the capacity to predict prices, due to their speculative nature and ability to efficiently price in forward-looking information. Andersen, Bollerslev, Diebold, Labys (2003) provide further evidence that exchange rates are correlated with news about future fundamentals, in agreement with Engel and West (2005), who offer evidence that currency markets are able to predict market fundamentals. Engel and West's conclusion is in line with the established present value model. They also stipulate that the statistical significance of predictability is not uniform, since they find that the causality from fundamentals to currency is weaker than in the opposite direction.

In addition, CRR offer further support to this line of thought with their finding, using quarterly data, that currencies have predictive power over the value of commodity price indices. Gargano and Timmerman (2014) claim similar results, namely, that currency markets possess predictive power over commodity indices. Their study demonstrates that predictability not only varies over time and across commodities, but also is a function of the economic cycle.

Academic works discussing the relationship between macroeconomic variables and asset prices form the third branch of research relevant to this paper. It is worth considering the fact that the present value models mentioned earlier are not the only models able to justify the mechanics of the currency market leading to a particular price of a commodity. For example, changes in currency values are likely to affect consumer prices, since currency value is passed onto domestic prices with some delay. Such an effect does not explain the evidence that the currency also leads to changes in commodity futures and baskets of financial commodity prices. Another argument is the fact that the value of currency can also cause fluctuations in the money supply, since policy makers monitor currency value and set monetary policy accordingly. Early work by Bessembender and Chan (1992) concludes that macroeconomic drivers can cause variations in the prices of commodities. Cheung, Chinn, Pascual (2005) and Chen, Rogoff, Rossi (2010) also suggest that macroeconomic conditions can be a predictor of the prices of stocks and bonds. More recently, Prokopczuk, Tharann, and Simen (2021) have confirmed the short- and long-term predictability of macroeconomic variables over commodity prices.

The fourth stream of research establishes the role of commodity markets as a stand-alone investment class. For example, the evidence of Sadorsky (2002) and Gorton and Rouwenhorst (2013) in support of this claim is based predominantly on the low correlation of the commodity sector with traditional asset classes. Another argument in favour of establishing commodities as a new investment class is offered by Erb and Harvey (2006), who demonstrate that commodities and equities have similar average returns (e.g. Gorton and Rouwenhorst 2013, Kogan, Livdan, and Yaron, 2009). Furthermore, Filer, Hanousek, and

Campos (2000) establish causality flowing from the stock market to currency value. Since the established literature unanimously agrees on the positive relationship between currency value and stock market performance (e.g. Swanson 2003) and argues in favour of commodities as an independent investment class, it is plausible to infer that a relationship also exists between the commodity and currency markets.

One important gap in the research literature is that only the currencies of exporters are used in the research. The proposal to utilize importers' currencies is only briefly mentioned by CRR (2010). The idea remains outside the scope of their discussion and, to the best of my knowledge, no other academic work investigates the topic further.

A prominent branch of the literature (e.g. CRR 2010, BKS (2014), FRR 2015, Zhang, Dufour, and Galbraith 2014) works with only a small sample of currency pairs, involving the AUD, CAD, CLP, ZAR, NZD, and NOK. I consider this to be a limitation, since these currency pairs fail to represent the global commodity trading well. Another constraint identified in scholarly work is the relatively few times monthly (Prokopczuk, Tharann, and Simen 2021), quarterly (Zhang, Dufour, and Galbraith 2014), and annual (Gargano and Timmermann 2014) data are used. And important gap is also revealed with the help of the proposed FXIM. The model extracts information from the joint relationship between different the currency pairs of commodity importers and exporters and thus conveys a unique metric for the implied short-term S&D market conditions. The proposed solution disputes one of the key assumptions behind the hypothesis of BKS, and, to the best of my knowledge, my idea is unique in the academic literature.

The direction of causality between commodity prices and currency pairs is another point of debate between this paper and the academic work. For example, Chen (2004) and Zhang, Dufour, and Galbraith (2014) report evidence of stronger causality from commodity prices (P) to FX rates. Furthermore, BKS (2014) argue in favour of a contemporaneous relationship between the FX markets and commodity prices (P) and find no evidence of causality flowing from FX to P. Both sets of authors make two assumptions: first, commodity prices, even physical prices, can be considered financial assets, according to Fama and French (1988). Second, commodity markets are efficient; that is, P is set efficiently by the relevant financial markets. Such conjectures are consistent with the efficient market hypothesis of Fama (1970), but contradict De Bondt and Thaler (1989), who find no evidence that the market price represents an unbiased gauge of changes in market fundamentals. Differences in reactions between Ps and Pf are a key driver behind the theory of cash and carry arbitrage as defined by Kawaller and Koch (1984) and Lien and Quirk (1984), amongst others. To the best of my knowledge, there is no significant analysis on the differences in impact that currency markets can have on Ps and Pf commodity prices.

The concepts of bivariate and multivariate causality and predictability are central to the hypotheses tested in this study. Three distinctly different tests are employed in the process of identifying and quantifying the causal link between custom-designed currency pairs and commodity prices. Causality is also tested within the VAR model/VECM environment with the help of impulse response functions (IRFs). The three tests are the pairwise Granger test, the CR test, and the SSP test. An important advantage of the Granger causality test is that endogenous variables can be treated as exogenous (Granger 1969). Additionally, according to Sørensen (2005), Granger tests appear to be most successful in detecting causal links in two-dimensional systems, or bivariate causal relationships, which is an important reason why this paper focuses on pairwise Granger causality tests. On the other hand, a disadvantage is the test's inefficiency at measuring multivariate causality. Moreover, causality is often hidden in long periods of data, which is logical, since causality is not likely to be a static process. This is precisely why I construct and run CR and SSP tests.

The SSP test involves a bivariate descriptive statistical analysis of the evolution of the cross-correlations between each pair of variables. The cross-correlation of multivariate time series involves more than one process and is thus a function of the relative time between the signals. Von Storch and Xu (1990) describe cross-correlation in principal signal oscillation processing analysis. They provide a detailed account of the measure of similarity of two waveforms as a function of a time lag applied to one of them, a process also defined as the sliding dot product (SSP) or sliding inner product.

Since the original (non-differenced) time series have a unit root, ordinary regression analysis is not appropriate for the estimation, because there could be one or more equilibrium (cointegrated) relationships, that is, they can have a common stochastic trend. Therefore, the time series are further tested for cointegration with Johansen's (1991) cointegration procedure. Johansen's approach is based on an unrestricted VAR approach. Unlike the

Granger test, Johansen's test allows for the hypotheses to be tested for an equilibrium relationship between the variables.

5.3. Hypothesis development

This paper advances three hypotheses that aim to address the gaps in the academic literature, as discussed in the previous section. The *first hypothesis* (H1) proposes that valuable information about future commodity price movements is contained in not only the traditional currency pairs of exporters, but also the currency values of the importers. Moreover, the proposed hypothesis challenges the assumption that the currencies of exporters and importers possess equal predictive power over the price of a commodity. Naturally, FXe represents supply-side pressure to the market, since the stronger domestic currency is likely to limit the incentive of producers to produce and sell. On the other hand, the opposite also applies, where *FXi* represents the demand side through the purchasing power channel. The research process also tests the sub-hypothesis that the price of commodity and the currency of exporters are positively correlated, as claimed by CRR (2010) and BKS (2014).

According to international trade theory, the value of exporters' currencies should be partly influenced by the value of sales generated on the international market, which directly captures the amount of commodity supplied. Demand, on the other hand, is best captured by measuring the buyer's purchasing power. An indirect demand component is included in the value of the currency, but only if the supply chain for this particular commodity is assumed to be demand pull, that is, highly responsive to changes in demand. Many of the trade flows in the global supply chain are supply push (Christopher and Towill 2001), which means that a significant part of the trade flows are not captured if only the currencies of commodity exporters are used. Therefore, I hypothesize that the explanatory power of the currencies of importers is stronger than that of the currencies of exporters traditionally used. Expanding the sample of currency pairs and increasing the data frequency lead to two sub-hypotheses.
A comprehensive body of academic research discusses the pros and cons of H1 (e.g. Meese and Rogoff 1983, Van Foreest and De Vries 2003, Engel and West 2005, Boz, Gopinath, and Plagborg- Møller 2017). This paper's contribution is placed in the second branch of scholarly work, as described earlier. For example, contrary to the findings of BKS (2014), the results of this paper support the view that FX possesses predictive power over P, which is a key empirical contribution.

The *second hypothesis* (H2) states that a causal relationship exists between the exchange rates and commodity prices. The debate in the academic literature about causality between the currency and commodity markets and whether the forex markets possess predictive properties over the commodity prices is not settled. There are two distinctly different and conflicting schools of thought. The first is supported by the work of Amano and van Norden (1998a&b), Chen and Rogoff (2003), Cashin, Céspedes, and Sahay (2004), and Chen (2004), who argue that commodity prices are important exchange rate fundamentals. Therefore, according to these authors, changes in commodity prices should cause changes in the exchange rate values for those countries most exposed to the production and export of a particular commodity. The argument in this case is largely supported by macroeconomics and trade theory, and it states that the FX value of an economy exposed to a disproportionately large value of commodity exports should appreciate as demand for its currency increases. Another line of thought, however, suggests that exchange rates have the capacity to predict prices due to their speculative nature and ability to efficiently price in forward-looking information (Meese and Rogoff 1983, Cheung, Chinn, Pascual (2005), Rogoff and Stavrakeva 2008). Studies have also proposed to determine the exchange rates by the net present value of fundamentals (Engel and West 2005, CRR 2010, Gargano and Timmerman 2014).

Under the *third hypothesis* (H3), I theorize that combining baskets of importers' and exporters' currencies into a joint FXIM produces a unique metric for the implied short-term S&D market conditions, with stronger predictive power over commodity pricing compared to the predictive powers of each of the $FXIM$ constituents FXi and FXe. In turn, this result disputes one of the key assumptions behind the financial asset hypothesis of BKS (2014). A further limitation of BKS's approach is that they base their conclusions exclusively on information on the behaviour of a handful of exporters' currency pairs. As discussed earlier, such a sample of currencies is incomplete, in view of the complexity of global commodity trading and the nature of the pressure along the supply chain, that is, demand pull versus supply push. Moreover, the proposed $FXIM$ conveys a unique metric for the implied S&D market conditions that possesses stronger predictive power over the price of the commodity market (P) compared to those of each of the $FXIM$ constituents FXi and FXe. The sub-hypothesis states that the FX market has stronger predictive power over the future commodity price (Pf) compared to the spot price (Ps). This result is tested after $FXIM$ is compared with the commodity price in the relevant term structure, that is, spot versus forward prices.

The proposed hypotheses reveal novel ideas that demand further research. For H1, which tests for a positive correlation between FX and commodity prices, the idea disputes the assumption that the currency of exporters and importers possess equally predictive power over the price of commodities. For H2, it involves a call for more comprehensive lists of commodities and the relevant importers' currencies. For H3, it is the need to experiment not only with bigger samples of commodities and currencies, but also with different weighted averages that ultimately arise in the model after a sample change. Further research is also warranted to compare the performance of the proposed synthetic S&D model in the face of FXIM with that of the traditional S&D models for each market.

5.4. Data, sources, and time frame selection criteria

The data consist of daily time series on the spot and futures commodity prices of five commodity markets, as well the exchange rates against the USD of the biggest importers and exporters of these commodities, between January 2013 and September 2019.[43] The markets (and relevant sectors) are as follows: crude oil (oil), soybean (agriculture), copper (non-ferrous metals), iron ore (ferrous metals), and freight rates (industrial transportation). The commodities selected for the study represent the biggest markets in their sectors by market value in USD per metric tonne traded. The sources for the market values are the Chicago Mercantile Exchange (CME), the Intercontinental Exchange (ICE), the Singapore Exchange SGX, the London Metals Exchange (LME), and the Baltic Exchange (BAX).

The *Ps* price is defined as the daily closing price of a cash commodity market. The sources for the Ps price time series are the US Department of Agriculture (USDA) for soybeans, Platts for iron ore, Bloomberg (BBG) for crude oil, the LME for copper, and BAX for freight. The forward price is the first futures contract for the commodity. A contract is rolled five trading days before expiry. The data sources for the first future contract are ICE for crude oil, LME for copper, SGX for iron ore, BAX for shipping, and CME for soybeans.[44]

Table 1 summarizes these spot and forward markets and their sources.

[43] The combined share of the FXiorters or FXeorters of any given commodity is at least 67% of the total.
[44] ICE is the Intercontinental Exchange, SGX is the Singapore Exchange, LME is the London Metals Exchange, BAX is the Baltic Exchange, and CME is the Chicago Mercantile Exchange.

Table 1: Market data sources
This table shows the markets studied and their data sources.

	Oil	Soybean	Copper	Iron ore	Freight
Spot	BBG	USDA	LME	Platts	BAX
Forward	ICE	CBT	CME	SGX	BAX

The time series of the currency pairs have a daily frequency (using closing values) and span from 1 January 2013 to 30 Sept 2019, for a total of 2,405 observations. The data are from Bloomberg.

The currency pairs are used to construct trade weighted indices, with the initial weighting per country determined by the imported or exported commodity's share of the total global trade. The sources of the data on shares per country and global total are the UN Comtrade database, the BACI International Trade database, and Simoes and Hidalgo (2011).[45] A filter of at least a 67% market share is applied to be included in a basket. This filter guarantees that a minimum of two-thirds of the trade flow for the selected commodity is accounted for. Such a threshold is necessary to reduce the noise in the model from small trade flows and the currencies of countries with a marginal influence on global trade. A secondary weighting for each pair is based on each initial weighting's share of the total weighting in the basket. The FX forex data are then indexed, and the weighted-average baskets with currency pairs of importers and exporters are calculated. Finally, weekly and monthly averages are derived from the daily data points of the FXIM.

5.5. Methodological framework

This paper examines the predictability of the spot and forward prices of key energy, metal, agriculture, and shipping commodity markets by the currency exchange rates of the major exporters and importers of these commodities. The three hypotheses tested can be described as follows:

[45] UN Comtrade is part of the United Nations Department of Economic and Social Affairs, Statistics Division; the BACI International Trade Database is a product of CEPII (Centre d'études prospectives et d'informations internationales), a leading French centre for research and FXeertise on the world economy.

H_0^1: Currencies of Exporters (FXi) and currencies of importers (FXe) have equal predictive power over the commodity price (P). Under a sub-hypothesis, P and FXe are positively correlated.

H_0^2: Causality flows from FXi and FXe to spot (Ps) and forward (Pf) commodity prices.

H_0^3: The FXIM ($FXIM$) has stronger predictive power over P compared to the predictive powers of each of its constituents FXi and FXe. The sub-hypothesis states that the predictive power of $FXIM$ is stronger over Pf than over Ps.

The empirical analysis proceeds in four steps. In Step 1, I create the trade-weighted currency indices $\boldsymbol{FXi}$ and $\boldsymbol{FXe}$ and the model $\boldsymbol{FXIM}$. Properties of the time series of the newly created indices and those relevant to each market's spot ($\boldsymbol{Ps}$) and future ($\boldsymbol{Pf}$) prices are tested in Step 2. Step 3 probes the relationship between the proposed indices and $\boldsymbol{Ps}$ and $\boldsymbol{Pf}$. This includes tests for correlation, causality, and cointegration with the help of the CR and SSP tests, as well as the widely used Granger causality and Johansen cointegration tests. Step 4 quantifies the interaction between $\boldsymbol{FXi}$, $\boldsymbol{FXe}$, and $\boldsymbol{FXIM}$ and $\boldsymbol{Ps}$ and $\boldsymbol{Pf}$ within the VECM framework (with cointegration detected). The strength of the indices' explanatory power and how it evolves over time are also measured with the help of the VAR IRF.

5.5.1. Step 1: Index construction

I construct trade-weighted indices from the time series of the currency pairs. The *initial* index weightings are determined by the particular imported or exported commodity's share of the total global trade, as discussed in Section 5.4 and displayed in Tables 2a and b.

Table 2a: Initial and secondary index weightings, Exporters

This table displays the initial weightings, as determined by the commodity's trade flow share of the total global trade. The initial weighting per country is determined by the particular imported or exported commodity's share of the total global trade. The secondary weighting for each pair is based on each initial weighting's share of the total weighting in the basket Source: Data on country and global total shares from UN Comtrade database, BACI International Trade database, Simoes and Hidalgo (2011). .

	Initial weighting					Secondary weighting				
Exporter	Oil	Soybean	Copper	Iron ore	Freight	Oil	Soybean	Copper	Iron ore	Freight
NIGERIA	0.045					0.0772				
S. ARABIA	0.14					0.2401				
VENEZUELA	0.028					0.048				
UAE	0.05					0.0858				
RUSSIA	0.12					0.2058				
IRAQ	0.073					0.1252				
CANADA	0.068					0.1166				
ANGOLA	0.034					0.0583				
MEXICO	0.025					0.0429				
BRAZIL		0.45					0.8094			
ARGENTINA		0.049					0.0881			
PARAGUAY		0.038					0.0683			
UKRAINE		0.019					0.0342			
CHILE			0.28					0.3966		
PERU			0.21					0.2975		
AUSTRALIA			0.072					0.102		
INDONESIA			0.054					0.0765		
CANADA			0.048					0.068		
BRAZIL			0.042					0.0595		
AUSTRALIA				0.52					0.5923	
BRAZIL				0.22					0.2506	
S. AFRICA				0.043					0.049	
CANADA				0.042					0.0478	
UKRAINE				0.028					0.0319	
EU				0.025					0.0285	
UAE					0.05					0.0833
IRAQ					0.073					0.1217
CANADA					0.068					0.1133
S. ARABIA					0.15					0.25
NORWAY					0.035					0.0583
NIGERIA					0.045					0.075
RUSSIA					0.12					0.2
ANGOLA					0.034					0.0567
MEXICO					0.025					0.0417

Table 2b: Initial and secondary index weightings, Importers

The table displays the secondary weightings as determined by the initial weightings' share of the total weighting in the basket.

	Initial weighting					Secondary weighting				
Importer	Oil	Soybean	Copper	Iron ore	Freight	Oil	Soybean	Copper	Iron ore	Freight
CHINA	0.18					0.2651				
EUROPE	0.236					0.3476				
JAPAN	0.073					0.1075				
KOREA	0.071					0.1046				
INDIA	0.094					0.1384				
SINGAPORE	0.025					0.0368				
CHINA		0.63					0.8678			
MEXICO		0.03					0.0413			
JAPAN		0.024					0.0331			
SPAIN		0.023					0.0317			
INDONESIA		0.019					0.0262			
CHINA			0.43					0.4886		
JAPAN			0.14					0.1591		
INDIA			0.076					0.0864		
KOREA			0.068					0.0773		
EU			0.166					0.1886		
CHINA				0.63					0.7184	
JAPAN				0.083					0.0946	
KOREA				0.051					0.0582	
EU				0.1					0.114	
MALAYSIA				0.013					0.0148	
CHINA					0.18					0.2651
EUROPE					0.236					0.3476
JAPAN					0.073					0.1075
KOREA					0.071					0.1046
INDIA					0.094					0.1384
SINGAPORE					0.025					0.0368

The *secondary* index weighting for each pair is based on each initial weighting's share of the total weighting in the basket. To calculate the coefficients, displayed in Tables 2a and 2b, I follow the following procedure.

Given

$$W_{ex} := \sum_{i=1}^{N} w_i \tag{1}$$

$$V_{im} := \sum_{i=1}^{M} v_i \quad (2)$$

with w_i and v_i being the individual countries with primary weightings i for N exporting and M importing countries, the secondary index weightings for exporting and importing countries are respectively defined as

$$\alpha_i := \frac{w_i}{W_{ex}} \quad (3)$$

and

$$\beta_i := \frac{v_i}{V_{im}} \quad (4)$$

The daily time series ($F^i := f^i_{t_0}, f^i_{t_1}, \ldots$) for the different countries i are anchored on start date t_0, which is set to 1 January 2013, and normalized as f_0, as follows:

$f^i_0 = f^i_{t_0} := f^i(t_0)$ (5)

with

$F^i_n := \left(\frac{f^i_n}{f^i_0}\right) \times 100$, where i is the country and n is the date.(6)

Then, the export baskets FX^{export}_n are computed for any time step t_n ($< t_0$) as

$FX^{export}_n := FX^{export}(t_n) = \sum_{i=1}^{M} \alpha_i \left(F^i_n\right)$ (7)

Similarly, for the import baskets,

$FX^{import}_n \coloneqq FX^{import}(t_n) = \sum_{i=1}^{N} \beta_i \left(F^i_n\right)$ (8)

Finally the ratio is computed as

$R_n := R(t_n) = \frac{FX^{import}_n}{FX^{export}_n}$ (9)

The final step is to calculate the synthetic S&D FXIM, as follows:

$$FXIM(t_n) \coloneqq R(t_n) - \frac{1}{30} \sum_{i=1}^{30} R(t_{n-i}) \quad (10)$$

where $t_n = 31$. Therefore

$$FXIM\ (t_{31}) = R(t_{31}) - \frac{1}{30}\{R_1 + \cdots + R_{30}\} \quad (11)$$

For the purpose of the relevant tests in the paper, weekly and monthly averages are derived from the daily data points of the $FXIM$ time series.

5.5.2. Step 2: Descriptive statistics

This stage concerns the standard evaluation of the time series properties, which includes descriptive statistics on the data across all three time frames (daily, weekly, and monthly), such as the mean, median, standard deviation, skewness, kurtosis, autocorrelation. Time series stationarity is tested with a standard augmented Dickey–Fuller (ADF) test. The complete results are displayed in Table A1 in the Appendix and discussed in the results in Section 5.6.

5.5.3. Step 3: Relationship between $\boldsymbol{FXi}$, $\boldsymbol{FXe}$, $\boldsymbol{FXIM}$, and P

The interactions between the individual time series form the core of H_0^1, H_0^2 and H_0^3, and are assessed with the help of Pearson correlation and the CR, SSP, Granger causality, and Johansen cointegration tests. The final test consists of running series of multivariate VAR models and comparing the extent to which the variation is explained by each equation, using R-squared values.

The CR and SSP tests are not part of the standard econometric software package, but they are widely used in signal processing, with the design procedure described below. All tests except the cointegration test require stationary data. Since both the ADF and Kwiatkowski–Phillips–Schmidt–Shin tests reveal the presence of a unit root for all time series across all three time frames except for *FXIM*, the data are differenced and tested again for stationarity. In this case, the ADF test results reject the null hypothesis of the test for non-stationarity.

One of the advantages of the Granger causality test is that an endogenous variable can be treated as exogenous (Granger 1969). According to Sørensen (2005), Granger tests appear to be most successful in detecting causal links in two-dimensional systems, or bivariate causal relationships. This is an important reason why this paper focuses on a pairwise Granger causality test. Granger also suggests caution when selecting the length of the sampling period. For example, long sampling period tends to hide causality. This result is logical, since causality is not likely to be a static process. This is why I choose to run the CR and SSP tests discussed above and described below.

5.5.3.1. CR test

Testing for a causal link between any of the currency indices FXi, FXe, and $FXIM$ and P (H1–H3) is performed with the help of a CR test, where the binary conditions of one and zero are used to define the reaction of the time series. First, the period variation for each of the time series is calculated, with $t_{n+1} - t_n = cons$:

$$\Delta \mathrm{FX}_t = FX_t - FX_{t-1} \tag{12a}$$
$$\Delta \mathrm{P}_t = P_t - P_{t-1} \tag{12b}$$

Where: ΔFX_t and $\Delta \mathrm{P}_t$ are the changes in price between times *t* and *t - 1*.

The pre-set rule searches for coincidental reactions along the timeline of $\{t_{0,}t_{1,\ldots,}t_{n,}\}$ and assigns the value of one if it finds any, and zero otherwise. In other words, if either of the two conditions is met, the test returns the value of one. If the two variables move in different directions, the result is zero. In essence, the test quantifies the number of coincidental reactions of the dependent variable $\Delta \mathrm{P}_t$ on any change in the independent variable $\Delta \mathrm{FX}_t$. Therefore, for the time series of lenght *i = 1, …, n,*

$$CRt(i) = \begin{cases} \frac{\Delta FXt1}{\Delta \mathrm{FXt2}} > 0 \ \rightarrow Zt = 1 \\ \frac{\Delta \mathrm{P}t1}{\Delta \mathrm{P}t2} < 0 \ \rightarrow Zt = 0 \end{cases} \tag{13}$$

Where: $CRt(i)$ is the outcome of the CR test, ΔFX is as specified above, and Z is a binary test variable.

The statistcs of the time-series from the Coincidental Response Test are calculated, as follows:

$$CRTt(i) = \frac{1}{n}\sum_{i=1}^{n} CRTi \tag{14}$$

The procedure is repeated for the relationships between $\Delta \mathrm{Ps}_{t,}\Delta \mathrm{FXi,e}_t$, and $\Delta \mathrm{FXIM}_t$, and between $\Delta \mathrm{Pf}_t, \Delta \mathrm{FXi,e}_t$, and $\Delta \mathrm{FXIM}_t$.

5.5.3.2. SSP test

The proposed SSP test is further used to test H_0^1, H_0^2 and H_0^3, which involves bivariate descriptive statistical analysis of the evolution of the cross-correlation between each pair. The cross-correlation of multivariate time series involves more than one process. It is thus a function of the relative time between the signals. Von Storch and Xu (1990) describe cross-correlation in principal signal oscillation processing analysis. They provide a detailed account of the measure of similarity of two waveforms as a function of a time lag applied to one of them, also defined as a sliding scalar product (SSP).

I compute the cross-correlation time series $P_{t=}\, p_{0,\dots,} p_T$ from two input time series $Y_{t=}\, y_{0,\dots,} y_T$ and $X_{t=}\, x_{0,\dots,} x_T$ by computing Pearson's correlation coefficient $\rho(X, Y)$ on a rolling window, as follows:

$$\rho(X, Y) = \frac{cov(X,Y)}{\sigma X \sigma Y} \tag{15}$$

which is the usual Pearson's coefficient, with $cov(X, Y)$ the covariance and σX and σY the standard deviations of the variables X and Y, respectively. For every time step t and lead–lag k in the constructed time series P_t, the correlation coefficient of a window of size n is computed. Explicitly, to compute P_t with a window size of n for a lead–lag step k = 0,

$$W_t := \{x_{t,\dots,} x_{t+n}\}, \text{ for } k = 0 \tag{16}$$

$$V_t := \{y_{t,\dots,} y_{t+n}\}, \text{ for } k = 0 \tag{17}$$

$$P_t := \rho(X_{t,} Y_t) \tag{18}$$

with the lead–lag k from 10 days beforehand to 10 days afterward, where $k = 0$ indicates a coincidental correlation. A negative k means that FX_t is lagged by k days relative to V_t.

The cross-correlation time series $P_{t=}\, p_{0,\dots,} p_{T-n}$ is constructed by repeating T - n time series for every p_t. Therefore:

$$P_0 := \rho(W_{0,} V_0) \tag{19a}$$

$$P_t := \rho(W_{t,} V_t) \tag{19b}$$

Using the procedure outlined, additional correlation time series are computed on the input pair in which the series FX_t^k is time lagged against the series P_t. A lead–lag operator is defined as:

$$L^k X_t = X_{t-k} \tag{20}$$

which is then applied as follows:

$$FX_t^k := L^k(FX_t) = \{X_{t+k,\ldots,}X_{t+n+k}\} \quad (21)$$

$$P_t^k := L^k(P_t) = \{Y_{t+k,\ldots,}Y_{t+n+k}\} \quad (22)$$

Where: k > 0 denotes a lead and k < 0 denotes a lag.

The new correlation time series on the input pair is then computed as

$$\theta_t^k := \rho(FX_t^k, P_t^k) \quad (23)$$

In the final step, the series of all lags of the cross-correlation time series mean θ_{mean}^k is constructed as

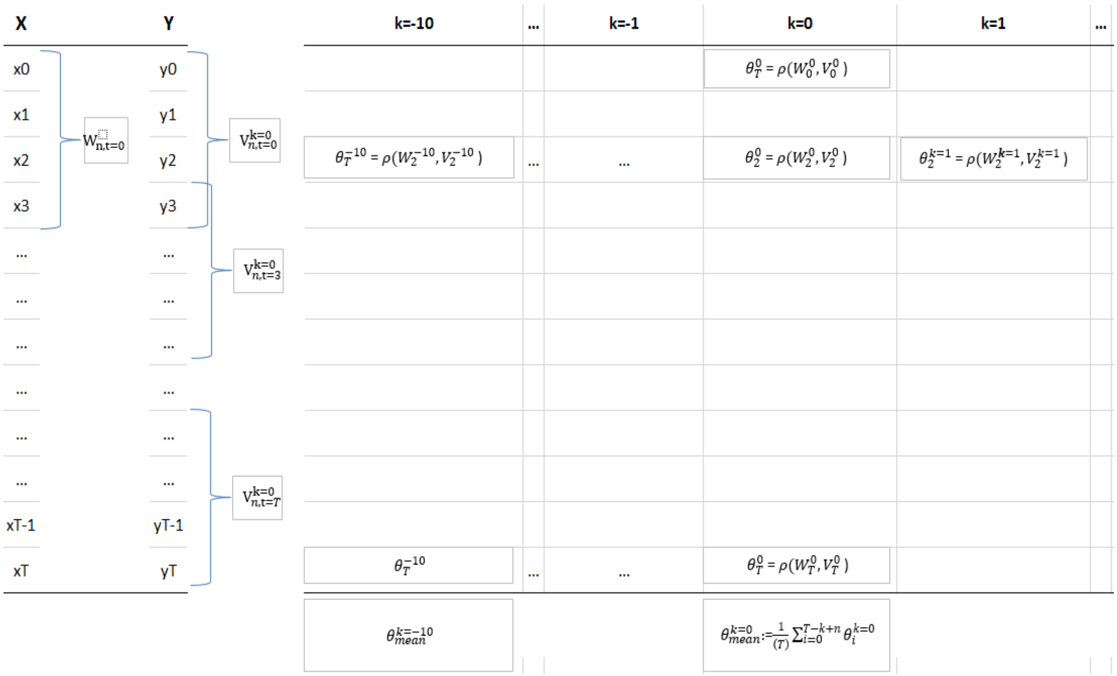
$$\theta_{mean}^k := \frac{1}{(T-|k|-n)} \sum_{i=0}^{T-|k|-n} \theta_i^k \quad (24)$$

$$\text{SSP(k)}: = \theta_{mean}^{-k}, \ldots, \theta_{mean}^{o}, \ldots, \theta_{mean}^{K} \quad (25)$$

The process is presented in the schematic in Figure 1.

Figure 1: Schematic of the proposed SSP model

This figure displays the elements of the proposed SSP model, where x and y are the time series, t is the time step, T is the total length of the time series, k is the lead–lag step, Wt and Vt are the lagged series, Pt is the cross-correlation time series of X and Y, n is the window size, θ_t^k is the new correlation series on the input pair, and θ_{mean}^k is the cross-correlation series mean.



The time frames tested in this paper vary from a daily frequency to weekly to monthly. Therefore, to accommodate practical considerations (e.g. there is no point in testing the lead–lag relationship between currency and price with a 24- or 36-month lag), different lags are considered for each of the time frames. In tests using monthly data points, a maximum of 12 lags will be considered (k = 12), because the impact from a change in the currency value is assumed to dissipate within a maximum of 12 months. For daily data, k = 12, and for weekly data, k = 12.

First, it allows for the precise (up to the time unit chosen for the study) identification of the lead–lag periods between the x and y variables. This is important for the process of building trading strategies, since it accounts for the better timing of a position entry and exit. Second, SSP test data can be plotted in a coordinate system for better visualization of the x–y relationship. Since the sign of the correlation does not matter (I examine the correlation strength, not the direction), the ideal outcome would be to record observations of lead periods clustered in the top-right or bottom-right corners of the scatter plot chart. In the case of a line chart, this would consist of lines starting from the top-right or bottom-right corners. The advantage of such a visualization is in the ability to quickly measure not only the lead–lag periods between the two variables along the x-axis, but also the strength of their lead–lag signal on the y-axis. Third, there are periods in the data sample when the lead property of the independent variable is clearly detected and displayed. However, there are also periods when its reaction lags. This finding does not clash with the null hypothesis of the test, which allows for changes in lead–lag regimes. It is important to be able to establish the existence of any long-term pattern in the x–y relationship. For example, higher conviction trades can be established at times when x has clear lead properties.

