# The Role of Financial Traders for Price Responses to Shocks in the Commodity Futures Markets

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## Abstract

I investigate the conditions under which financial traders amplify price responses to significant spot market price changes in 13 agricultural commodity futures markets. Financial traders dampen price changes during the Russia-Ukraine war but amplify them during the Global Financial Crisis. However, this mitigating effect depends on the market share of financial traders: as their market share grows, the mitigation effect weakens and eventually reverses, leading to amplified price changes. According to hedging pressure theory, financial traders help dampen price changes by providing liquidity to commercial hedgers in exchange for earning a risk premium. By identifying when they cease to act as liquidity providers, I offer robust support for the hypothesis that financial traders may amplify price changes under specific conditions.

**Keywords:** Commodity Futures Market, Financial Speculation, Non-Gaussianity, Shock Decomposition, Factor Analysis

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# 1 Introduction

An essential debate in the field of commodity futures revolves around the influence of financial traders, often driven by speculative motives, on price dynamics. Contrary to the negative connotation of speculators in public perception, the hedging pressure theory by Hirshleifer (1988) and Hirshleifer (1990) demonstrates that financial traders typically help dampen price fluctuations by providing liquidity to the commercial hedgers in exchange for earning a risk premium. In line with this, Boyd, Harris, and Li (2018), surveying empirical studies, concludes that there is generally little evidence of destabilising effects from financial speculators, whose primary role is to provide liquidity to hedgers.

This paper investigates the conditions under which financial traders amplify price responses to substantial spot market changes in 13 agricultural commodity futures markets. Unlike previous studies, I examine the conditional role of financial traders, arguing that when they fail to act as liquidity providers, their stabilising effect on markets diminishes, potentially leading to destabilisation. The analysis uses weekly trading position data from the Commodity Futures Trading Commission (CFTC), categorising market participants into commercial hedgers, financial speculators, and index traders.[1] Financial traders, as referred to in this study, include both financial speculators and index traders.[2] To my knowledge, this is the first study to quantify the state-dependent effects of financial traders in commodity futures markets in relation to the nature of market disruptions and their market share by decomposing futures returns into economically meaningful factors. I find that financial traders amplify price changes during the Global Financial Crises (GFC), whereas they dampen them during the Russia-Ukraine war. Yet, the mitigation effect is conditional on their market share. As financial traders increase their market share, their mitigation effect diminishes and eventually reverses, turning into an amplifying force.

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[1] The CFTC defines producers, merchants and users of futures contracts who hedge their risks as commercial traders, while speculative traders are identified as noncommercial investors. In particular, its explanatory note explicitly defines that the trading motives of commercial traders remain focused on hedging. Following the literature, such as Gorton, Hayashi, and Rouwenhorst (2012), I refer to commercial traders as commercial hedgers and to noncommercial traders as financial speculators.

[2] This grouping is in line with the literature, including the seminal work of Cheng, Kirilenko, and Xiong (2014).

My findings align with a logical inference from the hedging pressure theory: if financial traders do not engage in trading to provide liquidity to commercial traders in return for risk premia, they cease to systematically dampen price changes and may instead act as an amplifying force. To explore this, I compare two periods of market stress: one characterised by a financial shock, the GFC, and the other marked by greater distress for commercial traders, the Russia-Ukraine war. I hypothesise that financial turmoil restricts the liquidity provision role of financial traders, causing them to amplify price fluctuations, whereas the other type of shock does not. After confirming this hypothesis, I examine a second hypothetical condition: a higher market share of financial traders. When the trading volume of financial traders exceeds that of commercial traders, financial traders can no longer simply meet the demand of the counterparty by providing liquidity. Instead, their dominance in trading activity alters their role in the market.

This study has three methodological contributions. Firstly, it adopts a comprehensive approach in labelling estimated factors based on economic intuition and statistical assessment, using $R^2$ values from regressions of variables on these factors. Futures returns for each commodity are decomposed by constructing and estimating a structural model grounded in the hedging pressure theory. The model consists of five equations, each representing the key variables in the hedging pressure theory: price changes in the futures and spot markets, as well as the demand functions of three trader groups. Although the parameters of the structural model are statistically identifiable, this does not ensure that the resulting factors are economically interpretable, leaving them as latent. To address this, I combine common identification strategies from two distinct literatures: factor analysis, widely used in asset pricing, and structural shock identification, frequently applied in monetary policy studies. Specifically, it evaluates the impacts of shocks or latent factors, as outlined in Jarociński (2024), and assesses them statistically using $R^2$ values—a common practice in factor analysis, as demonstrated in Kozak, Nagel, and Santosh (2020). This integrated approach enhances both the interpretability and validity of the identified factors.

Second, decomposing returns into factors distils the underlying mechanism of futures return determination, offering a novel approach to quantify the impact of financial traders on futures returns. The structural form estimation decomposes futures returns into five factors because the model is based on five input variables. In other words, the structural form estimation in this study linearly transforms the original variables into a new factor space but is not designed to reduce dimensionality ex ante.[3] However, separate estimation results for all 13 commodities consistently confirm that dimensional reduction is achieved ex post. Specifically, substantial replication of futures returns can be achieved using only two factors across all 13 commodities. By comparing these two factors, the portion of futures returns influenced solely by spot market price fluctuations can be distinguished from that driven by trading between commercial and financial traders in the futures market. This distinction enables the unique quantification of financial traders' effects.

Finally, the simultaneous estimation of the structural form helps mitigate simultaneity bias when assessing the impact of different traders' demand on futures returns. The dimensional reduction reveals that factors solely representing the demand of financial speculators and index traders have negligible explanatory power for futures returns, suggesting their demand has a limited price impact. This finding is distinctive compared to previous empirical studies, which typically rely on reduced-form estimation and regress futures returns on traders' demand separately. Such studies fail to fully address the simultaneity between futures and spot prices and the dynamic interactions among different trader groups. In contrast, structural form estimation enables the simultaneous identification of key determinants of futures returns. This distinction is crucial for understanding the price determination mechanism in commodity futures markets, as the role of financial traders in insuring commercial hedgers' demand implies a negative correlation in their trading. This means that the impact of one group's trading on futures returns is partially offset by the other. The inability of reduced-form estimation to account for this interactive offset may result in biased results, which simultaneous estimation effectively overcomes.

The negative correlation in trading positions between financial traders and commercial hedgers remains stable over time, but it collapsed during the GFC. Figure 1 presents the pairwise correlation of position changes between commercial traders and financial traders, including both financial speculators (represented by the yellow line) and index traders (represented by

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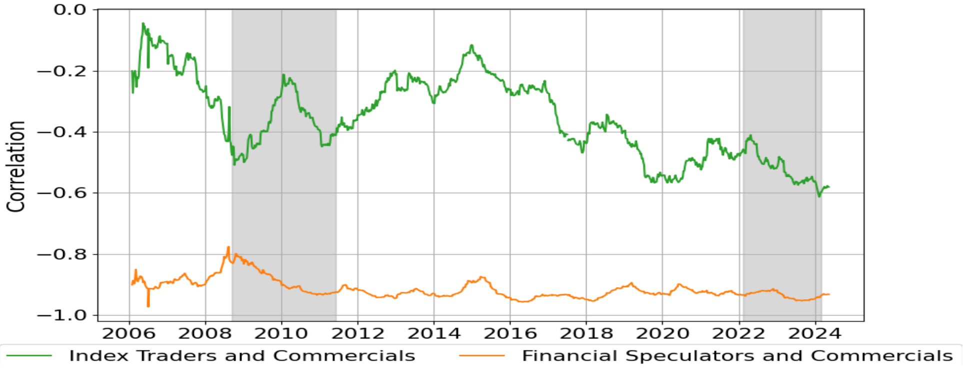
[3] For example, Principal Component Analysis, instead, is a linear transformation that inherently conducts dimensional reduction. It transforms the original variables into the new space, principal components that best capture the data's variability. It reduces the dataset's dimensions by focusing on the components that explain the largest variance, ensuring the simplified dataset still represents the most critical information.

the green line). Prior to the GFC, the correlation between financial speculators and commercial hedgers consistently hovered near -1, indicating a strong inverse relationship. However, this stable negative correlation broke down during the GFC, consistent with Cheng, Kirilenko, and Xiong (2014), which documents that financial traders became liquidity consumers and transmitted financial turmoil into the commodity futures markets. In contrast, the correlation between index traders and commercial hedgers does not exhibit as strong an inverse trading relationship, likely reflecting the more passive nature of index traders. Nevertheless, both correlations remain negative throughout, supporting the grouping of financial speculators and index traders under the term financial traders.

Figure 1: **Correlations Between Changes in Commercial Hedgers' Positions and Other Traders**
This figure shows the pairwise correlations of changes in net long positions between commercials and financial speculators, and between commercials and index traders. The weekly trading position data, which is the open interest data, is obtained from CFTC. The correlations are calculated using 52-week rolling windows.The period of the GFC is from September 15, 2008, to June 1, 2011, following Cheng, Kirilenko, and Xiong (2014). For the Russia-Ukraine war, the date, February 14, 2022, follows its operational announcement.



The estimation of the structural model based on the hedging pressure theory relies on a structural shock identification methodology that extends the approach developed by Jarociński (2024).[4] The estimated model represents futures returns as a linear combination of five Student-t distributed latent factors. This approach is well-suited to this study, considering the non-Gaussianity of the financial variables in the sample, as discussed in a later section. Accordingly, this study closely follows the methodology in Jarociński (2024), where a structural form is estimated using maximum likelihood with the Student-t distribution. This estimation statistically identifies the parameters of the structural model and yields five latent factors.

The five factors obtained are labelled as follows: the spot price factor, reflecting fluc-

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[4] According to Jarociński (2024), this estimation approach can be understood as a special case of a structural VAR (SVAR) that does not include lags of the dependent variables.

tuations in the spot market price; the commercial-financial factor, representing trading interactions between commercial and financial traders; the financial speculator and index trader factors, capturing the demand of these respective trader groups; and the residual component. Together, the spot price and commercial-financial factors explain, on average, 95% of the variance in futures returns across the 13 commodities, as measured by $R^2$. While the spot price, financial speculator, index trader, and residual factors are identified based on the explanatory power of their respective variables or the absence thereof, the commercial-financial factor requires a different approach for identification. Unlike the other factors, it cannot be determined solely using $R^2$ values, as it captures the interaction between commercial and financial traders rather than the trading demand of a single group. Instead, its identification relies on interpreting its impacts on the five variables in the model. The estimation results reveal that the commercial-financial factor is unrelated to spot price changes but drives the opposing trading dynamics between financial and commercial traders, which are associated with futures returns. Furthermore, these movements indicate that commercial traders are contrarians, while financial traders follow momentum strategies, consistent with findings in the literature, including Kang, Rouwenhorst, and Tang (2020). Based on this economic interpretation, I label the factor as the commercial-financial factor.

By using the spot price and the commercial-financial factors, I counterfactually measure the extent to which financial traders amplify futures return movements induced by spot price fluctuations. After completing the identification, this paper only focuses on the spot price and commercial-financial factors, as the other factors contribute minimally to explaining the futures return. The spot price factor denotes the portion of the futures return influenced solely by spot market price fluctuations, effectively representing the counterfactual futures return in the absence of financial traders, while the sum of the spot price and the commercial-financial factors represents the realised futures return. Thus, comparing the spot price factor with the sum of the two factors can counterfactually measure the extent to which financial traders amplify futures return movements induced by spot price fluctuations.

The counterfactual exercises reveal that financial traders amplify price changes during the GFC but dampen them during the Russia-Ukraine war, with the mitigating effect diminishing and eventually reversing to amplification as their market share increases. First, I compare the volatility of the combined spot price and commercial-financial factors to that of the spot price factor alone. The results show that financial traders reduce volatility in only the cotton, coffee, and sugar markets during the GFC, whereas this number increases to eight out of 13 markets during the Russia-Ukraine war. Given the high heterogeneity across commodities and potentially over time, regardless of the nature of the market disruption, I subsequently conduct panel regressions to control for commodity-specific and year-specific heterogeneities, as well as seasonality. The results show that in the absence of financial traders, price fluctuations would have been 44.6% smaller during the GFC and 28.3% larger during the Russia-Ukraine war. However, the mitigating effect persists only until the market share of financial traders reaches a threshold of 58%. Beyond this threshold, price fluctuations would have been smaller in the absence of financial traders, indicating a shift toward amplification effects by financial traders. With an average market share of 55% for financial traders during the Russia-Ukraine war, this threshold appears realistic.

## 1.1 Literature Review

I claim that the failure of financial traders to provide liquidity may cause their trading to amplify price changes rather than mitigate them, a scenario indirectly implied by the hedging pressure theory.[5] Hirshleifer (1988) and Hirshleifer (1990) paradoxically support the proposition put forth by Keynes (1930) and Hicks (1939) that the risk-averse nature of speculators ensures that risk premia are shaped by the prevailing hedging pressure in the market. These perspectives fundamentally suggest that financial traders play a stabilising role by offsetting the demands of commercial traders, provided they continue to act as liquidity providers. Equation 1 presents a mathematical expression of the hedging pressure by Hirshleifer (1988) and Hirshleifer (1990).

$$F(t,T) = E_t[S_T] - RP_t = E_t[S_T] - RP_t(\Delta X_t^{hedgers}, \Delta X_t^{financial}) \tag{1}$$

Using the example of price risk discussed by Keynes (1923) and Hicks (1939), commercial hedgers, who are typically risk-averse producers, create a demand for short futures positions.[6]

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[5] The literature often interchangeably uses the theory of Normal Backwardation, developed by Keynes (1930) and cited in Anttonen, Lanne, and Luoto (2024), or the Risk Premium Hypothesis, including Chow, McAleer, and Sequeira (2000), which reflects the contribution of Hicks (1939) in extending Keynes (1930) by incorporating the idea that risk-averse speculators require compensation for bearing price risk.

[6] Detailed examples illustrating the relationship between the expected spot price, the futures price, and the risk premium can be found in Gorton and Rouwenhorst (2006) and Weiser (2003)

As a result of this increased supply, the current futures price for maturity $T$, $F(t,T)$, falls below the current expected spot price for maturity $T$, $E_t[S_T]$.[7] This gap represents the risk premium, $RP_t$, which attracts speculators and incentivises them to provide liquidity by taking long positions.[8] Therefore, the risk premium can be expressed as a function of the demand from commercial hedgers, $\Delta X_t^{hedgers}$, and financial traders, $\Delta X_t^{financial}$. The inverse relationship between commercial hedgers and financial traders is evident from the negative correlation in their position changes, as illustrated in Figure 1. Conversely, when financial traders do not act as liquidity providers, there is no mechanism ensuring that they mitigate price fluctuations.