5.5.3.3. Bivariate Granger causality test

A bivariate Granger test is also used for examining H_0^1, H_0^2 and H_0^3. True causality is a debated concept in academia, and the Granger (1969) test claims to find only predictive causality. This is done with the help of t-tests and F-tests on lagged data points of FXi, FXe, $FXIM$, Ps, and Pf time-series at daily, weekly, and monthly frequencies, as follows:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_i y_{t-i} + \beta_1 x_{t-1} + \cdots + \beta_i x_{t-i} + \varepsilon_t \tag{26a}$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_i x_{t-i} + \beta_1 y_{t-1} + \cdots + \beta_i y_{t-i} + u_t \tag{26b}$$

where i is the lag period of the autoregressive model, x_t and y_t are the studied variables at time t, α_0 is the intercept, ε_t and u_t are the residual errors, and t = $(1, \dots, \mathrm{N})$ is the length of the time series. I choose lag i = 2 because it is reasonable to believe that the most liquid market in the world, such as foreign currency, is able to price in the available information within two days of an event's occurrence. When the specific variables of the test for the daily FXi and Ps series are substituted into equations (26a) and (26b), respectively, the result is

$$FXi_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i F\ FXi_{t-i} + \sum_{i=1}^{2} \beta_i\ F\ Ps_{t-i} + \varepsilon_t \tag{27a}$$

$$Ps_t = \alpha_0 + \sum_{i=1}^{2} \alpha_i F\ Ps_{t-i} + \sum_{i=1}^{2} \beta_i\ F\ FXi_{t-i} + u_t \tag{27b}$$

The process is repeated for all the other pairs within the five regression variables and the three time frames, namely, FXi, FXe, $FXIM$, Ps, and Pf at daily, weekly, and monthly frequencies.

5.5.3.4. Cointegration of time series test

Since the original (non-differenced) time series have a unit root, ordinary regression analysis is not appropriate for the estimation, because there could be one or more equilibrium (cointegrated) relationships; that is, they can have a common stochastic trend. Therefore, the time series are tested further for cointegration with Johansen's (1991) cointegration test. Johansen's approach is based on an unrestricted VAR approach. Unlike the Engle–Granger (1987) test, Johansen's test allows for the testing of hypotheses for an equilibrium relationship between the variables.

Cointegration is established by the rank of matrix Π via the number of its characteristic roots/eigenvalues. The two tests are λ_{trace} and λ_{max}. According to the literature (e.g. Granger and Joyeux 1980), differencing all the variables of the model to force them into stationarity is the correct approach for univariate models. However, if there are important relationships between the variables in the long run, such forced stationarity is seen as a weakness in the methodology. If a cointegration relationship is established, this would imply a stationary linear combination of some of the variables. The VECM, and not a standard VAR model, in first differences is the most suitable approach for non-stationary and cointegrated time series, since it allows for both long- and short-run relationships to be captured.

5.5.4. Step 4: VECM application

Cointegration relationships between the five variables FXi, FXe, $FXIM$, Ps, and Pf are detected by the Johansen test.Since matrix Π is defined as the product of matrices $\boldsymbol{\alpha}$ and β`, the matrix has the following form:

$$\Pi = \boldsymbol{\alpha}\beta` \tag{28}$$

or, in the case with five variables,

$$\Pi = \begin{bmatrix} \alpha 11 & \cdots & \alpha 15 \\ \vdots & \ddots & \vdots \\ \alpha 51 & \cdots & \alpha 75 \end{bmatrix} \begin{bmatrix} \beta 11 & \cdots & \beta 15 \\ \vdots & \ddots & \vdots \\ \beta 51 & \cdots & \beta 55 \end{bmatrix} \tag{29}$$

Once the number of cointegrating relationships between all five variables in the system is established, the VECM takes the following form:

$$\Delta P_t = b_1 \Delta Ps_t + b_2 \Delta Pf + b_3 \Delta FXII_t + b_4 \Delta FXi_{\ t} + b_5 \Delta FXe_t + b_7(Ps_{t-1} - \gamma_1 Pf_{t-1} - \gamma_2 FXi_{t-1} - \gamma_3 FXe_{t-1} - \gamma_4 FXII_{t-1}) + u_t \tag{30}$$

The same methodology is followed when testing the set with weekly and monthly frequencies. The residuals of the model need to be tested for stationarity, because they will be non-stationary if the variables are not cointegrated. This is done with the help of the ADF test with a null hypothesis for a unit root in the cointegrating regression residuals, or $H_0: u_t \sim I(1)$. Following Lütkepohl (1991), the optimal lag order of the model is estimated with the help of the Akaike information criterion (AIC), the Schwartz/Bayesian information criterion (BIC), the Hannan–Quinn information criterion (HQIC), as well as the final prediction error. The most important difference between the various criteria is the severity with which they penalize an increase in the model order. The motivation behind a strong penalty for high model orders is to reduce over-fitting, which has an impact on the model's forecasting ability.

I employ VECMs for reasons other from forecasting. The model investigates the interaction between selected endogenous variables. More specifically, the aim is to investigate the causal relationships in the processes described in equation (30). This means that I prefer to select an information criterion that does not impose too strong a penalty on the model order. As discussed by Lütkepohl (2005), the HQIC penalizes high model orders more than the AIC, but less than the BIC. I work with the HQIC when selecting the optimal number of lags of the VECM based on the size of the data sample as well. The consensus in the literature is that the AIC/final predication error outperforms the HQIC for small samples, but the HQIC is better for bigger samples (Lütkepohl 2005). An information criterion different from zero is a sign that the variables in the model are jointly significant.

Conclusions on possible causal relationships are also drawn from studying the responses of one variable to an impulse/shock introduced to another variable in a multivariable system. This view is derived by removing elements from the structural model that are expected at time t - 1. The VAR models focus only on modelling unexpected changes in a variable y at time t, which is a major difference with traditional modelling practice, where dynamic simultaneous equation models do not differentiate between expected and unexpected changes in y_t. The outcomes from the shock are exhibited in the form of IRFs.

5.6. Results

This section discusses the results of the tests. The data are first tested for a unit root with the ADF test, since the bivariate and multivariate regression analysis in the form of VAR models that are part of the proposed methodological framework requires stationarity. This also includes the correlation, CR, SSP, and Granger causality tests, as discussed in the methodology in Section 5.5. Time series are further tested for cointegration with the standard Johansen test. No cointegration is detected across any of the time frames, and I(1) stationary time series are therefore employed under an unrestricted VAR framework.

Descriptive statistics of all the time series involved in the analysis are displayed in Table A1 in the Appendix. Preliminary ADF test results on the pricing and trade flow data reveal the existence of a unit root in the time series at I(1), or stationarity in first differences. In the next step, all the time series are differenced and tested again for a unit root. In this case, the ADF test results reject the null hypothesis of the test of non-stationarity. The next step is the calculation of the correlation between all the time series. The results are displayed in Tables 3 and 4 and in Figures 2 and 3.

Table 3: Correlation coefficients

This table displays the Pearson correlation coefficient matrix of the stationary daily, weekly and monthly time series for the five commodity markets included in the study (copper, freight, iron ore, crude oil, and soybeans) against the five market drivers, namely, the currency indices of the major exporters, the currency indices of the major importers, the forward commodity price, the spot (Ps) commodity price, and the currency impact model.

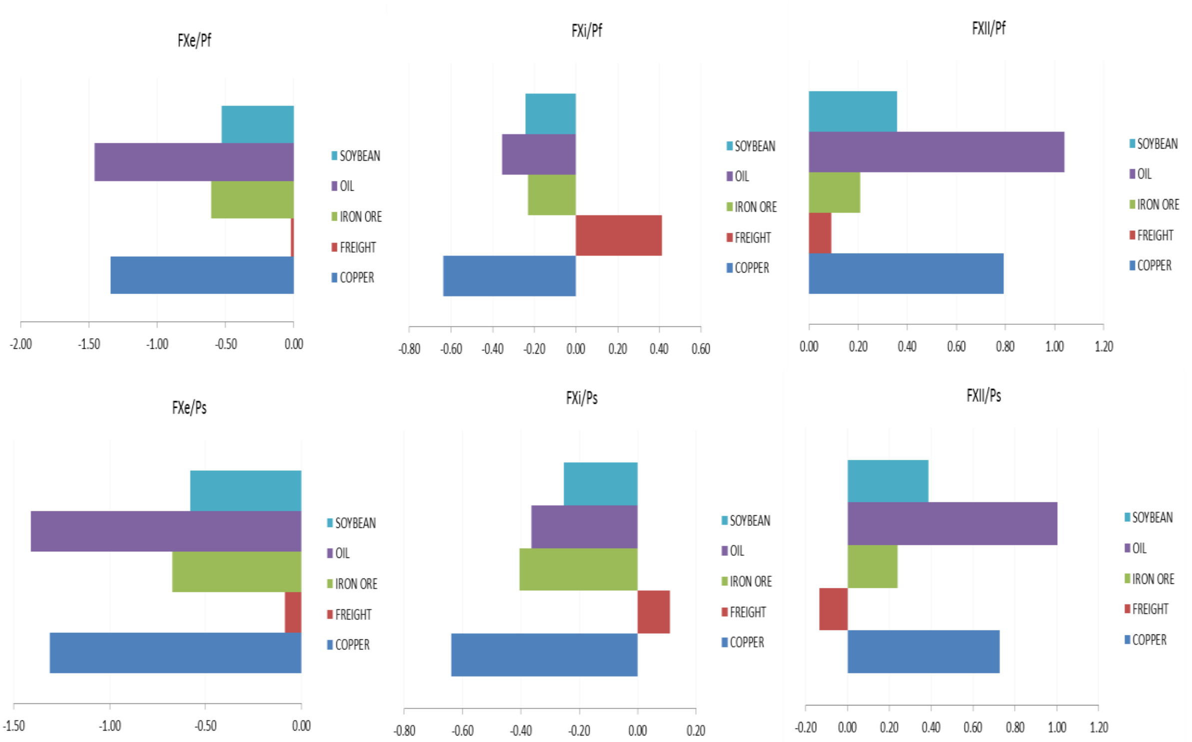
		Daily					Weekly					Monthly				
		Exporters	Forward	FXIM	Importers	Ps	Export	Forward	FXIM	Import	Ps	Export	Forward	FXIM	Import	Ps
Copper	FXe	1.00	-0.39	0.00	0.41	-0.38	1.00	-0.49	0.09	0.54	-0.48	1.00	-0.50	0.14	0.61	-0.49
	Pf	-0.39	1.00	0.07	-0.13	0.92	-0.49	1.00	-0.08	-0.26	0.98	-0.50	1.00	0.03	-0.25	0.99
	FXIM	0.00	0.07	1.00	0.00	0.04	0.09	-0.08	1.00	-0.08	-0.08	0.14	0.03	1.00	-0.04	0.02
	FXi	0.41	-0.13	0.00	1.00	-0.14	0.54	-0.26	-0.08	1.00	-0.26	0.61	-0.25	-0.04	1.00	-0.25
	Ps	-0.38	0.92	0.04	-0.14	1.00	-0.48	0.98	-0.08	-0.26	1.00	-0.49	0.99	0.02	-0.25	1.00
Freight	FXe	1.00	0.00	0.00	0.23	-0.02	1.00	-0.06	-0.04	0.32	-0.05	1.00	0.04	-0.01	0.45	-0.03
	Pf	0.00	1.00	0.00	0.02	0.25	-0.06	1.00	-0.01	0.09	0.43	0.04	1.00	-0.02	0.31	0.47
	FXIM	0.00	0.00	1.00	-0.01	-0.02	-0.04	-0.01	1.00	-0.04	0.03	-0.01	-0.02	1.00	-0.01	0.05
	FXi	0.23	0.02	-0.01	1.00	-0.01	0.32	0.09	-0.04	1.00	-0.01	0.45	0.31	-0.01	1.00	0.13
	Ps	-0.02	0.25	-0.02	-0.01	1.00	-0.05	0.43	0.03	-0.01	1.00	-0.03	0.47	0.05	0.13	1.00
Iron ore	FXe	1.00	-0.04	-0.01	0.40	-0.05	1.00	-0.22	-0.13	0.48	-0.28	1.00	-0.36	0.11	0.51	-0.36
	Pf	-0.04	1.00	-0.05	-0.01	0.38	-0.22	1.00	0.00	-0.08	0.75	-0.36	1.00	-0.22	-0.15	0.95
	FXIM	-0.01	-0.05	1.00	0.01	0.00	-0.13	0.00	1.00	-0.02	-0.02	0.11	-0.22	1.00	-0.08	-0.25
	FXi	0.40	-0.01	0.01	1.00	-0.09	0.48	-0.08	-0.02	1.00	-0.17	0.51	-0.15	-0.08	1.00	-0.16
	Ps	-0.05	0.38	0.00	-0.09	1.00	-0.28	0.75	-0.02	-0.17	1.00	-0.36	0.95	-0.25	-0.16	1.00
Oil	FXe01	1.00	-0.39	0.00	-0.16	-0.38	1.00	-0.47	-0.15	0.26	-0.44	1.00	-0.62	-0.01	0.41	-0.61
	Pf	-0.39	1.00	0.02	0.41	0.92	-0.47	1.00	0.06	-0.07	0.98	-0.62	1.00	-0.02	-0.24	1.00
	FXIM	0.00	0.02	1.00	-0.24	0.03	-0.15	0.06	1.00	0.01	0.06	-0.01	-0.02	1.00	-0.01	-0.02
	FXi	-0.03	0.47	0.05	1.00	-0.03	0.26	-0.07	0.01	1.00	-0.07	0.41	-0.24	-0.01	1.00	-0.23
	Ps	-0.38	0.92	0.03	0.31	1.00	-0.44	0.98	0.06	-0.07	1.00	-0.61	1.00	-0.02	-0.23	1.00
Soybean	FXe01	1.00	0.00	-0.14	0.32	-0.17	1.00	-0.16	-0.09	0.25	-0.17	1.00	-0.23	-0.02	0.41	-0.24
	FXIM	0.00	1.00	-0.02	0.00	-0.02	-0.16	1.00	0.05	-0.07	0.88	-0.23	1.00	0.03	-0.06	0.99
	Pf	-0.14	-0.02	1.00	-0.13	0.74	-0.09	0.05	1.00	0.01	0.06	-0.02	0.03	1.00	-0.05	0.04
	FXi	0.32	0.00	-0.13	1.00	-0.13	0.25	-0.07	0.01	1.00	-0.08	0.41	-0.06	-0.05	1.00	-0.06
	Ps	-0.17	-0.02	0.74	-0.13	1.00	-0.17	0.88	0.06	-0.08	1.00	-0.24	0.99	0.04	-0.06	1.00

The coefficients displayed with Table 3 reveal that the relationship of *FXe* with *Ps* and *Pf* is stronger when compared to that of *FXi* for copper, shipping, iron ore, and soybeans. Crude oil, on the other hand, appears to be correlated more closely with the value of the currencies of importers, as represented by *FXi*. The data from Table 3 are transformed and displayed in Table 4.

Table 4: Summary of correlation coefficients after transformations (x), (y), and (z)
This table displays the sum of the correlation coefficients between FXI, FXE, FXIM, and Ps and Pf. This can be represented as follows: $R^{m}_{e,s} = \sum_{i=1}^{k} r_s$, where R is the sum of Pearson correlation coefficients r_s between Ps and FXe across time frequency k (k = daily, weekly, monthly), where m denotes a specific market, such as copper, freight, iron ore, oil, or soybeans, e = FXe, and s = Ps.

	Copper		Freight		Iron ore		Oil		Soybean	
	Ps	Pf	Ps	Pf	Ps	Pf	Ps	Pf	Ps	Pf
Exporters	-1.31	-1.34	-0.09	-0.02	-0.67	-0.61	-1.41	-1.46	-0.58	-0.53
Importers	-0.64	-0.64	0.11	0.41	-0.41	-0.23	-0.36	-0.35	-0.25	-0.24
FXIM	0.73	0.79	-0.14	0.09	0.24	0.21	1.00	1.04	0.39	0.36

Figure 2: Display of the summary data in Table 3
The first row of charts summarizes the correlation coefficients between FXe and Pf. The second row summarizes the correlation coefficients between FXe and Pf.

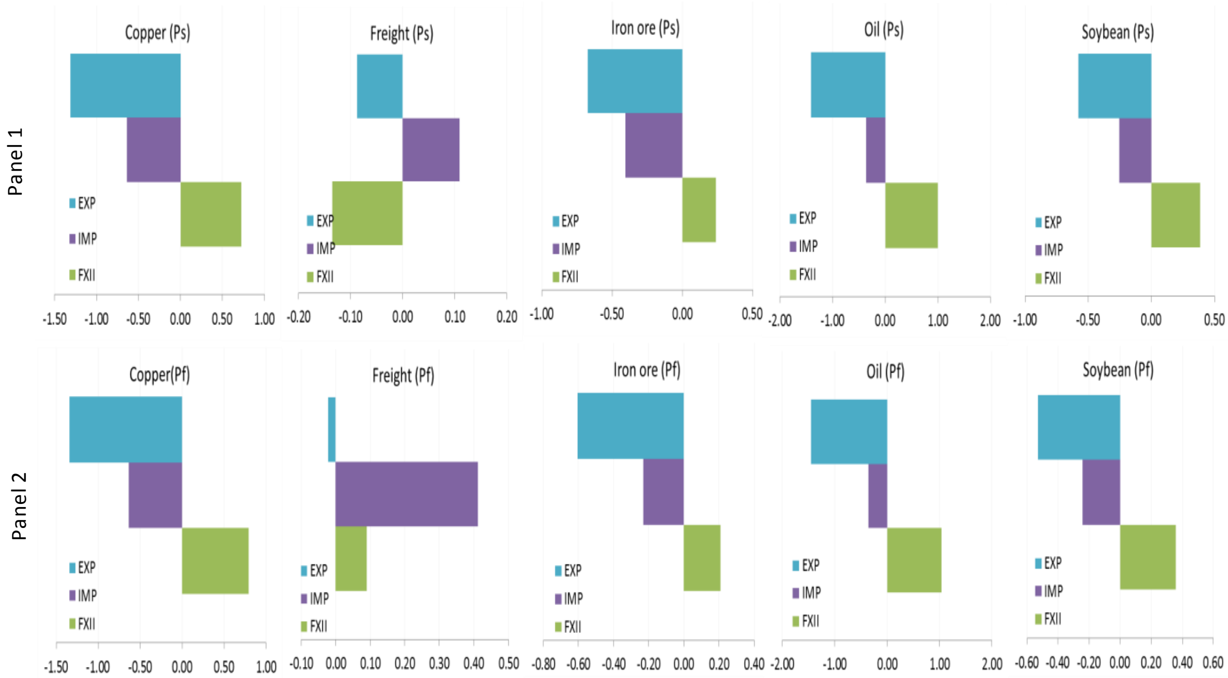


Significant differences appear in the relationships between the FX indices and the spot (Ps) and forward (Pf) commodity prices. For example, it is evident from Figure 2 that the correlation between *FXe* and *Pf* is strongest (negative) for the crude oil market, while that between *FXi* and *Pf* is highest (negative) for copper. The FX Impact Index (*FXIM*) is clearly influential (positive) for the oil market as displayed in the diagram for *FXIM–Pf*.

Spot prices *(Ps)* seem to be most closely (negatively) correlated with *FXe* on the crude oil market, while *FXi* is (negatively) correlated best with *Ps* on the copper market, which is no different from the previous examples using forward prices. The correlation between *FXIM* and *Ps* is similar to that between *FXIM* and *Pf*, with the strongest (positive) link maintained for oil.

Figure 3: Consolidated correlation coefficients across all three time frames for *Ps* and *FXe*, *FXi*, and *FXIM*

This set of charts consists of two panels. Panel 1, in the top row, displays the sum of the correlation coefficients between FXI, FXE, and FXIM and Ps. Panel 2, in the bottom row, displays the sum of the correlations between the same variables against Pf. The original data for the charts can be found in Table 3.



It is evident from Panel 1 of Figure 3 that, for copper, iron ore, and oil, the correlation between *Ps* and *FXe* is the strongest. Freight is the exception, with the correlation between *FXi* and *Ps* being the strongest. Another important exception is the soybean spot market, which demonstrates the strongest correlation with *FXIM*. Panel 2 displays the same pairs, but with *Pf* instead of *Ps*. It can be inferred that *FXe* versus *Pf* exhibits the strongest correlation across all the markets, with the exception of freight. The correlation coefficients from the original correlation matrix displayed in Figure 2 are consolidated in the form of Table 5 for further analysis.

Table 5: Summary of correlation coefficients

This table consists of four panels summarizing, for different combinations and data frequencies, the correlation coefficients between *FXi*, *FXe*, and *FXIM*, on the one hand, and *Ps* and *Pf* on the other. The first two panels summarize the correlation coefficients for *Ps* versus *FXe* across all five markets for the three time frequencies, which can be represented as follows: $R_s^e = \sum_{i=1}^{k} r_s^e$, where i = 1,…, k for daily, weekly, and monthly frequencies; r is Pearson correlation coefficient between *FXe* and *Ps*; and R_s^e is the sum of the individual r coefficients between *FXe* and *Ps* for each market. The process is replicated across all pairs and frequencies for *Ps*. The process for *Pf* takes the form $R_s^e = \sum_{i=1}^{k} r_f^e$, and the results are displayed in panel b. Panel c summarizes the results for all the markets across *Ps* and *Pf* under $\Pi_{s,e}^{market} = R_{s,e}^{copper} + R_{s,e}^{freight} + R_{s,e}^{ore} + R_{es,}^{oil} + R_{s,e}^{soy}$, where $R_{s,e}^{market}$ is the sum of the correlation coefficients between *FXe* and *Ps* for each market. The calculation is repeated for *FXi* and *FXIM* in relation to Ps under $\Pi_{s,i}^{market}$ and $\Pi_{s,fxii}^{market}$. The same calculation is repeated for *Pf* under $\Pi_{f,e}^{market}$, $\Pi_{f,i}^{market}$, and $\Pi_{f,fxii}^{market}$. Panel d presents the sums of the coefficients for both the *Ps* and forward markets, which can be described as follows: $\Gamma_A^{market} = \sum_{i=1}^{k} R_{e,A}^{market}$, where i = 1, …, k as the daily, weekly, and monthly frequencies, $R_{e,A}^{market}$ is the sum of correlation coefficients across all frequencies, and A is the average between *Ps* and *Pf*.

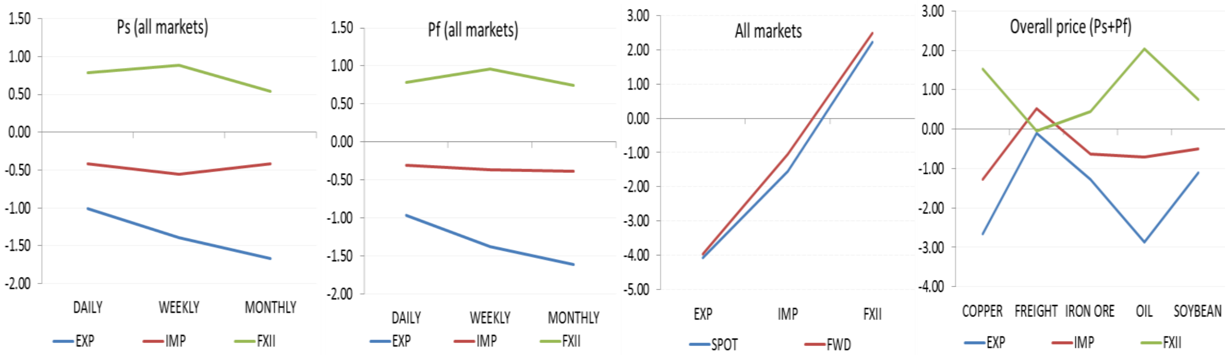
	Ps (all markets)			Forward (all markets)			All markets		Overall price (Ps + Pf) correlation				
	Daily	Weekly	Monthly	Daily	Weekly	Monthly	Ps	Pf	Copper	Freight	I. Ore	Oil	Soybean
Exporter	-1.00	-1.39	-1.67	-0.97	-1.38	-1.61	-4.06	-3.96	-2.65	-0.11	-1.28	-2.87	-1.11
Importers	-0.42	-0.56	-0.42	-0.30	-0.37	-0.38	-1.55	-1.05	-1.28	0.52	-0.64	-0.72	-0.50
FXIM	0.79	0.88	0.55	0.78	0.96	0.74	2.22	2.49	1.52	-0.05	0.45	2.04	0.74

The results, part of sub-hypothesis H1, confirm the claims of CRR (2010) and BKS (2014) that commodity prices and the currencies of exporters are positively correlated. Since each of the currency indices consists of a currency pair with the USD in the numerator of the currency cross, any weakness in the FX index equates to strength in the currency of the exporter (or importer) in the denominator of the FX cross.

When the correlations of *Ps* are consolidated by data frequency, as displayed in Table 5, they are found to be strongest for *FXe* at a monthly frequency and for *FXi* and *FXIM* at a weekly frequency. This result is indicative of the data frequency most suitable for explaining the relationship. Consolidation across markets suggests that the correlation between *P* and *FXe* is strongest for the oil market, that between *P* and *FXi* is strongest for copper, and that between *P* and *FXIM* is strongest for crude oil.

Figures 4a–d: Summary of the correlation coefficients

The data for these charts can be found in Table 5. The charts summarize the correlation coefficients for different combinations and data frequencies between FXI, FXE, and FXIM, on one hand, and Ps and Pf, on the other. The first two charts summarize the correlation coefficients between Ps and FXe across all five markets at the three time frequencies.



Furthermore, the following conclusions can be inferred from the results in Table 5 and Figures 4a to 4d. First, the correlation between *FXe* and *P* is the strongest one across all the time frames. Second, the correlation is stronger for *Ps*, not *Pf*. Third, all the commodities exhibit an inverse correlation between price *P* and *FXe* or *FXi*, except freight, which shows a positive correlation for *FXi*. Fourth, the correlation strength increases with decreasing frequency, that is, the correlation appears to be stronger for a monthly frequency compared to daily or weekly. Fifth, the correlation between *FXe* and *P* is stronger than that between *FXi* and *P* for all commodities except freight. Sixth, a significant correlation is detected between *FXIM* and *P* with a daily frequency, but its strength declines steadily and the correlation disappears for weekly and monthly frequencies. Finally, seventh, the correlations between *FXi, FXe,* and *FXIM* and P are stronger for *Ps* compared to Pf.

These results are supported by purchasing power parity theory and general trade theory, which dictate that, for goods traded in USD, the currency value of an importer should have an impact on the purchasing power in USD terms. In turn, this affects the quantity purchased on the market, which alters demand. The positive relationship between P and FXe is also explained by general trade theory, since higher international prices incentivize exporters to produce and ultimately export more. In turn, this has a positive impact on their trade balance, which increases the demand for the local currency and its value.

However, correlation does not imply causation, which is key element of the proposed hypotheses, H_0^1, H_0^2, and H_0^2. This is why the CR and SSP tests and the universally accepted Granger causality test are applied to the daily, weekly, and monthly time series with *Ps, Pf, FXe, FXi,* and *FXIM* data. The first of the three tests used to examine the causal forces between FX and commodity prices is the CR test, described in Section 5.5.3.1. The results from the tests across all three time frames (daily, weekly, monthly), commodities, and regimes can be found in Table 6. Figures A1 and A2 in the Appendix illustrate the results.

Table 6: CR test results, by regime

This table displays the results of the CR test by market, by time frame (daily, weekly, monthly), lead period, and by pair tested. A CR coefficient greater than 0.50 indicates that the percentage of times variable A reacts to changes in variable B is greater 50% of all instances in the sample. For example, within the daily time frame for copper, the number of positive reactions of *Ps* to changes in *FXIM* is highest for the lagged variables, as in the columns called "Coincidental". In other words, the reaction of *Ps* to changes in *FXIM* is the strongest as a coincidental move. If *FXIM* is forced to lead by one to five periods, the number of positive reactions declines to less than 50% of the entire sample.

	Daily						Weekly						Monthly					
	Coincidental	1	2	3	4	5	Coincidental	1	2	3	4	5	Coincidental	1	2	3	4	5
	FXIM vs. Ps						FXIM vs. Ps						FXIM vs. Ps					
Copper	0.56	0.49	0.49	0.48	0.51	0.5	0.63	0.57	0.51	0.46	0.49	0.49	0.56	0.56	0.39	0.49	0.52	0.57
Freight	0.49	0.5	0.49	0.49	0.5	0.49	0.47	0.52	0.5	0.49	0.52	0.53	0.47	0.53	0.57	0.53	0.41	0.42
Iron ore	0.5	0.51	0.5	0.49	0.49	0.51	0.58	0.55	0.49	0.49	0.48	0.49	0.49	0.57	0.47	0.32	0.51	0.53
Oil	0.57	0.5	0.5	0.49	0.49	0.5	0.61	0.56	0.49	0.48	0.46	0.45	0.62	0.54	0.49	0.56	0.38	0.51
Soybean	0.54	0.49	0.5	0.5	0.5	0.5	0.54	0.53	0.49	0.48	0.47	0.47	0.53	0.53	0.59	0.44	0.41	0.49
	FXIM vs. Pf						FXIM vs. Pf						FXIM vs. Pf					
Copper	0.58	0.49	0.5	0.49	0.5	0.51	0.64	0.59	0.49	0.44	0.47	0.49	0.57	0.52	0.41	0.53	0.48	0.58
Freight	0.5	0.5	0.51	0.5	0.5	0.5	0.52	0.53	0.51	0.47	0.51	0.51	0.49	0.43	0.65	0.53	0.41	0.43
Iron ore	0.51	0.5	0.5	0.51	0.49	0.5	0.58	0.55	0.52	0.5	0.48	0.49	0.47	0.57	0.47	0.37	0.48	0.58
Oil	0.57	0.51	0.5	0.5	0.5	0.51	0.61	0.54	0.47	0.47	0.45	0.43	0.62	0.54	0.49	0.56	0.38	0.51
Soybean	0.53	0.5	0.5	0.5	0.5	0.5	0.56	0.53	0.51	0.48	0.48	0.47	0.56	0.51	0.57	0.39	0.46	0.49
	Fxe vs. Ps						Fxe vs. Ps						Fxe vs. Ps					
Copper	0.56	0.57	0.51	0.51	0.48	0.49	0.31	0.43	0.48	0.5	0.53	0.5	0.33	0.44	0.56	0.47	0.38	0.39
Freight	0.64	0.58	0.52	0.51	0.5	0.5	0.47	0.51	0.53	0.53	0.48	0.49	0.48	0.48	0.41	0.57	0.58	0.51
Iron ore	0.62	0.56	0.52	0.54	0.53	0.53	0.41	0.45	0.45	0.48	0.5	0.49	0.35	0.44	0.56	0.52	0.42	0.42
Oil	0.55	0.58	0.5	0.49	0.49	0.47	0.36	0.43	0.47	0.46	0.45	0.47	0.32	0.48	0.57	0.56	0.49	0.53
Soybean	0.59	0.57	0.51	0.49	0.5	0.5	0.42	0.43	0.46	0.5	0.49	0.47	0.37	0.48	0.49	0.56	0.57	0.48
	Fxe vs. Pf						Fxe vs. Pf						Fxe vs. Pf					
Copper	0.55	0.58	0.5	0.51	0.5	0.49	0.29	0.42	0.49	0.52	0.55	0.49	0.29	0.43	0.49	0.43	0.39	0.38
Freight	0.62	0.57	0.52	0.52	0.51	0.5	0.51	0.53	0.54	0.53	0.5	0.5	0.51	0.51	0.43	0.59	0.56	0.54
Iron ore	0.63	0.56	0.49	0.5	0.51	0.5	0.41	0.42	0.44	0.46	0.47	0.51	0.41	0.42	0.53	0.52	0.44	0.42
Oil	0.54	0.58	0.5	0.49	0.49	0.48	0.39	0.44	0.49	0.45	0.47	0.47	0.32	0.48	0.57	0.56	0.49	0.53
Soybean	0.59	0.57	0.5	0.49	0.5	0.5	0.42	0.43	0.48	0.52	0.49	0.47	0.39	0.48	0.47	0.51	0.52	0.46
	Fxi vs. Ps						Fxi vs. Ps						Fxi vs. Ps					
Copper	0.6	0.57	0.51	0.49	0.47	0.48	0.39	0.43	0.49	0.45	0.46	0.49	0.38	0.52	0.46	0.49	0.38	0.35
Freight	0.65	0.59	0.51	0.51	0.5	0.5	0.47	0.49	0.53	0.55	0.54	0.52	0.54	0.65	0.56	0.52	0.63	0.57
Iron ore	0.61	0.57	0.51	0.52	0.52	0.52	0.43	0.48	0.47	0.49	0.47	0.47	0.47	0.48	0.54	0.49	0.47	0.49
Oil	0.63	0.58	0.51	0.49	0.48	0.48	0.47	0.46	0.44	0.44	0.45	0.48	0.32	0.41	0.41	0.52	0.38	0.51
Soybean	0.62	0.57	0.51	0.5	0.5	0.5	0.47	0.45	0.49	0.47	0.47	0.48	0.52	0.48	0.49	0.47	0.48	0.48
	Fxi vs. Pf						Fxi vs. Pf						Fxi vs. Pf					
Copper	0.6	0.57	0.5	0.48	0.49	0.48	0.39	0.44	0.48	0.45	0.48	0.49	0.37	0.46	0.47	0.48	0.34	0.39
Freight	0.64	0.59	0.54	0.51	0.51	0.5	0.54	0.54	0.54	0.51	0.51	0.49	0.62	0.59	0.56	0.49	0.58	0.51
Iron ore	0.63	0.58	0.49	0.51	0.5	0.47	0.47	0.49	0.46	0.45	0.48	0.47	0.47	0.48	0.52	0.49	0.47	0.49
Oil	0.63	0.58	0.5	0.49	0.48	0.48	0.47	0.45	0.43	0.45	0.45	0.49	0.32	0.41	0.41	0.52	0.38	0.51
Soybean	0.61	0.57	0.51	0.5	0.5	0.5	0.47	0.5	0.53	0.49	0.49	0.48	0.54	0.48	0.44	0.49	0.56	0.51

Analysis of the CR test coefficients reveals that both Ps and Pf appear to be the most responsive to changes in $FXIM$ in the copper market for the weekly and monthly time frequency, since they present the highest CR test coefficients. On the other hand, FXi is strongest for the daily frequency. The reaction of Ps to changes in FXi in the freight market is strongest for all three frequencies. On the other hand, the highest CR coefficient is found in the iron ore market, for the daily reaction of Ps to changes in FXi, while the price reaction to changes of $FXIM$ is strongest for the weekly and monthly frequencies. The same result is noted for the crude oil market, where the coefficient is strongest for FXi and Ps at for daily frequency, while weekly and monthly frequencies reveal FXIM to be the main price driver. The strongest coefficients with a daily frequency are between FXi and Ps, Pf and $FXIM$ for the soybean market at a weekly frequency, and FXi within a monthly frequency. These results are significant in the following ways.