My paper is closely related to a recent and growing body of research that reassesses the assumption of financial traders as liquidity providers. However, it is distinct in adopting structural form estimation, whereas previous studies primarily use reduced form estimation, which regresses futures returns on the demand of a single trader group solely. Cheng, Kirilenko, and Xiong (2014) was among the first to demonstrate that financial traders can act as liquidity consumers rather than suppliers, highlighting their distressed financial conditions during the GFC. Similarly, Kang, Rouwenhorst, and Tang (2020) was the first to distinguish between two contrasting directions of risk-sharing: from commercial hedgers to financial traders, as traditionally understood, and from financial traders to commercial hedgers, representing a newer perspective. Building on this, Cho, Ganepola, and Garrett (2019) classified the first risk premium as the insurance premium and the second as the liquidity premium, associating them with bull and bear market trends, respectively. Further, Bonnier (2021) found that the liquidity premium remained a key driver of market activity long after the GFC. My findings align with those of Nikitopoulos, Thomas, and Wang (2024), who showed that the insurance premium is negatively related to volatility, while the liquidity premium is positively related to volatility. This body of research generally assumes that the long-term component of commercial hedgers' demand is driven by insurance needs, while the short-term component reflects speculators' liquidity demands to distinguish the two premia. In contrast, my study does not adopt this assumption, and the reduced form estimation. Nevertheless, my findings are consistent with their results.

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[7] Hirshleifer (1990, p. 411) refers to this as *price bias*, meaning deviations of the futures price from the expected value of the future spot price.

[8] Theoretical studies, including Basak and Pavlova (2016) and Baker (2021), more frequently define the risk premium as the difference between $F(t,T)$ and $E_t[S_T]$.

Second, I contribute to the empirical literature on the impacts of financial speculators and index traders within the broader context of research on the financialisation of commodity markets by demonstrating that changes in the trading positions of financial speculators and index traders alone have little impact on prices. Those studies assessing financial speculators tend to focus on extreme price movement (Kim (2015), Bierbaumer, Rieth, and Velinov (2021)) and excess volatility (Bonnier (2021)) or both (Brunetti, Büyükşahin, and Harris (2016), Sifat, Ghafoor, and Ah Mand (2021)). The focus on the extreme movements in assessing the role of financial traders stems from a simple thought: Should speculators cause market instability, their effects would be most pronounced during periods of large price movements. Thus, focusing on these substantial price movements provides a stricter test compared to other empirical studies, which find little evidence of the price destabilisation effect of financial traders, as concluded by the two survey papers in the literature, Haase, Seiler Zimmermann, and Zimmermann (2016) and Boyd, Harris, and Li (2018). Nevertheless, Kim (2015) and Brunetti, Büyükşahin, and Harris (2016) conclude that financial speculators tend to stabilise the market, while Bierbaumer, Rieth, and Velinov (2021) highlights their increased liquidity provision capacity during periods of high volatility. Empirical studies on the effect of index traders generally focus on price co-movements, either between the futures market and the stock market or across different commodity futures markets (Tang and Xiong (2012), Da, Tang, Tao, and Yang (2024), Kang, Tang, and Wang (2023)).

Third, this paper is methodologically related to the literature on assessing the impact of monetary policy through the application of SVAR. A notable focus in this domain has been the application of non-Gaussianity to detect structural shocks in monetary policy, as demonstrated by studies such as Gourièroux, Monfort, and Renne (2017), Lanne and Luoto (2020), and Lanne and Luoto (2021). This approach is particularly relevant to this study, as the financial variables analysed exhibit non-Gaussian properties. Accordingly, this paper adopts the methodology outlined in Jarociński (2024), where maximum likelihood estimation is applied to a Student-t distribution to model non-Gaussian behaviour. By assuming non-Gaussianity, this paper circumvents the need for imposing sign restrictions.

Fourth, therefore, this paper is related to, but different from, the strand of macroeconomic empirical literature that estimates structural models using SVAR with sign restrictions to understand commodity price dynamics, particularly oil prices (e.g., Kilian and Murphy (2014);

Antolín-Díaz and Rubio-Ramírez (2018); Baumeister and Hamilton (2019); Brown, Davies, and Ringgenberg (2020)). Notably, Kilian and Murphy (2014) and Juvenal and Petrella (2015) investigate the impact of speculative demand on oil prices by employing structural estimation instead of reduced form estimation, which involves the use of sign restrictions. Baumeister and Hamilton (2019) revisits Kilian and Murphy (2014) by allowing for less restrictive prior information and finds a larger contribution of supply disruptions to oil price movements. Brown, Davies, and Ringgenberg (2020) imposes non-Gaussianity in the structural form estimation established by Baumeister and Hamilton (2019) and documents that the information gained via non-Gaussianity seemingly dominates the weakly informative prior distribution used in Baumeister and Hamilton (2019). My approach is similar to Baumeister and Hamilton (2019) and Brown, Davies, and Ringgenberg (2020) in that I also construct a structural commodity market model consisting of simultaneous equations to express price and demand functions. However, unlike them, my focus is on the futures market price determinants, and constructing a structural commodity futures market model based on the hedging pressure theory, combined with the non-Gaussian assumption, leads to an estimation process that does not require sign restrictions.

Finally, in labelling the obtained shocks or transforming latent factors into interpretable factors, I draw on the factor model literature applied across various topics (e.g., Gürkaynak, Sack, and Swanson (2004); Chen, Dolado, and Gonzalo (2021); Kozak, Nagel, and Santosh (2020)). The macroeconomic empirical literature discussed above typically relies on economic intuition and observation to label identified shocks, which can be more effective than factor analysis, as it is, in some cases, more naive for interpreting the obtained factors. In contrast, factor analysis typically validates the obtained factors using a simple statistical measure, such as the $R^2$ from regressing each target variable on the factors. This paper adopts both approaches to labelling factors, ensuring a comprehensive identification strategy where factors have economic interpretations and pass statistical evaluation.

# 2 Model, Estimation and Data

## 2.1 Model

I estimate a structural form based on the hedging pressure theory from Hirshleifer (1988) and Hirshleifer (1990), incorporating trading position data provided by the CFTC. The structural form estimation is conducted separately for each commodity. In this model, the futures market includes four types of traders: commercial hedgers, financial speculators, index traders, and others, as defined by the CFTC. According to the CFTC, commercial traders are hedgers, traditional traders who participate in the commodity futures market to hedge against the price risk associated with their commercial activities. In contrast, financial speculators engage in the futures market to earn financial profits through trading. Index traders participate in the commodity futures market for portfolio diversification. The "others" category corresponds to non-reportable traders in the CFTC report, representing non-institutional investors, i.e., retail investors.

Drawing from the dynamics of the hedging pressure theory, the structural commodity futures market model is represented by the following simultaneous equations:

$$\text{Spot price difference:} \quad \Delta S_t = \epsilon_t^{spot} \tag{2}$$

$$\text{Demand of commercial hedgers:} \quad \Delta X_t^h = \beta^h \Delta F_t + \gamma^h \Delta S_t + \epsilon_t^h \tag{3}$$

$$\text{Demand of financial speculators:} \quad \Delta X_t^f = \beta^f \Delta F_t + \gamma^f \Delta S_t + \epsilon_t^f \tag{4}$$

$$\text{Demand of index traders:} \quad \Delta X_t^{idx} = \beta^{idx} \Delta F_t + \gamma^{idx} \Delta S_t + \epsilon_t^{idx} \tag{5}$$

$$\text{Futures return:} \quad \beta^o \Delta F_t = -\Delta X_t^h - \Delta X_t^f - \Delta X_t^{idx} - \gamma^o \Delta S_t - \epsilon_t^o, \tag{6}$$

where $\epsilon_{\mathbf{t}} = [\epsilon_t^{spot}, \epsilon_t^h, \epsilon_t^f, \epsilon_t^{idx}, \epsilon_t^o]' \sim i.i.d.(0, \Sigma_\epsilon)$ and $\Sigma_\epsilon := E[\epsilon_{\mathbf{t}} \epsilon_{\mathbf{t}}']$ is a diagonal matrix. In words, $\epsilon_{\mathbf{t}}$ is a vector of unobserved structural shocks that are independently and identically distributed. $\Delta x_i$ denotes the change in the net long futures position of trader group $i$. The coefficients $\beta^i$ represent the slope of the respective demand curve for trader group $i$, measuring the price elasticity of futures returns, $\Delta F_t$, which is defined as the log difference of futures prices. The coefficients $\gamma^i$ similarly measure the elasticity, but with respect to the spot price difference. Obtaining Equation 6 leverages the market clearing conditions and the demand functions for the others trader as defined follows.

$$\text{Market clearing condition:} \quad \sum_{i\in\{h,f,\text{idx},\text{o}\}} \Delta X^i = 0 \tag{7}$$

$$\text{Demand of others:} \quad \Delta X_t^o = \beta^o \Delta F_t + \gamma^o \Delta S_t + \epsilon_t^o. \tag{8}$$

Combining the hedging pressure theory and the market clearing condition consequently guarantees that the price is jointly determined by the demand of all the traders and also the spot price. Besides, I impose an additional assumption that the spot price is exogenous. The spot price affects the other variables, but not the other way around. This is a plausible assumption as the demand from traders pertains to position changes in the futures market, not the spot market. Moreover, in reality, only commercial traders operate in the spot market. Simply put, financial institutions and index traders do not buy or sell physical commodity products. Additionally, Dimpfl, Flad, and Jung (2017) examines the lead-lag relationship between the spot and futures markets in agricultural commodity markets, finding evidence that the prices of these commodities are primarily formed in the spot market.[9] I conduct several robustness checks in the Appendix to test this assumption, including applying two different types of VAR models, following the literature on the lead-lag relationship between the spot and futures markets.

The simultaneous equation system can be written as a structural model in matrix notation as follows:

$$\underbrace{\begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ -\gamma^h & 1 & 0 & 0 & -\beta^h \\ -\gamma^f & 0 & 1 & 0 & -\beta^f \\ -\gamma^{idx} & 0 & 0 & 1 & -\beta^{idx} \\ \gamma^o & 1 & 1 & 1 & \beta^o \end{pmatrix}}_{:=\mathbf{W}'} \underbrace{\begin{pmatrix} \Delta S_t \\ \Delta X_t^h \\ \Delta X_t^f \\ \Delta X_t^{idx} \\ \Delta F_t \end{pmatrix}}_{:=\mathbf{y_t}} = \underbrace{\begin{pmatrix} \epsilon_t^{spot} \\ \epsilon_t^s \\ \epsilon_t^f \\ \epsilon_t^{idx} \\ \epsilon_t^o \end{pmatrix}}_{:=\epsilon_\mathbf{t}}, \tag{9}$$

where $\mathbf{y_t} = (\Delta S_t, \Delta x_t^h, \Delta x_t^f, \Delta x_t^{idx}, \Delta F_t)'$ is a column vector of the observed variables. Equation 9 shows that there are 8 structural parameters, while the variance-covariance matrix of $\mathbf{y_t}$ provides 15 reduced-form parameters. This implies that the model is over-identified. To solve this problem, I loosen particularly the normalisation restrictions so that the model is just-identified with 7 more structural parameters, which are indicated as $\alpha$ in the following matrix,

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[9] Related to Dimpfl, Flad, and Jung (2017) and my paper, Bohl and Stephan (2013) concludes that the influence of futures speculation on the stability of commodity spot prices is, at a minimum, uncertain.

$\mathbf{W}$:

$$\mathbf{W} = \begin{pmatrix} \alpha_1 & -\gamma^h & -\gamma^f & -\gamma^{idx} & -\gamma^o \\ 0 & \alpha_2 & 0 & 0 & \alpha_5 \\ 0 & 0 & \alpha_3 & 0 & \alpha_6 \\ 0 & 0 & 0 & \alpha_4 & \alpha_7 \\ 0 & -\beta^h & -\beta^f & -\beta^{idx} & \beta^o \end{pmatrix}. \tag{10}$$

## 2.2 Estimation

The model expressed by Equation 9 implies that the observed variables, $\mathbf{y_t}$, representing the response of the commodity futures markets to substantial price changes in the spot market, are driven by structural shocks, $\epsilon_\mathbf{t}$. Multiplying Equation 9 by $\mathbf{C} := \mathbf{W}^{-1}$ highlights the point:

$$\mathbf{y_t} = \mathbf{C}'\epsilon_t, \tag{11}$$

where $\mathbf{C}'$ maps the structural shocks, $\epsilon_\mathbf{t}$ to the observed variables $y_t$. I assume that these shocks are independent and identically distributed according to a Student-t distribution.

$$\epsilon_\mathbf{t} \sim \text{i.i.d. } p(\epsilon_t), \tag{12}$$

where $p(\epsilon_t)$ denotes density, which may exhibit fat tails.

Thus, the structural shocks $\epsilon_\mathbf{t}$ are both independent across time and across components at any given time $t$. Consequently, the model for the observed variables $\mathbf{y_t}$ driven by these shocks is given by:

$$\mathbf{y_t} = \mathbf{C}'\epsilon_t, \quad \epsilon_t \sim i.i.d.p(\epsilon_t). \tag{13}$$

In the following, for a sample of the selected $T$ observations, I will write the model as:

$$\mathbf{Y} = \mathcal{E}\mathbf{C}, \tag{14}$$

where $\mathbf{Y}$ is the $T \times N$ matrix with $\mathbf{y}_\mathbf{t}^{'}$ in row $t$ and $\mathcal{E}$ is the corresponding $T \times N$ matrix of shocks.

The system estimation follows the approach in Jarociński (2024), which also assumes a Student-t density for structural shocks and determines optimal values for $\mathbf{W}$ and the degrees of freedom parameters, $\nu = (\nu_{spot}, \nu_s, \nu_f, \nu_{idx}, \nu_o)$, that maximise the likelihood of the sample

$\mathbf{Y}$. The model assumes that the shocks in period $t$ follow independent Student-t distributions. Specifically, the probability density function $p(\epsilon_t)$ is the product of the individual densities $p(\epsilon_{n,t})$ (for $n \in \{spot, s, f, idx, o\}$), where $\epsilon_{n,t}$ is distributed as $\mathcal{T}(\nu_n)$, a Student-t distribution with $\nu_n$ degrees of freedom.

The probability density function for $\epsilon_{n,t}$, which follows a Student-t distribution with $\nu_n$ degrees of freedom is given by:

$$p(\epsilon_{n,t}) = c(\nu_n)\left(1 + \frac{\epsilon_{n,t}^2}{\nu_n}\right)^{-\frac{\nu_n+1}{2}}, \tag{15}$$

where $c(\nu_n) = \nu_n^{-1/2} B\left(\frac{1}{2}, \frac{\nu_n}{2}\right)^{-1}$ is the normalisation constant ensuring the integral over all possible values equals one for given $\nu_n$, which includes the beta function $B(\cdot,\cdot)$. Importantly, as $\nu_n \to \infty$, the Student-t distribution converges to the Gaussian distribution, allowing the model to account for situations where some or even all shocks exhibit Gaussian properties.

Given $\mathbf{YW} = \mathcal{E}$, the log-likelihood of the samples $\mathbf{Y}$ given the parameters $\mathbf{W}$ and $\nu$ is expressed as the sum of the log probabilities of individual shocks $\epsilon_{n,t}$:

$$\log p(Y|W,\nu) = \sum_{t=1}^{T}\sum_{n=1}^{N} \log p(\epsilon_{n,t}). \tag{16}$$

Thus, the estimation aims to find optimal $\mathbf{W}$ and $\nu$ that maximise the likelihood:

$$\log p(Y|W,\nu) = T\log|\det W| - \sum_{t=1}^{T}\sum_{n=1}^{N}\left(\frac{\nu_n+1}{2}\log\left(1+\frac{\epsilon_{n,t}^2}{\nu_n}\right)\right) + T\sum_{n=1}^{N}\log c(\nu_n), \tag{17}$$

where $\epsilon_{n,t} = \mathbf{y_t}'\mathbf{w_{\cdot n}}$, with $\mathbf{w_{\cdot n}}$ the $n$th column of $\mathbf{W}$. The term $T\log|\det W|$ accounts for the normalisation of the covariance structure $\mathbf{W}$.

## 2.3 Data

CFTC publishes a weekly Commitments of Traders report every Friday, based on data collected the previous Tuesday. I use its supplemental report, which includes the positions of a set of index traders since January 3, 2006. It provides a breakdown of the total long and short positions held by participants in the commodity futures market, classified into four types of traders: commercials (commercial hedgers), noncommercials (financial speculators), index traders, and nonreportables. Following the literature, including Kang, Rouwenhorst, and Tang (2020) and Nikitopoulos, Thomas, and Wang (2024), I define the demand measure as the change in their net long position for each trader type $i \in \{h, f, idx, o\}$ between weeks $t-1$ and $t$, normalised by the total open interest at the beginning of the week $(OI_{t-1})$ held by all the traders for commodity $c$:

$$\Delta X^i_{c,t} = \frac{netlong\_position^i_{c,t} - netlong\_position^i_{c,t-1}}{OI_{c,t-1}}. \tag{18}$$

Future and spot price data is collected from Bloomberg. I calculate weekly excess returns (from Tuesday to Tuesday) to align with CFTC's position measurements. The excess return for commodities in week $t$ is determined using the front-month contract and roll positions on the seventh calendar day of the maturity month into the next-to-maturity contract. The futures excess return on commodity $c$ in week $t$ is calculated:

$$\Delta F_{c,t} = lnF_c(t,T) - lnF_c(t-1,T), \tag{19}$$

where $F(t,T)$ represents the futures price at the end of week $t$ for a futures contract maturing on date $T$. Finally, the change in the spot pric for commodity $c$ in week $t$, is defined as:

$$\Delta S_{c,t} = S_{c,t} - S_{c,t-1}. \tag{20}$$

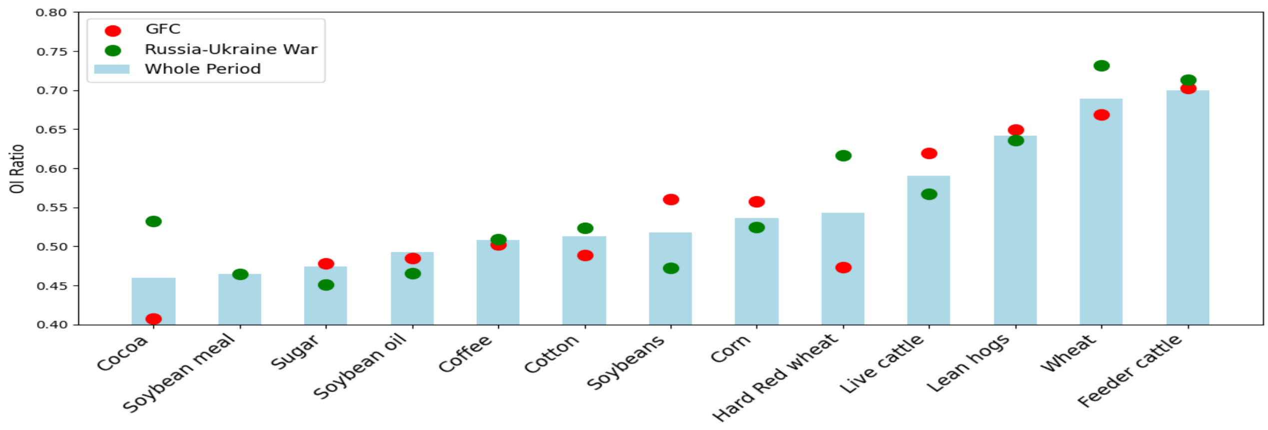
Market share of trader $i \in \{h, f, idx, o\}$ for commodity $c$ is defined as :

$$\text{OI ratio}^i_{t,c} = \frac{OI^i_{c,t}}{OI_{c,t}}. \tag{21}$$

The market share of financial traders varies substantially across commodities, as shown in Figure 2. On average, the market share of financial traders remains relatively stable over time, at approximately 55% during both the GFC and the Russia-Ukraine war. However, there is significant heterogeneity among commodities. Cocoa has the lowest market share of financial traders, averaging 46% over the entire period, while feeder cattle has a market share of 70%. Notably, for Hard Red Wheat and Wheat, there is a significant increase in the presence of financial traders during the Russia-Ukraine war, which is due to a decline in trading by commercial traders, possibly as a result of the war.

I restrict observations to those based on daily spot price changes on Mondays from January 10, 2006, to June 11, 2024, to analyse the futures market's reaction to substantial price shocks in the spot market. The estimation relies on price and trading data calculated for Tuesdays,

Figure 2: **Average market share of financial traders across 13 agricultural commodities:** This figure shows the average market share, measured by Open Interest (OI), of financial traders across 13 agricultural commodity futures markets during GFC, Russia-Ukraine war, and over the whole sample period.



following significant price changes observed on Mondays. In other words, the samples used in the empirical analysis include only weeks that exhibit substantial spot market price changes on Mondays. Specifically, the constructed sample includes data points where the spot price change on Mondays is greater than or equal to one standard deviation, calculated from the entire dataset. Descriptive statistics for the sample across the 13 commodities are provided in Table A.17 in the appendix.

The assumption of non-Gaussianity in the structural shocks arises directly from the observation of the data. Equation 13 states that the observed market reactions are linear combinations of the structural shocks. If the distributions of the observed variables are non-Gaussian, this implies that at least one of these shocks must be non-Gaussian. Although Maxand (2020) demonstrates that unique identification can still be valid even in the presence of multiple Gaussian shocks, all five observable variables in my model exhibit strong non-Gaussianity. Table 1 presents the results of three different normality tests: the Shapiro-Wilk (SW) test, the Jarque-Bera (JB) test, and the Anderson-Darling (AD) test, showing none of the variables fails to reject the null hypothesis that the data follow a normal distribution at the 5% significance level for the SW and JB tests, and at the 1% significance level for AD test except for the spot price change of Lean Hog in AD test.

Table 1: **Results of normality tests: Shapiro-Wilk (SW) test, the Jarque-Bera (JB) test, and the Anderson-Darling (AD) test**

The table below shows the number of variables that fail to reject the null hypothesis that the data follow a normal distribution at the 5% significance level for the SW and JB tests, and at the 1% significance level for AD test.

| Category | SW test | JB test | AD test |
|---|---|---|---|
| Soybean oil | 0 | 0 | 0 |
| Corn | 0 | 0 | 0 |
| Cocoa | 0 | 0 | 0 |
| Cotton | 0 | 0 | 0 |
| Feather cattle | 0 | 0 | 0 |
| Coffee | 0 | 0 | 0 |
| Hard Red wheat | 0 | 0 | 0 |
| Live cattle | 0 | 0 | 0 |
| Lean hogs | 0 | 0 | 1 |
| Soybean | 0 | 0 | 0 |
| Sugar | 0 | 0 | 0 |
| Soybean meal | 0 | 0 | 0 |
| Wheat | 0 | 0 | 0 |

# 3 Structural Form Estimation Results

The structural form estimation outputs $\epsilon_{\mathbf{t}} = (\epsilon_t^{spot}, \epsilon_t^h, \epsilon_t^f, \epsilon_t^{idx}, \epsilon_t^o)'$, as expressed in Equation 9, but these statistically identified shocks must be labelled and assigned economic interpretations to be considered structural shocks. In other words, I need to convert the obtained latent factors into interpretable factors. This section first validates the identified factors: the spot price factor, the commercial-financial factor, the financial speculator factor, the index trader factor, and the residual factor. The identification process consists of two steps. The first step involves determining which factor(s) best explain the futures returns, as the goal of the structural estimation is to decompose them. The results confirm that dimensional reduction is successful, with only two factors, the spot price and commercial-financial factors, sufficient to explain the futures returns. The second step identifies the remaining three factors. After completing the identification process, I compare the volatility of the combined spot price and commercial-financial factors with that of the spot price factor alone. The sum of the two factors can be considered the futures return itself, given its strong explanatory power, while the spot price factor alone represents the counterfactual return in the absence of financial traders. The comparison of the two volatilities reveals that financial traders dampened price changes in eight out of 13 commodities during the Russia-Ukraine war but in only three commodities during the GFC. Finally, I confirm that financial market disruptions affected traders demands during the GFC but not during the Russia-Ukraine war, underscoring the distinct disruptive nature of these two shocks from the perspective of futures markets.

## 3.1 Identification of Five Factors

The identification of the obtained five latent factors relies on both a statistical measure and economic intuition. The statistical measure is $R^2$ obtained by regressing each variable on one or more factors, and the resulting $R^2$ indicates which factor(s) explain each variable. The economic intuition can be obtained via interpreting coefficients of the estimated $\mathbf{C}$ matrix. Recall that $\mathbf{y_t} = \mathbf{C}'\epsilon_t$ in Equation 13. This implies that $\mathbf{y_t}$ is a linear combination of $\epsilon_t$. The matrix $\mathbf{C}'$ determines how each element of the factors $\epsilon_t$ contributes to forming $\mathbf{y_t}$. Hence, the $j$th column of $\mathbf{C}'$, or equivalently, the $j$th row of $\mathbf{C}$ matrix, indicates how a specific $\epsilon_{j,t}$ influences the different elements of $\mathbf{y_t}$. Therefore, I use the corresponding row of $\mathbf{C}$ matrix to understand the impact of the factors and obtain economic intuition to identify them.

Since the goal of the structural form estimation is to decompose the futures return into five factors, I start by identifying which combination of two latent factors explain the futures return the most. Following, I identify these two latent factors as the spot price factor, due to its high explanatory power of spot price differences measured by $R^2$, and the commercial-financial factor, based on economic intuition that it reflects the counterbalancing trading relationship between the two types of traders implied by its name. After completing the first block of the identification, I move to identify the three latent factors left as the financial speculator, the index trader, and the residual factors. The first two identification validations stem from the high $R^2$ in explaining position changes of financial speculators and the index trader, respectively, and the identification of the residual factors is due to its inability to explain any variables in terms of $R^2$.

The identification process begins by finding the combinations of factors that best explain the futures returns, identified as the spot price factor and the commercial-financial factor. Table 2 shows the $R^2$ values from regressions of the futures returns on different factor combinations, conducted separately for each of the 13 agricultural commodities. The first column reports the $R^2$ when using only the spot price factor as a regressor, as represented in Equation 22. The second column includes both the spot price factor and the commercial-financial factor, $\epsilon_t^{CF}$, as regressors (Equation 23), and the third column includes the spot price factor combined with the financial speculator factor, $\epsilon_t^{FS}$ (Equation 24):

$$\Delta F_t = \kappa_1 \epsilon_t^{spot} + e_t \tag{22}$$

$$\Delta F_t = \kappa_1 \epsilon_t^{spot} + \kappa_2 \epsilon_t^{CF} + e_t \tag{23}$$

$$\Delta F_t = \kappa_1 \epsilon_t^{spot} + \kappa_2 \epsilon_t^{FS} + e_t. \tag{24}$$

The spot price factor alone has the highest explanatory power for the futures return. However, adding the commercial-financial factor results in a substantial improvement, increasing the average $R^2$ from 0.58 with the spot price factor alone to 0.95. The third column shows the second highest $R^2$ value, achieved by combining the financial speculator factor with the spot price factor. For all 13 commodities, the combination of the spot price and the commercial-financial factors explains substantially more than the second-best combination, which includes the spot price and the financial speculator factors. On top of that, the high $R^2$ values presented in the second column of Table 2 provide evidence that the estimation successfully reduces dimensionality in explaining the futures returns by transforming the original variables into the factor space. Simply put, five variables are no longer needed, as only two factors can sufficiently represent the futures returns.

One of the two factors whose combination yields the highest explanatory power for futures returns is the spot price factor, which primarily accounts for spot price differences. The identification of the spot price factor is based on the statistical measure, $R^2$, from regressions of the spot price difference on the spot price factor. Table 3 shows the $R^2$ values from these regressions, which are close to 1.0 for all 13 commodities.[10]

In contrast to the strong explanatory power of the spot price factor for differences in spot prices, the commercial-financial factor alone does not significantly explain any of the input variables. Table 4 displays the $R^2$ values from regressions of each of the five input variables on

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[10] The $R^2$ values from regressions of all input variables on the spot price factor, as well as on all factors collectively, are provided in Section B.1 to demonstrate the robustness of the labels and the identification of the factors

Table 2: **Explanatory Power of Different Factor Combinations for Futures Returns**

This table presents the $R^2$ values for three different sets of factor combinations regressed against futures returns for 13 commodities. The first column represents the $R^2$ when using only the spot price factor. The second column includes both the spot price factor and the commercial-financial factor, showing the highest explanatory power. The third column combines the spot price factor with the financial speculator factor. The results demonstrate that the combination of the spot price and commercial-financial factors consistently provides a significantly higher $R^2$, indicating superior explanatory power across all commodities.

| Commodity | **Spot Price Factor** | **Spot Price Factor & Commercial-Financial Factor** | **Spot Price Factor & Financial-Speculator Factor** |
|---|---|---|---|
| Soybean oil | 0.6780 | 0.9902 | 0.6859 |
| Corn | 0.7831 | 0.9845 | 0.7901 |
| Cocoa | 0.5385 | 0.7876 | 0.7418 |
| Cotton | 0.7144 | 0.9789 | 0.7266 |
| Feather cattle | 0.1759 | 0.9352 | 0.2040 |
| Coffee | 0.6606 | 0.9431 | 0.7014 |
| Hard Red wheat | 0.8289 | 0.9952 | 0.8327 |
| Live cattle | 0.2310 | 0.8341 | 0.3981 |
| Lean hogs | 0.2475 | 0.9363 | 0.2948 |
| Soybean | 0.8275 | 0.9915 | 0.8331 |
| Sugar | 0.7868 | 0.9948 | 0.7892 |
| Soybean meal | 0.5303 | 0.9988 | 0.5307 |
| Wheat | 0.7434 | 0.9657 | 0.7702 |

Table 3: **Explanatory Power of the Spot Price Factor**

This table shows the $\mathbf{R}^2$ values of regressions of the spot price difference on the spot price factor. These values represent the explanatory power of the spot price factor for the spot price difference in each of the 13 commodities, respectively.

| Commodity | $R^2$ |
|---|---|
| Soybean oil | 0.9994 |
| Corn | 1.0000 |
| Cocoa | 0.9997 |
| Cotton | 0.9996 |
| Feather cattle | 0.9993 |
| Coffee | 0.9999 |
| Hard Red wheat | 0.9996 |
| Live cattle | 0.9996 |
| Lean hogs | 0.9997 |
| Soybean | 0.9997 |
| Sugar | 0.9999 |
| Soybean meal | 0.9994 |
| Wheat | 0.9996 |

the commercial-financial factor. This indicates that the statistical measure approach cannot be used to identify the commercial-financial factor; therefore, I rely on the corresponding rows of **C** matrix to interpret the commercial-financial factor.