All the markets appear to respond strongly to changes in FXi. The reaction to FXi is significantly stronger than to FXe. This is particularly the case for the daily data frequency. Therefore, H_0^1 can be rejected. Furthermore, all the markets respond strongly to the proposed synthetic S&D, that is, $FXIM$. The reaction is mainly concentrated within the weekly and monthly time frequencies. Furthermore, contrary to the results discussed in the literature, FXi appears to play an important role in relation to both spot and forward prices Ps and Pf, respectively. Such results are significant because they cast doubt on the claims made in the academic literature regarding the importance of FXe in commodity market price formation.

The links between the time series of $FXIM$, FXi, FXe, Ps, and Pf are next tested with the help of the SSP test, as described in Section 5.3.3.2. This is a test on the lead–lag relationship between each pair, called regimes, which quantifies the period of the lead–lag reaction. The initial results for the daily data frequency are displayed in Table 7 and summarized across all time frames and regimes in Table 8 and Figures 7a and 7b. The results for the weekly and monthly frequencies can be found in Tables 3A and 4A in the Appendix.

Table 7: SSP test results, by market and term

This table displays the results of the SSP test on the time series with daily data, by market, regime, and lead–lag period. Column zero shows coincidental reactions. Columns -1 to -8 show the lead coefficients for the variables *FXIM*, *FXi*, and *FXe*, respectively, tested against *Ps* and *Pf*. Columns +1 to +8 show the lag coefficients of the variables tested against price. The lead and lag coefficients are summed in columns ∑- and ∑+, and the absolute values of their sums are displayed in columns ABS- and ABS+, respectively. The sign represents the direction of the relationship between the two variables, and in this case it is removed in order to focus attention on the overall strength of this relationship. Tables with weekly and monthly data frequencies can be found in the Appendix.

		-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	∑-	ABS-	∑-	ABS+
FRT_Ps	FXIM_Ps	-0.005	-0.001	0.003	-0.002	-0.007	-0.006	-0.009	-0.005	-0.002	-0.009	-0.024	-0.039	-0.056	-0.067	-0.085	-0.089	-0.091	-0.032	0.032	-0.460	0.460
	FXE_Ps	0.006	0.001	-0.006	0.002	0.005	0.005	0.009	0.002	-0.009	-0.017	-0.016	-0.018	-0.010	-0.003	0.014	0.027	0.043	0.025	0.025	0.019	0.019
	FXI_Ps	0.048	0.038	0.029	0.027	0.021	0.019	0.016	0.013	0.004	-0.006	-0.016	-0.026	-0.029	-0.028	-0.026	-0.013	-0.002	0.211	0.211	-0.145	0.145
FRT_Pf	FXIM_Pf	0.026	0.035	0.051	0.065	0.072	0.074	0.079	0.069	0.066	0.058	0.035	0.019	0.008	-0.015	-0.047	-0.067	-0.077	0.472	0.472	-0.087	0.087
	FXE_Pf	0.026	0.017	-0.002	-0.011	-0.022	-0.020	-0.021	-0.019	-0.021	-0.014	0.008	0.021	0.021	0.021	0.033	0.044	0.050	-0.052	0.052	0.185	0.185
	FXI_Pf	0.069	0.063	0.057	0.056	0.054	0.059	0.067	0.070	0.065	0.068	0.067	0.066	0.059	0.040	0.021	0.016	0.020	0.495	0.495	0.357	0.357
COP_Ps	FXIM_Ps	0.111	0.121	0.134	0.143	0.157	0.165	0.191	0.231	0.289	0.217	0.156	0.110	0.059	0.016	-0.027	-0.041	-0.055	1.252	1.252	0.436	0.436
	FXE_Ps	-0.148	-0.158	-0.170	-0.195	-0.225	-0.250	-0.293	-0.348	-0.434	-0.358	-0.287	-0.238	-0.188	-0.148	-0.097	-0.074	-0.055	-1.787	1.787	-1.444	1.444
	FXI_P	-0.088	-0.094	-0.087	-0.107	-0.130	-0.153	-0.173	-0.194	-0.222	-0.189	-0.157	-0.136	-0.115	-0.101	-0.079	-0.070	-0.057	-1.027	1.027	-0.905	0.905
COP_Pf	FXIM_Pf	0.127	0.134	0.146	0.154	0.169	0.181	0.208	0.251	0.313	0.238	0.178	0.126	0.075	0.029	-0.015	-0.036	-0.054	1.371	1.371	0.539	0.539
	FXE_Pf	-0.148	-0.158	-0.171	-0.197	-0.228	-0.257	-0.302	-0.362	-0.448	-0.372	-0.300	-0.248	-0.195	-0.151	-0.100	-0.071	-0.048	-1.823	1.823	-1.485	1.485
	FXI_Pf	-0.088	-0.095	-0.088	-0.106	-0.127	-0.148	-0.168	-0.194	-0.222	-0.192	-0.159	-0.142	-0.121	-0.105	-0.083	-0.073	-0.059	-1.012	1.012	-0.934	0.934

Table 7 (continued)

		-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	∑-	ABS-	∑-	ABS+
OIL_Ps	FXIM_Ps	0.066	0.079	0.094	0.114	0.132	0.155	0.188	0.223	0.285	0.227	0.191	0.156	0.136	0.113	0.095	0.067	0.049	1.050	1.050	1.033	1.033
	FXE_Ps	-0.085	-0.087	-0.097	-0.121	-0.150	-0.194	-0.243	-0.301	-0.386	-0.320	-0.269	-0.226	-0.203	-0.173	-0.154	-0.127	-0.117	-1.277	1.277	-1.588	1.588
	FXI_Ps	-0.066	-0.062	-0.053	-0.052	-0.058	-0.072	-0.081	-0.091	-0.101	-0.089	-0.068	-0.053	-0.039	-0.023	-0.011	-0.009	-0.013	-0.533	0.533	-0.306	0.306
OIL_Pf	FXIM_Pf	0.053	0.065	0.083	0.104	0.131	0.162	0.196	0.235	0.294	0.229	0.195	0.157	0.135	0.111	0.095	0.070	0.054	1.029	1.029	1.046	1.046
	FXE_Pf	-0.064	-0.069	-0.090	-0.116	-0.149	-0.197	-0.247	-0.308	-0.390	-0.320	-0.272	-0.232	-0.210	-0.175	-0.152	-0.128	-0.120	-1.240	1.240	-1.610	1.610
	FXI_Pf	-0.069	-0.066	-0.064	-0.064	-0.066	-0.076	-0.085	-0.094	-0.104	-0.097	-0.073	-0.062	-0.050	-0.033	-0.015	-0.012	-0.017	-0.583	0.583	-0.358	0.358
SOY_Ps	FXIM_Ps	-0.006	-0.006	0.004	0.030	0.051	0.066	0.098	0.138	0.165	0.123	0.076	0.038	0.023	0.008	-0.007	-0.016	-0.018	0.375	0.375	0.226	0.226
	FXE_Ps	-0.022	-0.023	-0.034	-0.057	-0.073	-0.089	-0.126	-0.174	-0.210	-0.158	-0.107	-0.070	-0.055	-0.039	-0.024	-0.018	-0.026	-0.598	0.598	-0.497	0.497
	FXI_Ps	0.001	-0.002	-0.003	-0.011	-0.021	-0.030	-0.052	-0.083	-0.112	-0.074	-0.039	-0.024	-0.010	0.016	0.038	0.057	0.048	-0.201	0.201	0.013	0.013
SOY_Pf	FXIM_Pf	-0.004	-0.005	0.009	0.032	0.048	0.060	0.094	0.141	0.169	0.134	0.087	0.054	0.046	0.038	0.024	0.012	0.005	0.374	0.374	0.400	0.400
	FXE_Pf	-0.017	-0.016	-0.034	-0.053	-0.064	-0.075	-0.112	-0.164	-0.201	-0.153	-0.101	-0.068	-0.061	-0.051	-0.037	-0.030	-0.034	-0.534	0.534	-0.535	0.535
	FXI_Pf	0.020	0.013	0.001	-0.010	-0.017	-0.027	-0.050	-0.084	-0.116	-0.075	-0.043	-0.028	-0.019	0.007	0.032	0.048	0.046	-0.156	0.156	-0.032	0.032

Table 7 (continued)

		-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	∑-	ABS-	∑-	ABS+
IO_Ps	FXIM_Ps	0.055	0.078	0.095	0.105	0.104	0.109	0.121	0.135	0.117	0.102	0.084	0.057	0.037	0.021	0.005	0.004	-0.006	0.802	0.802	0.304	0.304
	FXE_Ps	-0.101	-0.122	-0.138	-0.152	-0.162	-0.177	-0.197	-0.220	-0.216	-0.199	-0.178	-0.156	-0.145	-0.133	-0.124	-0.127	-0.117	-1.269	1.269	-1.180	1.180
	FXI_Ps	-0.076	-0.082	-0.084	-0.091	-0.098	-0.104	-0.104	-0.111	-0.115	-0.097	-0.084	-0.076	-0.075	-0.077	-0.086	-0.095	-0.092	-0.750	0.750	-0.682	0.682
IO_Pf	FXIM_Pf	0.079	0.089	0.096	0.112	0.122	0.127	0.120	0.119	0.100	0.063	0.041	0.014	-0.003	-0.026	-0.040	-0.054	-0.048	0.864	0.864	-0.052	0.052
	FXE_Pf	-0.136	-0.142	-0.148	-0.160	-0.170	-0.175	-0.170	-0.173	-0.162	-0.138	-0.126	-0.111	-0.109	-0.102	-0.102	-0.096	-0.094	-1.275	1.275	-0.879	0.879
	FXI_Pf	-0.051	-0.043	-0.045	-0.058	-0.051	-0.050	-0.042	-0.038	-0.035	-0.032	-0.030	-0.035	-0.043	-0.055	-0.076	-0.091	-0.086	-0.378	0.378	-0.448	0.448

Table 8: Consolidated SSP test results

This table displays the consolidated results from the ABS+ and ABS- columns in Table 7. A value of zero indicates that no leading properties are detected for the particular regime. A value of one indicates that leading properties are detected. The number of occurrences per time frame, that is, daily, weekly, and monthly, is displayed at the bottom of the table. This number indicates the data frequency at which the proposed indicators are most likely to exhibit lead properties over price. The values of lead occurrences per regime against Ps and Pf are displayed in the Ps regime and forward regime columns.

Market	Regime	Daily	Weekly	Monthly	Regime	Daily	Weekly	Monthly	Ps regime	Forward regime
Freight	FXIM_Ps	0	0	1	FXIM_PF	1	0	0	1	1
	FXE_Ps	1	0	1	FXE_PF	0	0	0	2	0
	FXI_Ps	1	0	0	FXI_PF	1	0	1	1	2
Copper	FXIM_Ps	1	0	0	FXIM_PF	1	0	0	1	1
	FXE_Ps	1	0	1	FXE_PF	1	0	1	2	2
	FXI_Ps	1	0	0	FXI_PF	1	0	0	1	1
Oil	FXIM_Ps	1	1	0	FXIM_PF	0	1	0	2	1
	FXE_Ps	0	0	1	FXE_PF	0	0	1	1	1
	FXI_Ps	1	1	1	FXI_PF	1	1	1	3	3
Soybean	FXIM_Ps	1	1	1	FXIM_PF	0	1	1	3	2
	FXE_Ps	1	0	0	FXE_PF	0	0	0	1	0
	FXI_Ps	1	1	1	FXI_PF	1	1	1	3	3
Iron ore	FXIM_Ps	1	1	1	FXIM_PF	1	1	0	3	2
	FXE_Ps	1	0	0	FXE_PF	1	0	0	1	1
	FXI_Ps	1	0	0	FXI_PF	0	0	0	1	0
Total	∑ occurrences	13	5	8		9	5	6	26	20

Figure 5a: SSP test results, by data frequency and response to Ps or forward prices

This figure shows the strength and data frequency with which the proposed indicators are most likely to lead price.

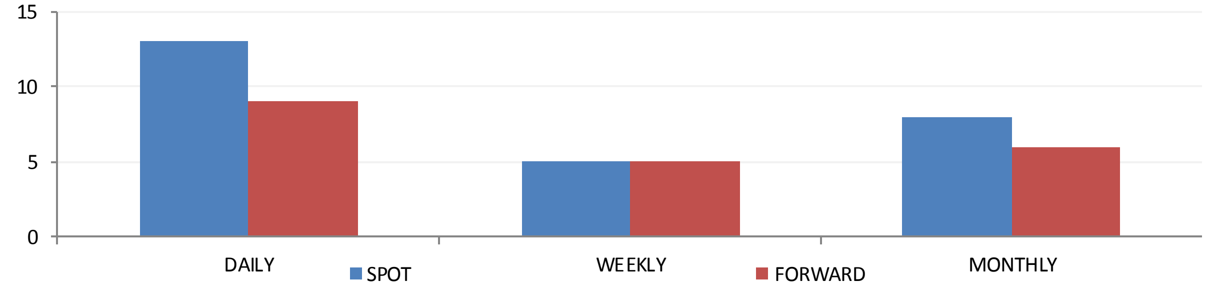
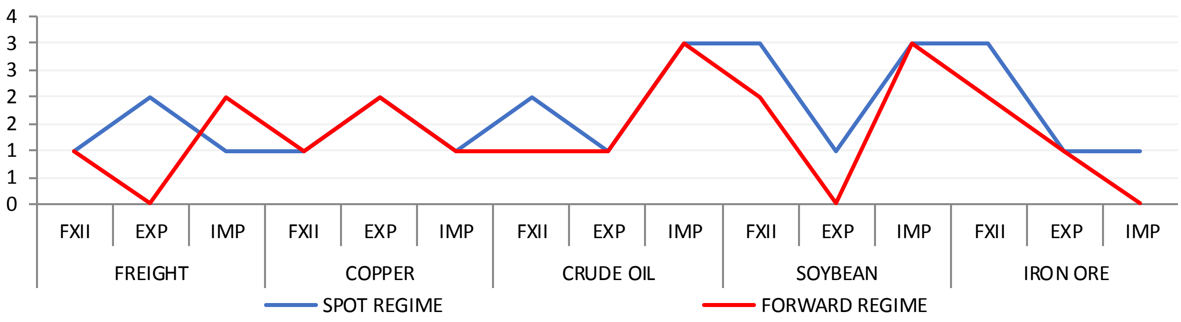


Figure 5b: SSP test results, by regime data frequency and response to Ps or forward prices

This figure shows the strength and data frequency with which the proposed indicators are most likely to lead price.



First, it is evident from the data in Tables 7 and 8 that the proposed and tested variables *FXIM*, *FXi*, and *FXe* exhibit stronger lead properties over *Ps* compared to *Pf*. Second, the lead properties appear to be stronger for the daily data frequency (see Figure 5a). The signal is lost at the weekly frequency, but it reappears, albeit weakly, at the monthly frequency. This result is significant because it provides guidance on the most suitable data frequency when applying the proposed FX indices. The data in Figure 5b show the results by individual markets across all three time frames. Freight, for example, shows higher responses for Ps to *FXe* and for *Pf* to *FXi*. Copper's response is highest for *FXe*, while oil's response is strongest to *FXi*.

The final test used to examine the causal forces between FX and prices is the commonly used bivariate Granger causality test, as described in Section 5.3.3.3.

Table 9: Bivariate Granger causality tests

The three panels of this table display the results from the Granger causality tests for the daily, weekly, and monthly time series of *FXi*, *FXe*, *FXIM*, *Ps*, and *Pf*. The null hypothesis (H_0) is dismissed at p-value ≤ 0.05.

	Copper	Prob. H0: rejected	Freight	Prob. H0: rejected	Iron ore	Prob. H0: rejected	Oil	Prob. H0: rejected	Soybean	Prob. H0: rejected
Daily	Pf_FXe	0.6502	Pf_FXe	0.5676	Pf_FXe	0.7813	Pf_FXe	0.6618	Pf_FXe	0.3128
	FXe_Pf	0.3225	FXe_Pf	0.9737	FXe_Pf	0.3345	FXe_Pf	0.1727	FXe_Pf	0.5882
	FXIM_FXe	0.8134	FXIM_FXe	0.9235	FXIM_FXe	0.4514	FXIM_FXe	0.9764	FXIM_FXe	0.3501
	FXe_FXIM	0.02	FXe_FXIM	0	FXe_FXIM	0	FXe_FXIM	0	FXe_FXIM	0.012
	FXi_FXe	0.4004	FXi_FXe	0.804	FXi_FXe	0.2927	FXi_FXe	0.8612	FXi_FXe	0.0814
	FXe_FXi	0.0169	FXe_FXi	0.1119	FXe_FXi	0.0003	FXe_FXi	0.099	FXe_FXi	0.0186
	Ps_FXe	0.4793	Ps_FXe	0.4943	Ps_FXe	0.3771	Ps_FXe	0.8345	Ps_FXe	0.638
	FXe_Ps	0.2504	FXe_Ps	0.0977	FXe_Ps	0.0021	FXe_Ps	0.1235	FXe_Ps	0.5638
	FXIM_Pf	0.8603	FXIM_Pf	0.9044	FXIM_Pf	0.5416	FXIM_Pf	0.4219	FXIM_Pf	0.5147
	Pf_FXIM	0.7259	Pf_FXIM	0.7287	Pf_FXIM	0.6706	Pf_FXIM	0.0952	Pf_FXIM	0.1008
	FXi_Pf	0.1608	FXi_Pf	0.7393	FXi_Pf	0.8623	FXi_Pf	0.5965	FXi_Pf	0.544
	Pf_FXi	0.3218	Pf_FXi	0.6038	Pf_FXi	0.2311	Pf_FXi	0.0746	Pf_FXi	0.3597
	Ps_Pf	0.006	Ps_Pf	0.0011	Ps_Pf	0.506	Ps_Pf	0	Ps_Pf	0.1009
	Pf_Ps	0.0002	Pf_Ps	0.0068	Pf_Ps	0	Pf_Ps	0.1117	Pf_Ps	0.8288
	Fxi_FXIM	0.2123	Fxi_FXIM	0.0603	Fxi_FXIM	0.0015	Fxi_FXIM	0.0437	Fxi_FXIM	0.3535
	FXIM_FXi	0.0156	FXIM_FXi	0.2646	FXIM_FXi	0.0011	FXIM_FXi	0.2514	FXIM_FXi	0.1134
	Ps_FXIM	0.347	Ps_FXIM	0.9046	Ps_FXIM	0.6628	Ps_FXIM	0.8225	Ps_FXIM	0.8641
	FXIM_Ps	0.7181	FXIM_Ps	0.0702	FXIM_Ps	0.0049	FXIM_Ps	0.2613	FXIM_Ps	0.4928
	Ps_FXi	0.5245	Ps_FXi	0.4084	Ps_FXi	0.3709	Ps_FXi	0.397	Ps_FXi	0.4604
	FXi_Ps	0.2608	FXi_Ps	0.8706	FXi_Ps	0.6676	FXi_Ps	0.7418	FXi_Ps	0.7195

Table 9 (continued)

	Copper	Prob. H0: rejected	Freight	Prob. H0: rejected	Iron ore	Prob. H0: rejected	Oil	Prob. H0: rejected	Soybean	Prob. H0: rejected
Weekly	Pf_FXe	0.4668	Pf_FXe	0.1171	Pf_FXe	0.2566	Pf_FXe	0.0289	Pf_FXe	0.5949
	FXe_Pf	0.8046	FXe_Pf	0.7294	FXe_Pf	0.019	FXe_Pf	0.697	FXe_Pf	0.9399
	FXIM_FXe	0.9763	FXIM_FXe	0.1244	FXIM_FXe	0.3582	FXIM_FXe	0.148	FXIM_FXe	0.1976
	FXe_FXIM	0.6583	FXe_FXIM	0.4101	FXe_FXIM	0.2447	FXe_FXIM	0.3137	FXe_FXIM	0.488
	FXi_FXe	0.5224	FXi_FXe	0.0439	FXi_FXe	0.5956	FXi_FXe	0.0712	FXi_FXe	0.0869
	FXe_FXi	0.6599	FXe_FXi	0.17	FXe_FXi	0.759	FXe_FXi	0.1568	FXe_FXi	0.1679
	Ps_FXe	0.5406	Ps_FXe	0.209	Ps_FXe	0.5112	Ps_FXe	0.0175	Ps_FXe	0.7802
	FXe_Ps	0.8506	FXe_Ps	0.6164	FXe_Ps	0.4425	FXe_Ps	0.463	FXe_Ps	0.9411
	FXIM_Pf	0.9359	FXIM_Pf	0.1882	FXIM_Pf	0.0733	FXIM_Pf	0.876	FXIM_Pf	0.4994
	Pf_FXIM	0.5351	Pf_FXIM	0.3111	Pf_FXIM	0.6432	Pf_FXIM	0.0094	Pf_FXIM	0.2496
	FXi_Pf	0.39	FXi_Pf	0.1267	FXi_Pf	0.1982	FXi_Pf	0.5954	FXi_Pf	0.8373
	Pf_FXi	0.6305	Pf_FXi	0.3868	Pf_FXi	0.2244	Pf_FXi	0.218	Pf_FXi	0.5954
	Ps_Pf	0.7378	Ps_Pf	0.4057	Ps_Pf	0	Ps_Pf	0.6369	Ps_Pf	0
	Pf_Ps	0.9261	Pf_Ps	0.0251	Pf_Ps	0	Pf_Ps	0.2458	Pf_Ps	0.7344
	Fxi_FXIM	0.8269	Fxi_FXIM	0.372	Fxi_FXIM	0.5161	Fxi_FXIM	0.2699	Fxi_FXIM	0.3355
	FXIM_FXi	0.9246	FXIM_FXi	0.3156	FXIM_FXi	0.6931	FXIM_FXi	0.3147	FXIM_FXi	0.7604
	Ps_FXIM	0.5661	Ps_FXIM	0.2606	Ps_FXIM	0.761	Ps_FXIM	0.0039	Ps_FXIM	0.3629
	FXIM_Ps	0.9572	FXIM_Ps	0.2749	FXIM_Ps	0.5713	FXIM_Ps	0.959	FXIM_Ps	0.5893
	Ps_FXi	0.7229	Ps_FXi	0.5623	Ps_FXi	0.4895	Ps_FXi	0.274	Ps_FXi	0.4118
	FXi_Ps	0.3977	FXi_Ps	0.3216	FXi_Ps	0.7519	FXi_Ps	0.5848	FXi_Ps	0.7844

Table 9 (continued)

	Copper	Prob. H0: rejected	Freight	Prob. H0: rejected	Iron ore	Prob. H0: rejected	Oil	Prob. H0: rejected	Soybean	Prob. H0: rejected
Monthly	Pf_FXe	0.0704	Pf_FXe	0.1626	Pf_FXe	0.6915	Pf_FXe	0.776	Pf_FXe	0.5804
	FXe_Pf	0.6077	FXe_Pf	0.9852	FXe_Pf	0.2071	FXe_Pf	0.0266	FXe_Pf	0.7949
	FXIM_FXe	0.9741	FXIM_FXe	0.7538	FXIM_FXe	0.2552	FXIM_FXe	0.1744	FXIM_FXe	0.2566
	FXe_FXIM	0.2785	FXe_FXIM	0.0275	FXe_FXIM	0.1242	FXe_FXIM	0.7795	FXe_FXIM	0.3524
	FXi_FXe	0.4792	FXi_FXe	0.6778	FXi_FXe	0.2675	FXi_FXe	0.587	FXi_FXe	0.2454
	FXe_FXi	0.9485	FXe_FXi	0.8033	FXe_FXi	0.9966	FXe_FXi	0.7418	FXe_FXi	0.9485
	Ps_FXe	0.1059	Ps_FXe	0	Ps_FXe	0.4871	Ps_FXe	0.169	Ps_FXe	0.7004
	FXe_Ps	0.5107	FXe_Ps	0.6776	FXe_Ps	0.0902	FXe_Ps	0.8228	FXe_Ps	0.7813
	FXIM_Pf	0.2105	FXIM_Pf	0.4193	FXIM_Pf	0.0928	FXIM_Pf	0.7287	FXIM_Pf	0.693
	Pf_FXIM	0.3083	Pf_FXIM	0.5822	Pf_FXIM	0.3308	Pf_FXIM	0.7911	Pf_FXIM	0.4004
	FXi_Pf	0.764	FXi_Pf	0.4347	FXi_Pf	0.2425	FXi_Pf	0.0208	FXi_Pf	0.7421
	Pf_FXi	0.7189	Pf_FXi	0.3656	Pf_FXi	0.9959	Pf_FXi	0.8274	Pf_FXi	0.7059
	Ps_Pf	0.085	Ps_Pf	0.9586	Ps_Pf	0.1794	Ps_Pf	0.7466	Ps_Pf	0.2244
	Pf_Ps	0.0321	Pf_Ps	0.259	Pf_Ps	0.2486	Pf_Ps	0.8339	Pf_Ps	0.4786
	Fxi_FXIM	0.5629	Fxi_FXIM	0.0272	Fxi_FXIM	0.2974	Fxi_FXIM	0.2819	Fxi_FXIM	0.6146
	FXIM_FXi	0.8192	FXIM_FXi	0.8688	FXIM_FXi	0.4181	FXIM_FXi	0.6469	FXIM_FXi	0.8213
	Ps_FXIM	0.3229	Ps_FXIM	0.0774	Ps_FXIM	0.0005	Ps_FXIM	0.8745	Ps_FXIM	0.4586
	FXIM_Ps	0.1817	FXIM_Ps	0.4767	FXIM_Ps	0.0598	FXIM_Ps	0.9461	FXIM_Ps	0.6946
	Ps_FXi	0.8219	Ps_FXi	0.0076	Ps_FXi	0.285	Ps_FXi	0.5402	Ps_FXi	0.7735
	FXi_Ps	0.6971	FXi_Ps	0.057	FXi_Ps	0.4173	FXi_Ps	0.2956	FXi_Ps	0.7666

It is evident from the results displayed in Table 9 and Figure 5a that most of the causal links are detected within the higher-frequency domain, namely, for the daily time series. Amongst other causal links, the indicator (*FXIM)* representing the synthetic S&D balance for each market as proposed in this paper is found to Granger-cause Ps for the freight and iron ore markets and Pf for the iron ore market at the daily frequency. The signal associated with potential predictive power of *FXIM* completely vanishes with decreasing data frequencies, namely, weekly and monthly. This result is also evident from the summary of causality signals in Table 10 and Figures 6a and 6b.

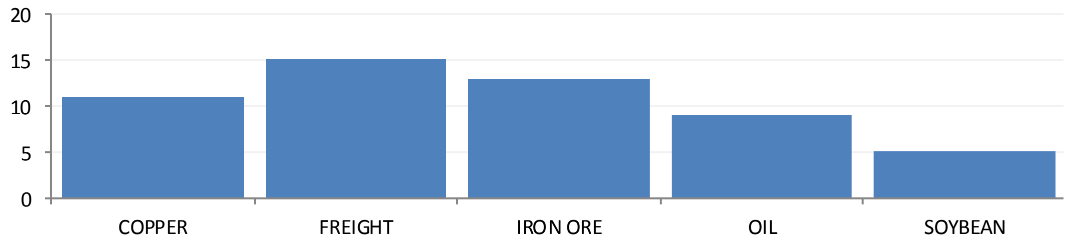
Table 10: Summary of bivariate Granger causality tests

This table displays the sums of the pairs for which H_0 was rejected for all three time frequencies (daily, weekly, monthly) for the *FXi, FXe, FXIM, Ps,* and *Pf* time series, as initially shown in Table 7.

	Copper	Freight	Iron ore	Oil	Soybean	Time frequency
Daily	5	6	7	3	2	23
Weekly	3	4	4	4	2	17
Monthly	3	5	2	2	1	13
Per market	11	15	13	9	5	

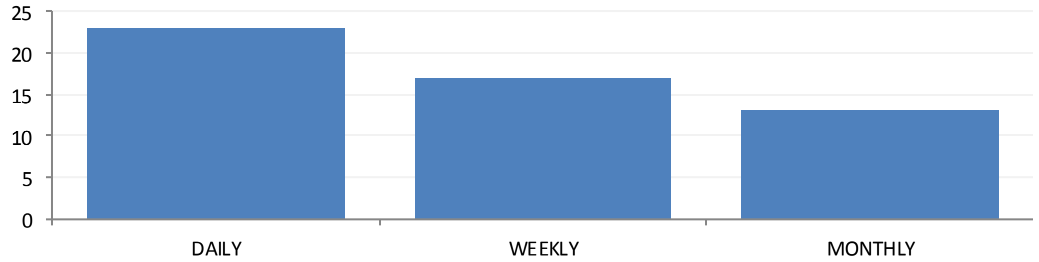
Figures 6a: Summary of Granger causality tests

This figure displays the number of causal links detected, by market. The data for the charts can be found in Table 10, which displays the sums of the pairs for which H_0 was rejected for all free time frequencies of the *FXi, FXe, FXIM, Ps,* and *Pf* time series.