Table 4: **Explanatory Power of the Commercial-Financial Factor**

This table shows $\mathbf{R}^2$ values from regressions of each of the five input variables on the commercial-financial factor. These values indicate the explanatory power of the commercial-financial factor for the input variable in the corresponding column.

| | **Spot Price Difference** | **Hedgers Position** | **Speculators Position** | **Index Traders Position** | **Futures Return** |
|---|---|---|---|---|---|
| All | 0.0231 | 0.0065 | 0.0075 | 0.0003 | 0.0025 |
| Soybean oil | 0.1539 | 0.0015 | 0.0005 | 0.0002 | 0.0410 |
| Corn | 0.0016 | 0.0042 | 0.0000 | 0.0000 | 0.1703 |
| Cocoa | 0.1718 | 0.2673 | 0.2369 | 0.0796 | 0.0261 |
| Cotton | 0.0074 | 0.0052 | 0.0015 | 0.0222 | 0.1880 |
| Feather cattle | 0.0052 | 0.0019 | 0.0056 | 0.0083 | 0.8021 |
| Coffee | 0.0015 | 0.0000 | 0.0007 | 0.0002 | 0.2538 |
| Hard Red wheat | 0.0035 | 0.0342 | 0.0219 | 0.0148 | 0.1192 |
| Live cattle | 0.0119 | 0.0281 | 0.0540 | 0.0189 | 0.6707 |
| Lean hogs | 0.0173 | 0.0019 | 0.0015 | 0.0110 | 0.7820 |
| Soybean | 0.0380 | 0.0025 | 0.0005 | 0.0030 | 0.0491 |
| Sugar | 0.0547 | 0.0106 | 0.0143 | 0.0011 | 0.0548 |
| Soybean meal | 0.1795 | 0.0854 | 0.0790 | 0.0441 | 0.1086 |
| Wheat | 0.0057 | 0.0458 | 0.0412 | 0.0001 | 0.1578 |

The economic intuition based on the estimated **C** matrix reveals that the commercial-financial factor captures trading habits of the traders and therefore ex-post captures the counterbalancing relationship between the two traders. Table 5 shows the respective rows of the estimated **C** matrix for the commercial-financial factor across the 13 agricultural commodities. The estimated coefficients are scaled according to the standard deviation of the commercial-financial factor, allowing them to represent the response of each variable to a one standard deviation change in the commercial-financial factor. In Table 5, coefficients in the second column are opposite those in the fifth column, indicating that commercial hedgers are contrarians. Meanwhile, coefficients in the third column are the same as those in the fifth column, indicating that financial speculators are momentum traders. This trading behaviour is consistent with the observations in Rouwenhorst and Tang (2012), Fishe and Smith (2019) and Kang, Rouwenhorst, and Tang (2020) and is confirmed using the sample in this paper, of which results are in Table 6.

Table 5: **Estimation Results for the Commercial-Financial Factor Across 13 Commodities**

This table shows the coefficients of the row for the commercial-financial factor in the estimated **C** matrix. Each column corresponds to the input variables, whose linear combination forms the resulting factor, i.e., the commercial-financial factor.

| | Corresponding Row in **C** Matrix | | | | |
|---|---|---|---|---|---|
| Commodity | **Spot Price Difference** | **Hedgers Position** | **Speculators Position** | **Index Traders Position** | **Futures Return** |
| Soybean oil | 0.0064 | 0.3012 | -0.1532 | -0.1132 | -0.3450 |
| Corn | -0.0003 | 0.1241 | -0.0400 | -0.1404 | -0.3387 |
| Cocoa | -0.0117 | -0.8669 | 0.6209 | 0.2109 | 0.4039 |
| Cotton | -0.0038 | 0.0700 | -0.1106 | -0.0870 | -0.2353 |
| Feather cattle | -0.0068 | 0.0288 | -0.0679 | 0.0109 | -0.7665 |
| Coffee | -0.0038 | -0.0486 | 0.0568 | 0.0720 | 0.5835 |
| Hard Red wheat | 0.0069 | -0.2058 | 0.1424 | 0.2059 | 0.4266 |
| Live cattle | 0.0111 | 0.8657 | -1.0928 | -0.1254 | -0.3761 |
| Lean hogs | -0.0024 | 0.7964 | -1.2398 | -0.0708 | -0.2705 |
| Soybean | 0.0008 | 0.1048 | -0.0671 | -0.0193 | -0.2072 |
| Sugar | -0.0013 | 0.1560 | -0.2518 | -0.0255 | -0.2665 |
| Soybean meal | 0.0138 | 0.6432 | -0.3824 | -0.1880 | -0.4423 |
| Wheat | -0.0075 | 0.2257 | -0.2510 | -0.0335 | -0.4167 |

Table 6 presents the estimated coefficients from OLS regressions analysing the trading behaviour of three types of traders: commercial hedgers, financial speculators, and index traders. The dependent variables are the changes in net long positions, $\Delta X_t^h$, $\Delta X_t^f$, and $\Delta X_t^{idx}$, for each trader type, regressed on the futures return $\Delta F_t$ and the spot price differences $\Delta S_t$. The negative coefficients for $\Delta F_t$ in the first and second columns indicate that commercial hedgers exhibit contrarian behaviour, while the positive coefficients in the remaining columns suggest that financial speculators and index traders follow a momentum strategy.

After identifying the two most important factors, the identification of the three latent factors is conducted purely based on $R^2$. Table 7 highlights the strong explanatory power of the financial speculator factor and the index trader factor for changes in the positions of financial speculators and index traders, respectively. Although there is an intermediate step, these factors ultimately have the highest $R^2$ values for explaining their respective variables among all five factors, with the exception of cocoa in relation to the financial speculator factor. The $R^2$ of the financial speculator factor for cocoa is only 0.15, the lowest among the 13 commodities, while the commercial-financial factor achieves an $R^2$ of 0.24 in explaining changes in speculators' positions, as shown in the second column for cocoa. However, neither factor captures the demand

Table 6: **Trading Patterns of Each Trader:**

This table shows estimated coefficients of OLS regressions of the net long position changes of the commercials hedgers, the financial speculators, and the index traders on two predictors: $\Delta F$ is the futures return; $\Delta S$ the spot price difference; ***, **, * denote 10%, 5%, and 1% significance, respectively. t-statistics are in parentheses.

| | Commercial Hedgers $\Delta X_t^h$ | Commercial Hedgers $\Delta X_t^h$ | Financial Speculators $\Delta X_t^f$ | Financial Speculators $\Delta X_t^f$ | Index Traders $\Delta X_t^{idx}$ | Index Traders $\Delta X_t^{idx}$ |
|---|---|---|---|---|---|---|
| $\Delta F_t$ | -0.4567*** | -0.6099*** | 0.4024*** | 0.5640*** | 0.2000*** | 0.2366*** |
| | (-14.5692) | (-28.9242) | (13.5156) | (27.2275) | (6.8188) | (11.9706) |
| $\Delta S_t$ | -0.2049*** | | 0.2162*** | | 0.0491* | |
| | (-7.2568) | | (7.8414) | | (1.8927) | |
| Constant | -0.1405 | -0.1753 | 0.0654 | 0.1021 | 0.4185*** | 0.4268*** |
| | (-1.2282) | (-1.5628) | (0.5091) | (0.8024) | (2.6132) | (2.6763) |
| Commodity FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.4046 | 0.3867 | 0.3483 | 0.3284 | 0.1030 | 0.1020 |
| Observations | 2984 | 2984 | 2984 | 2984 | 2984 | 2984 |

for financial speculators as effectively for cocoa as the financial speculator factor does for other commodities, as shown in the second column. For the other 12 commodities, it is evident that the financial speculator factor best explains changes in financial speculators' positions, as demonstrated by comparing the first and second columns in Table 7. Regarding the index trader factor, its explanatory power for index traders' position changes remains strong, with a minimum $R^2$ of 0.8928 for cocoa and an average of 0.94.

Last and least, the residual factor is identified as having no ability to explain any variables, which Table 8 gives the evidence of. Table 8 shows the $R^2$ values when regressing each variable on the residual factor separately.

Table 7: **Explanatory Power of Financial Speculator Factor and Index Trader Factor**

The table below shows $R^2$ values from regressions of dependent variables in the *Dependent Variable* row on the independent variables in the *Independent Variable* row.

| *Dependent Variable* | **Financial Speculators Position** | **Financial Speculators Position** | **Index Traders Position** |
|---|---|---|---|
| *Independent Variable* | **Financial Speculator Factor** | **Commercial-Financial Factor** | **Index Trader Factor** |
| Soybean oil | 0.7210 | 0.0005 | 0.9024 |
| Corn | 0.6609 | 0.0000 | 0.9054 |
| Cocoa | 0.1514 | 0.2369 | 0.8928 |
| Cotton | 0.7931 | 0.0015 | 0.9709 |
| Feather cattle | 0.8940 | 0.0056 | 0.9959 |
| Coffee | 0.4646 | 0.0007 | 0.9321 |
| Hard Red wheat | 0.7345 | 0.0219 | 0.9181 |
| Live cattle | 0.6247 | 0.0540 | 0.9602 |
| Lean hogs | 0.4854 | 0.0015 | 0.9479 |
| Soybean | 0.5896 | 0.0005 | 0.9055 |
| Sugar | 0.5761 | 0.0143 | 0.9989 |
| Soybean meal | 0.3196 | 0.0790 | 0.9150 |
| Wheat | 0.8281 | 0.0412 | 0.9557 |

Table 8: **Explanatory Power of the Residual Factor**

The table below shows $\mathbf{R}^2$ values of regressions of dependent variables in the *Dependent Variable* row on the residual factor.

| *Dependent Variable* | **Spot Price Difference** | **Commercial Hedgers Position** | **Financial Speculators Position** | **Index Traders Position** | **Futures Return** |
|---|---|---|---|---|---|
| Soybean oil | 0.0000 | 0.0363 | 0.0004 | 0.0000 | 0.0010 |
| Corn | 0.0000 | 0.0001 | 0.0615 | 0.0000 | 0.0018 |
| Cocoa | 0.0124 | 0.0271 | 0.0016 | 0.0037 | 0.0049 |
| Cotton | 0.0000 | 0.0005 | 0.0315 | 0.0000 | 0.0000 |
| Feather cattle | 0.0008 | 0.3995 | 0.0066 | 0.0001 | 0.0254 |
| Coffee | 0.0000 | 0.0225 | 0.0008 | 0.0000 | 0.0031 |
| Hard Red wheat | 0.0011 | 0.0863 | 0.0022 | 0.0013 | 0.0031 |
| Live cattle | 0.0000 | 0.0015 | 0.0522 | 0.0004 | 0.0122 |
| Lean hogs | 0.0004 | 0.0046 | 0.0483 | 0.0001 | 0.0031 |
| Soybean | 0.0000 | 0.0222 | 0.0000 | 0.0000 | 0.0003 |
| Sugar | 0.0002 | 0.0003 | 0.0504 | 0.0000 | 0.0015 |
| Soybean meal | 0.0000 | 0.0319 | 0.0000 | 0.0000 | 0.0000 |
| Wheat | 0.0009 | 0.0701 | 0.0025 | 0.0000 | 0.0103 |

## 3.2 Futures Return Decomposition

The rest of the paper focuses on the spot price and commercial-financial factors to further analyse the effect of financial traders on futures returns. This focus is justified by the success in dimensional reduction, as the combination of these two factors significantly explains the futures returns, as shown in Table 2.

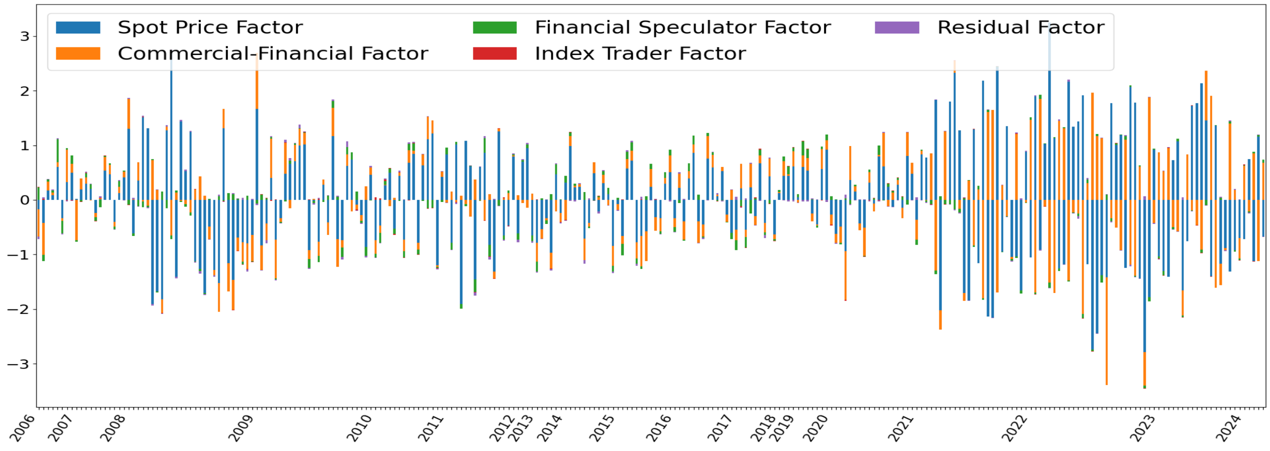
The visualisation of the success in the dimensional reduction is depicted by Figure 3, which exemplifies the factor decomposition of the futures return from the soybean oil futures market. Recall that in Equation 14, $\mathbf{Y} = \mathcal{E}\mathbf{C}$. By taking the corresponding column of the estimated $\mathbf{C}$ matrix for the futures return, the estimated futures return can be rewritten as:

$$\mathbf{\Delta\hat{F}} = \epsilon^{\mathbf{spot}} \cdot c_{spot,return} + \epsilon^{\mathbf{CF}} \cdot c_{CF,return} + \epsilon^{\mathbf{FS}} \cdot c_{FS,return} + \epsilon^{\mathbf{index}} \cdot c_{Index,return} + \epsilon^{\mathbf{redidual}} \cdot c_{redidual,return}, \tag{25}$$

where $\mathbf{\Delta\hat{F}}$ is a $T \times 1$ column vector. In Figure 3 shows each term in Equation 26 in differently coloured bars, so that the sum of all the bars is the actual futures return. The figure illustrates that the spot price and commercial-financial factors are the predominant determinants of the futures return. Conversely, the limited contribution of the factors corresponding to financial speculators and index traders indicates that they do not significantly influence prices. This is likely the outcome of addressing simultaneity issues, as it reveals the importance of contemporaneous trading among the three trader groups.