Figures 6b: Summary of Granger causality tests

This figure displays the number of causal links detected, by data frequency. The data for the charts can be found in Table 10, which displays the sums of the pairs for which H_0 was rejected for all free time frequencies of the FXi, FXe, FXIM, Ps, and Pf time series.



The result suggests that the higher the frequency, the stronger the causality signal amongst the five variables in the study. Furthermore, the freight, iron ore, and oil markets appear to possess stronger causality processes compared to copper and soybean.

All three causality tests discussed earlier require a stationary time series, which is why the data are first tested for a unit root with the ADF test. Stationarity is also a necessary condition for the deployment of a multivariate VAR framework, which is an important part of the hypotheses tested in this paper. A multivariate VAR model is employed because causality can be successfully tested with the help of the IRF of the VAR model/VECM environment as well. Since the original time series are not stationary in levels, their properties are further tested for cointegration with the standard (Johansen 1991) cointegration test. No cointegration is detected across the time frames, and I(1) stationary time series are therefore employed under the unrestricted VAR framework. Since the data are stationary in first differences, the deterministic trend specification of the VAR model involves no trend or intercept. The lag structure of the VAR model is calculated according to the methodology in Section 5.5 and Lütkepohl (2005). The HQIC returns the lowest lag length of two.

Before exposing the results of the actual IRF analysis, it is important to reiterate that a higher FX index value indicates weaker domestic currencies in the basket. In turn and according to international trade and purchasing power theories, the incentive to produce and export commodities increases and the purchasing power of the consumers/importers decreases. Both conditions promote lower commodity prices.

The *first hypothesis* of the study investigates the flow of causality between FX and P. Analysis of the impulse responses of all five markets across the three data frequencies (daily, weekly, monthly) confirms earlier findings of the three bivariate causality tests, namely, the CR, SSP, and Granger tests, and it reveals strong evidence in support of the hypothesis that *FX* causes *P*. Moreover, the IRF analysis fails to find a single occasion in which the causal link P towards FX is stronger than that of *FX* to *P*. Consolidated results from the IRFs of all 30 VAR models are presented in Tables 11 and 12 and displayed in Figures 7a to 7f. It is evident that the number of causal occurrences between FX and *Ps* and *Pf* is significantly higher than the instances of spillover from *P* to *FX*. The complete results for the IRFs across all the markets and frequencies can be found in the Appendix.

The *second hypothesis* of the paper, which asserts that *FXi* and *FXe* have equal predictive power over *P* (not differentiating between *Ps* and *Pf*), is also tested with the help of the impulse responses of the 30 VAR models proposed. The sub-hypothesis stipulating that the predictive power of *FX* is stronger for *Ps* than for *Pf* is also examined. The hypothesis is rejected, since the consolidated results, displayed in Tables 11 and 12 and Figures 7a to 7f, demonstrate that the causal processes between *FXe* and *P* are both stronger and more frequent than the processes between *FXi* and *P*. The evidence is strongest for the daily frequency (Figure 7a), where only the soybean market registers equal numbers of causal reactions of *FXe* to *P* as of *FXi* to *P*. For the weekly frequency (Figure 8b), soybean again exhibits equal numbers of causal reactions, while freight clearly favours the link from *FXi* to P. Such an outcome for the freight market suggests that the value of the currencies of commodity importers is more important than the currencies of exporters, evidence in line with the discussion in the introduction about changing pressure along the global supply chains (demand pull growing in importance versus supply push). Further analysis of the monthly data reveals that copper and oil register the same numbers of causal occurrences of reactions of *FXi* to *P* as of *FXe* to P (Figure 7c), while freight again favours the signal flowing from *FXi* to *P*. The iron ore market is the only market in the sample where *FXi* does not seem to have any influence for the daily or weekly frequency, since all the causal links are observed from FXe to P. Therefore, it can be inferred that the currencies of exporters have a disproportionately stronger impact on the price of iron ore compared to the currencies of importers.

The proposed sub-hypothesis tests the different strengths of the causal process between FXi and FXe and Ps and Pf. This evidence is based on the same 30 VAR models with the corresponding IRFs reported in Tables 11 and 12, Figures 7d and 7e, and Figures A3 in the Appendix. The results confirm the sub-hypothesis for FXe as noted in Figure 7d. However, the hypothesis cannot be confirmed or rejected for Ps, since the number of causal reactions from the spillover effect of the introduced shock is equal to the number of reactions of Pf (see Figures 7d and 7e).

Table 11: Results from the VAR IRFs for all markets, prices, and frequencies

This table displays the results for the VAR IRFs. Causal signals detected by the VAR IRFs due to the positive shock introduced to the system are marked with a value of one. A lack of a causal reaction is denoted by a value of zero. These results are based on the diagrams of IRFs displayed in Figure A3 in the Appendix.

Daily, Ps	FXi causes Ps	Ps causes FXi	FXe causes Ps	Ps causes FXe
Copper			1	
Freight			1	
Iron ore	1		1	
Oil			1	
Soybean	1		1	
Daily, forward	FXi causes Ps	Ps causes FXi	FXe causes Ps	Ps causes FXe
Copper			1	
Freight				
Iron ore			1	
Oil	1		1	
Soybean	1		1	
Weekly, Ps	FXi causes Ps	Ps causes FXi	FXe causes Ps	Ps causes FXe
Copper	1		1	
Freight	1		1	
Iron ore			1	
Oil			1	
Soybean	1		1	
Weekly, forward	FXi causes Ps	Ps causes FXi	FXe causes Ps	Ps causes FXe
Copper			1	
Freight	1			
Iron ore			1	
Oil			1	
Soybean	1		1	
Monthly, Ps	FXi causes Ps	Ps causes FXi	FXe causes Ps	Ps causes FXe
Copper	1		1	
Freight	1		1	
Iron ore			1	
Oil	1		1	
Soybean			1	
Monthly, forward	FXi causes Ps	Ps causes FXi	FXe causes Ps	Ps causes FXe
Copper	1		1	
Freight	1			
Iron ore			1	
Oil	1		1	
Soybean	1		1	

Table 12: Sums of the results from the VAR IRFs for all markets, prices, and frequencies
This table displays the sums of the results from the VAR IRFs as displayed in Table 11.

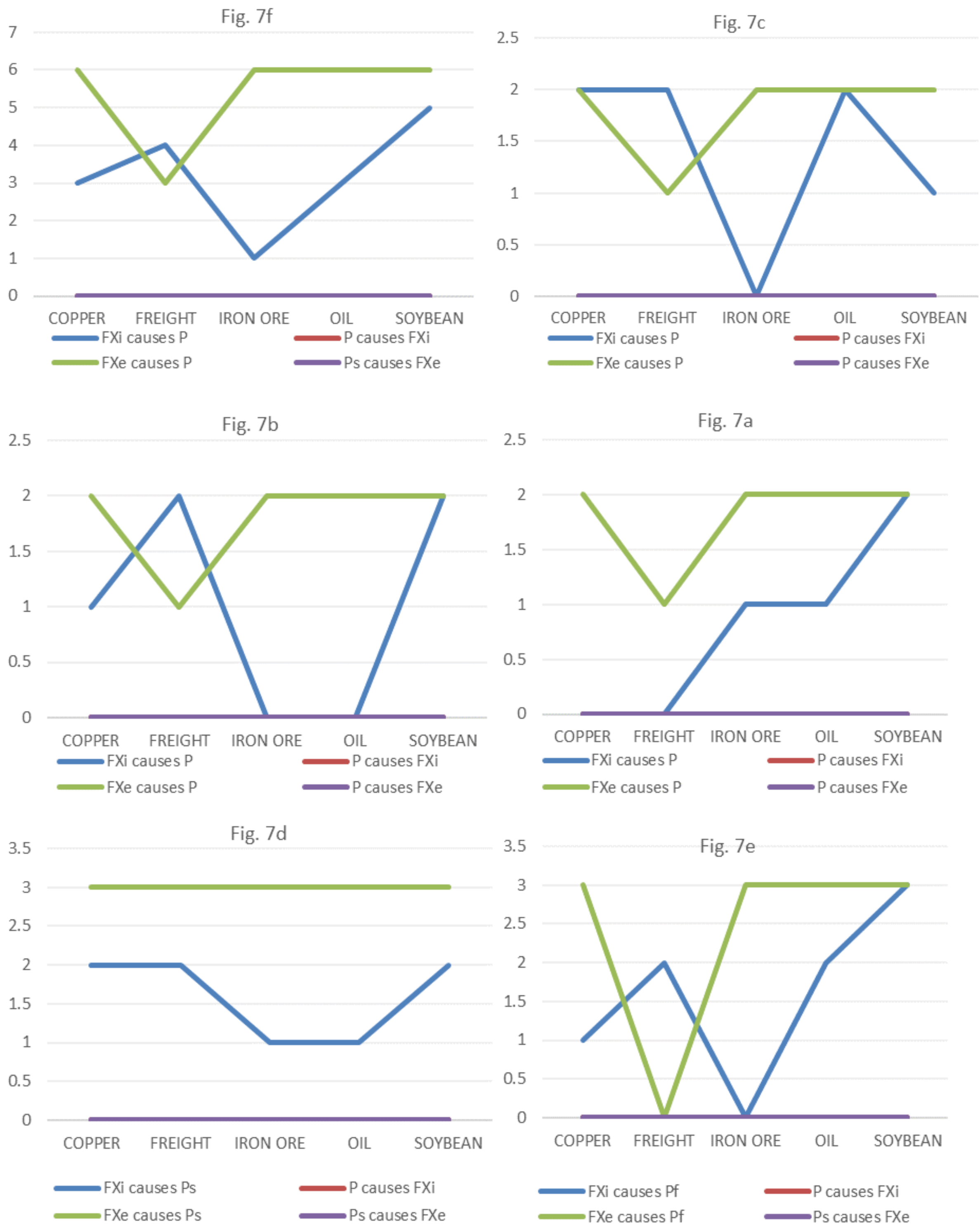
Weekly	FXi causes P	P causes FXi	FXe causes P	P causes FXe
Copper	1	0	2	0
Freight	2	0	1	0
Iron ore	0	0	2	0
Oil	0	0	2	0
Soybean	2	0	2	0

Monthly	FXi causes P	P causes FXi	FXe causes P	P causes FXe
Copper	2	0	2	0
Freight	2	0	1	0
Iron ore	0	0	2	0
Oil	2	0	2	0
Soybean	1	0	2	0

Total	FXi causes P	P causes FXi	FXe causes P	Ps causes FXe
Copper	3	0	6	0
Freight	4	0	3	0
Iron ore	1	0	6	0
Oil	3	0	6	0
Soybean	5	0	6	0

Figures 7a to 7f: Summary of IRF results for the three data frequencies

This charts display the sums of the responses detected by the VAR IRF and presented in Table 12. Figure 7a displays the results for the daily frequency, Figure 7b the results for the weekly frequency, Figure 7c the results for the monthly frequency, Figure 7d the results for the reaction of Ps, Figure 7e the results for the reaction of Pf, and Figure 7f the results for the sums across all frequencies (daily, weekly, monthly) and prices (Ps, Pf).



The *third hypothesis* states that FXIM has stronger predictive power over P compared to the predictive power of each of its constituents *FXe* and *FXi*. The sub-hypothesis states that the predictive power of *FXIM* is stronger over *Pf* than over *Ps*. The hypotheses verification is carried out by comparing the R-squared value of the ordinary least squares (OLS) regression models.

The results reveal that the explanatory power of the proposed currency indices *FXi*, *FXe*, and *FXIM* is strongest for the oil market (Figures 8d and 8f), followed by copper and iron ore. The explanatory power appears to increase with decreasing data frequency, that is, noisier daily data register lower R-squared coefficients for the OLS compared to monthly data (see the trends of the lines in Figure 8f). Furthermore, the evidence in Table 13 and Figures 8a to 8f suggests that the OLS regression involving *FXIM* delivers stronger results compared to the R-squared values of the other OLS regressions, namely, OLS 1 *(FXi, P*), OLS 2 (*FXe, P*), OLS 3 (*FXIM, P*), and OLS 4 (*FXi, FXe, P*).

The third hypothesis is thus not confirmed, because the results of the bivariate OLS (*FX, Pf*) and OLS (*FXIM, P*) regression models produce stronger results than those of OLS (*FX, P*). Therefore, it can be inferred that *FXIM* alone does not possess stronger predictive power over P in comparison with the FX indices.

The results from the tests displayed in Table 13 and Figures 8a to 8f also reveal that the sub-hypothesis can be confirmed only for the copper market. Data from freight reveal that, for the monthly frequency, the *FXIM* has stronger explanatory power over *Ps* than over *Pf*. This is the case for iron ore for the weekly frequency, oil for the weekly and monthly frequencies, and soybeans for the daily and weekly frequencies.

Table 13: R-Squared values of the OLS regression models

This table displays the results of the OLS regressions for each market and combination of dependent (*Ps*, *Pf*) and independent (*FXi*, *FXe*, *FXIM*) variables. The last row of each panel is the sum (∑) of all the R-squared coefficients, which demonstrates the difference in the OLS regression models' explanatory power across commodities and dependent variables.

`		Dependent					
		Daily		Weekly		Monthly	
	Independent	Ps	Pf	Ps	Pf	Ps	Pf
Copper	FXi	0.0211	0.0181	0.0569	0.0589	0.0599	0.0602
	FXe	0.1435	0.1511	0.2232	0.2368	0.2117	0.2172
	FXIM	0.0954	0.1057	0.0923	0.1064	0	0.0026
	FXi, FXe	0.1437	0.1519	0.2233	0.2369	0.2126	0.2182
	FXi, FXe, FXIM	0.1441	0.1524	0.2234	0.2373	0.2249	0.2249
	∑	0.5478	0.5792	0.8191	0.8763	0.7091	0.7231
Freight	FXi	0	0.0002	0	0.008	0.0163	0.0931
	FXe	0.0002	0	0.0013	0.0027	0	0.0015
	FXIM	0	0	0.0003	0.0027	0.0123	0.0001
	FXi, FXe	0.0002	0.0003	0.0012	0.0157	0.0244	0.1057
	FXi, FXe, FXIM	0.0008	0.0008	0.0103	0.0217	0.0571	0.11
	∑	0.0012	0.0013	0.0131	0.0508	0.1101	0.3104
Iron ore	FXi	0.0071	0.0001	0.0231	0.0031	0.0214	0.0161
	FXe	0.0022	0.0013	0.0727	0.0457	0.1228	0.1215
	FXIM	0.0001	0.0002	0.0126	0.0029	0.0001	0.0015
	FXi, FXe	0.0075	0.0013	0.0739	0.0464	0.1232	0.1231
	FXi, FXe, FXIM	0.0082	0.0032	0.0799	0.062	0.1272	0.1271
	∑	0.0251	0.0061	0.2622	0.1601	0.3947	0.3893
Oil	FXi	0.0023	0.0018	0.0001	0.0001	0.0499	0.0525
	FXe	0.1474	0.1524	0.1879	0.2137	0.3502	0.3649
	FXIM	0.0999	0.1058	0.0915	0.1116	0.1209	0.1179
	FXi, FXe	0.1477	0.1529	0.1895	0.217	0.3502	0.3649
	FXi, FXe, FXIM	0.1479	0.1529	0.1906	0.2187	0.3939	0.4051
	∑	0.5452	0.5658	0.6596	0.7611	1.2651	1.3053
Soybean	FXi	0.0155	0.0152	0.0006	0.0005	0	0
	FXe	0.0294	0.0203	0.0266	0.0223	0.0534	0.0508
	FXIM	0.02	0.0092	0.0184	0.0159	0	0
	FXi, FXe	0.0351	0.0273	0.028	0.0234	0.0555	0.053
	FXi, FXe, FXIM	0.0365	0.0273	0.0333	0.0281	0.0563	0.0531
	∑	0.1365	0.0993	0.1069	0.0902	0.1652	0.1569

5.7. Conclusions

This paper examines the predictability of key energy, metal, grain, and shipping commodity markets by the FX rates of major exporters and importers of these commodities. The results suggest that it is too simplistic to focus exclusively on the relationship between prices and the currency of exporters, which is the dominant theme of research in scholarly work. The evidence found in this study indicates that valuable information can be extracted from both the currency values of the importers and the proposed synthetic S&D model, also known as the FX Impact Index, or *FXIM*.

Initial correlation analysis across FX indices, prices, markets, and data frequencies reveals that the relationship between *FXe* and *P* is the strongest across all time frames. This result is in line with the view of the established academic literature. The correlation is particularly strong for *Ps* prices, and not future prices. The weaker signal against *Pf* can be explained by the forward-looking nature of the futures markets and the faster speeds at which they price in available information. Additionally, all commodities in the sample exhibit an inverse correlation between prices and the proposed FX indices, except freight, which has a positive correlation with *FXi*. This finding is due to the fact that higher FX index values indicate weaker domestic currencies in the basket. In turn and according to international trade and purchasing power theories, the incentive to produce and export commodities increases and the purchasing power of the consumers/importers decreases. Both conditions promote lower commodity prices. A significant correlation is also detected between prices and the *FXIM* relevant to the specific market at a daily frequency. The correlation declines steadily in strength and disappears at the weekly and monthly frequencies.

The fact that correlation does not imply causation is a fundamental principle of modern science. However, this paper concludes that that the strong correlations between currency rates and price and especially between *FXe* and *P* transform into strong causation. The bivariate causal tests in the study show that all markets appear to respond to changes in *FXi, FXe*, and *FXIM*. Further analysis of the IRFs of the 30 VAR models involving all five markets across the three data frequencies (daily, weekly, monthly) confirms the flow of causality from FX to P. The IRF analysis fails to find a single instance when the causal link P towards FX is stronger than that of FX towards P.

The currencies of the importers of commodities (*FXi)* appear to play an important role in relation to both *Ps* and forward prices *Ps* and *Pf,* respectively. These results are significant, because they cast doubt on the claims made in the academic literature in relation to the Importance of *FXe* for commodity market price formation. Therefore, this paper concludes that valuable information about future commodity price movements is contained not only in the traditional currency pairs of exporters, but also in the currency values of the importers, a claim supported by purchasing power theory. In addition, the methodological approach adopted in this paper produces a significantly more relevant representation of the specific commodity markets, compared to the small basket of currency pairs widely used in the literature.

Another important inference that can be drawn from the results of this study is that spot and forward commodity prices react differently to the information contained in the FX markets and transmitted by the suggested FX models. This finding provides a significant advantage to the professional investment community in building trading or risk management strategies. Market regulatory bodies are also likely to benefit from the findings, in view of their interest in market signals, price formation, and the impact on end users through Consumer Price Index baskets.

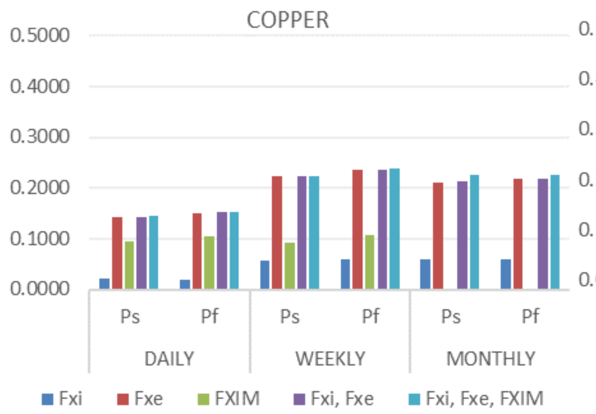
One common trait of the correlation and causation analyses in the paper is the data frequency at which the relationships between the three proposed FX indices and commodity prices peak. It is concluded that the frequency at which correlation and causation return the strongest signals is daily. The signal associated with the potential predictive power of *FXIM* completely vanishes as the data frequency decreases to weekly and monthly. This result suggests that the higher the frequency, the stronger the causality signal amongst the five variables in the study. Therefore, the conclusion can be drawn that the value of the proposed FX indices is more valuable for short-term trading strategies, as opposed to longer-term investment strategies.

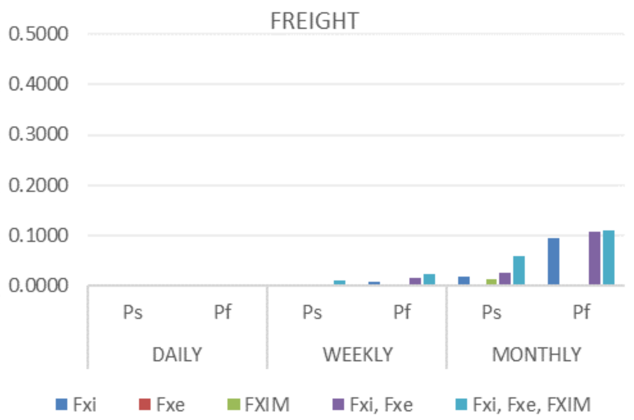
Furthermore, the evidence suggests that, even though *FXIM* does not possess stronger predictive qualities over P than FX, inclusion of *FXIM* in a model is found to improve its explanatory power. The construction of a synthetic S&D balance based exclusively on the currencies of the main importers and exporters of a particular commodity presents a distinctly different theoretical perspective from that of the literature. Such a novel approach is a departure from traditional methodology. It is therefore a valuable tool for both practitioners and regulators in measuring the short-term S&D balance of a given commodity market. Further research is encouraged into the differences between the bivariate and multivariate causality tests for some commodity markets. In addition, even if the markets chosen for this paper are key representatives of the energy, agricultural, metal, and shipping sectors, the results clearly demonstrate significant variations in the outcomes between individual markets. Therefore, the topic of the causal flow between currencies and commodity markets will also benefit from the inclusion of more markets in studies.

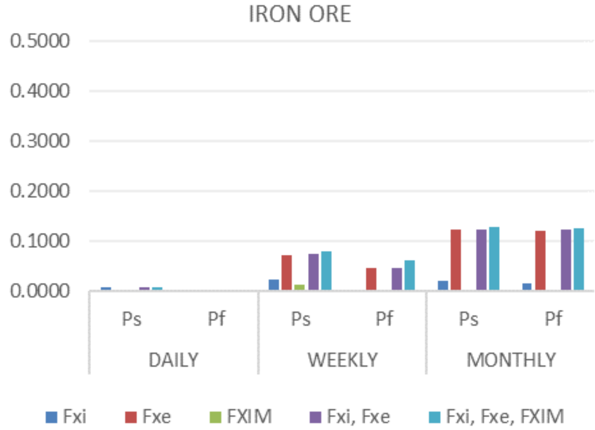
Appendix of Chapter 5

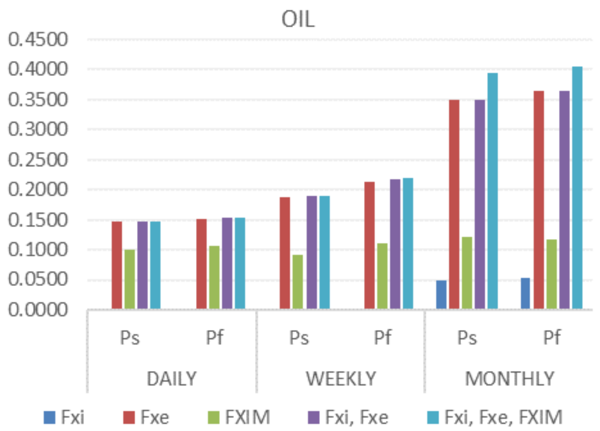
Figures A8a to A8f: R-squared coefficients of the OLS regressions

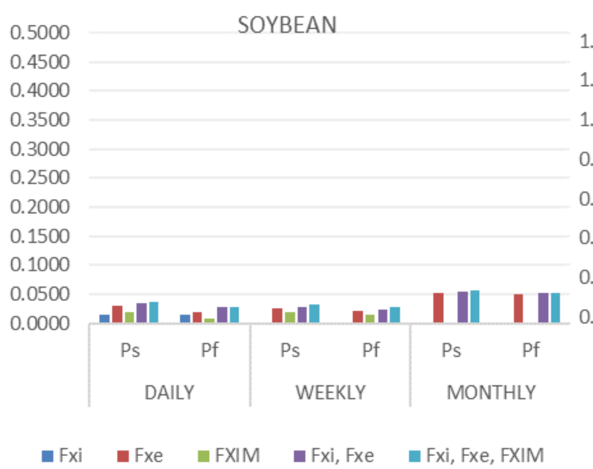
These charts display the OLS regression R-squared coefficients from Table 11, split by markets. The x-axis shows the dependent variable, the y-axis is the coefficient strength, and the different-coloured histogram bars represent the independent variables/groups of variables. Figure 8f displays the sums of the R-squared coefficients (y-axis) by dataset frequency and against *Ps* or *Pf* (x-axis).











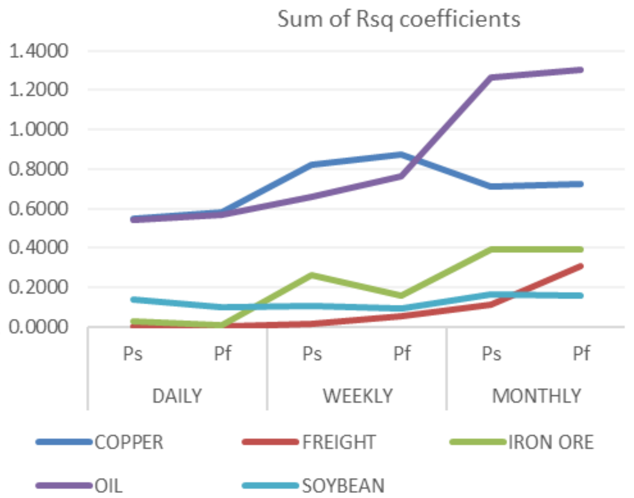
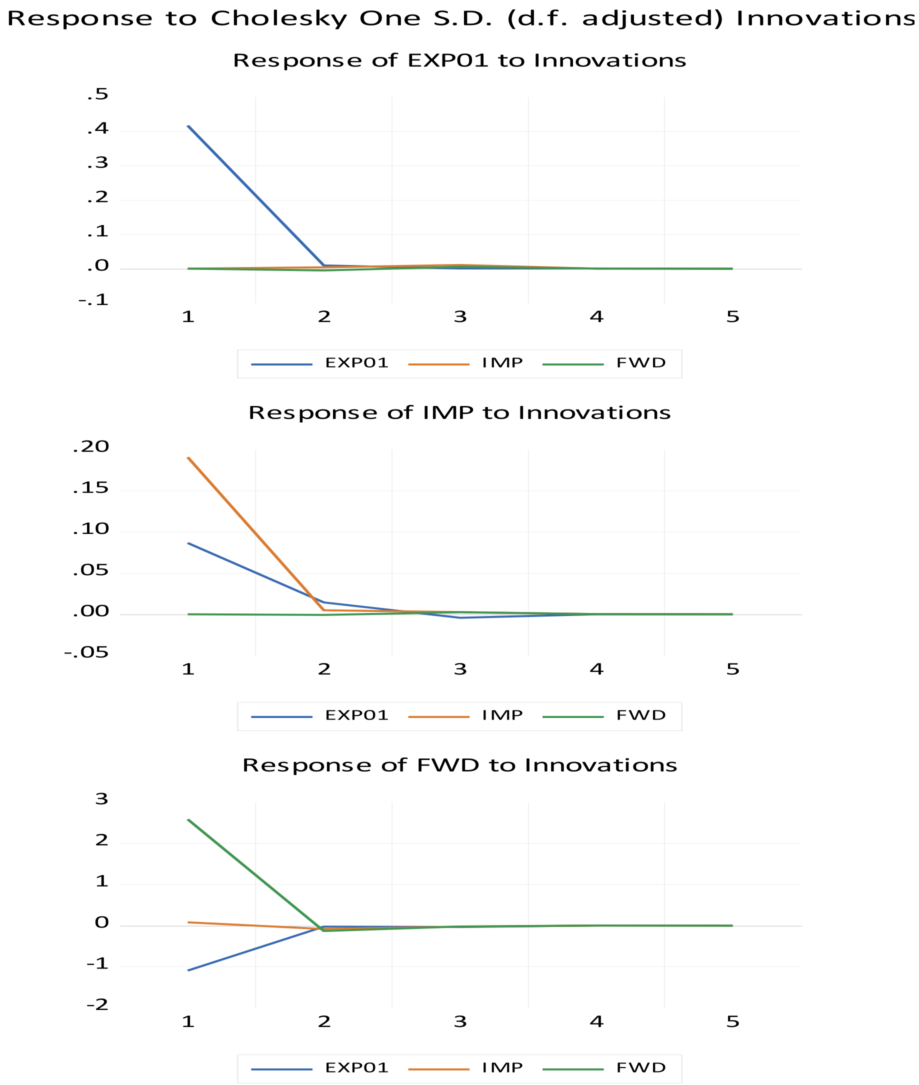


Figure A3A: VAR model IRFs (daily, copper)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to a positive shock of one standard deviation.

Copper, daily, spot



Copper, daily, forward

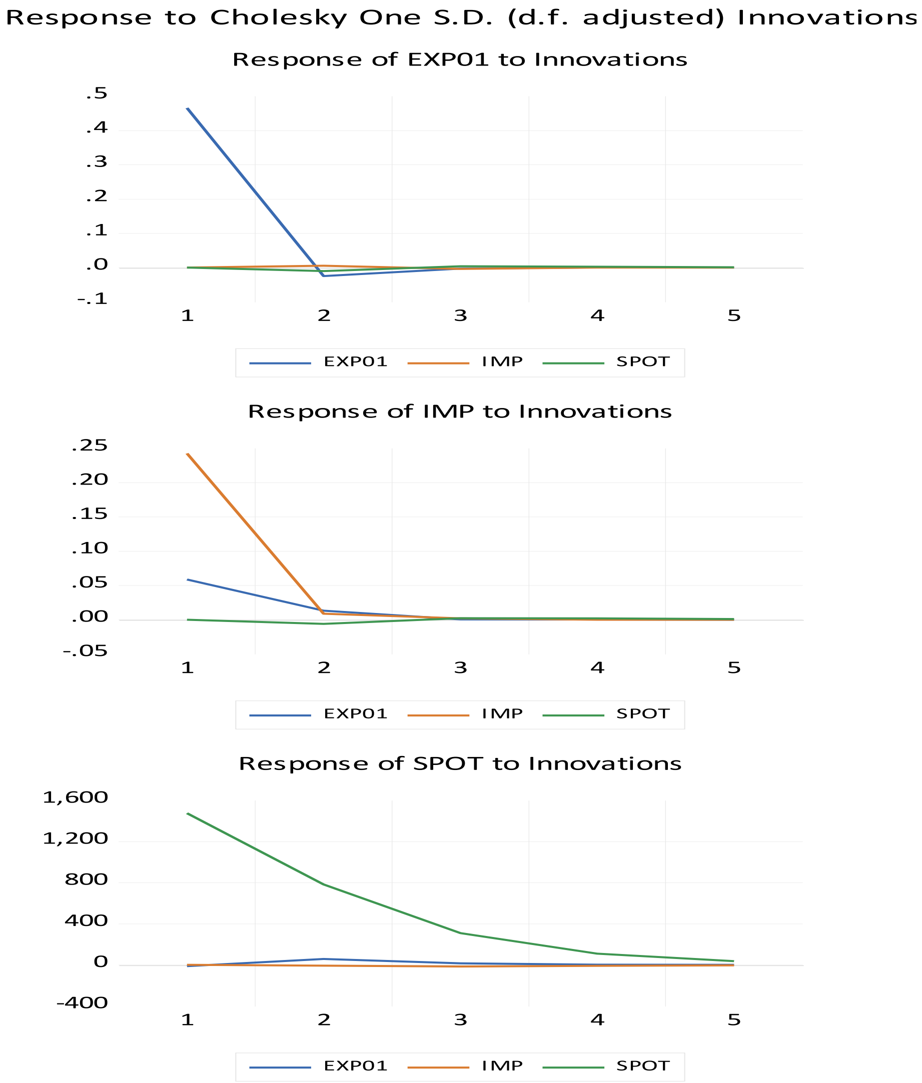
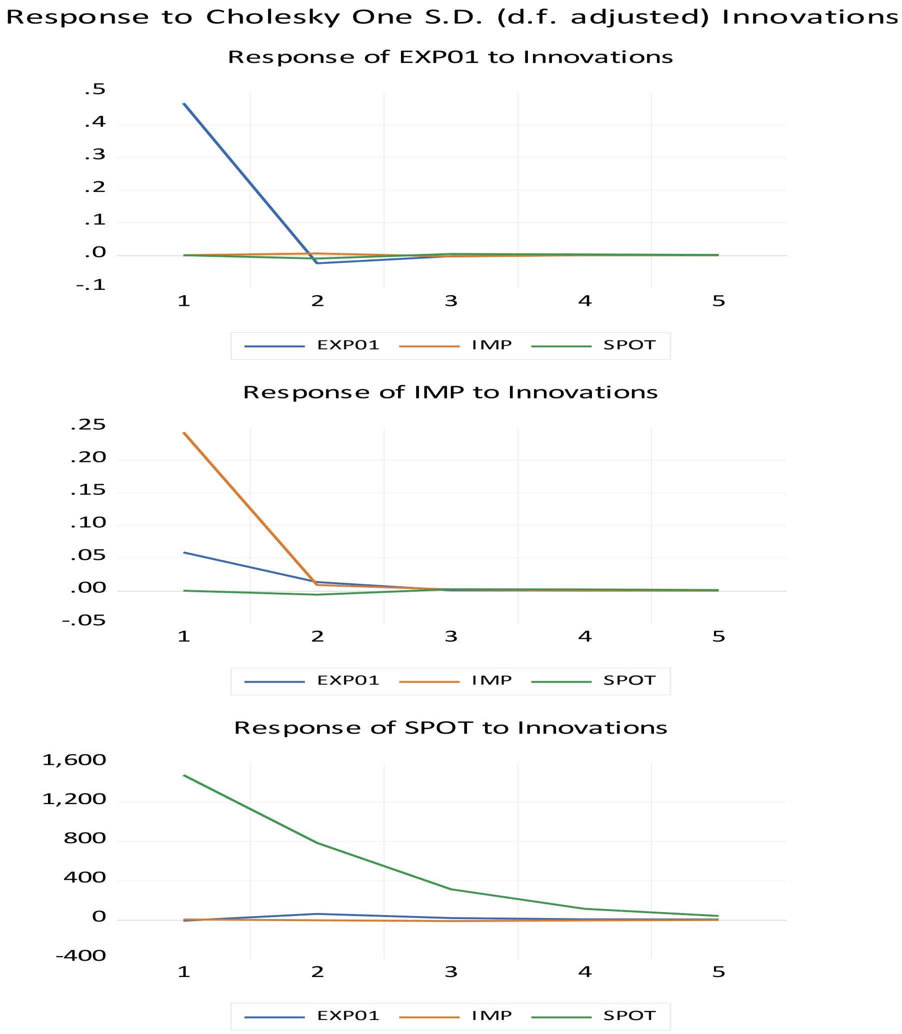


Figure A3B: VAR model IRFs (daily, freight)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Freight, daily, spot



Freight, daily, forward

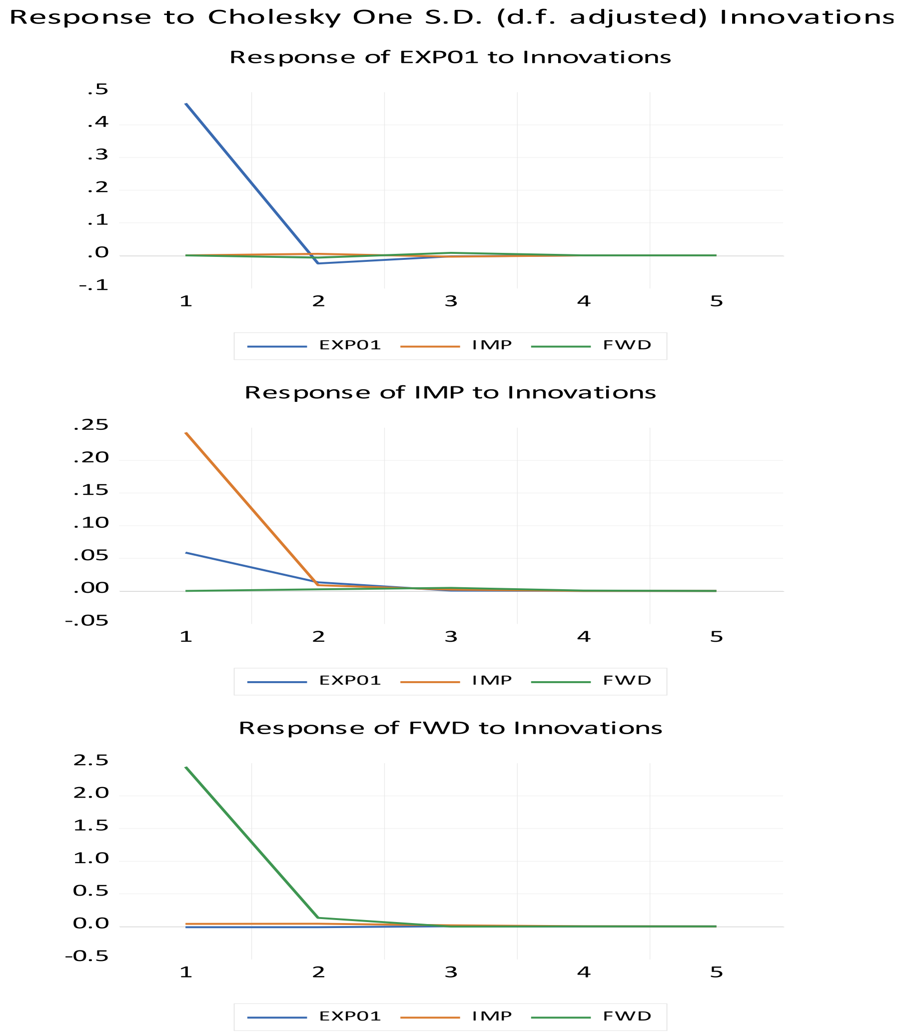
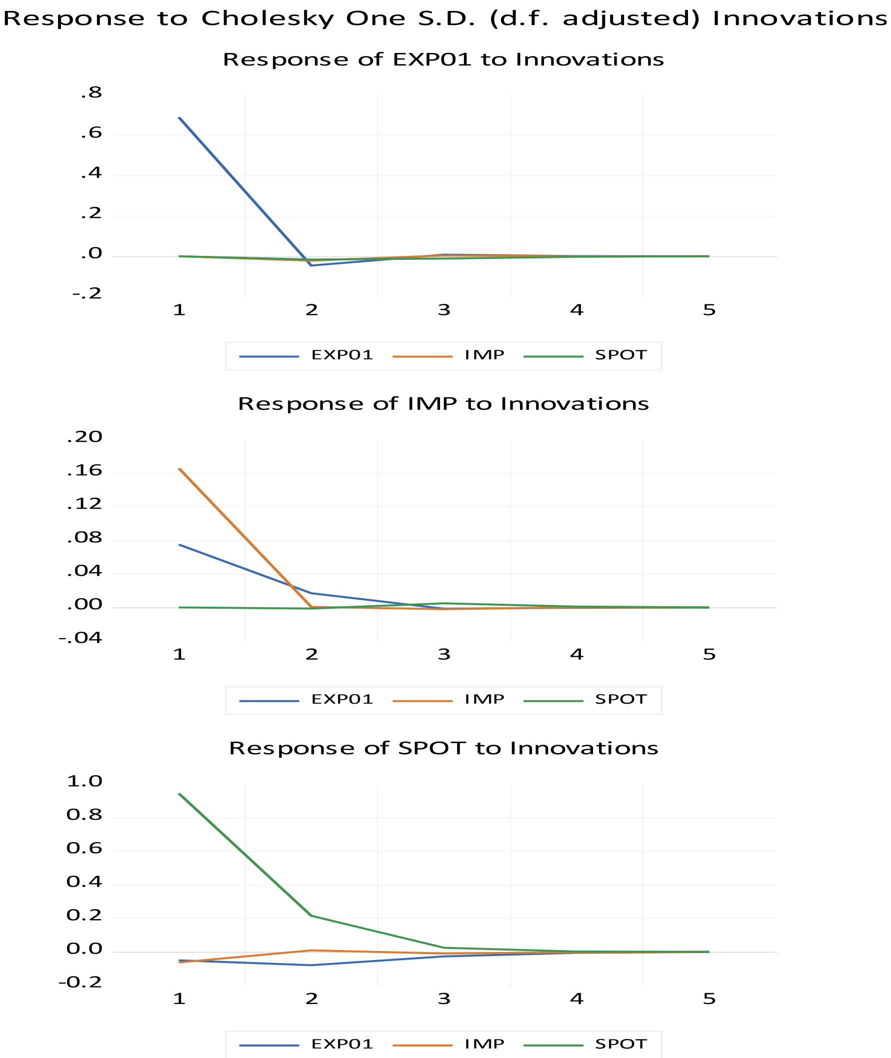


Figure A3C: VAR model IRFs (daily, iron ore)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Iron ore, daily, spot



Iron ore, daily, forward

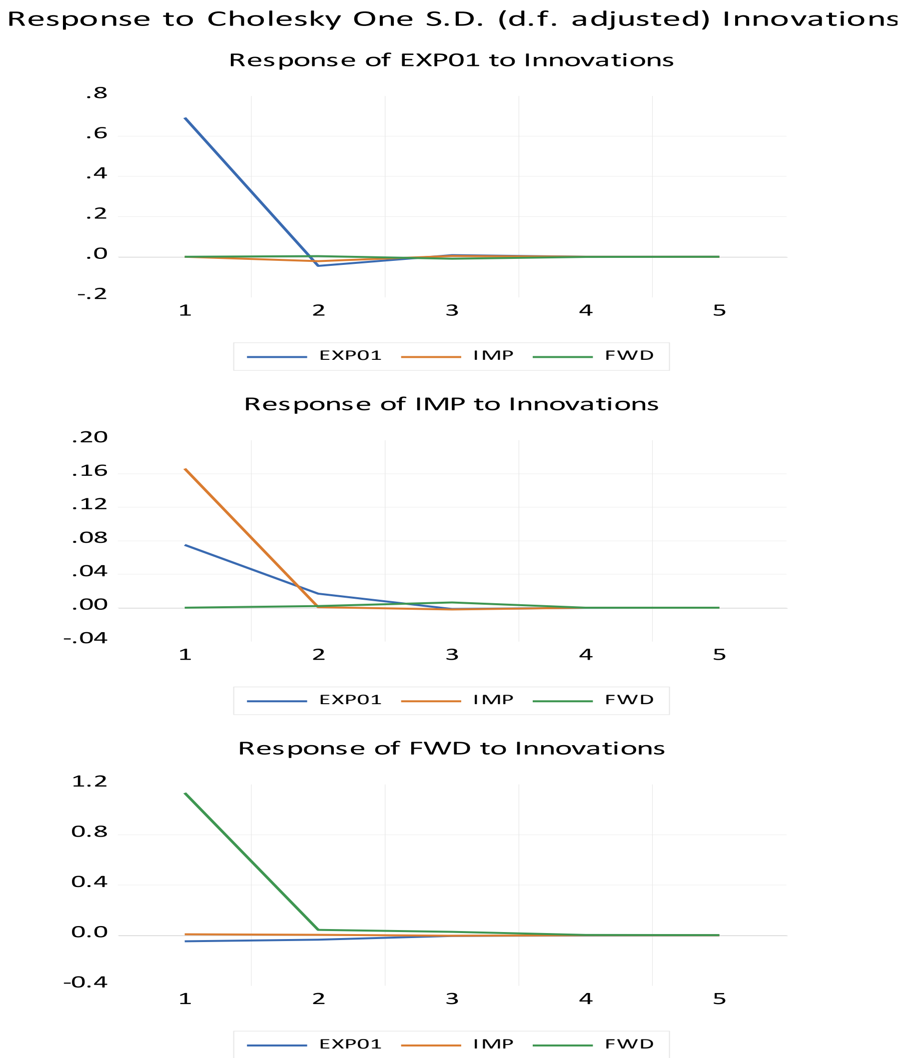
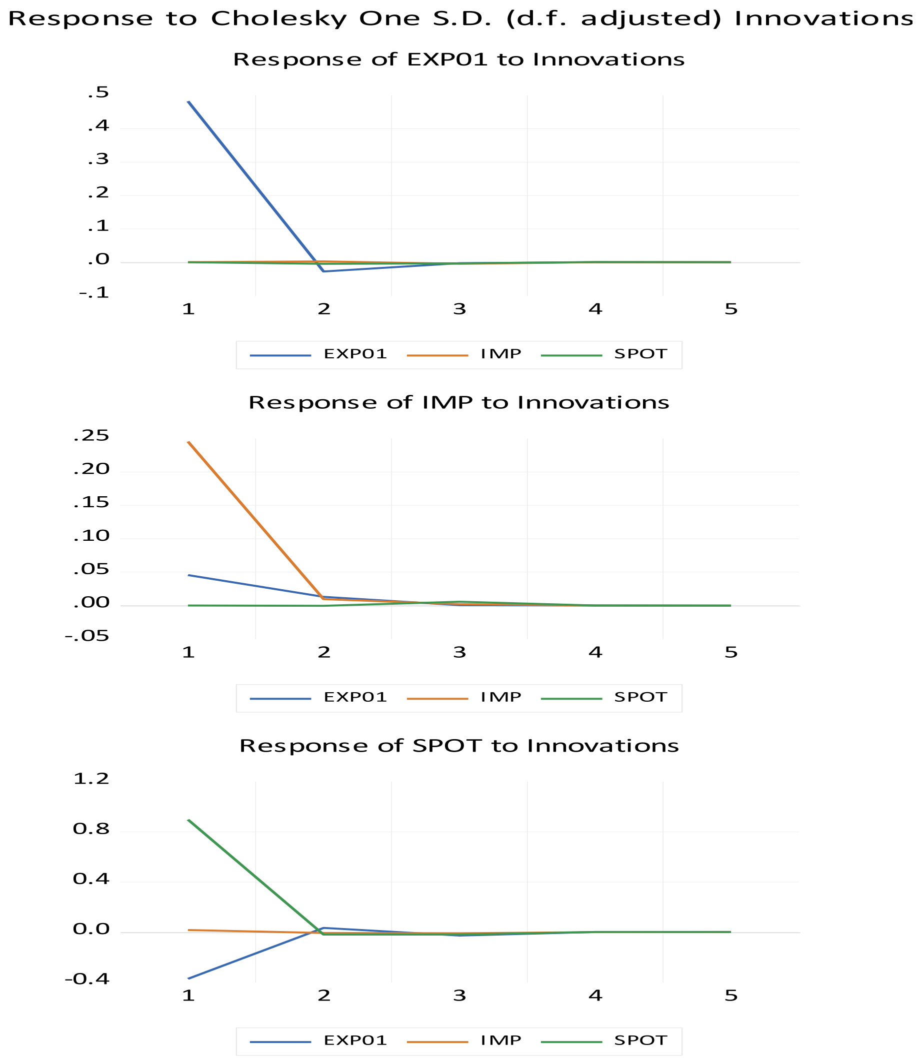


Figure A3D: VAR model IRFs (daily, oil)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Oil, daily, spot



Oil, daily, forward

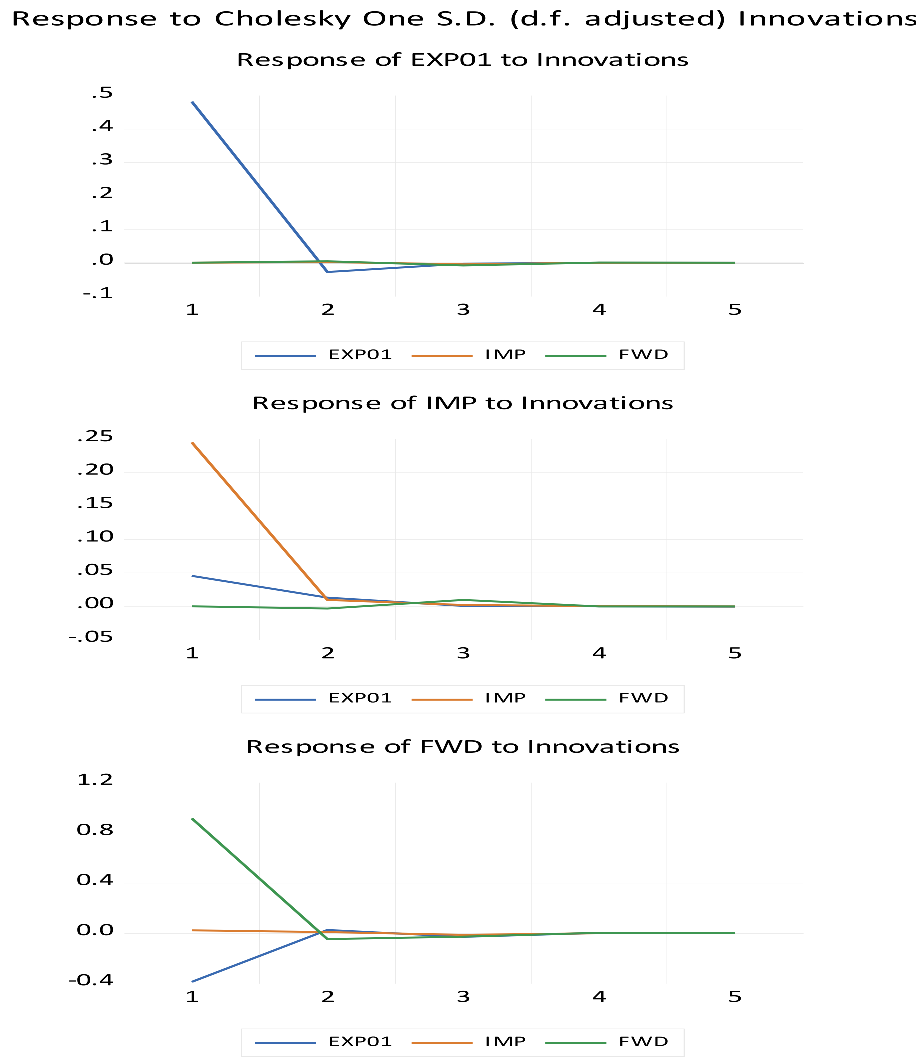
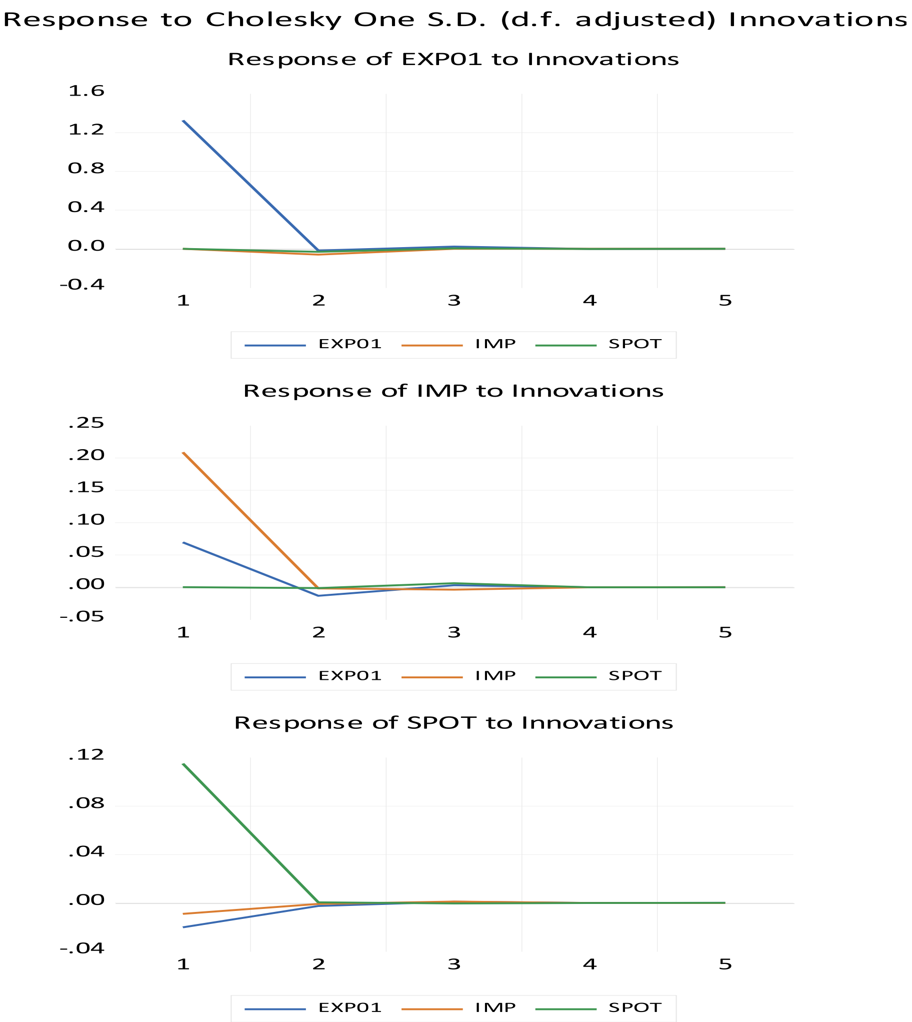


Figure A3E: VAR model IRFs (daily, soybeans)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Soybeans, daily, spot



Soybeans, daily, forward

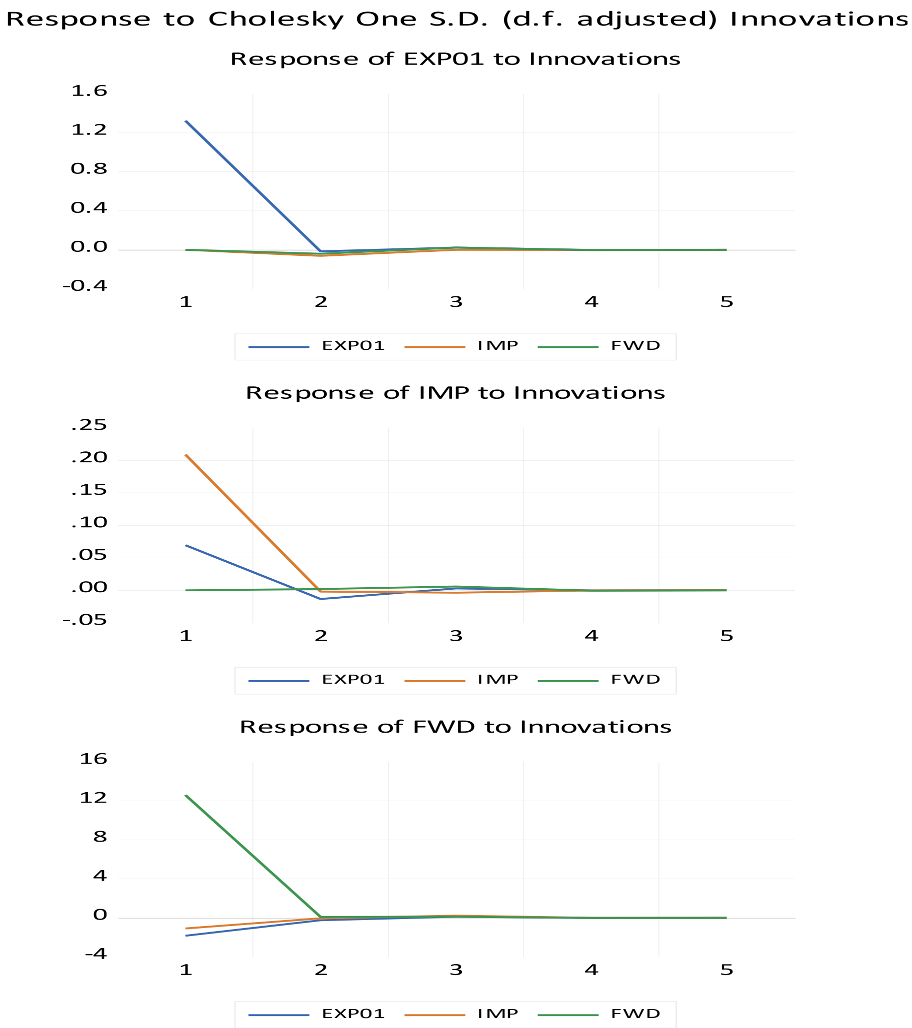
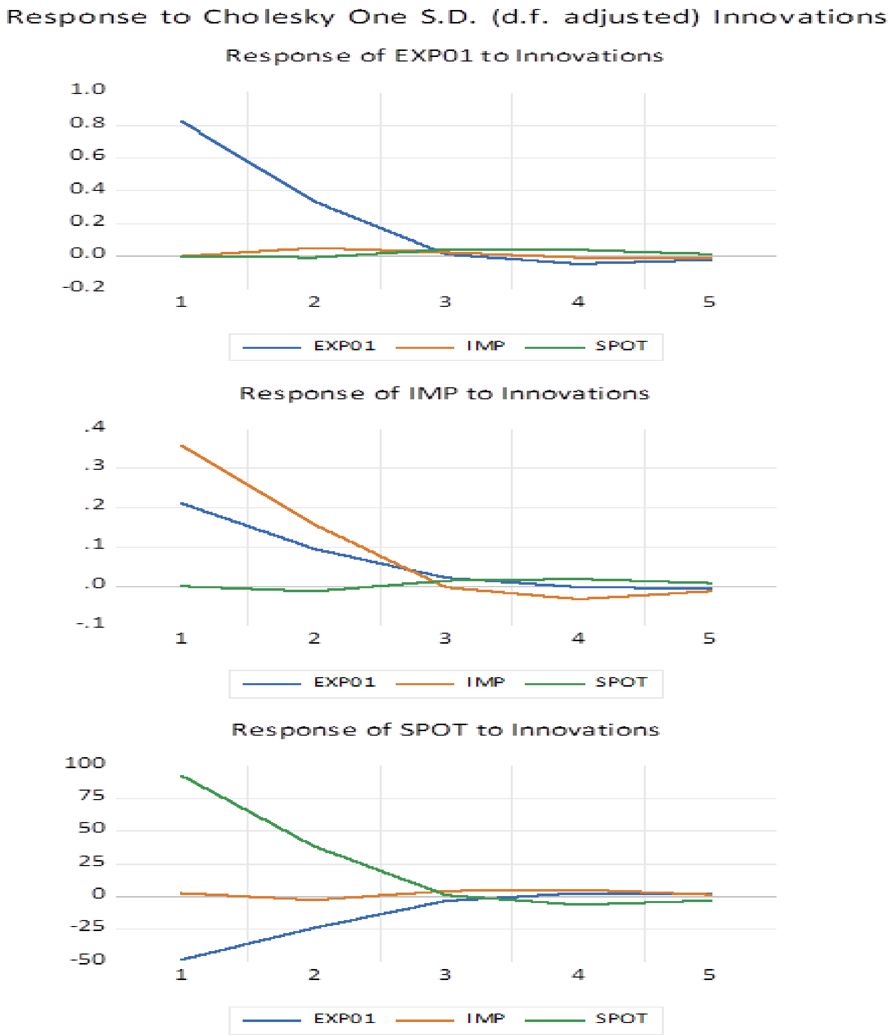


Figure A4A: VAR model IRFs (weekly, copper)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation inno vation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Copper, weekly, spot



Copper, weekly, forward

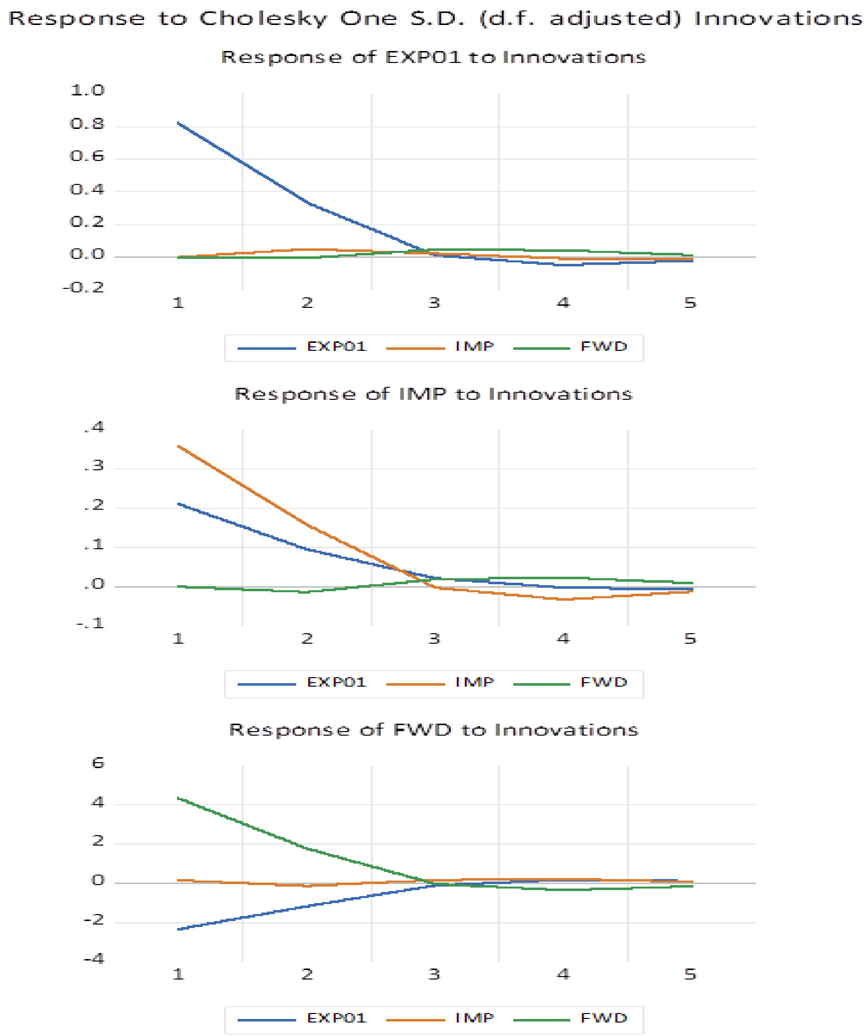


Figure A4B: VAR model IRFs (weekly, freight)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

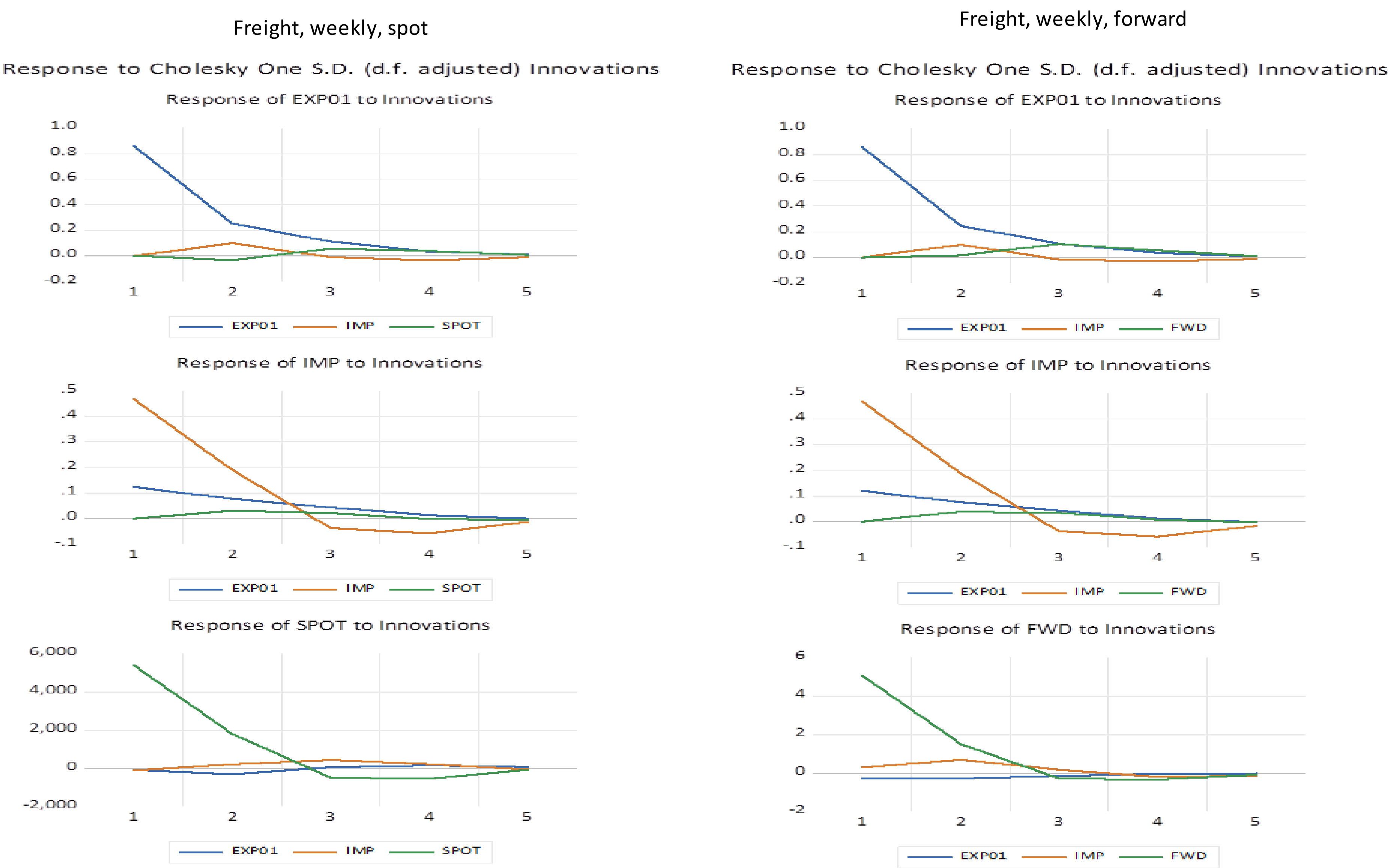


Figure A4C: VAR model IRFs (weekly, iron ore)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