Figure 3: **Time Series of the Return Decomposition for the Soybean Oil Futures Market**

This figure shows the result of the rerun decomposition from the soybean oil futures market as an example. The sum of all the factors is the actual futures returns. Each bar in the figure represents the contribution of one of the five factors to $\mathbf{\Delta\hat{F}}$, corresponding to the terms in Equation 26: the blue bar represents $\epsilon^{\mathbf{spot}} \cdot c_{spot,return}$, the orange bar represents $\epsilon^{\mathbf{CF}} \cdot c_{CF,return}$, the green bar represents $\epsilon^{\mathbf{FS}} \cdot c_{FS,return}$, the red bar represents $\epsilon^{\mathbf{index}} \cdot c_{Index,return}$, and the purple bar represents $\epsilon^{\mathbf{residual}} \cdot c_{residual,return}$.



Because of the success in the dimensional reduction, it is possible to rewrite the futures return as follows.

$$\mathbf{\Delta\tilde{F}} = \epsilon^{\mathbf{spot}} \cdot c_{spot,return} + \epsilon^{\mathbf{CF}} \cdot c_{CF,return}. \tag{26}$$

In contrast, when considering only the spot price factor or the first term in Equation 26, the representation is:

$$\mathbf{\Delta\hat{F}}_{spot} = \epsilon^{\mathbf{spot}} \cdot c_{spot,return}, \tag{27}$$

where $\mathbf{\Delta\hat{F}}_{spot}$ represents the portion of the futures return explained purely by the spot market. This can be interpreted as a counterfactual futures return in the absence of the impact of trading in the futures market. Therefore, comparing $\mathbf{\Delta\hat{F}}_{spot}$ and $\mathbf{\Delta\tilde{F}}$ provides a counterfactual experiment to assess what the futures return would have been if financial traders were absent from the market.

This paper attributes the time-varying effects of the commercial-financial factor to the changing role of financial traders, rather than commercial traders, even though the factor captures trading between both groups. First, this interpretation is supported by the CFTC's definition of commercial hedgers, which specifies that the trading motives and behaviour of commercial traders remain focused on hedging. [11] Second, this perspective aligns with findings by Cheng, Kirilenko, and Xiong (2014), Bonnier (2021), and Nikitopoulos, Thomas, and Wang (2024), which emphasise the importance of understanding how the effect of financial traders in the commodity futures market changes over time and depends on their variable trading motivations.

Following Equation 26, Figure 4 illustrates the return decomposition for the soybean oil futures market as an example using two primary factors: the spot price factor and the commercial-financial factor. This visualisation highlights the core relationship between the two key components of the futures return: the first term, or $\mathbf{\Delta\hat{F}}_{spot}$ (shown in blue bars) and the second term, $\epsilon^{\mathbf{CF}} \cdot c_{CF,return}$ (shown in orange bars) in Equation 26. Simply, when the commercial-financial factor aligns with the spot price factor, financial traders' responses in the futures market amplify the spot price movement, transmitting it to futures returns. In contrast, when the two bars move in opposite directions, financial traders dampen the price fluctuations from

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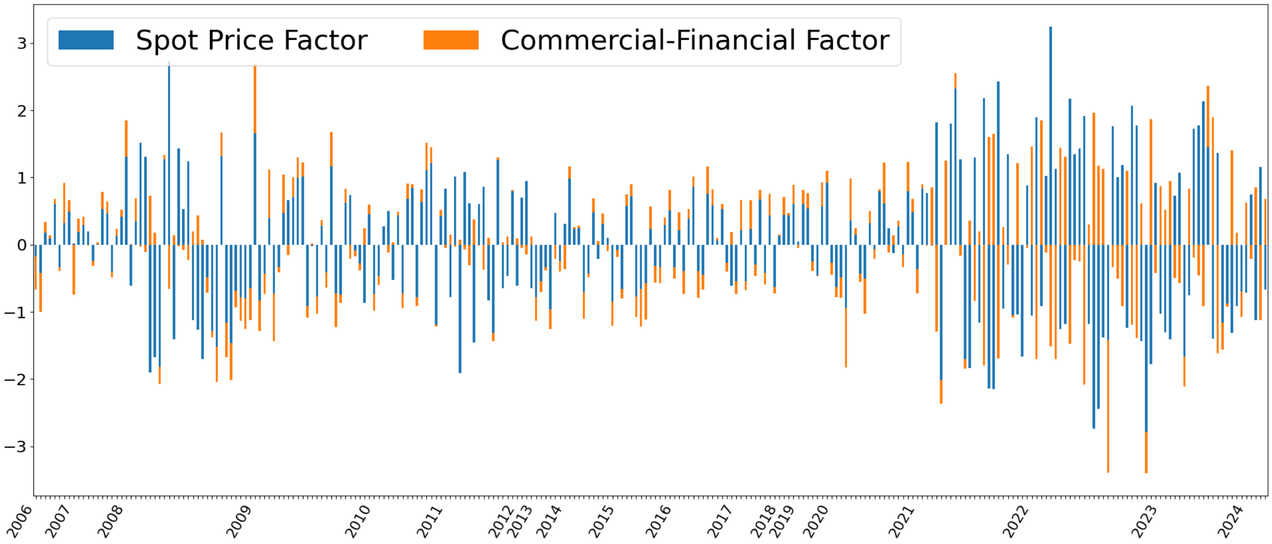
[11] See the explanatory note from CFTC, which says *all of a trader's reported futures positions in a commodity are classified as commercial if the trader uses futures contracts in that particular commodity for hedging as defined in CFTC Regulation 1.3, 17 CFR 1.3(z).*

the spot market. This amplification and mitigation role of the financial traders is time-varying, and in particular, the mitigation effects seem more concentrated during the Russia-Ukraine war. Figure 5 presents a modified version of Figure 4 to explicitly highlight the concentrated dampening effects during the Russia-Ukraine war. To achieve this, I apply a transformation to the data: whenever the spot price factor is negative in Figure 4, I multiply both the spot price factor and the commercial-financial factor by -1. This transformation ensures that the spot price factor consistently appears on the positive side, making it easier to observe changes in the amplification or dampening effects over time. In Figure 5, it is explicit that during the Russia-Ukraine war, the mitigation effects of the financial traders are dominant while the amplification effects are dominant during the GFC.

Figure 4: **Simplified Return Decomposition for the Soybean Oil Futures Market**

This figure emphasises how the spot price and the commercial financial factor differently react to each other in determining the futures return over time. Recall $\mathbf{\Delta\tilde{F}} := \epsilon^{\mathbf{spot}} \cdot c_{spot,return} + \epsilon^{\mathbf{CF}} \cdot c_{CF,return}$. In this figure, the blue bar represents $\epsilon^{\mathbf{spot}} \cdot c_{spot,return}$ and the orange bar represents $\epsilon^{\mathbf{CF}} \cdot c_{CF,return}$.



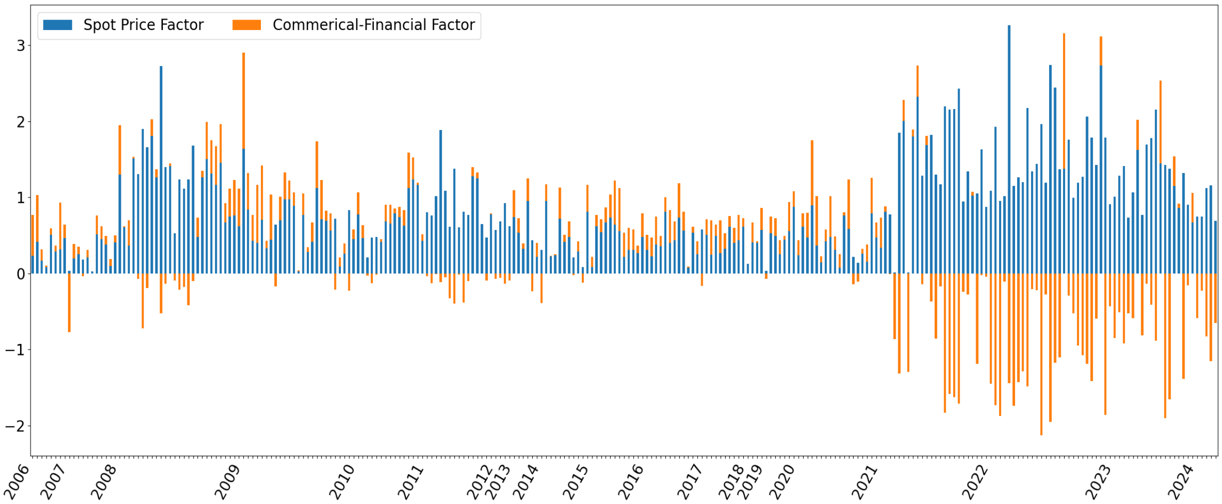
I quantify the effect of financial traders by calculating the relative change in volatility due to the addition of the commercial-financial factor to the spot factor during the periods of the GFC and the Russia-Ukraine war, using the following equation:

$$\text{Relative change in volatility} = \frac{\text{vol}(\mathbf{\Delta\tilde{F}}) - \text{vol}(\mathbf{\Delta\hat{F}}_{spot})}{\text{vol}(\mathbf{\Delta\hat{F}}_{spot})}. \tag{28}$$

The result of 0.289 for the relative change in volatility during the GFC indicates that, in the absence of financial traders, volatility would have been 28.9% lower than the observed volatility. Conversely, the result of -0.2746 during the Russia-Ukraine war implies that volatility

Figure 5: **Modifed Version of the Simplified Return Decomposition for the Soybean Oil Futures Market**

This figure shows a modified version of Figure 4. I apply a transformation to the data: whenever the spot price factor is negative in Figure 4, I multiply both the spot price factor and the commercial-financial factor by -1. By keeping the spot price factor consistently positive, this transformation facilitates tracking changes in its amplification and dampening effects of the commercial-financial factor over time.



would have been 27.5% higher without financial traders. Simply put, financial traders amplified volatility by 28.9% during the GFC, while they dampened it to nearly the same degree during the Russia-Ukraine war.

Table 9 presents the calculated relative change in volatility across 13 agricultural futures markets, highlighting considerable heterogeneity in the extent to which financial traders stabilise or destabilise price changes. Financial traders reduce volatility in only the cotton, coffeee, and sugar markets during the GFC. However, this number increases to 8 out of the 13 markets during the Russia-Ukraine war. The soybean-related futures markets see the most significant reductions: 31.4% in the soybean market, 27.5% in the soybean oil market, and 18.2% in the soybean meal market. Conversely, markets with increased volatility due to financial traders are primarily in the livestock category, with increases of 70.1% in the live cattle market and 49.7% in the feeder cattle market.

To confirm that the impacts of the two distressing events, the GFC and the Russia-Ukraine war, on traders are different, I regress traders' position changes on the VIX, following Cheng, Kirilenko, and Xiong (2014), Kang, Rouwenhorst, and Tang (2020), and Bonnier (2021). My unique approach to addressing simultaneity issues still yields findings similar to those commonly observed in the literature, such as in Cheng, Kirilenko, and Xiong (2014) and Bonnier (2021).

Table 9: **Contribution of the Commercial-Financial Factor to the Volatility**

The table shows the relative change in volatility of the 13 agricultural commodities. The calculation is based on Equation 28. Note that the soybean meal data is available only after 2014.

| **Commodity** | **GFC** | **Russia-Ukraine war** |
|---|---|---|
| Soybean oil | 0.2894 | -0.2746 |
| Corn | 0.2373 | 0.0957 |
| Cocoa | 0.0715 | -0.4352 |
| Cotton | -0.1456 | 0.1975 |
| Feather cattle | 3.8012 | 0.4972 |
| Coffee | -0.0384 | -0.0496 |
| Hard Red wheat | 0.1144 | -0.1771 |
| Live cattle | 1.1958 | -0.3963 |
| Lean hogs | 2.3317 | 0.7017 |
| Soybean | 0.1841 | -0.3142 |
| Sugar | -0.1818 | -0.1495 |
| Soybean meal | | -0.1820 |
| Wheat | 0.2793 | 0.0042 |

Specifically, the financialisation of the commodity futures market had a negative impact during the GFC, as it transmitted financial market turmoil to the commodity futures market. In line with Cheng, Kirilenko, and Xiong (2014), Kang, Rouwenhorst, and Tang (2020), and Bonnier (2021), I also confirm that a disruption in trading behaviour occurred during the GFC within my sample. Table 10 presents the regression results. The trading behaviour of the three trading groups was disrupted during the GFC, as indicated by the statistically significant coefficients of the VIX variable in the first three columns. By contrast, these significant results are absent for the period of the Russia-Ukraine war, indicating that the same disruption does not occur.[12]

# 4 Panel Regression Results

Recognising the differing impacts of financial traders on futures market price responses to substantial spot market changes across 13 agricultural commodities, this paper further investigates whether this heterogeneity correlates with the market share of financial traders as measured by open interest. Specifically, I run four regressions. The first regression confirms the robustness of the finding that financial traders act as amplifiers during the GFC and as mitigators during the

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[12] The result that larger VIX coefficients for hedgers compared to speculators is also observed Bonnier (2021).

Table 10: **Trader Positions Conditional on Shocks to the VIX and Returns**

This table shows OLS regressions of the net long position changes of the commercial hedgers, financial speculators, and index traders on three predictors: $\Delta VIX_t$ is the change in VIX, the variable of interest; $\Delta F$ is the futures return; $\Delta S$ is the spot price change. All regressors arestandardisedd at time $t$, as is the dependent variable. ***, **, * denote 10%, 5%, and 1% significance, respectively. t-statistics are in parentheses. The period of the GFC is from September 15, 2008, to June 1, 2011, following Cheng, Kirilenko, and Xiong (2014). For the Russia-Ukraine war, the date February 14, 2022, follows its operational announcement.

| | GFC | | | Russia-Ukraine War | | |
|---|---|---|---|---|---|---|
| | Commercials Hedgers $\Delta X_t^h$ | Financial Speculators $\Delta X_t^f$ | Index Traders $\Delta X_t^{idx}$ | Commercials Hedgers $\Delta X_t^h$ | Financial Speculators $\Delta X_t^f$ | Index Traders Traders $\Delta X_t^{idx}$ |
| $\Delta VIX_t$ | 0.0554*** | -0.0400*** | -0.0487*** | 0.0181 | -0.0178 | 0.0006 |
| | (6.381) | (-4.828) | (-4.643) | (0.989) | (-0.997) | (0.978) |
| $\Delta F_{t-1}$ | -0.0052 | 0.0389 | -0.0826 | -0.1149 | 0.1197** | 0.0317 |
| | (-0.123) | (0.954) | (-1.600) | (-2.372) | (2.547) | (0.556) |
| $\Delta VIX_{t-1}$ | 0.0053 | 0.0022 | -0.0290** | -3.005e-05 | 0.0034 | 0.0009 |
| | (0.558) | (0.249) | (-2.546) | (-0.002) | (0.202) | (0.963) |
| Commodity FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 573 | 573 | 573 | 396 | 396 | 396 |
| $R^2$ | 0.110 | 0.067 | 0.068 | 0.068 | 0.056 | 0.062 |

Russia-Ukraine war, even after controlling for year- and commodity-specific heterogeneity and seasonality. The second regression indicates that, on average, a higher share of financial traders is consistently associated with an amplification effect on price changes, whether during the GFC or the Russia-Ukraine war. The third regression confirms that the amplification effects associated with the market share of financial traders are the primary drivers behind their amplifying role observed during the GFC and are significantly stronger than those seen during the Russia-Ukraine war. Finally, the fourth regression extends the third by adopting a non-linear form, confirming that the mitigating role of financial traders observed during the Russia-Ukraine war weakens as their market share increases, eventually shifting to an amplifying role once their market share surpasses a certain threshold.