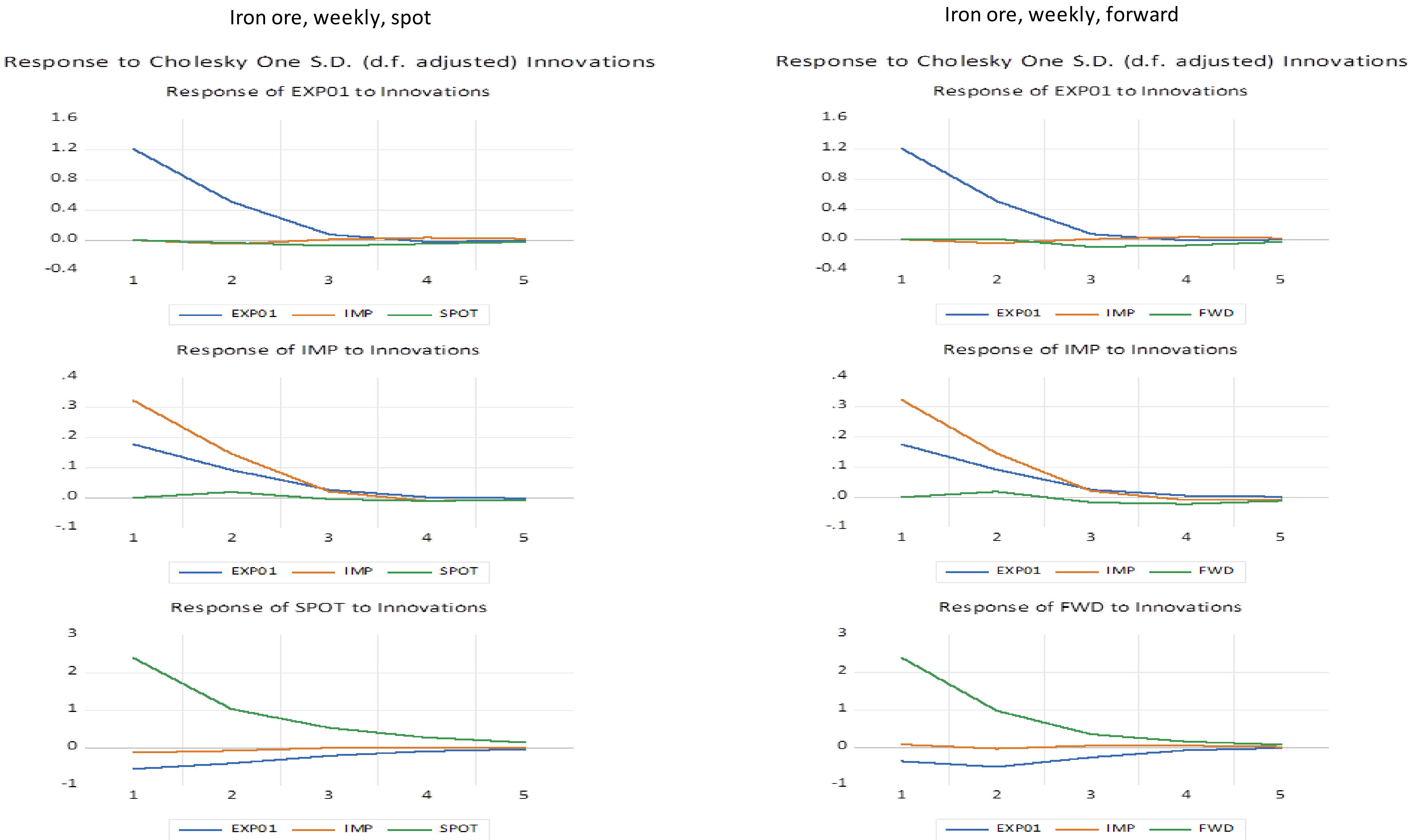
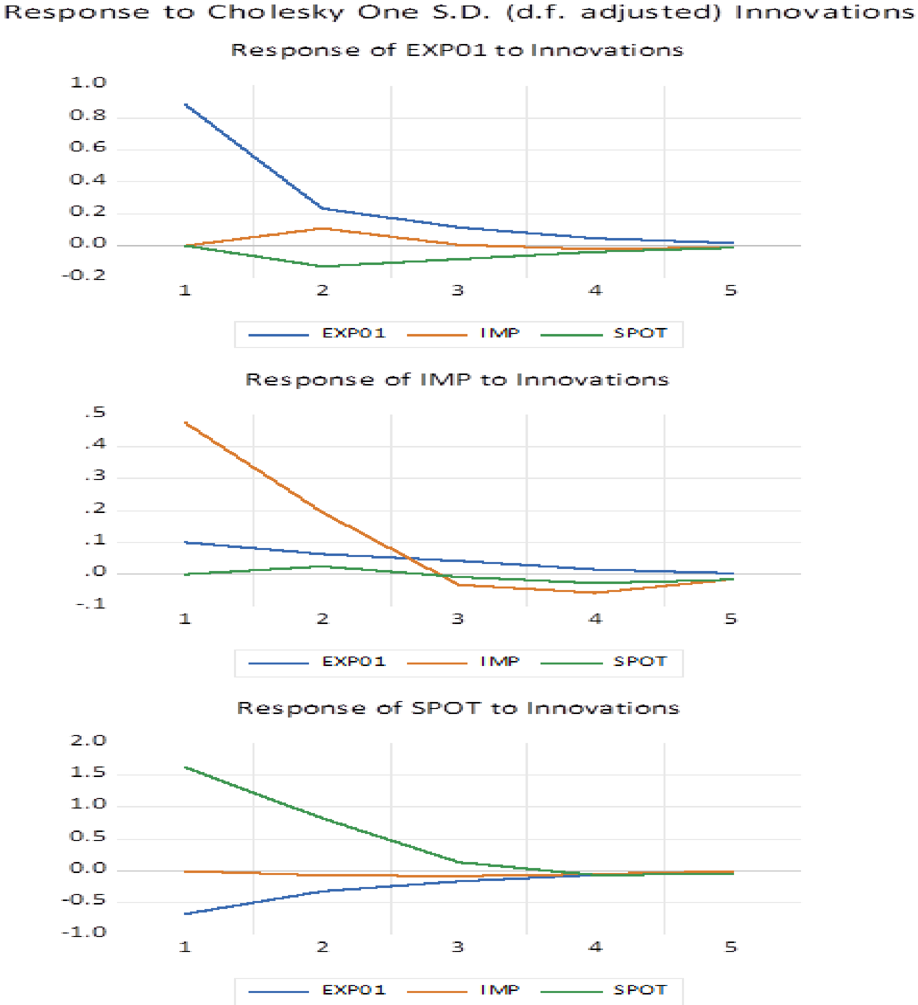


Figure A4D: VAR model IRFs (weekly, oil)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Oil, weekly, spot



Oil, weekly, forward

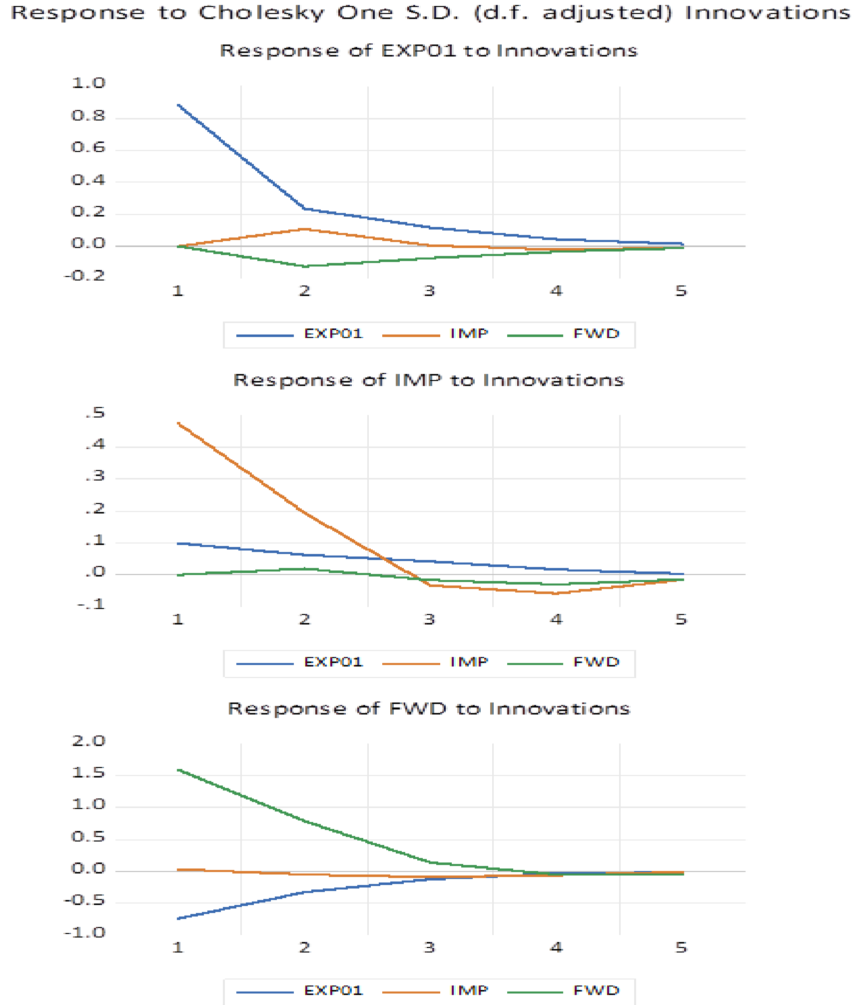
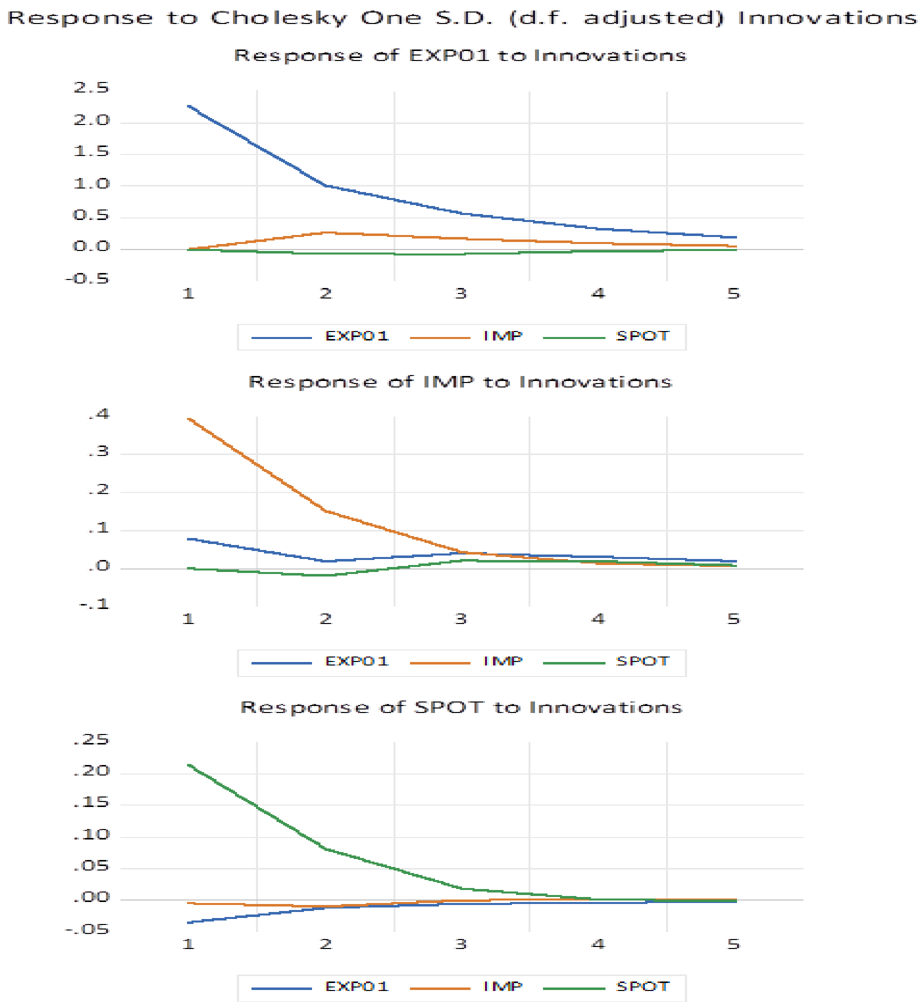


Figure A4E: VAR model IRFs (weekly, soybeans)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Soybeans, weekly, spot



Soybeans, weekly, forward

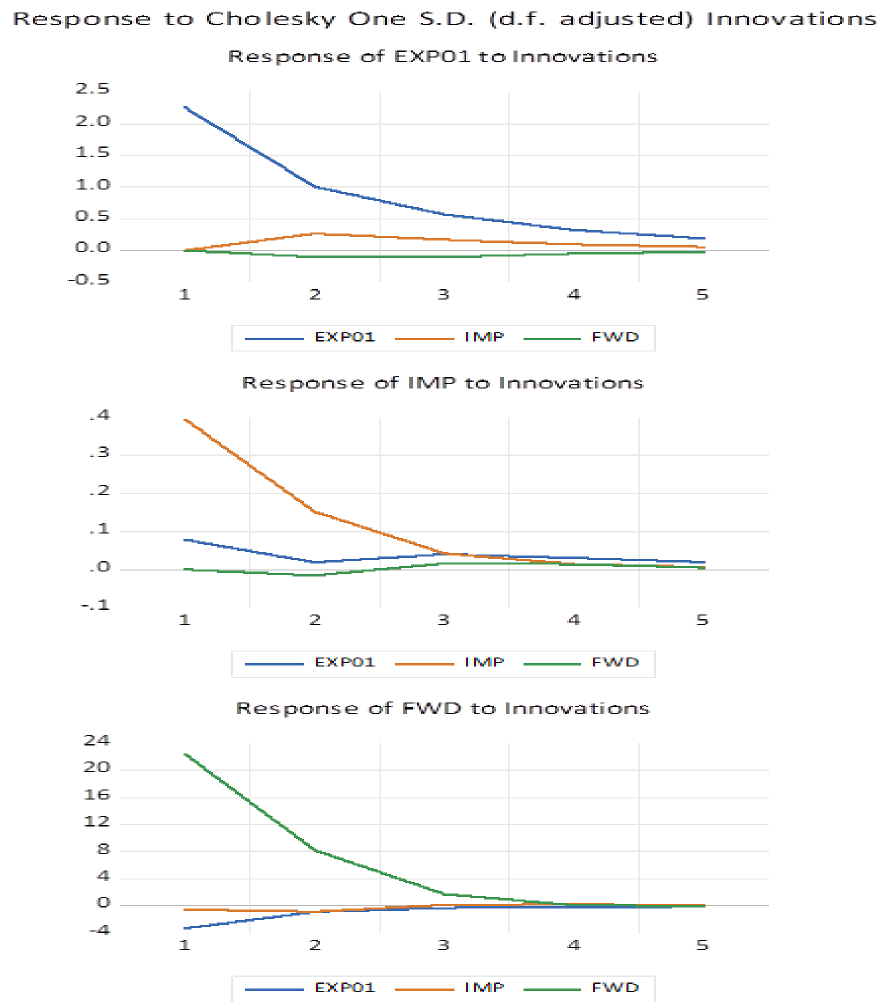


Figure A5A: VAR model IRFs (monthly, copper)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

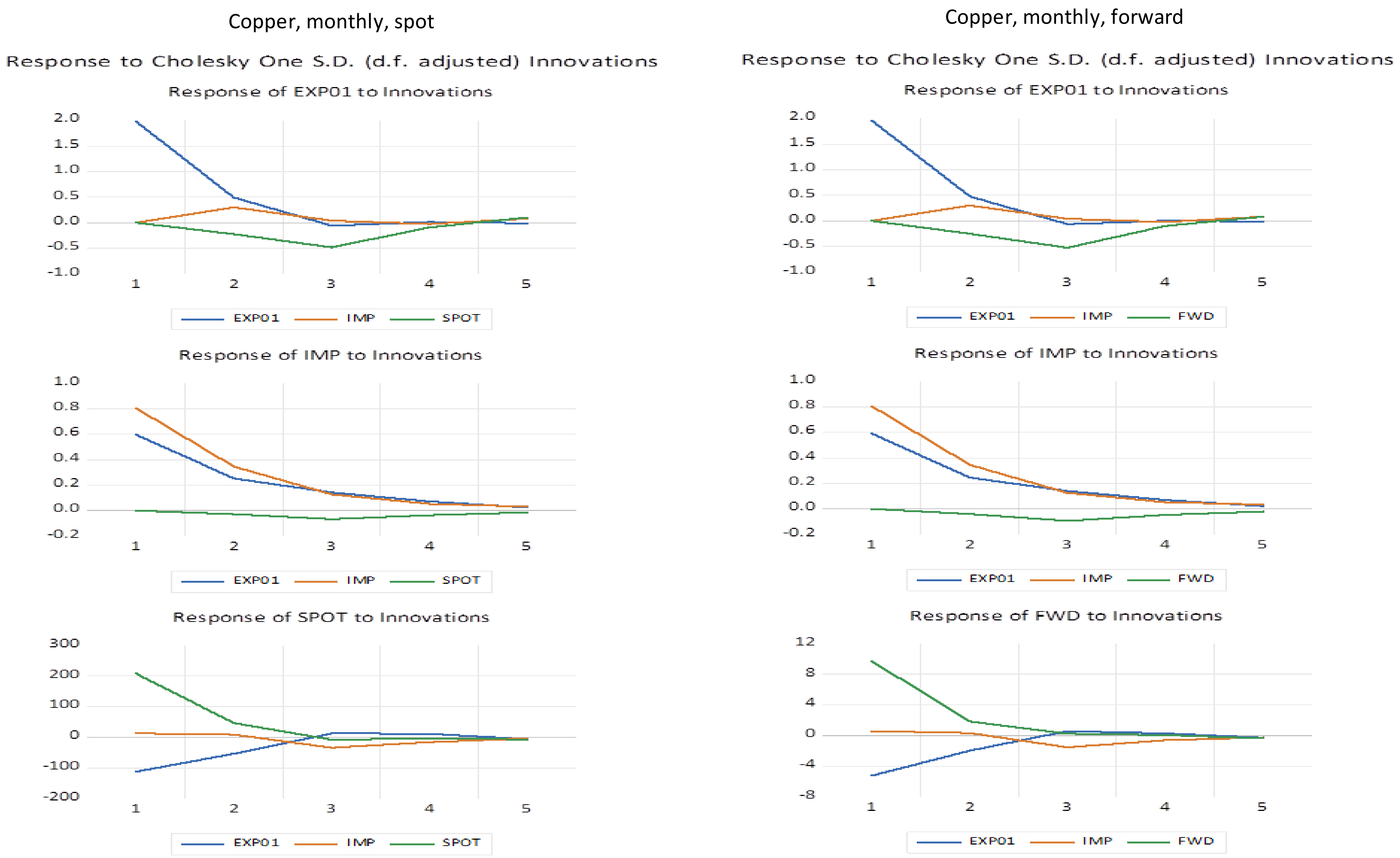
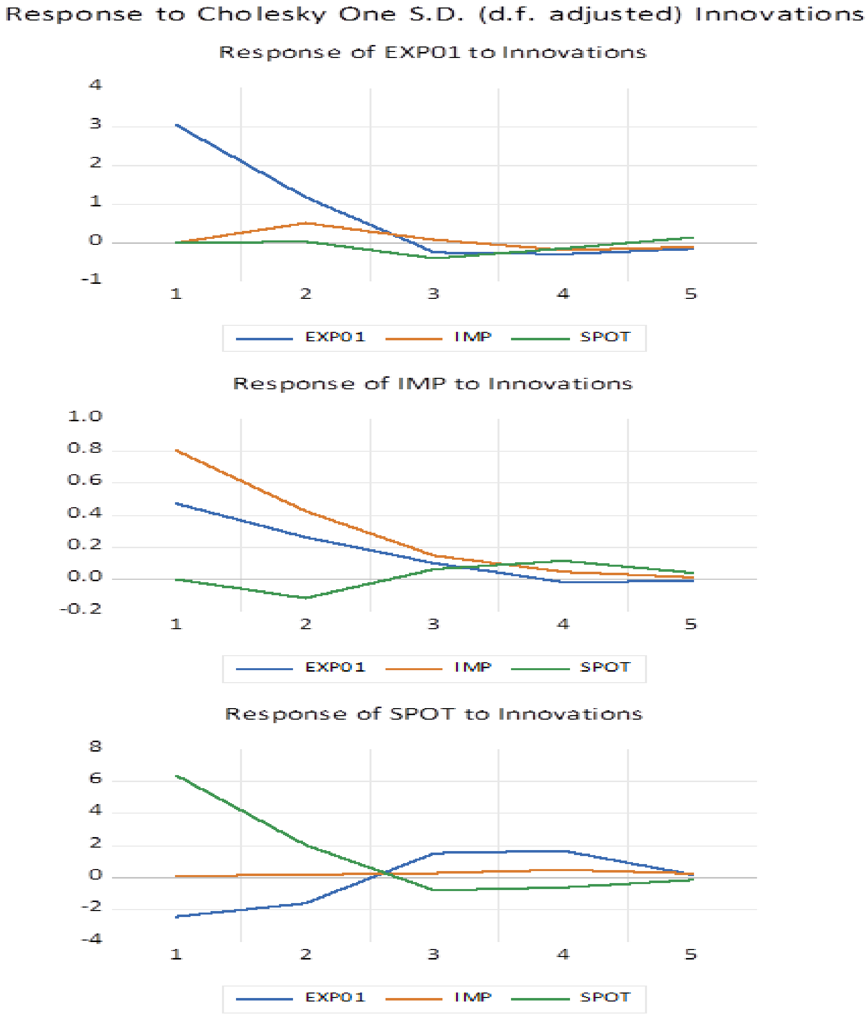


Figure A5B: VAR model IRFs (monthly, iron ore)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Iron ore, monthly, spot



Iron ore, monthly, forward

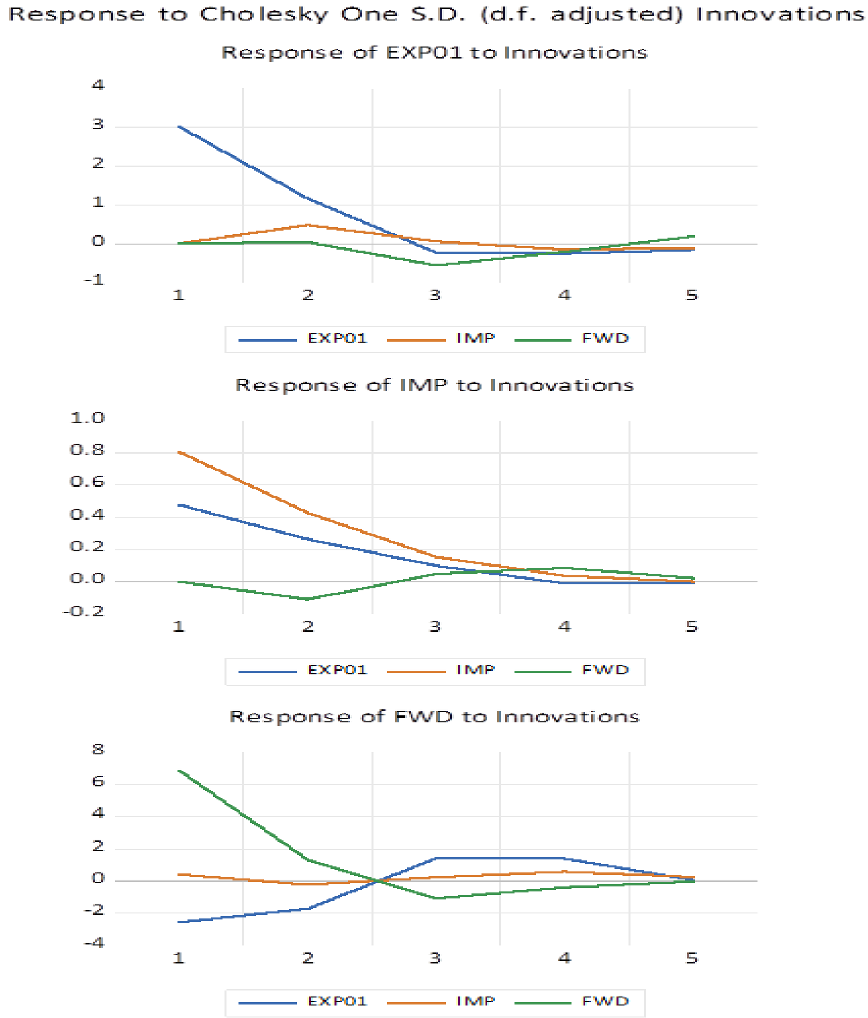
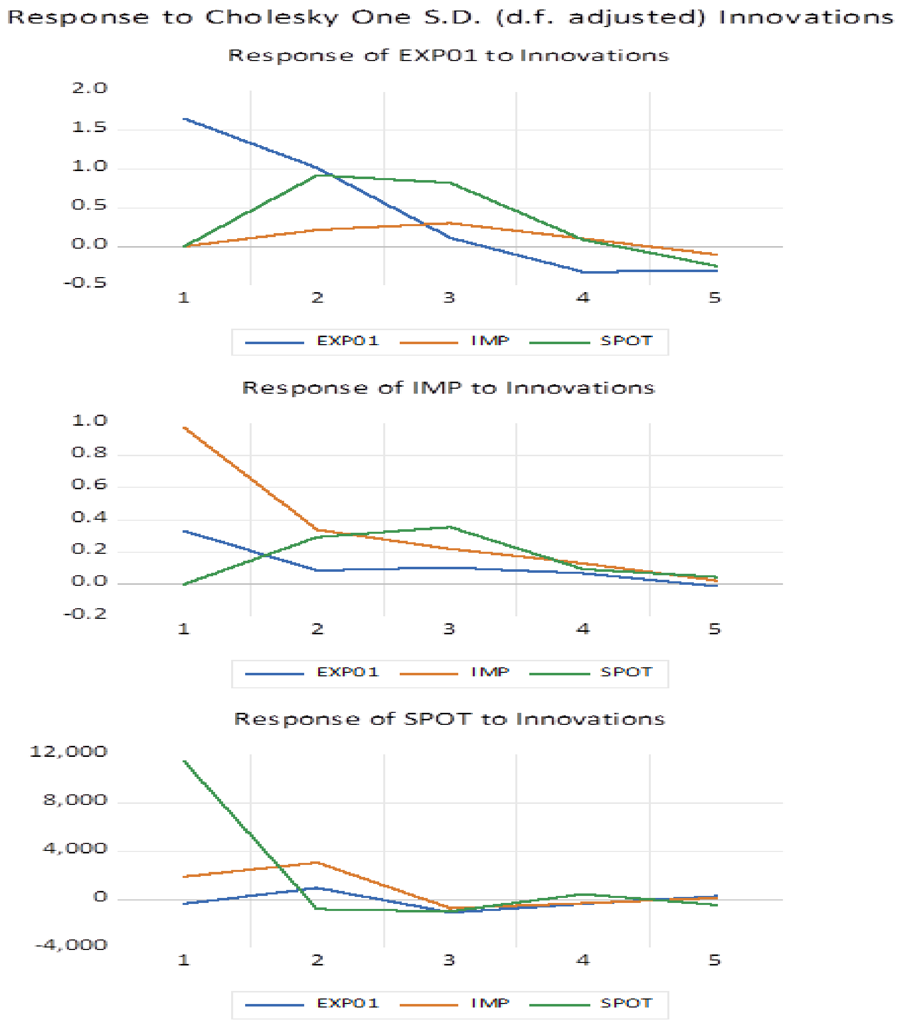


Figure A5C: VAR model IRFs (monthly, freight)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Freight, monthly, spot



Freight, monthly, forward

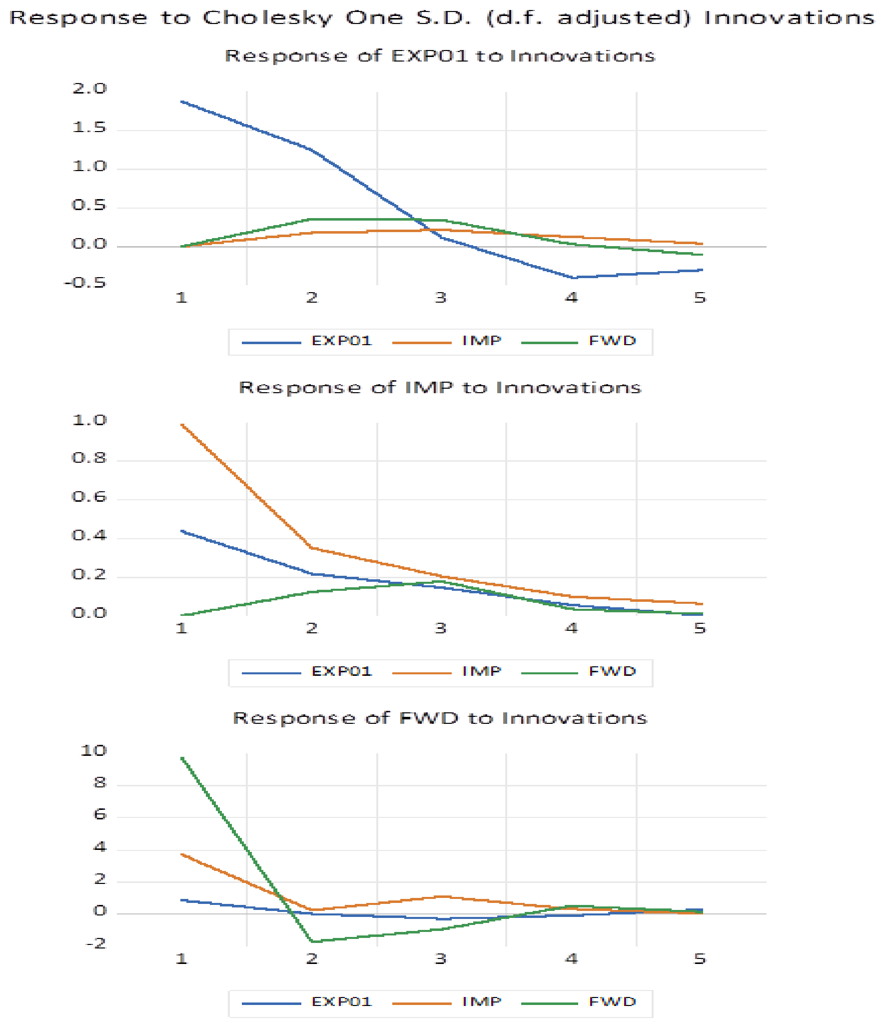
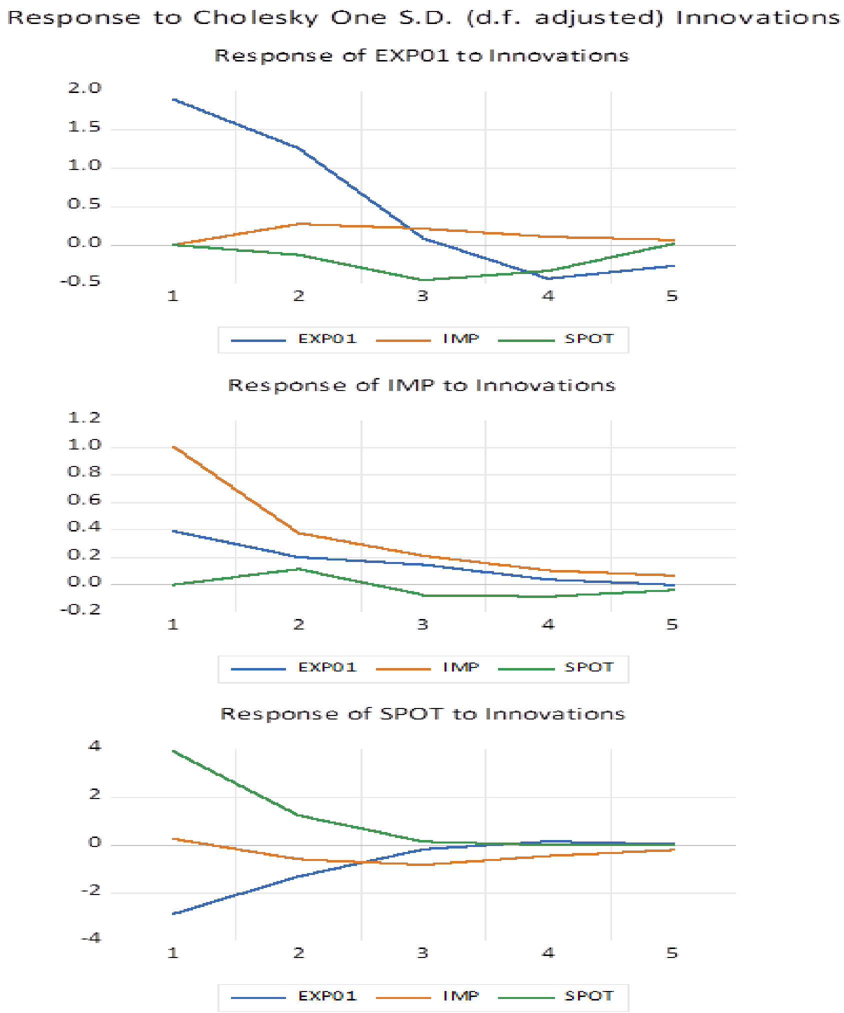