The four panel regressions use *Offset Value* as the primary dependent variable, derived from the spot price factor and the commercial-financial factor, to measure the extent to which the addition of the commercial-financial factor changes the overall magnitude of the spot price factor. The offset value of each commodity is a continuous variable defined as follows:

$$\mathit{Offset\ Value} = \ln\left|\mathbf{\Delta}\tilde{\mathbf{F}}\right| - \ln\left|\mathbf{\Delta}\hat{\mathbf{F}}_{spot}\right|. \tag{29}$$

Transforming into logarithmic space is necessary to evaluate the magnitudes of amplification and mitigation effects equally. Without this transformation, amplification effects would be overestimated because mitigation effects are always less than 1, while amplification effects have no upper limit. This imbalance is highlighted by the minimum and maximum values of the absolute version of the *Offset Value*, shown in the third and fourth columns of Table 11, which presents descriptive statistics for the two offset measures as well as the absolute version of the offset value. As a result, the mean of the absolute version of the offset value remains above 1, indicating that, on average, the effect of financial traders is amplification across all 13 commodities. However, when examining the offset value in its defined logarithmic form, this imbalance is corrected: negative values indicate mitigation effects, while positive values indicate amplification. Consequently, for soybean oil, soybean meal, and wheat, the average effect is actually mitigation, as shown by the negative means in the fifth column.

Table 11: **Descriptive statistics of the offset measures**

This table shows the descriptive statistics of *Offset Value* and *Offset Dummy*

| | | *Offest Value* | | | | | | | *Offset Dummy* |
|---|---|---|---|---|---|---|---|---|---|
| | | Absolute Value | | | Logarithm | | | | |
| Commodity | Observation | Mean | Min | Max | Mean | Min | Max | Std | Mean |
| Soybean oil | 259 | 2.733 | 0.012 | 306.525 | -0.041 | -4.398 | 5.725 | 0.982 | 0.606 |
| Corn | 227 | 1.513 | 0.000 | 40.762 | 0.024 | -7.602 | 3.708 | 0.956 | 0.577 |
| Cocoa | 228 | 1.632 | 0.012 | 59.646 | 0.015 | -4.423 | 4.088 | 0.879 | 0.583 |
| Cotton | 214 | 2.596 | 0.017 | 108.109 | 0.251 | -4.072 | 4.683 | 0.914 | 0.659 |
| Feather cattle | 238 | 3.239 | 0.003 | 54.603 | 0.449 | -5.688 | 4.000 | 1.340 | 0.689 |
| Coffee | 230 | 1.864 | 0.127 | 30.712 | 0.237 | -2.061 | 3.425 | 0.782 | 0.626 |
| Hard Red wheat | 266 | 1.378 | 0.014 | 6.265 | 0.128 | -4.291 | 1.835 | 0.715 | 0.647 |
| Live cattle | 253 | 14.348 | 0.011 | 2105.622 | 0.389 | -4.532 | 7.652 | 1.434 | 0.656 |
| Lean hogs | 261 | 2.271 | 0.025 | 65.981 | 0.113 | -3.689 | 4.189 | 1.249 | 0.582 |
| Soybean | 248 | 7.902 | 0.015 | 1669.947 | 0.008 | -4.179 | 7.421 | 0.768 | 0.536 |
| Sugar | 214 | 1.275 | 0.012 | 6.991 | 0.100 | -4.437 | 1.945 | 0.630 | 0.673 |
| Soybean meal | 111 | 1.271 | 0.020 | 15.301 | -0.039 | -3.892 | 2.728 | 0.825 | 0.640 |
| Wheat | 235 | 1.835 | 0.004 | 65.226 | -0.091 | -5.480 | 4.178 | 1.161 | 0.591 |

In addition to the offset value, the four regressions include a second dependent variable, the offset dummy, which serves as an effective robustness check. First, as a simple binary variable, it offers a straightforward and intuitive way to distinguish between amplification and mitigation effects, taking a value of 1 in the case of amplification, i.e., when $|\textit{spot price factor}+\textit{CF factor}| >$

$|spot\ price\ factor|$. Second, evidence of mitigation effects is more reliable when it aligns with the offset dummy. The mean of the offset dummy, shown in the sixth column of Table 11, suggests a bias towards amplification effects, as it is above 0.5 for all commodities. This indicates that financial traders amplify price changes in more than half of the sample weeks. Hence, using the *offset dummy* in regression analysis provides a stricter assessment of mitigation effects compared to the offset value.

Firstly, I validate the finding's robustness by showing that financial traders served as amplifiers in the GFC and as mitigators in the Russia-Ukraine war, even after controlling for year- and commodity-specific heterogeneity and seasonality.

$$offset\ measure_{c,y,m,t} = \beta_0 + \beta_1 GFC\ dummy_{c,y,m,t} + \beta_2 RU\ dummy_{c,y,m,t} + \omega_c + \eta_y + \psi_m + e_{c,y,m,t}, \tag{30}$$

where c, y, m index commodity, year, and month. The *offset measure* refers to either the *offset dummy* or the *offset value*, and Table 12 reports the estimation results. All specifications statistically support the mitigation effects of financial traders during the Russia-Ukraine war, even when the offset dummy is used as the dependent variable. This is not the case for the amplification role of financial traders during the GFC. However, once yearly trends are controlled, the effect becomes statistically significant for both the offset dummy and offset value. For interpreting the magnitude, an additional calculation step is needed for the offset value due to its logarithmic form. Using the estimated coefficients in the eighth column, if financial traders had not been in the market, price changes would have been 44.6% smaller during the GFC (as $e^{0.369} \approx 1.446$), and 28.3% larger during the Russia-Ukraine war (as $e^{-0.333} \approx 0.717$). In other words, financial traders amplified price changes by 28.3% during the GFC while dampening them by 28.3% during the Russia-Ukraine war.

The next regression examines the relevance of financial traders' market share on their variable roles in either amplifying or mitigating price changes in futures markets, using the following regression form:

$$\begin{aligned} offset\ measure_{c,y,m,t} = {} & \beta_0 + \beta_1 GFC\ dummy_{c,y,m,t} + \beta_2 RU\ dummy_{c,y,m,t} \\ & + \beta_3 OI\ ratio\ Financial\ traders_{c,y,m,t} + \beta_4 OI\ ratio\ Index\ traders_{c,y,m,t} \\ & + \omega_c + \eta_y + \psi_m + e_{c,y,m,t}, \end{aligned} \tag{31}$$

where the OI ratios of financial traders and index traders are defined in the data section,

Table 12: **Panel Regression Results for the Impact of the Two Market Disruptions on Offsetting Measures**

This table presents the regression results based on the specification shown in Equation 30. The dependent variable is the *offset measure* (*offset_dummy* or *Offset Value*), while the independent variables include the *GFC dummy* and the *RU dummy*, capturing the periods of the Global Financial Crisis (GFC) and the Russia-Ukraine war, respectively. The inclusion of fixed effects, such as commodity, year, and month fixed effects ($\omega_c$, $\eta_y$, and $\psi_m$), varies across model specifications, as indicated in the table. ***, **, and * denote 1%, 5%, and 10% significance, respectively. T-statistics are in parentheses, except. The period of the GFC is from September 15, 2008, to June 1, 2011, following Cheng, Kirilenko, and Xiong (2014). For the Russia-Ukraine war, the date, February 14, 2022, follows its operational announcement.

| | **Offset Dummy** | | | | **Offset Value** | | | |
|---|---|---|---|---|---|---|---|---|
| GFC Dummy | -0.0174 | -0.0152 | 0.2412*** | 0.2447*** | 0.0204 | 0.0439 | 0.3557*** | 0.3686*** |
| | (-0.7653) | (-0.6618) | (5.4328) | (5.4648) | (0.4130) | (0.8881) | (3.7101) | (3.9374) |
| RU Dummy | -0.2844*** | -0.2932*** | -0.2529*** | -0.2486*** | -0.4470*** | -0.4286*** | -0.3402** | -0.3329** |
| | (-10.2976) | (-10.5015) | (-3.4241) | (-3.0083) | (-8.1720) | (-8.1554) | (-2.9631) | (-2.8562) |
| Constant | 0.6566*** | 0.6782*** | 0.6835*** | 0.7015*** | 0.1750*** | 0.3022*** | 0.1845 | 0.1229 |
| | (62.6229) | (21.0874) | (13.0797) | (11.5246) | (8.1720) | (5.6799) | (1.6358) | (0.8551) |
| Commodity FE | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Year FE | No | No | Yes | Yes | No | No | Yes | Yes |
| Month FE | No | No | No | Yes | No | No | No | Yes |
| R-squared | 0.0356 | 0.0450 | 0.1213 | 0.1251 | 0.0207 | 0.0443 | 0.0799 | 0.0828 |
| Observations | 2984 | 2984 | 2984 | 2984 | 2984 | 2984 | 2984 | 2984 |

and Table 13 presents the estimation results. It is important to emphasise that the market share of index traders is included as a control variable. Therefore, the interpretation of the impact of the market share of financial traders reflects an increase specifically in financial speculators, even though the variable of interest remains the OI ratio of financial traders rather than financial speculators. This focus is due, firstly, to the fact that the commercial-financial factor encompasses the trading impacts of both speculators and index traders. Secondly, the market share of financial speculators is considered more crucial due to the higher price elasticity of their demand, in contrast to the lower price elasticity of index traders. The results for the GFC and Russia-Ukraine war period dummies are consistent with those in Table 12. Furthermore, it is evident that a higher market share of financial traders is statistically significantly associated with stronger amplification effects, regardless of whether it is during the GFC or the Russia-Ukraine war. Hence, for the average market share of financial traders, which is 55%, the CF factor amplifies price fluctuations nearly twofold (as $e^{0.55\times 1.263} \approx 2.003$) given the market share of the index traders.[13] Overall, Table 13 clearly shows a statistically significant and strong

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[13] Please note that, since market share is calculated as a ratio, a one-unit change in the OI ratios of financial

correlation between the amplification effects of financial traders and their market share.

Table 13: **Panel Regression Results for the Impact of Open Interest Ratios and Market Disruptions on Offsetting Measures**

This table presents the regression results based on the specification shown in Equation 31. The inclusion of fixed effects, such as commodity, year, and month fixed effects ($\omega_c$, $\eta_y$, and $\psi_m$), varies across model specifications, as indicated in the table. ***, **, and * denote 1%, 5%, and 10% significance, respectively. t-statistics are in parentheses. The periods of the GFC and the Russia-Ukraine war follow the same definitions as before.

| | **Offset Dummy** | | | | **Offset Value** | | | |
|---|---|---|---|---|---|---|---|---|
| GFC Dummy | -0.0007 | 0.0020 | 0.2419*** | 0.2462*** | 0.0557 | 0.0494 | 0.3558*** | 0.3706*** |
| | (-0.0317) | (0.0849) | (5.4537) | (5.4913) | (1.1087) | (0.9780) | (3.7115) | (3.9577) |
| RU Dummy | -0.2719*** | -0.2882*** | -0.2831*** | -0.2783*** | -0.4189*** | -0.4362*** | -0.3882** | -0.3823*** |
| | (-9.7578) | (-10.2382) | (-3.8180) | (-3.3392) | (-6.4134) | (-6.5663) | (-2.4219) | (-2.6483) |
| OI ratio Financial traders | 0.3558*** | 0.9191*** | 0.7784*** | 0.7538*** | 1.0003*** | 0.9584** | 1.2463*** | 1.2629*** |
| | (3.0215) | (4.7504) | (3.5967) | (3.3824) | (3.6088) | (2.3813) | (2.6641) | (2.6761) |
| OI ratio Index | -0.5421*** | -0.5875** | -0.2694 | -0.2711 | -0.9740** | -0.0427 | -0.5577 | -0.6084 |
| | (-2.6258) | (-2.4880) | (-0.8814) | (-0.8807) | (-2.0835) | (-0.0815) | (-0.8442) | (-0.8999) |
| Constant | 0.5631*** | 0.3128*** | 0.3486*** | 0.3811*** | -0.1933* | -0.1668 | -0.3306 | -0.3882 |
| | (10.5935) | (3.2413) | (3.3556) | (3.5017) | (-1.6572) | (-0.8501) | (-1.4722) | (-1.6082) |
| Commodity FE | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Year FE | No | No | Yes | Yes | No | No | Yes | Yes |
| Month FE | No | No | No | Yes | No | No | No | Yes |
| R-squared | 0.0389 | 0.0523 | 0.1256 | 0.1290 | 0.0259 | 0.0462 | 0.0822 | 0.0852 |
| Observations | 2984 | 2984 | 2984 | 2984 | 2984 | 2984 | 2984 | 2984 |

The third regression aims to measure the association between the role of financial traders and their market share separately during the GFC and the Russia-Ukraine war by utilizing interaction terms between financial traders' market share and the respective period dummies for the GFC and the Russia-Ukraine war. Specifically, the regression follows this form:

$$\begin{aligned}
\mathit{offset\ measure}_{c,y,m,t} = {} & \beta_0 + \beta_1 \mathit{GFC\ dummy}_{c,y,m,t} + \beta_2 \mathit{RU\ dummy}_{c,y,m,t} \\
& + \beta_3 \mathit{OI\ ratio\ Financial\ traders}_{c,y,m,t} + \beta_4 \mathit{OI\ ratio\ Index\ traders}_{c,y,m,t} \\
& + \beta_5 \left(\mathit{OI\ ratio\ Financial\ traders}_{c,y,m,t} \times \mathit{GFC\ dummy}_{c,y,m,t}\right) \\
& + \beta_6 \left(\mathit{OI\ ratio\ Financial\ traders}_{c,y,m,t} \times \mathit{RU\ dummy}_{c,y,m,t}\right) \\
& + \omega_c + \eta_y + \psi_m + e_{c,y,m,t}. \qquad (32)
\end{aligned}$$

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traders and index traders represents a 100% market share for each.