Figure A5D: VAR model IRFs (monthly, oil)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Crude oil, monthly, spot



Crude oil, monthly, forward

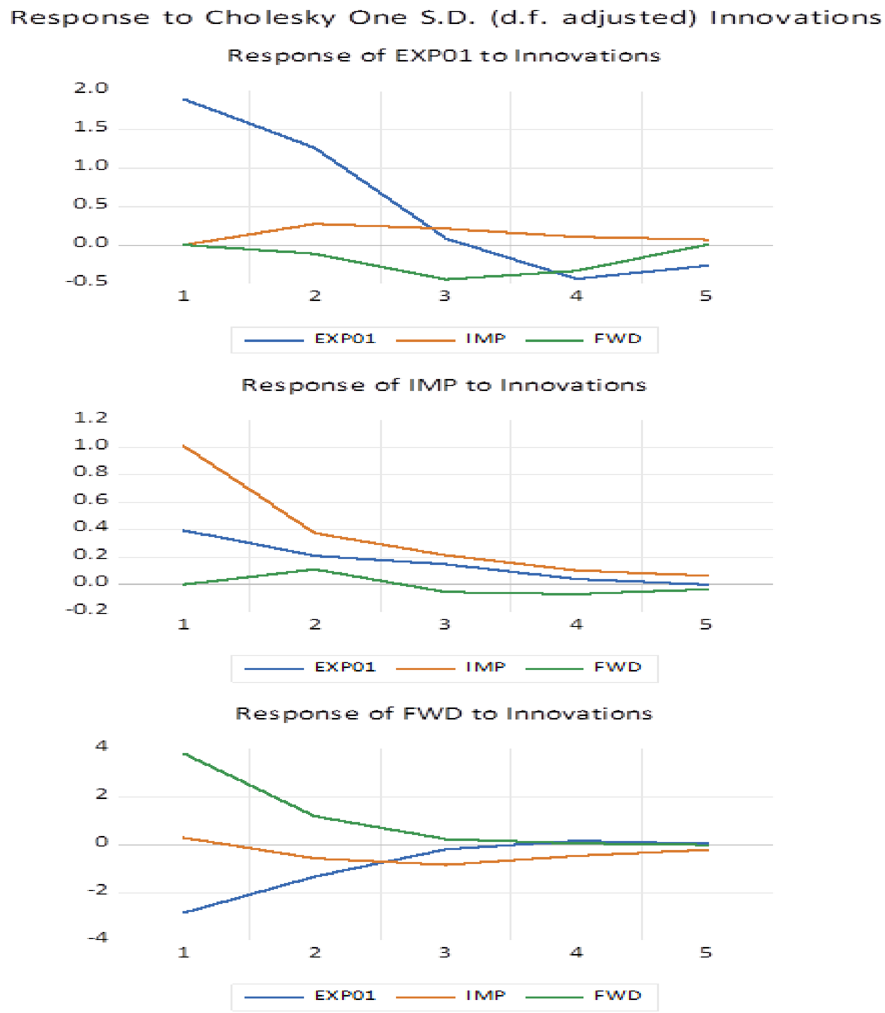
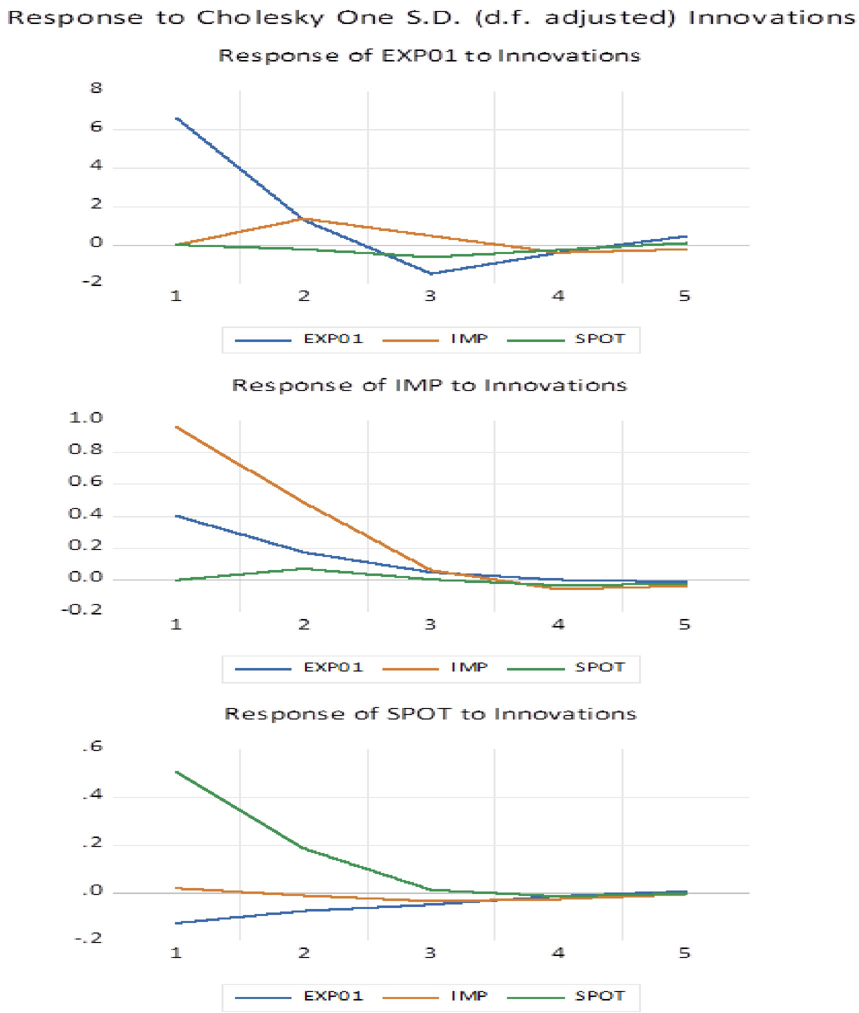


Figure A5E: VAR model IRFs (monthly, soybeans)

The individual charts plot the VECM IRFs with projected accumulated responses based on a Cholesky one standard deviation innovation on the model variables, by market. The x-axis represents time. The coefficient on the y-axis displays the IRF value in reaction to the positive shock of one standard deviation.

Soybeans, monthly, spot



Soybeans, monthly, forward

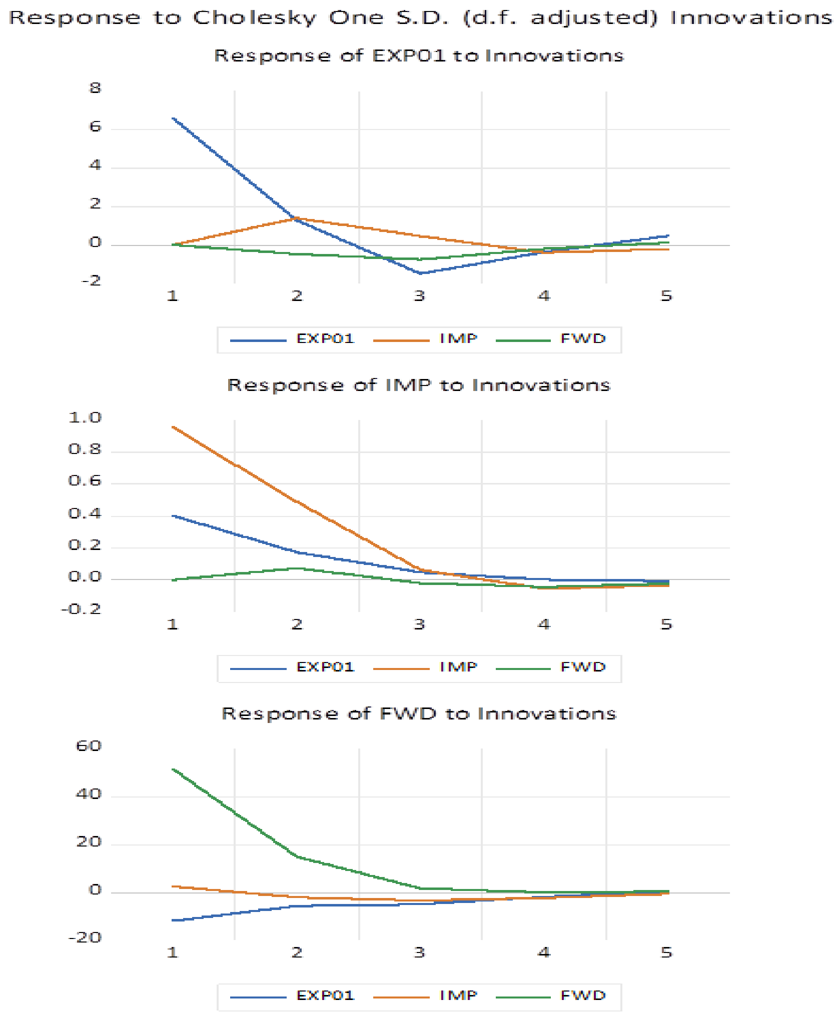


Table A1A: Descriptive statistics of the time series for copper and *FXi, FXe, FXIM, Ps and Pf*

		Copper				
		FXe	Pf	FXIM	FXi	Ps
Daily	Mean	129.2606	279.8376	0.00	110.2871	6177.373
	Median	133.7851	279.5500	0.00	111.8570	6223.500
	Maximum	148.6322	378.4500	0.021600	119.6225	8267.250
	Minimum	99.14900	194.3500	-0.04	100.0959	4327.500
	Std. Dev.	13.04571	39.69027	0.007644	5.250272	861.2739
	Skewness	-0.80	-0.26	-0.22	-0.48	-0.28
	Kurtosis	2.400540	2.275299	3.810665	1.839628	2.238953
	Jarque–Bera	290.0219	79.57988	84.39185	225.8589	90.47656
	Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Sum	310871.8	673009.4	-3.09	265240.4	14856582
	Sum Sq. Dev.	409138.0	3787064.	0.140483	66267.12	1.78E+09
	Observations	2405	2405	2405	2405	2405
Weekly	Mean	129.2474	280.0356	0.00	110.2753	6181.592
	Median	133.6568	279.0929	0.00	111.8530	6223.000
	Maximum	147.9932	375.8500	0.017900	119.2888	8235.040
	Minimum	99.31900	196.7500	-0.03	100.2828	4380.710
	Std. Dev.	13.07758	39.80197	0.007043	5.250387	863.1999
	Skewness	-0.79	-0.26	-0.22	-0.48	-0.29
	Kurtosis	2.393388	2.265334	3.628822	1.838427	2.232428
	Jarque–Bera	41.89575	11.64651	8.574704	33.04911	13.29890
	Probability	0.000000	0.002958	0.013741	0.000000	0.001295
	Sum	45107.34	97732.43	-0.45	38486.08	2157376.
	Sum Sq. Dev.	59516.03	551300.6	0.017261	9593.165	2.59E+08
	Observations	349	349	349	349	349
Monthly	Mean	128.8800	280.9687	0.00	110.1581	6201.454
	Median	133.6698	278.3121	0.00	111.8078	6239.000
	Maximum	147.1426	368.3000	0.010600	118.5059	8076.320
	Minimum	99.27010	202.2145	-0.02	100.1501	4490.690
	Std. Dev.	13.42272	40.40108	0.005408	5.341185	876.0692
	Skewness	-0.79	-0.21	-0.41	-0.48	-0.23
	Kurtosis	2.362746	2.315647	3.590446	1.802720	2.280407
	Jarque–Bera	9.764155	2.127867	3.355506	7.835596	2.462026
	Probability	0.007581	0.345096	0.186793	0.019885	0.291997
	Sum	10310.40	22477.49	-0.10	8812.646	496116.3
	Sum Sq. Dev.	14233.39	128947.6	0.002311	2253.732	60632279
	Observations	80	80	80	80	80

Table A1B: Descriptive statistics of the time series for freight and *FXi*, *FXe*, *FXIM*, *Ps* and *Pf*

		Freight				
		FXe	Pf	FXIM	FXi	Ps
Daily	Mean	131.1108	52.36986	0.00	111.3898	16828.18
	Median	138.0003	50.51000	0.00	113.6939	10658.00
	Maximum	159.0802	101.2370	0.039900	121.7909	92635.00
	Minimum	99.36960	0.000000	-0.09	99.43650	-19,028.00
	Std. Dev.	18.53582	14.15061	0.009046	6.003870	21760.35
	Skewness	-0.46	0.360149	-1.05	-0.56	0.966451
	Kurtosis	1.822330	5.225661	10.01051	1.861887	3.667237
	Jarque–Bera	225.2142	548.3795	5363.482	254.3771	419.0026
	Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Sum	315321.6	125949.5	-3.75	267892.5	40471775
	Sum Sq. Dev.	825958.5	481376.5	0.196730	86655.67	1.14E+12
	Observations	2405	2405	2405	2405	2405
Weekly	Mean	131.0983	52.37429	0.00	111.3719	17064.38
	Median	138.0431	50.49160	0.00	113.6987	10504.71
	Maximum	158.6383	101.2370	0.029600	121.3929	88807.29
	Minimum	99.59790	0.000000	-0.05	99.63250	-18,575.57
	Std. Dev.	18.56904	13.85764	0.008317	6.004853	21856.45
	Skewness	-0.46	0.423482	-0.79	-0.56	0.962723
	Kurtosis	1.822602	5.123526	7.389291	1.859142	3.650811
	Jarque–Bera	32.54365	76.00507	316.6436	37.14636	60.07015
	Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Sum	45753.32	18278.63	-0.56	38868.80	5955468.
	Sum Sq. Dev.	119993.6	66827.89	0.024073	12548.27	1.66E+11
	Observations	349	349	349	349	349
Monthly	Mean	130.7242	52.18839	0.00	111.2456	16528.00
	Median	138.2095	49.48640	0.00	113.7354	9668.020
	Maximum	157.8671	87.01990	0.017900	120.5244	86941.84
	Minimum	99.70380	12.27450	-0.02	99.92010	-17,013.36
	Std. Dev.	18.83019	13.16209	0.006851	6.105230	21106.58
	Skewness	-0.44	0.363258	-0.27	-0.55	0.887475
	Kurtosis	1.781989	3.677941	4.521533	1.811848	3.387492
	Jarque–Bera	7.556227	3.291437	8.700106	8.792131	11.00200
	Probability	0.022866	0.192874	0.012906	0.012326	0.004083
	Sum	10457.93	4175.071	-0.13	8899.645	1322240.
	Sum Sq. Dev.	28011.50	13686.00	0.003708	2944.633	3.52E+10
	Observations	80	80	80	80	80

Table A1C: Descriptive statistics of the time series for iron ore and *FXi*, *FXe*, *FXIM*, *Ps* and *Pf*

		Iron ore				
		FXe	Pf	FXIM	FXi	Ps
Daily	Mean	140.9546	81.36451	0.00	107.2836	80.53243
	Median	147.5866	72.28000	0.00	108.3912	71.24000
	Maximum	171.0996	158.5000	0.038800	116.3776	158.0000
	Minimum	98.62100	38.15000	-0.04	98.89460	37.50000
	Std. Dev.	20.20601	28.41756	0.010309	4.910150	28.02846
	Skewness	-0.64	0.839406	-0.35	-0.20	0.915752
	Kurtosis	2.029643	2.651561	3.874718	1.742092	2.769525
	Jarque–Bera	258.0926	294.5942	126.5766	174.1360	341.4627
	Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Sum	338995.8	195681.6	-4.87	258017.0	193680.5
	Sum Sq. Dev.	981511.7	1941369.	0.255464	57959.43	1888569.
	Observations	2405	2405	2405	2405	2405
Weekly	Mean	140.9393	81.38968	0.00	107.2698	80.57077
	Median	147.4538	71.77140	0.00	108.4210	70.95000
	Maximum	170.5441	157.5829	0.026700	116.1646	155.4286
	Minimum	99.05570	38.59710	-0.04	99.04450	38.01430
	Std. Dev.	20.23546	28.55091	0.009547	4.908633	28.14795
	Skewness	-0.64	0.840069	-0.36	-0.20	0.917141
	Kurtosis	2.024465	2.647261	3.712977	1.740085	2.763267
	Jarque–Bera	37.49419	42.85847	14.96826	25.41241	49.74171
	Probability	0.000000	0.000000	0.000562	0.000003	0.000000
	Sum	49187.83	28405.00	-0.71	37437.17	28119.20
	Sum Sq. Dev.	142496.9	283673.8	0.031721	8384.949	275723.0
	Observations	349	349	349	349	349
Monthly	Mean	140.4334	82.23389	0.00	107.1889	81.41342
	Median	147.7210	73.21200	0.00	108.3473	72.43950
	Maximum	168.6263	155.9500	0.016600	115.3490	153.0714
	Minimum	99.35660	38.92230	-0.03	99.38260	39.75160
	Std. Dev.	20.66889	29.34539	0.008278	4.950530	28.90102
	Skewness	-0.63	0.834740	-0.42	-0.19	0.913425
	Kurtosis	1.993683	2.609991	3.474371	1.699908	2.715025
	Jarque–Bera	8.668780	9.797571	3.137718	6.115156	11.39532
	Probability	0.013110	0.007456	0.208283	0.047001	0.003354
	Sum	11234.67	6578.711	-0.16	8575.111	6513.073
	Sum Sq. Dev.	33749.04	68030.99	0.005413	1936.112	65986.27
	Observations	80	80	80	80	80

Table A1D: Descriptive statistics of the time series for oil and *FXi*, *FXe*, *FXIM*, *Ps* and *Pf*

		Oil				
		FXe	Pf	FXIM	FXi	Ps
Daily	Mean	129.7806	71.02311	0.00	111.3898	70.43948
	Median	136.6286	63.80000	0.00	113.6939	63.49000
	Maximum	156.7202	118.9000	0.042600	121.7909	119.3400
	Minimum	98.59740	27.88000	-0.09	99.43650	26.39000
	Std. Dev.	18.35942	23.98140	0.009735	6.003870	24.29349
	Skewness	-0.47	0.564508	-0.96	-0.56	0.563205
	Kurtosis	1.811099	1.980988	9.512546	1.861887	1.990590
	Jarque–Bera	229.8264	231.7883	4621.186	254.3771	229.2475
	Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Sum	312122.4	170810.6	-3.72	267892.5	169407.0
	Sum Sq. Dev.	810311.9	1382559.	0.227812	86655.67	1418777.
	Observations	2405	2405	2405	2405	2405
Weekly	Mean	129.7688	70.99317	0.00	111.3718	70.41210
	Median	136.6955	63.81570	0.00	113.6987	63.33570
	Maximum	156.2356	118.2471	0.031900	121.3929	118.9171
	Minimum	98.80910	29.67710	-0.05	99.63250	28.48570
	Std. Dev.	18.39232	24.03848	0.008948	6.004683	24.35581
	Skewness	-0.47	0.568435	-0.71	-0.56	0.567098
	Kurtosis	1.811617	1.978580	7.049973	1.859110	1.988295
	Jarque–Bera	33.21109	33.96603	268.0220	37.15353	33.59045
	Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Sum	45289.31	24776.61	-0.56	38868.76	24573.82
	Sum Sq. Dev.	117720.5	201091.2	0.027860	12547.56	206435.5
	Observations	349	349	349	349	349
Monthly	Mean	129.4006	71.53693	0.00	111.2451	70.96929
	Median	136.7473	64.23790	0.00	113.7354	64.10910
	Maximum	155.5172	116.2961	0.019200	120.5244	116.6843
	Minimum	98.87280	32.55390	-0.02	99.92010	31.20870
	Std. Dev.	18.64479	24.31722	0.007348	6.104713	24.64588
	Skewness	-0.45	0.544320	-0.20	-0.55	0.543560
	Kurtosis	1.770718	1.916703	4.441584	1.811824	1.925132
	Jarque–Bera	7.707349	7.862228	7.471778	8.795706	7.790575
	Probability	0.021202	0.019622	0.023852	0.012304	0.020338
	Sum	10352.05	5722.955	-0.12	8899.610	5677.543
	Sum Sq. Dev.	27462.64	46714.86	0.004266	2944.134	47986.15
	Observations	80	80	80	80	80

Table A1E: Descriptive statistics of the time series for soybeans and *FXi*, *FXe*, *FXIM*, *Ps* and *Pf*

		Soybean				
		FXe	Pf	FXIM	FXi	Ps
Daily	Mean	170.8833	1057.786	0.00	106.9347	10.43830
	Median	175.3837	985.7500	0.00	107.4479	9.705000
	Maximum	291.0062	1613.250	0.044400	118.0321	16.10750
	Minimum	95.72780	791.0000	-0.06	98.37540	7.550000
	Std. Dev.	46.38928	202.6080	0.013697	5.511168	2.123697
	Skewness	0.201883	1.089723	-0.45	-0.05	1.063977
	Kurtosis	2.225727	2.856646	3.728667	1.623614	2.840570
	Jarque–Bera	76.41144	478.0472	135.4293	191.0090	456.3090
	Probability	0.000000	0.000000	0.000000	0.000000	0.000000
	Sum	410974.5	2543976.	-8.81	257178.1	25104.10
	Sum Sq. Dev.	5173324.	98684160	0.450994	73016.63	10842.25
	Observations	2405	2405	2405	2405	2405
Weekly	Mean	170.8584	1057.575	0.00	106.9225	10.43664
	Median	175.4630	985.9643	0.00	107.5077	9.702100
	Maximum	287.3283	1590.000	0.029600	117.8394	15.76210
	Minimum	96.39460	810.4643	-0.05	98.49560	7.717900
	Std. Dev.	46.44641	202.1735	0.012775	5.509414	2.121010
	Skewness	0.197527	1.086670	-0.41	-0.06	1.061107
	Kurtosis	2.210490	2.833067	3.478078	1.620419	2.815255
	Jarque–Bera	11.33368	69.09137	12.89498	27.85997	65.98890
	Probability	0.003459	0.000000	0.001584	0.000001	0.000000
	Sum	59629.60	369093.6	-1.29	37315.96	3642.388
	Sum Sq. Dev.	750729.6	14224195	0.056795	10563.07	1565.542
	Observations	349	349	349	349	349
Monthly	Mean	169.9767	1062.464	0.00	106.8392	10.48681
	Median	175.5053	987.6822	0.00	107.2012	9.683950
	Maximum	272.8990	1523.830	0.020200	116.6440	15.30470
	Minimum	96.86620	827.9355	-0.04	98.66310	7.871300
	Std. Dev.	46.93646	204.6004	0.011339	5.542277	2.148451
	Skewness	0.195199	1.034110	-0.25	-0.04	1.013062
	Kurtosis	2.176754	2.639016	3.297722	1.595670	2.640122
	Jarque–Bera	2.767144	14.69281	1.142592	6.598774	14.11564
	Probability	0.250681	0.000645	0.564793	0.036906	0.000861
	Sum	13598.14	84997.09	-0.27	8547.132	838.9447
	Sum Sq. Dev.	174039.4	3307045.	0.010157	2426.630	364.6515
	Observations	80	80	80	80	80

Table A3A: SSP weekly test results, by market and by term

This table displays the results of the SSP test on the time series with weekly data, per market, regime, and lead–lag period. The values in the column 0 indicate coincidental reactions. The values in columns -1 to -8 indicate the lead coefficients for the tested variables *FXIM, FXi, or FXe* against *Ps* or *Pf*. The values in columns +1 to +8 indicate the lag coefficients of the tested variables against price. The lead and lag coefficients are summed up in columns ∑- and ∑+, and the absolute values of the sums are displayed in columns ABS- and ABS+. The sign represents the direction of the relationship between the two variables and in this case it is removed, to focus attention exclusively on the overall strength of this relationship.

		-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8
FRT_PS	FXIM_Ps	0.1032	0.1274	0.1669	0.1870	0.1620	0.1041	0.0458	-0.0204	-0.1045	-0.1941	-0.2442	-0.2345	-0.1530	-0.0726	-0.0227	-0.0143	0.0053
	FXE_Ps	-0.0183	-0.0366	-0.0526	-0.0666	-0.0599	-0.0234	0.0146	0.0469	0.0795	0.1311	0.1939	0.2397	0.2510	0.2560	0.2625	0.2642	0.2439
	FXI_Ps	0.0765	0.1100	0.1650	0.2007	0.2323	0.2750	0.3031	0.2919	0.2663	0.2533	0.2438	0.2301	0.2449	0.2886	0.3235	0.3214	0.3194
FRT_PF	FXIM_Pf	0.2013	0.1416	0.0954	0.0783	0.0631	0.0482	0.0561	0.0536	-0.0056	-0.1205	-0.2111	-0.2225	-0.1721	-0.1156	-0.0664	-0.0277	0.0036
	FXE_Pf	0.0580	0.0492	0.0492	0.0386	0.0270	0.0313	0.0409	0.0615	0.0961	0.1591	0.2264	0.2695	0.2812	0.2879	0.2909	0.2758	0.2539
	FXI_Pf	0.1898	0.2084	0.2323	0.2366	0.2359	0.2581	0.3016	0.3401	0.3520	0.3526	0.3383	0.3212	0.3016	0.2977	0.3036	0.2911	0.2761
COP_PS	FXIM_Ps	0.0867	0.1439	0.1464	0.1108	0.0922	0.1340	0.2048	0.2457	0.1987	0.0177	-0.1435	-0.2226	-0.2442	-0.2126	-0.1624	-0.1222	-0.1070
	FXE_Ps	-0.0525	-0.1108	-0.1620	-0.1879	-0.2161	-0.2759	-0.3598	-0.4553	-0.5000	-0.4250	-0.3258	-0.2584	-0.2148	-0.1997	-0.1896	-0.1641	-0.1286
	FXI_Ps	-0.0777	-0.0870	-0.1068	-0.1190	-0.1441	-0.1864	-0.2336	-0.2954	-0.3323	-0.3107	-0.2636	-0.2278	-0.2289	-0.2648	-0.2747	-0.2466	-0.2008
COP_PF	FXIM_Pf	0.0688	0.1193	0.1184	0.0899	0.0750	0.1238	0.2113	0.2663	0.2274	0.0414	-0.1271	-0.2113	-0.2413	-0.2212	-0.1840	-0.1421	-0.1167
	FXE_Pf	-0.0618	-0.1111	-0.1529	-0.1759	-0.2008	-0.2609	-0.3536	-0.4594	-0.5116	-0.4376	-0.3406	-0.2777	-0.2372	-0.2191	-0.2019	-0.1741	-0.1397
	FXI_Pf	-0.0888	-0.0948	-0.1146	-0.1268	-0.1489	-0.1884	-0.2378	-0.2986	-0.3347	-0.3124	-0.2641	-0.2294	-0.2369	-0.2757	-0.2914	-0.2683	-0.2259
OIL_PS	FXIM_Ps	0.2128	0.2679	0.2538	0.2042	0.1663	0.1816	0.2404	0.2891	0.2835	0.1807	0.0504	-0.0309	-0.0777	-0.1015	-0.1145	-0.1384	-0.1634
	FXE_Ps	0.0365	0.0070	-0.0343	-0.0749	-0.1121	-0.1606	-0.2221	-0.2991	-0.3585	-0.3504	-0.3160	-0.2772	-0.2286	-0.1886	-0.1696	-0.1496	-0.1133
	FXI_Ps	-0.2254	-0.1915	-0.1940	-0.1996	-0.1972	-0.1899	-0.1673	-0.1399	-0.1093	-0.0766	-0.0567	-0.0251	0.0123	0.0376	0.0318	0.0105	-0.0087
OIL_PF	FXIM_Pf	0.1440	0.2183	0.2725	0.2592	0.2087	0.1657	0.1742	0.2327	0.2906	0.2882	0.1775	0.0404	-0.0378	-0.0765	-0.0975	-0.1109	-0.1395
	FXE_Pf	0.0499	0.0294	0.0016	-0.0387	-0.0799	-0.1207	-0.1684	-0.2270	-0.3055	-0.3644	-0.3557	-0.3135	-0.2670	-0.2170	-0.1776	-0.1603	-0.1381
	FXI_Pf	-0.2811	-0.2336	-0.1956	-0.1977	-0.2028	-0.2044	-0.1990	-0.1737	-0.1460	-0.1188	-0.0922	-0.0683	-0.0271	0.0159	0.0436	0.0378	0.0130
SOY_PS	FXIM_Ps	0.1858	0.1548	0.1098	0.0828	0.0726	0.0918	0.1291	0.1597	0.1862	0.1333	0.0451	-0.0336	-0.0700	-0.0893	-0.0809	-0.0647	-0.0610
	FXE_Ps	-0.0757	-0.0974	-0.1023	-0.1033	-0.1020	-0.1162	-0.1560	-0.2090	-0.2625	-0.2658	-0.2415	-0.2156	-0.2114	-0.2066	-0.2065	-0.2118	-0.2123
	FXI_Ps	-0.0923	-0.1200	-0.1348	-0.1261	-0.0993	-0.0710	-0.0449	-0.0298	-0.0133	0.0208	0.0413	0.0233	-0.0133	-0.0442	-0.0575	-0.0670	-0.0687
SOY_PF	FXIM_Pf	0.1740	0.1345	0.0879	0.0641	0.0600	0.0844	0.1301	0.1696	0.2023	0.1536	0.0637	-0.0151	-0.0541	-0.0867	-0.0918	-0.0753	-0.0630
	FXE_Pf	-0.0847	-0.1018	-0.1034	-0.1014	-0.0968	-0.1074	-0.1476	-0.2024	-0.2611	-0.2700	-0.2491	-0.2274	-0.2269	-0.2207	-0.2179	-0.2259	-0.2297
	FXI_Pf	-0.0840	-0.1121	-0.1312	-0.1246	-0.0951	-0.0605	-0.0275	-0.0060	0.0124	0.0459	0.0692	0.0553	0.0151	-0.0258	-0.0466	-0.0595	-0.0636
IO_PS	FXIM_Ps	0.1606	0.2540	0.2846	0.2607	0.2219	0.1964	0.1652	0.1383	0.0949	0.0136	-0.0727	-0.1366	-0.1427	-0.1101	-0.0791	-0.0522	-0.0453
	FXE_Ps	0.1447	0.0562	-0.0361	-0.1138	-0.1758	-0.2357	-0.2834	-0.3218	-0.3405	-0.3163	-0.2771	-0.2374	-0.2160	-0.2016	-0.1781	-0.1595	-0.1473
	FXI_Ps	0.0509	0.0199	-0.0298	-0.0786	-0.1139	-0.1507	-0.1871	-0.2176	-0.2418	-0.2400	-0.2303	-0.2249	-0.2385	-0.2459	-0.2224	-0.1869	-0.1502
IO_PF	FXIM_Pf	0.1712	0.2188	0.2604	0.2596	0.2233	0.1987	0.1715	0.1368	0.0724	-0.0208	-0.0923	-0.1310	-0.1400	-0.1214	-0.0926	-0.0564	-0.0260
	FXE_Pf	0.1157	0.0414	-0.0472	-0.1194	-0.1745	-0.2321	-0.2806	-0.3161	-0.3183	-0.2889	-0.2583	-0.2275	-0.1970	-0.1710	-0.1496	-0.1414	-0.1393
	FXI_Pf	0.0422	0.0023	-0.0422	-0.0769	-0.1120	-0.1472	-0.1744	-0.1976	-0.2092	-0.2159	-0.2250	-0.2316	-0.2405	-0.2384	-0.2122	-0.1752	-0.1391

Table A3A (continued)

		∑-	ABS-	∑-	ABS+
FRT_PS	FXIM_Ps	0.8760	0.8760	-0.9302	0.9302
	FXE_Ps	-0.1961	0.1961	1.8421	1.8421
	FXI_Ps	1.6543	1.6543	2.2250	2.2250
FRT_PF	FXIM_Pf	0.7374	0.7374	-0.9322	0.9322
	FXE_Pf	0.3557	0.3557	2.0447	2.0447
	FXI_Pf	2.0027	2.0027	2.4824	2.4824
COP_PS	FXIM_P	1.1645	1.1645	-1.1968	1.1968
	FXE_Ps	-1.8203	1.8203	-1.9061	1.9061
	FXI_Ps	-1.2499	1.2499	-2.0179	2.0179
COP_PF	FXIM_Pf	1.0729	1.0729	-1.2023	1.2023
	FXE_Pf	-1.7764	1.7764	-2.0279	2.0279
	FXI_Pf	-1.2987	1.2987	-2.1041	2.1041
OIL_PS	FXIM_Ps	1.8161	1.8161	-0.3953	0.3953
	FXE_Ps	-0.8598	0.8598	-1.7933	1.7933
	FXI_Ps	-1.5047	1.5047	-0.0749	0.0749
OIL_PF	FXIM_Pf	1.6754	1.6754	0.0439	0.0439
	FXE_Pf	-0.5536	0.5536	-1.9934	1.9934
	FXI_Pf	-1.6879	1.6879	-0.1961	0.1961
SOY_PS	FXIM_Ps	0.9863	0.9863	-0.2211	0.2211
	FXE_Ps	-0.9619	0.9619	-1.7716	1.7716
	FXI_Ps	-0.7182	0.7182	-0.1653	0.1653
SOY_PF	FXIM_Pf	0.9047	0.9047	-0.1686	0.1686
	FXE_Pf	-0.9455	0.9455	-1.8676	1.8676
	FXI_Pf	-0.6410	0.6410	-0.0100	0.0100
IO_PS	FXIM_Ps	1.6819	1.6819	-0.6252	0.6252
	FXE_Ps	-0.9658	0.9658	-1.7334	1.7334
	FXI_Ps	-0.7071	0.7071	-1.7391	1.7391
IO_PF	FXIM_Pf	1.6403	1.6403	-0.6805	0.6805
	FXE_Pf	-1.0128	1.0128	-1.5730	1.5730
	FXI_Pf	-0.7058	0.7058	-1.6778	1.6778

Table A4: SSP test results consolidated by market and term

This table displays the results of the SSP test on the time series with weekly data, per market, regime, and lead–lag period. The values in the column 0 indicate coincidental reactions. The values in columns -1 to -8 indicate the lead coefficients for the tested variables *FXIM*, *FXi*, or *FXe* against *Ps* or *Pf*. The values in columns +1 to +8 indicate the lag coefficients of the tested variables against price. The lead and lag coefficients are summed up in columns ∑- and ∑+, and the absolute values of the sums are displayed in columns ABS- and ABS+. The sign represents the direction of the relationship between the two variables and in this case it is removed, to focus attention exclusively on the overall strength of this relationship.

		-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8
FRT_PS	FXIM_Ps	0.2628	0.1307	-0.0212	-0.1020	-0.1544	0.0359	0.1921	0.2134	0.0376	-0.0904	0.0154	0.0781	0.0997	0.0133	-0.1426	-0.1714	-0.0861
	FXE_Ps	0.0020	-0.0362	0.0187	0.1548	0.2847	0.3328	0.3034	0.2738	0.2489	0.2822	0.2136	0.0897	-0.0022	-0.0620	-0.0071	0.1214	0.1723
	FXI_Ps	-0.1530	-0.0912	0.0026	0.1283	0.2464	0.3228	0.4044	0.5423	0.5983	0.6181	0.5275	0.3498	0.2022	0.1102	0.0887	0.0986	0.0566
FRT_PF	FXIM_Pf	0.2228	0.1101	-0.0425	-0.1599	-0.1680	-0.0042	0.2067	0.1583	0.0559	-0.1667	-0.1621	-0.1276	-0.0085	-0.0250	-0.0920	-0.0718	0.0082
	FXE_Pf	-0.0182	-0.0949	-0.0639	0.0765	0.2123	0.2712	0.2452	0.2302	0.2183	0.2299	0.1650	0.0657	0.0266	0.0208	0.1325	0.2779	0.3603
	FXI_Pf	-0.0644	-0.0751	-0.0179	0.0644	0.1726	0.2362	0.3435	0.4675	0.5583	0.5249	0.3841	0.1287	-0.0211	-0.1147	-0.0969	-0.0350	0.0201
COP_PS	FXIM_Ps	0.0319	-0.0116	0.0168	0.0650	0.0002	-0.0922	-0.0165	0.0421	-0.0343	-0.1908	-0.2793	-0.2662	-0.1856	-0.0726	-0.0885	-0.0682	-0.0845
	FXE_Ps	-0.4736	-0.5197	-0.5699	-0.6537	-0.7091	-0.7151	-0.7344	-0.7810	-0.8095	-0.7499	-0.6424	-0.5138	-0.3992	-0.3399	-0.2666	-0.1981	-0.1207
	FXI_Ps	-0.1468	-0.2063	-0.2702	-0.3507	-0.3921	-0.4223	-0.4360	-0.4658	-0.4971	-0.5013	-0.4847	-0.4544	-0.4269	-0.4228	-0.3940	-0.3379	-0.2727
COP_PF	FXIM_Pf	0.0388	-0.0048	0.0235	0.0613	0.0064	-0.0801	-0.0253	0.0375	-0.0324	-0.1951	-0.2832	-0.2735	-0.1978	-0.0798	-0.0870	-0.0657	-0.0811
	FXE_Pf	-0.4513	-0.4966	-0.5497	-0.6343	-0.6957	-0.7111	-0.7345	-0.7844	-0.8205	-0.7664	-0.6616	-0.5336	-0.4161	-0.3557	-0.2833	-0.2160	-0.1366
	FXI_Pf	-0.1236	-0.1779	-0.2388	-0.3217	-0.3672	-0.4023	-0.4207	-0.4556	-0.4946	-0.5057	-0.4952	-0.4673	-0.4405	-0.4372	-0.4101	-0.3598	-0.2942
OIL_PS	FXIM_Ps	-0.1345	-0.0889	-0.1539	-0.1176	-0.0086	0.1212	0.1934	0.2140	0.1689	-0.0814	-0.1769	-0.1887	-0.0159	0.0781	0.0810	0.0262	-0.0018
	FXE_Ps	-0.2830	-0.2713	-0.2117	-0.1308	-0.1029	-0.1140	-0.1709	-0.2405	-0.3116	-0.2666	-0.1754	-0.0801	-0.0674	-0.0877	-0.1012	-0.1048	-0.1143
	FXI_Ps	-0.3606	-0.4498	-0.5410	-0.5833	-0.5923	-0.5592	-0.5246	-0.4687	-0.3955	-0.3156	-0.2572	-0.2292	-0.2000	-0.1613	-0.1065	-0.0830	-0.1084
OIL_PF	FXIM_Pf	-0.1324	-0.0866	-0.1531	-0.1179	-0.0088	0.1190	0.1985	0.2170	0.1694	-0.0808	-0.1711	-0.1832	-0.0094	0.0819	0.0895	0.0241	0.0001
	FXE_Pf	-0.2811	-0.2705	-0.2117	-0.1281	-0.1013	-0.1121	-0.1694	-0.2383	-0.3079	-0.2553	-0.1634	-0.0708	-0.0615	-0.0844	-0.1045	-0.1081	-0.1174
	FXI_Pf	-0.3669	-0.4560	-0.5507	-0.5896	-0.5993	-0.5668	-0.5314	-0.4716	-0.3933	-0.3086	-0.2450	-0.2155	-0.1863	-0.1464	-0.0912	-0.0704	-0.0980
SOY_PS	FXIM_Ps	0.1457	0.2338	0.1270	0.0659	0.0978	0.2451	0.2944	0.2742	0.2019	0.0674	-0.0245	-0.1522	-0.1096	-0.1122	-0.0978	-0.0272	0.0357
	FXE_Ps	-0.0743	-0.1282	-0.1414	-0.1231	-0.1272	-0.1931	-0.3034	-0.4248	-0.5364	-0.5943	-0.6116	-0.5551	-0.4779	-0.3870	-0.3310	-0.3454	-0.3968
	FXI_Ps	-0.0575	-0.0757	-0.0844	-0.0934	-0.1534	-0.2431	-0.3097	-0.3426	-0.3246	-0.2778	-0.2485	-0.1960	-0.1252	-0.0293	0.0087	-0.0195	-0.0727
SOY_PF	FXIM_Pf	0.1461	0.2264	0.1147	0.0617	0.1074	0.2586	0.2884	0.2563	0.1942	0.0551	-0.0395	-0.1689	-0.1266	-0.1264	-0.1164	-0.0419	0.0363
	FXE_Pf	-0.0782	-0.1289	-0.1362	-0.1121	-0.1187	-0.1958	-0.3102	-0.4261	-0.5339	-0.5905	-0.6096	-0.5506	-0.4666	-0.3711	-0.3119	-0.3230	-0.3746
	FXI_Pf	-0.0507	-0.0634	-0.0645	-0.0644	-0.1203	-0.2157	-0.2906	-0.3304	-0.3163	-0.2757	-0.2560	-0.2075	-0.1349	-0.0373	0.0009	-0.0269	-0.0802
IO_PS	FXIM_Ps	0.1439	0.2039	0.2051	0.2593	0.0947	-0.0079	0.1763	0.2600	0.0442	-0.1551	-0.1781	-0.1742	-0.0791	0.0167	-0.1042	-0.2105	-0.2064
	FXE_Ps	-0.0075	-0.1194	-0.2319	-0.3129	-0.2863	-0.1995	-0.2259	-0.3846	-0.4820	-0.4800	-0.4189	-0.3541	-0.3721	-0.4668	-0.5010	-0.4353	-0.3550
	FXI_Ps	-0.0675	-0.0971	-0.1371	-0.1305	-0.0633	0.0213	0.0590	0.0135	-0.0522	-0.1121	-0.1124	-0.1205	-0.1881	-0.2903	-0.3670	-0.3838	-0.3982
IO_PF	FXIM_Pf	0.1290	0.2012	0.2054	0.2387	0.0597	-0.0002	0.2054	0.2408	0.0337	-0.1655	-0.1646	-0.1558	-0.0348	0.0274	-0.1209	-0.2125	-0.2204
	FXE_Pf	-0.0287	-0.1460	-0.2586	-0.3244	-0.2713	-0.1829	-0.2249	-0.3757	-0.4593	-0.4511	-0.3877	-0.3221	-0.3577	-0.4618	-0.4817	-0.4101	-0.3357
	FXI_Pf	-0.0798	-0.1248	-0.1641	-0.1540	-0.0852	0.0015	0.0373	-0.0082	-0.0627	-0.1195	-0.1074	-0.1046	-0.1687	-0.2651	-0.3274	-0.3339	-0.3573

Table A4 (continued)

		∑-	ABS-	∑-	ABS+
FRT_PS	FXIM_Ps	0.5574	0.5574	-0.2841	0.2841
	FXE_Ps	1.3340	1.3340	0.8078	0.8078
	FXI_Ps	1.4026	1.4026	2.0517	2.0517
FRT_PF	FXIM_Pf	0.3233	0.3233	-0.6455	0.6455
	FXE_Pf	0.8584	0.8584	1.2788	1.2788
	FXI_Pf	1.1267	1.1267	0.7900	0.7900
COP_PS	FXIM_Ps	0.0358	0.0358	-1.2357	1.2357
	FXE_Ps	-5.1566	5.1566	-3.2305	3.2305
	FXI_Ps	-2.6903	2.6903	-3.2947	3.2947
COP_PF	FXIM_Pf	0.0573	0.0573	-1.2632	1.2632
	FXE_Pf	-5.0576	5.0576	-3.3693	3.3693
	FXI_Pf	-2.5078	2.5078	-3.4099	3.4099
OIL_PS	FXIM_Ps	0.0253	0.0253	-0.2793	0.2793
	FXE_Ps	-1.5250	1.5250	-0.9974	0.9974
	FXI_Ps	-4.0795	4.0795	-1.4612	1.4612
OIL_PF	FXIM_Pf	0.0357	0.0357	-0.2488	0.2488
	FXE_Pf	-1.5126	1.5126	-0.9655	0.9655
	FXI_Pf	-4.1323	4.1323	-1.3613	1.3613
SOY_PS	FXIM_Ps	1.4840	1.4840	-0.4205	0.4205
	FXE_Ps	-1.5155	1.5155	-3.6990	3.6990
	FXI_Ps	-1.3596	1.3596	-0.9603	0.9603
SOY_PF	FXIM_Pf	1.4595	1.4595	-0.5284	0.5284
	FXE_Pf	-1.5062	1.5062	-3.5980	3.5980
	FXI_Pf	-1.2000	1.2000	-1.0175	1.0175
IO_PS	FXIM_Ps	1.3353	1.3353	-1.0910	1.0910
	FXE_Ps	-1.7680	1.7680	-3.3831	3.3831
	FXI_Ps	-0.4017	0.4017	-1.9724	1.9724
IO_PF	FXIM_Pf	1.2799	1.2799	-1.0470	1.0470
	FXE_Pf	-1.8126	1.8126	-3.2078	3.2078
	FXI_Pf	-0.5773	0.5773	-1.7838	1.7838

Part III

Conclusion

6. Conclusion, contributions, and further research

This thesis examines the role played by the shape and gradient of the crude oil market forward curve in the formation of a speculative short-term supply shock on the physical market. This implies that the supply needs to increase simultaneously or briefly after the forward curve shifts into backwardation. Furthermore, the investigation focuses on the impact of the relative strength of the economic activities and distance between two countries on their net cross-border electricity flow. The effect from changes of electricity flow between two markets on flows between another pair of markets and their market price is also examined. Moreover, the thesis probes the predictability of the FX rates of major exporters and importers over the prices of key energy, metal, grain, and shipping markets. Such predictability is based on the ability of the currency markets to accumulate unique information about producers' incentives to supply the market with a commodity and consumers' incentives to purchase the required amount of commodity on the international market.

6.1. Contributions to academic research

To the best of my knowledge, the following gaps exist in the scholarly literature. Specifically, the first empirical chapter notes the following:

First, there has not yet been a study on the interaction between the position of the forward curve (contango vs. backwardation) and short-term supply shock. The academic literature, with the important exception of Litzenberger and Rabinowitz (1995), appears to agree that such an interaction occurs between the forward curve and inventory, but not between forward curve and direct supply. In contrast, this paper documents a direct link between changes in the position of the market forward curve and the appearance of a short-term speculative supply shock on the physical market.

Second, the study includes not only the binary position of the curve (contango vs. backwardation), but also the curve's slope steepness, that is, the gradient,. The gradient of the forward curve is found to contribute directly to the intensity of the speculative supply shock, which constitutes an important contribution.

The third gap is revealed by this thesis through the examination of short-term supply shocks, that is, daily or weekly, as opposed to longer-term (monthly, quarterly, or annual) supply shocks. A weekly dataset is thus utilized. All studies focusing on crude oil supply shocks use monthly or quarterly data. Higher-frequency data are significantly noisier but, when handled properly from a statistical perspective, the weekly dataset yields valuable information on changes in short-term direct supply on the physical oil market.

Fourth, I propose a form of short-term general equilibrium and vector error correction models for the global crude oil market that have not been previously documented in the literature under their proposed form, or with the frequency of time series employed. The model, which aims to test the relationships between five variables representing short-term supply and demand conditions on the crude oil physical spot market, exhibits significantly stronger explanatory power for the price of crude oil compared to the form without the forward curve gradient.

The second empirical chapter identifies the following gaps: The fifth gap quantifies causal processes between cross-border electricity trade flow and electricity prices, which lead to the price lagging behind the flow. Contrary to the established literature, which considers the trade flow to be the dependent variable (Kiesel and Kustermann 2016), this paper finds that changes in cross-border electricity flow anticipate changes in price. The evidence collected corroborates the notion that the Italian, Swiss, and French markets are the three most responsive to cross-border trade flow markets in the study's sample.

Contrary to the results of Gebhardt and Hoffler (2013), strong incentive for participation in cross-border trading on the European power market is detected by the proposed algorithm, which is based on the identification of causal relationships between electricity flow and price, where flow leads price. This finding fills the sixth gap. Since the tradable instrument is the electricity price, and not the flow, the algorithm searches for causal signal only for instances in which the volume leads the price. The evidence collected in this study yields an annualized total accrued return of 129.10% for the sample period, with a Sharpe ratio of 2.15for the risk-adjusted return.

Seventh, examination of the reaction of one cross-border electricity trade flow to changes in another trade flow, that is, the flow-on-flow reaction, allows one to forecast electricity flows between two countries based on the flows between another pair of countries, some of which do not even have a common border.

The analysis of the influence of the economic activity and geographical distance between two electricity markets by applying Jan Tinbergen's (1962) Gravity model for International Trade is contribution number eight, and which also confirms the claim by Bergstrand and Egger (2010) that the model is applicable to any commodity market.

The third empirical chapter identifies the following gaps. As the ninth gap, I investigate the importance of the currencies of the importers of key industrial commodities in the overall price formation for each of the commodities. The academic literature discusses only the currencies of exporters, and many of the trade flows in the global supply chain are supply pull (i.e. production is based on actual demand; e.g., Christopher (2011). If only the currencies of commodity exporters are used in the analysis, important drivers of trade flows will not be captured.

As the 10th gap in the academic literature, not only are other studies (e.g. CRR (2010), BKS (2014, FRR (2015), Zhang, Dufour, Galbraith 2014) based on only exporters' currencies, but the sample of chosen foreign exchange pairs is also limited to six pairs for the local currency against the USD. The increasing complexity and varieties of trade flows (Krugman 1995) and the world of global commodity trading dictate the need for significantly larger samples of currency pairs, which are likely to capture more information about the forces driving these flows.

The 11th gap covered is the proposed synthetic supply and demand balance model that combines currency pairs of the importers and exporters of commodities, thus extracting information from their joint relationship. The currencies of commodity exporters represent supply-side pressure to the market, as a stronger (weaker) domestic currency is likely to limit (create) producers' incentives to produce and sell. Importers' currencies, on the other hand, represent the demand side through the purchasing power channel. Combining the two signals warrants taking into account valuable information on the pressures from both supply and demand channels.

A markedly different perspective is offered by this thesis in the employment of higher-frequency data in comparison to the relatively low frequency of monthly (Prokopczuk, Tharann, and Wesse-Simen 2021), quarterly (Zhang, Dufour, and Galbraith, 2014), and annual data (Gargano and Timmermann 2014) used in academic research. This contribution fills the 12th gap.

The 13th gap involves the currency markets' predictive power over the prices of commodities, an important point of contention between this paper and the literature. For example, Chen (2004) and Zhang, Dufour, and Galbraith (2014) report evidence of stronger causality from commodity prices to the foreign exchange market. Bork, Kaltwasser, and Sercu (2014) argue in favour of a contemporaneous relationship between currency and price and find no evidence of currency's predictive power over price. The results in the current paper support the view that the currency market has predictive power over commodity prices. This is an important empirical contribution of the study.

Finally, covering the 14th gap, this study measures the differences in the reactions of Ps and forward commodity prices to the information contained in currency markets. An important practical inference is drawn from the results, where Ps and forward commodity prices react differently to the information contained in and transmitted by the global currency markets.

6.2. Contributions to practice

The implications for the activity of market practitioners resulting from the findings of the first empirical chapter are categorized into two groups: impact on practitioners who are active on the physical market, and impact on those who are active on the derivatives markets.

The effect on the physical market from the position of the oil forward curve and its gradient is related to the short-term alteration of crude oil availability and the subsequent supply shock. Any short-term stress along industrial supply chains due to a short-term speculative supply shock is likely to affect price formation, in terms of both price value and price volatility. On one hand, overstretched supply chains of raw materials can lead to disruptions in the production process downstream, which affects the financial performance of the companies involved. The logical reaction is the accumulation of excessive amounts of inventory, which also negatively affects the results of firms, since working capital is locked up in idle inventory. On the other hand, given the fact that global oil inventories have remained above the long-term average for the last five years and price volatility and inventory have a positive relationship when long-term inventory levels are above average, speculative supply shocks are likely to increase price volatility and, with it, the uncertainty of the cost of production. Therefore, it is plausible to assume that there can be economic impacts at both the micro and macro levels.

At the microeconomic level, companies are forced to increase their hedging ratios which, comes at a cost and, in turn, leads to higher costs of production and higher unit costs. At the macroeconomic level, inflationary pressure could arise, since producers typically attempt to pass on higher costs to end users/consumers. In other words, due to the very high level of oil and oil product usage in the economy of any developed country, a higher unit cost might not only put producers in a difficult financial situation, but also cause inflationary pressure in the broader economy.

Moreover, forward prices rising above the current spot level can potentially change the speed at which producers extract the commodity from the ground. This triggers a reaction throughout the entire production and supply chain, affecting numerous related physical and financial markets and activities. For example, hedging and borrowing become costlier when uncertainty increases. Storage costs rise as companies scramble to secure supply and increase inventory. Shipping, as one of the best examples of derived demand, is directly affected when the supply of oil on the physical market fluctuates. Due to the high integration of crude oil and its derivatives in the manufacturing process, volatility of the costs along the global supply chain is likely to attract the attention of policy makers.

Derivative markets react to speculative short-term supply changes, which creates trading opportunities for the participants involved in crude oil derivatives market operations. This is captured by the proposed general market equilibrium model, which offers insight into how to improve further short-term oil derivatives trading analytics and risk management for crude oil.

The implications from the findings discussed with the second empirical chapter affect are split into two groups, related to market practitioners or to policy. For example, the European Energy Union is a priority project for the European Commission. The role of the Directorate-General for Competition is to ensure that the energy markets function properly and deliver reliable energy supplies at reasonable prices for businesses and consumers. Evidence of deliberately introduced price volatility, as well as higher energy prices for the end user, is likely to attract the attention of regulators. Another likely concern of policy makers is inflationary pressure, as discussed earlier.

Furthermore, the importance of quantifying flow-on-flow reactions is encapsulated in Europe’s electricity market integration, which makes the results of the econometric flow-on-flow tests and models developed in this thesis very topical. The research into the flow-on-price and flow-on-flow relationships expands market participants' understanding of the electricity flow within the entire system. Evidence of systemic mispricing is demonstrated with the proposed trading algorithm, which delivers a return on investment (ROI) of 129.1% after adjustments for transaction costs for the sample period, or an annualized ROI of 26.3%. The proposed algorithm also allows for the forecasting of electricity flows between two countries based on the flows between two others, sometimes even if they do not have a common border.

Last but not least, using Tinbergen's (1962) gravity model for international trade, the documented direct link between economic activity and geographical distance between two electricity markets is found to have an impact on the operations of market practitioners. The model explains electricity flow formation and direction with the help of the gravity equation of trade, and it is beneficial for market players Exposed to multiple markets within the European Union (EU) electricity network. Different weightings of forecasting models, given Improved understanding of how the economic activity in one country is likely to affect the electricity market in another country, are a direct consequence of the ideas and results discussed in the second empirical chapter.

The implications for market players from the results of the third empirical chapter include ways to identify divergence in behaviour between spot and forward prices due to the impact of currency values, which creates trading opportunities such as for cash and carry arbitrage.

Furthermore, quantifying the direction in which the causality between commodity prices and currency values flows is an important step in studying the predictability of any trading model. The results of the third empirical chapter serve as evidence of the currency market's predictive power over the price of commodities. Whether the aim is to construct a directional or statistical arbitrage trading model or to inform policy makers about future changes in commodity prices and exchange rates, a causal link between the two variables needs to be established and documented.

The evidence also suggests that the currencies of importers have higher explanatory power than the currencies of exporters. This finding is not only a major departure from the established consensus in the academic literature, but also valuable information for the calibration of any model that utilizes information from the global currency markets.

All the commodity markets in the study are found to conform well to the proposed currency-based supply and demand model, which significantly improves the explanatory power of the vector error correction model. This finding strongly argues in favour of implementing the proposed foreign exchange model into practical trading and risk management systems. The global currency markets have the potential to accumulate unique information about producers' incentives to supply the market with a commodity and consumers' incentives to purchase the required amount of material on the international market. Currency market's ability to gather and channel forward-looking information is also acknowledged. They are also significantly bigger than any of the commodity markets in terms of transactional value, which is a prerequisite for more efficient price discovery. Consequently, higher liquidity and efficient price discovery lead to lower costs for executing a trading strategy.

Just as importantly, the higher data frequency used for all the tests and models in this thesis has important implications for market practitioners. A low data frequency is common in the academic literature, due to data availability and data reliability considerations. Such data frequencies could be the norm in macroeconomic research, long-term investing, and policy decision making, where slower-moving and often more reliable data are used; however, trading and risk management require higher data frequencies, due the number and speed of the decisions made within a limited amount of time. Lower-frequency macroeconomic data are typically released with a delay of 10 to 30 days after the period they describe (monthly, quarterly, or annual). The ability to remove this lag is invaluable from both trading and risk management perspectives. The solution is to work with higher-frequency (daily, weekly) data that allow for the modelling of processes developing during the period the data describe, and not after it. Higher-frequency data points allow for the construction of models that explore shorter-term price fluctuations. Market practitioners are the direct beneficiaries of the improved forecast ability and new trading opportunities.

6.3. Suggestions for further research

Several hypotheses and results presented in this thesis can be extended and are thus deemed suitable in further research. First, any changes in the availability of short-term crude oil on the spot physical market due to a shift in the forward curve is likely to affect not only the short-term supply and demand balance on the oil market, but also the demand for shipping capacity. Deeper understanding of the origins of the short-term demand shocks for crude oil tanker freight offer an opportunity for further research. Shipping is derived demand, and changes in the crude oil supply thus directly affect the freight market. Unlike dry bulk shipping, crude oil has no substitutes as a shipping capacity demand driver. Therefore, changes in the availability of short-term crude oil on the physical market are likely to affect freight rates.

Second, transformation of the dynamics of cost, insurance, and freight and free on board price formation on the back of deliberate short-term supply changes on the physical market combined with trader's increased ability to purchase oil at different points along the supply chain can cause a positive volatility feedback loop between free on board and cost, insurance, and freight pricing points. This possibility is acknowledged as part of the investigation in the first empirical chapter, but more detailed research into the impact of such a volatility feedback loop is recommended.

One of the preliminary tests of causality identifies multi-year cyclicality in the lead–lag relationship between the forward curve and the reaction of supply, which is the third suggestion for additional research. Periods of reaction detected by the tests have a convincingly high ratio of +65% that persists for many months, in some cases entire years. Periods of no reaction to changes in the curve can also be pronounced. For example, this particular test finds no evidence to suggest that crude oil availability was influenced by the position of the curve between 2011 and 2014. Analysing the existence of such cyclicality is not the aim of this thesis, but the topic deserves further investigation.

Fourth, the proposed models reveal no meaningful reaction of the price of spot crude oil after the introduction of a positive structural shock to short-term supply, demand, and inventory. This finding clearly contradicts economic theory, cannot be easily explained, and therefore warrants further, more detailed investigation.

Fifth, it is not immediately obvious why crude oil stocks should fall steadily after an initial increase when the curve slope steepens. A contango market should theoretically create the incentive for steady inventory accumulation, as dictated by the positive economics of cash and carry arbitrage. Therefore, the reaction of inventory to a steepening forward curve also deserves further investigation.

Sixth, there is a lack of research on the electricity flow-on-flow impact on the electricity market. Poor connectivity between the various national grids in the past and, therefore, a lack of meaningful cross-border electricity flows could be one explanation for this gap in the literature. However, EU market coupling regulation significantly changed the cross-border flows. Although a stream of academic research on international trade (e.g. Krugman 1979) helps identify the potential link between different trade flows, further research is warranted, specifically into the impact of short-term flow on flow on electricity markets.

Seventh, sizeable markets are omitted from this study, which, if included, could alter some of the outcomes discussed with the second empirical chapter. Therefore, further research is needed to obtain an even more detailed understanding of the EU-wide electricity market. The issue here would be the length of available pricing and trade flow time series, since the number of degrees of freedom of the multivariate regression model drop too low as the number of variables n increases. Therefore, significantly longer time-series are required if the rest of the EU power market is to be analysed.

Eight, the trading model suggested in the second empirical chapter, based on cross-border trade flow signals, could benefit from further investigation into the ROI. This is because the relatively high frequencies of the recommended transactions are likely to deliver a strong ROI only if the transaction costs are carefully considered.

The gravity flow coincidental response test, which is currently based on the binary conditions +1 and -1, indicates the reaction of flow to changes in the gravity of trade. As the ninth topic suggested for future research, I propose testing with the actual coefficient of the intercept. It is plausible that information about the changing dynamics will be revealed through the steepness of the regression line, which, in turn, would indicate the higher or lower probability of occurrence of the event in question.

The 10th suggested area of future research involves tests of the gravity–price and flow–price relationships performed not only with outright, or flat, prices, but also with price spreads. Spreads tend to behave differently from flat prices, since they are influenced by both statistical arbitrage trading flows and diverging fundamental views in the two markets comprising the spread. Further study on the gravity-price and flow-price relationships with selected calendar and location spreads has the potential of delivering different results for the proposed trading model.

The 11th proposed area of research, as well as part of the third empirical chapter, involves the construction of a synthetic supply and demand balance based exclusively on the currencies of the main importers and exporters of a particular commodity, representing a distinctly different theoretical perspective from that of the literature. Such a novel approach is a departure from traditional methodology, and further research is thus warranted to compare the performance between the proposed synthetic supply and demand model and the foreign exchange impact model, as well as the traditional supply and demand models for each of the markets in the study.

Finally, the 12th suggested avenue of additional research involves the different bivariate and multivariate causality test results for some commodity markets. Even if the markets chosen for the third empirical chapter are key representatives of the energy, agricultural, metal, and shipping sectors, the results clearly demonstrate significant variations in the outcomes between individual markets. Therefore, research into the causal flow between the currency and commodity markets will benefit from not only larger sample of markets, but also the application of different weighted averages.

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