Table 14 shows the estimated results, where the coefficient for the GFC dummy becomes significantly negative, whereas it is significantly positive in Table 12 without the interaction term with financial traders' market share. The positive significance of this interaction term in Table 14 suggests that the amplification effect observed during the GFC operates through the financial traders' market share channel. Despite the negative baseline effect, the statistically significant and strongly positive interaction term ensures that the total estimated effect of the GFC on the offset measure remains an amplification effect. For example, with financial traders' average market share at 55%, the overall GFC effect on the offset value implies that the financial traders amplify price changes by 47.7% using the results in the 8th column (as $e^{(-0.6142+0.55\times1.8259)} \approx 1.477$). In contrast, the overall effect of the Russia-Ukraine war on the offset measure suggests that financial traders dampen price changes by 31.6% at the average financial traders' market share, 55% (as $e^{(-1.1735+0.55\times1.4428)} \approx 0.684$).[14]

The fourth regression aims at testing if quadratic and cubic forms building on the third regression model is preferred, confirming that the linear form expressed by Equation 9 and the respective results reported in Table 14 is the preferred model. The regression results for the quadratic and the cubic form are in Table 15, where the column for *Linear Model* represents the result of the last column in Table 14. I base the model comparisons on the log-likelihood ratio test, AIC, and BIC. The log-likelihood ratio test column in Table 15 reports the resulting p-values for comparing the linear model against the quadratic and the cubic model are well above 0.05. The linear model has the smallest AIC and BIC. This indicates that adding quadratic and cubic terms does not result in a statistically significant improvement in fit. Therefore, I conclude that the linear model is preferred.

Figure 6 visualises the predicted offset values derived from the results in the last column of Table 14, based on the linear model specified in Equation 32. The figure illustrates the estimated offset values for three distinct periods as functions of the ratio of financial traders: the GFC period (green), the Russia-Ukraine war period (yellow), and the remaining period outside these two, referred to as the base period (blue). These predicted values differ because the two period dummies in Equation 32, *GFC dummy* and *RU dummy*, take on different values: both dummies are 0 for the base period, *GFC dummy* is 1 for the GFC period, and *RU dummy*

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[14] Please note that the average market share is calculated separately for the GFC and the Russia-Ukraine war periods, but in both cases, it is 55%.

Table 14: **Panel Regression Results for Offsetting Measures: Interaction Effects of Market Disruptions and Marke Share**

This table presents the regression results based on the specification shown in Equation 32. The inclusion of fixed effects, such as commodity, year, and month fixed effects ($\omega_c$, $\eta_y$, and $\psi_m$), varies across model specifications, as indicated in the table. ***, **, and * denote 1%, 5%, and 10% significance, respectively. t-statistics are in parentheses. The periods of the GFC and the Russia-Ukraine war follow the same definitions as before.

| | **Offset Dummy** | | | | **Offset Value** | | | |
|---|---|---|---|---|---|---|---|---|
| GFC Dummy | -0.5763*** | -0.5910*** | -0.2960** | -0.2856** | -0.8814*** | -0.9931*** | -0.6113** | -0.6142* |
| | (-4.4520) | (-4.4821) | (-2.1976) | (-2.1101) | (-2.8492) | (-3.2283) | (-2.0900) | (-1.9433) |
| RU Dummy | -0.9322*** | -0.9227*** | -0.7515*** | -0.7651*** | -1.0512*** | -1.1962*** | -1.1653*** | -1.1735*** |
| | (-5.9627) | (-5.7698) | (-4.2140) | (-3.9633) | (-3.0347) | (-3.4254) | (-3.0995) | (-3.0870) |
| Ratio of Financial Trader | 0.0199 | 0.5106** | 0.5394** | 0.5170** | 0.5705* | 0.3568 | 0.6634 | 0.6730 |
| | (0.1505) | (2.4639) | (2.3482) | (2.1942) | (1.8707) | (0.8274) | (1.3459) | (1.3519) |
| Interaction with GFC Dummy | 1.0600*** | 1.0939*** | 0.9933*** | 0.9821*** | 1.7307*** | 1.9252*** | 1.7913*** | 1.8259*** |
| | (4.5669) | (4.6436) | (4.2136) | (4.2294) | (2.8819) | (3.2388) | (3.4994) | (3.0924) |
| Interaction with RU Dummy | 1.2166*** | 1.1733*** | 1.2724*** | 1.2790*** | 1.1640* | 1.4058** | 1.4165** | 1.4428** |
| | (4.2323) | (3.9849) | (4.4638) | (4.2273) | (1.8243) | (2.1689) | (2.2936) | (2.2386) |
| Ratio of Index Traders | -0.6320*** | -0.6775*** | -0.4664 | -0.4606 | -1.1580** | -0.2323 | -0.7397 | -0.8007 |
| | (-3.0481) | (-2.8490) | (-1.5170) | (-1.4978) | (-2.4645) | (-0.4390) | (-1.1128) | (-1.1775) |
| Constant | 0.7668*** | 0.5121*** | 0.5861*** | 0.6177*** | 0.0805 | 0.1852 | 0.0103 | -0.0476 |
| | (11.9723) | (5.1631) | (5.5141) | (5.5558) | (0.5852) | (0.8649) | (0.0428) | (-0.1862) |
| Commodity FE | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Year FE | No | No | Yes | Yes | No | No | Yes | Yes |
| Month FE | No | No | No | Yes | No | No | No | Yes |
| R-squared | 0.0491 | 0.0622 | 0.1392 | 0.1419 | 0.0301 | 0.0516 | 0.0869 | 0.0901 |
| Observations | 2984 | 2984 | 2984 | 2984 | 2984 | 2984 | 2984 | 2984 |

Table 15: **Results Comparison of Non-Linearity During the Two Market Disruptions**

This table shows panel regression results for the quadratic and cubic models as well as the linear model, which is identical to the specification shown in Equation 32. The last column from Table 14 represents the linear model result. ***, **, and * denote 1%, 5%, and 10% significance, respectively. T-statistics are in parentheses. The log-likelihood ratio column shows the p-values from the log-likelihood ratio tests comparing the linear model against the quadratic and cubic models respectively.

| | **Offset Value** | | |
|---|---|---|---|
| | **Linear Model** | **Quadratic Model** | **Cubic Model** |
| GFC Dummy | -0.6142* | 0.4041 | -7.3077 |
| | (-1.9433) | (0.2379) | (-0.7482) |
| RU Dummy | -1.1735*** | -1.2032 | 2.1520 |
| | (-3.0870) | (-0.4962) | (0.1582) |
| Ratio of Financial Trader | 0.6730 | 1.8470 | -18.5179 |
| | (1.3519) | (0.5693) | (-0.8311) |
| Squared: Ratio of Financials | | -1.0321 | 34.8630 |
| | | (-0.3425) | (0.8747) |
| Cubic: Ratio of Financials | | | -20.6002 |
| | | | (-0.8836) |
| Financial Ratio × GFC Dummy | 1.8259*** | -1.8920 | 40.5531 |
| | (3.0924) | (-0.3054) | (0.7550) |
| Squared: Ratio of Financials × GFC Dummy | | 3.2794 | -72.9649 |
| | | (0.5938) | (-0.7538) |
| Cubic: Ratio of Financials × GFC Dummy | | | 44.6966 |
| | | | (0.7828) |
| Ratio of Financials × RU Dummy | 1.4428** | 1.5312 | -16.3928 |
| | (2.2386) | (0.1763) | (-0.2211) |
| Squared: Ratio of Financials × RU Dummy | | -0.0538 | 31.1612 |
| | | (-0.0071) | (0.2350) |
| Cubic: Ratio of Financials × RU Dummy | | | -17.7550 |
| | | | (-0.2285) |
| Ratio of Index Traders | -0.8007 | -0.7600 | -0.7092 |
| | (-1.1775) | (-1.1068) | (-1.0144) |
| Constant | -0.0476 | -0.5055 | 2.9812 |
| | (-0.1862) | (-0.6264) | (0.7920) |
| Commodity FE | Yes | Yes | Yes |
| Monthly FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 2984 | 2984 | 2984 |
| Log-Likelihood | -4166 | -4165.7 | -4164.9 |
| Log-Likelihood Ratio Test | | 0.9999 | 0.9992 |
| AIC | 8426 | 8431 | 8436 |
| BIC | 8708 | 8731 | 8754 |
| R-squared | 0.0901 | 0.090 | 0.091 |

is 1 for the Russia-Ukraine war period.[15]

Figure 6: **Estimated Offset Values for Different Periods Based on the Market Share of Financial Traders measured by OI Ratio**

This plot visualises the estimated offset values for the base period, the Global Financial Crisis (GFC) period, and the Russia-Ukraine (RU) war period as functions of the ratio of financial traders. The solid lines represent the estimated offset values during each period: the base period (blue), GFC period (green), and RU war period (yellow). The red vertical dashed line indicate the average market share of financial traders both during the GFC and the RU war, which is 55%.

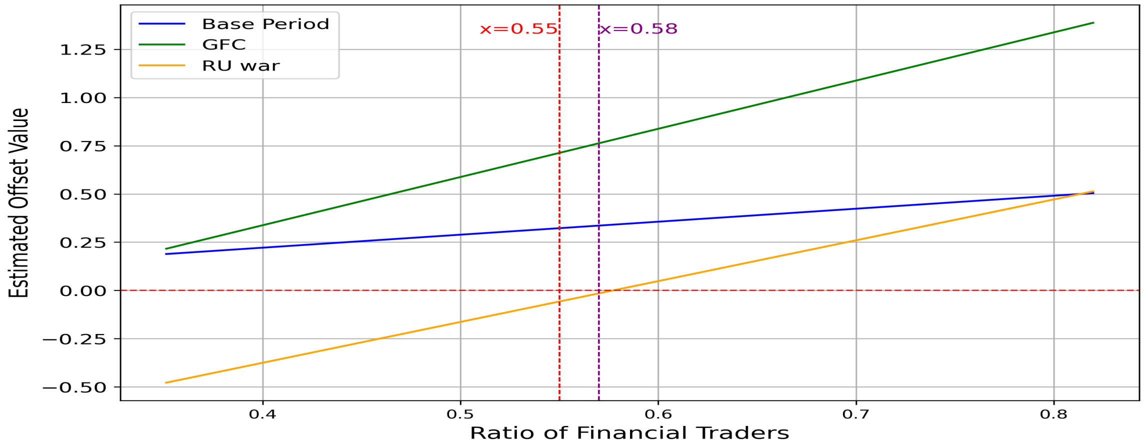

Figure 6 explicitly illustrates the two primary findings of this paper: the role of financial traders depends on both the nature of market disruptions and their market share. Firstly, the green line, representing the estimated offset value during the GFC, remains consistently positive regardless of the ratio of financial traders. This indicates that financial traders amplified price changes during this period, irrespective of their market share. Conversely, the yellow line, representing the Russia-Ukraine war period, initially shows negative offset values, indicating that financial traders act as a mitigating force at lower market shares by offsetting price changes. As the yellow line slopes upward, the offset value approaches zero and eventually shifts to positive as financial traders' market share increases. This transition implies that as financial traders dominate a larger share of the market, their role shifts from mitigating price changes to amplifying them, resulting in greater price fluctuations. It is noteworthy that at the average market ratio of 55% in both periods, the estimated offset value is substantially positive for the GFC, while it is close to zero for the Russia-Ukraine war. This observation aligns with

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[15] The visualisation indicates that the marginal effect of an increase in financial traders' market share is the same for both periods, as seen through the seemingly parallel slopes of the GFC and Russia-Ukraine lines. The coefficients in Table 14 represent the impact of a one-unit change. For meaningful interpretation, the coefficients related to the market share should be multiplied by 0.01 to reflect a 0.01-unit change.

Table 9, which shows that financial traders reduced volatility in only three commodities during the GFC, compared to nearly half of the 13 commodities during the Russia-Ukraine war.

# 5 Conclusion

This paper documents the state-dependent role of financial traders by leveraging exogenous shocks that stress different groups of traders and the micro-market structure. Financial traders amplify price changes during their own distress, as observed during the GFC, but mitigate them during commercial trader distress, such as during the Russia-Ukraine war. However, this stabilising effect reverses when financial traders dominate the market beyond a certain threshold, shifting their role from offsetting price fluctuations to amplifying them. This is a novel contribution, as it is the first study to highlight that the impact of financial traders on price changes is conditional on the nature of market disruptions and their market share.

The findings are consistent with the hedging pressure theory, which posits that financial traders provide liquidity to earn a risk premium and stabilise prices by offsetting commercial traders' hedging demands. I argue that when financial traders fail to provide liquidity, their trading no longer systematically mitigates price changes and may instead intensify them, a possibility inversely implied by the hedging pressure theory. The findings support this argument by confirming two key hypotheses: first, financial turmoil restricts the liquidity provision role of financial traders, leading them to amplify price changes; and second, when the trading volume of financial traders exceeds that of commercial traders, their dominance disrupts their liquidity-providing role, similarly resulting in amplified price changes.

To obtain these findings, I employ a two-step procedure. In the first step, I construct and estimate a structural model based on the hedging pressure theory, which decomposes futures returns primarily into spot price and commercial-financial factors. This decomposition enables a unique measurement of how trading between financial and commercial traders amplifies or dampens futures market price responses to significant fluctuations in each commodity's spot market. The results from the first step show that financial traders reduced volatility in only three commodities during the GFC, whereas this number increased to eight out of 13 markets during the Russia-Ukraine war. Consequently, the second step involves panel regressions to analyse all 13 commodities collectively, aiming to identify and confirm instances where financial traders amplify price changes across commodities while controlling for commodity- and year-specific heterogeneity, as well as seasonality. This analysis underscores the distinctive and conditional role of financial traders during the two market disruptions, as well as their market share.

Overall, these results position this paper alongside Cheng, Kirilenko, and Xiong (2014) and Bonnier (2021) in emphasising the complexity of financial traders' roles and highlighting the importance of acknowledging heterogeneity across commodity markets. Specifically, this paper focuses on the conditions that may cause financial traders to shift from being liquidity providers to liquidity consumers, narrowing the research question to when financial traders potentially destabilise commodity futures markets. These findings point to the potential importance of regulatory measures, such as monitoring financial traders' market share, to enhance market stability by mitigating the risk of excessive price fluctuations. By shedding light on the mechanisms through which financial traders assume different roles in the commodity futures market, this paper informs future research and introduces a new focus on the micro-market structure for developing effective policy responses.

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# Appendix A

## A Data description

### A.1 Selection of samples

I select shocks based purely on the standard error calculated from the entire sample, while asset pricing studies typically rely on abnormal returns, especially for event studies. However, this paper cannot adopt that approach, as the selection criteria yield too few data points during global crises, such as the Global Financial Crisis and the Russia-Ukraine war. To illustrate this point, the following table lists the number of selected samples based on different methods of calculating substantial return movements. The calculation of abnormal returns, $AR_t$, and standardized abnormal returns, $SAR_t$ follows McKenzie, Thomsen, and Dixon (2004):

$$AR_t = \Delta F_t - \Delta \bar{F}_t$$

$$SAR_t = \frac{AR_t}{\sqrt{s^2 \left(1 + \frac{1}{T}\right)}}$$

, where $\Delta \bar{F}_t$ is the arithmetic mean of $\Delta F_t$ over the $T = 4$ weeks prior to $t$.

Table A.16: **Number of observations based on different criteria of extreme return on Monday**
The period of the GFC is from September 15, 2008, to June 1, 2011, as defined in Cheng, Kirilenko, and Xiong (2014). The beginning date of the Russia-Ukraine war is February 14, 2022, following its operational announcement. Note that the whole sample period is from January 10, 2006, to 31st May, 2024, which leaves 964 observations without any selection.

| **Commodity** | **Criteria** | **Whole Period** | **GFC** | **RU War** |
|---|---|---|---|---|
| Soybean oil | Extraordinary Return (Base) | 256 | 53 | 44 |
| | Abnormal Return | 203 | 43 | 1 |
| | Standardized Abnormal Return | 203 | 43 | 1 |
| Corn | Extraordinary Return (Base) | 222 | 51 | 22 |
| | Abnormal Return | 189 | 38 | 30 |
| | Standardized Abnormal Return | 189 | 38 | 30 |
| Cocoa | Extraordinary Return (Base) | 229 | 52 | 32 |
| | Abnormal Return | 123 | 28 | 33 |
| | Standardized Abnormal Return | 123 | 28 | 33 |
| Cotton | Extraordinary Return (Base) | 212 | 60 | 40 |
| | Abnormal Return | 155 | 43 | 38 |
| | Standardized Abnormal Return | 155 | 43 | 38 |
| Feather cattle | Extraordinary Return (Base) | 231 | 25 | 23 |
| | Abnormal Return | 181 | 8 | 40 |
| | Standardized Abnormal Return | 181 | 8 | 40 |
| Coffee | Extraordinary Return (Base) | 226 | 36 | 38 |
| | Abnormal Return | 178 | 29 | 47 |

*Continued on next page*

Table A.16: (Continued) Number of observations according to different criteria of extreme return on Monday

| **Commodity** | **Criteria** | **Whole Period** | **GFC** | **RU War** |
|---|---|---|---|---|
| | Standardized Abnormal Return | 178 | 29 | 47 |
| Hard Red wheat | Extraordinary Return (Base) | 262 | 52 | 29 |
| | Abnormal Return | 196 | 46 | 42 |
| | Standardized Abnormal Return | 196 | 46 | 42 |
| Live cattle | Extraordinary Return (Base) | 250 | 41 | 12 |
| | Abnormal Return | 150 | 19 | 11 |
| | Standardized Abnormal Return | 150 | 19 | 11 |
| Lean hogs | Extraordinary Return (Base) | 258 | 35 | 8 |
| | Abnormal Return | 256 | 32 | 25 |
| | Standardized Abnormal Return | 256 | 32 | 25 |
| Soybean | Extraordinary Return (Base) | 245 | 52 | 29 |
| | Abnormal Return | 207 | 42 | 36 |
| | Standardized Abnormal Return | 207 | 42 | 36 |
| Sugar | Extraordinary Return (Base) | 199 | 46 | 18 |
| | Abnormal Return | 146 | 41 | 28 |
| | Standardized Abnormal Return | 146 | 41 | 28 |
| Soybean meal | Extraordinary Return (Base) | 111 | 0 | 30 |
| | Abnormal Return | 107 | 0 | 0 |
| | Standardized Abnormal Return | 107 | 0 | 0 |
| Wheat | Extraordinary Return (Base) | 234 | 61 | 30 |
| | Abnormal Return | 196 | 43 | 37 |
| | Standardized Abnormal Return | 196 | 43 | 37 |

## A.2 Summary Statistics of the samples

This section reports the number of observations, the mean, the standard deviation, the minimum value, and the maximum value of the five variables used in the structural form estimation for the 13 agricultural commodities, respectively.

Table A.17: Summary Statistics of the samples

| Category | Observations | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Spot Price | | | | | |
| Soybean oil | 259 | 3.80 | 3.1122 | -8.1400 | 9.7800 |
| Corn | 227 | -137.78 | 34.5281 | -94.7500 | 94.0000 |
| Cocoa | 228 | 1594.74 | 211.5345 | -396.0000 | 1544.0000 |
| Cotton | 214 | -1.47 | 6.8532 | -23.2800 | 20.0800 |
| Feather cattle | 238 | -18.44 | 5.1952 | -19.2700 | 14.5700 |
| Coffee | 230 | 20.74 | 10.4830 | -26.2300 | 37.0800 |
| Hard Red wheat | 266 | -138.72 | 50.2231 | -169.0000 | 192.7500 |
| Live cattle | 253 | -4.81 | 4.6081 | -13.8700 | 14.4400 |
| Lean hogs | 261 | 15.50 | 4.7855 | -11.4900 | 10.4770 |
| Soybean | 248 | -109.12 | 63.8895 | -207.0000 | 133.0000 |
| Sugar | 214 | -1.14 | 1.3924 | -6.8100 | 4.5000 |
| Soybean meal | 111 | 220.63 | 34.9220 | -152.7000 | 67.6000 |
| Wheat | 235 | 23.72 | 52.6317 | -197.0000 | 182.2500 |
| Commercials' trading | | | | | |
| Soybean oil | 259 | -0.23 | 0.0439 | -0.1851 | 0.1426 |
| Corn | 227 | 0.11 | 0.0246 | -0.0853 | 0.0861 |
| Cocoa | 228 | -0.04 | 0.0350 | -0.0996 | 0.0893 |
| Cotton | 214 | -0.33 | 0.0416 | -0.1221 | 0.1309 |

*Continued from previous page*

| Category | Observations | Mean(%) | SD | Min | Max |
|---|---|---|---|---|---|
| Feather cattle | 238 | -0.02 | 0.0222 | -0.0821 | 0.0860 |
| Coffee | 230 | -0.11 | 0.0381 | -0.1077 | 0.1039 |
| Hard Red wheat | 266 | 0.02 | 0.0305 | -0.1038 | 0.0873 |
| Live cattle | 253 | 0.09 | 0.0195 | -0.0535 | 0.0620 |
| Lean hogs | 261 | -0.28 | 0.0245 | -0.1071 | 0.0596 |
| Soybean | 248 | -0.03 | 0.0344 | -0.1224 | 0.0875 |
| Sugar | 214 | 0.24 | 0.0319 | -0.1003 | 0.1152 |
| Soybean meal | 111 | -0.74 | 0.0392 | -0.1216 | 0.0751 |
| Wheat | 235 | -0.24 | 0.0234 | -0.0924 | 0.0602 |
| Financials' trading | | | | | |
| Soybean oil | 259 | 0.17 | 0.0337 | -0.0921 | 0.1439 |
| Corn | 227 | -0.11 | 0.0212 | -0.0749 | 0.0804 |
| Cocoa | 228 | -0.05 | 0.0283 | -0.0872 | 0.0869 |
| Cotton | 214 | 0.30 | 0.0328 | -0.1246 | 0.0990 |
| Feather cattle | 238 | -0.02 | 0.0322 | -0.1046 | 0.1004 |
| Coffee | 230 | 0.10 | 0.0347 | -0.1061 | 0.0965 |
| Hard Red wheat | 266 | 0.00 | 0.0255 | -0.0627 | 0.0837 |
| Live cattle | 253 | -0.05 | 0.0210 | -0.0598 | 0.0596 |
| Lean hogs | 261 | 0.31 | 0.0233 | -0.0824 | 0.1048 |
| Soybean | 248 | 0.05 | 0.0282 | -0.0699 | 0.1029 |
| Sugar | 214 | -0.09 | 0.0252 | -0.1084 | 0.0806 |
| Soybean meal | 111 | 0.52 | 0.0309 | -0.0567 | 0.0872 |
| Wheat | 235 | 0.33 | 0.0224 | -0.0568 | 0.0991 |
| Index Trders' trading | | | | | |
| Soybean oil | 259 | 0.07 | 0.0083 | -0.0279 | 0.0467 |
| Corn | 227 | 0.00 | 0.0056 | -0.0197 | 0.0242 |
| Cocoa | 228 | 0.04 | 0.0106 | -0.0537 | 0.0338 |
| Cotton | 214 | -0.05 | 0.0078 | -0.0258 | 0.0356 |
| Feather cattle | 238 | -0.02 | 0.0112 | -0.0376 | 0.0685 |
| Coffee | 230 | 0.02 | 0.0072 | -0.0212 | 0.0272 |
| Hard Red wheat | 266 | 0.08 | 0.0111 | -0.0415 | 0.0842 |
| Live cattle | 253 | -0.03 | 0.0069 | -0.0427 | 0.0241 |
| Lean hogs | 261 | 0.02 | 0.0105 | -0.0584 | 0.0620 |
| Soybean | 248 | -0.01 | 0.0070 | -0.0257 | 0.0311 |
| Sugar | 214 | -0.10 | 0.0071 | -0.0283 | 0.0298 |
| Soybean meal | 111 | 0.09 | 0.0082 | -0.0194 | 0.0243 |
| Wheat | 235 | -0.05 | 0.0079 | -0.0201 | 0.0284 |
| Futures Return | | | | | |
| Soybean oil | 259 | 0.40 | 0.0541 | -0.1655 | 0.1538 |
| Corn | 227 | 0.29 | 0.0652 | -0.2063 | 0.2021 |
| Cocoa | 228 | 0.88 | 0.0575 | -0.1540 | 0.1987 |
| Cotton | 214 | 0.04 | 0.0712 | -0.3296 | 0.1753 |
| Feather cattle | 238 | -0.09 | 0.0330 | -0.1525 | 0.1350 |
| Coffee | 230 | 0.78 | 0.0752 | -0.1349 | 0.2242 |
| Hard Red wheat | 266 | 0.07 | 0.0650 | -0.1510 | 0.2192 |
| Live cattle | 253 | -0.29 | 0.0319 | -0.1672 | 0.1237 |
| Lean hogs | 261 | 0.34 | 0.0671 | -0.2145 | 0.3053 |
| Soybean | 248 | 0.16 | 0.0515 | -0.1409 | 0.1295 |
| Sugar | 214 | 0.25 | 0.0683 | -0.2054 | 0.2519 |
| Soybean meal | 111 | 1.10 | 0.0596 | -0.1201 | 0.1580 |
| Wheat | 235 | 0.40 | 0.0689 | -0.1616 | 0.2201 |

## A.3 Non-Gaussianity of the Samples

Table A.18: **Results of normality tests: Shapiro-Wilk (SW) test, the Jarque-Bera (JB) test and the Anderson-Darling (AD) test**

The table below shows p-values of the Shapiro-Wilk (SW) test, the Jarque-Bera (JB) test and AD test statistics, and its critical value at 1% significance level.

| Category | Variable | Shapiro-Wilk p-value | JB p-value | A-D Statistic | A-D Critical Value (1%) |
|---|---|---|---|---|---|
| Soybean oil | Spot Change | 0.00 | 0.00 | 15.95 | 1.09 |
| | Commercials | 0.00 | 0.00 | 3.44 | 1.09 |
| | Financials | 0.00 | 0.00 | 3.46 | 1.09 |
| | Index | 0.00 | 0.00 | 12.38 | 1.09 |
| | Futures Return | 0.00 | 0.00 | 2.28 | 1.09 |
| Corn | Spot Change | 0.00 | 0.00 | 14.01 | 1.09 |
| | Commercials | 0.00 | 0.00 | 3.27 | 1.09 |
| | Financials | 0.00 | 0.00 | 4.11 | 1.09 |
| | Index | 0.00 | 0.00 | 11.45 | 1.09 |
| | Futures Return | 0.00 | 0.00 | 8.94 | 1.09 |
| Cocoa | Spot Change | 0.00 | 0.00 | 11.64 | 1.09 |
| | Commercials | 0.00 | 0.00 | 2.96 | 1.09 |
| | Financials | 0.00 | 0.00 | 4.36 | 1.09 |
| | Index | 0.00 | 0.00 | 20.55 | 1.09 |
| | Futures Return | 0.00 | 0.00 | 2.58 | 1.09 |
| Cotton | Spot Change | 0.00 | 0.00 | 23.65 | 1.09 |
| | Commercials | 0.00 | 0.00 | 4.59 | 1.09 |
| | Financials | 0.00 | 0.00 | 5.71 | 1.09 |
| | Index | 0.00 | 0.00 | 8.12 | 1.09 |
| | Futures Return | 0.00 | 0.00 | 7.59 | 1.09 |
| Feather cattle | Spot Change | 0.00 | 0.00 | 10.24 | 1.09 |
| | Commercials | 0.00 | 0.00 | 3.59 | 1.09 |
| | Financials | 0.00 | 0.00 | 3.84 | 1.09 |
| | Index | 0.00 | 0.00 | 16.43 | 1.09 |
| | Futures Return | 0.00 | 0.00 | 5.84 | 1.09 |
| Coffee | Spot Change | 0.00 | 0.00 | 2.53 | 1.09 |
| | Commercials | 0.00 | 0.00 | 3.57 | 1.09 |
| | Financials | 0.00 | 0.00 | 3.03 | 1.09 |
| | Index | 0.00 | 0.00 | 19.05 | 1.09 |
| | Futures Return | 0.00 | 0.00 | 1.78 | 1.09 |
| Hard Red wheat | Spot Change | 0.00 | 0.00 | 10.80 | 1.09 |
| | Commercials | 0.00 | 0.00 | 2.10 | 1.09 |
| | Financials | 0.00 | 0.00 | 3.03 | 1.09 |
| | Index | 0.00 | 0.00 | 12.06 | 1.09 |
| | Futures Return | 0.00 | 0.00 | 2.92 | 1.09 |
| Live cattle | Spot Change | 0.00 | 0.00 | 7.84 | 1.09 |
| | Commercials | 0.00 | 0.00 | 3.55 | 1.09 |
| | Financials | 0.00 | 0.00 | 2.70 | 1.09 |
| | Index | 0.00 | 0.00 | 16.41 | 1.09 |
| | Futures Return | 0.00 | 0.00 | 4.49 | 1.09 |
| Lean hogs | Spot Change | 0.00 | 0.00 | 1.01 | 1.09 |
| | Commercials | 0.00 | 0.00 | 2.33 | 1.09 |
| | Financials | 0.00 | 0.00 | 2.13 | 1.09 |
| | Index | 0.00 | 0.00 | 17.84 | 1.09 |
| | Futures Return | 0.00 | 0.00 | 11.65 | 1.09 |
| Soybean | Spot Change | 0.00 | 0.00 | 6.71 | 1.09 |
| | Commercials | 0.00 | 0.00 | 1.61 | 1.09 |
| | Financials | 0.00 | 0.00 | 2.27 | 1.09 |

*Continued on next page*

| Category | Variable | Shapiro-Wilk p-value | JB p-value | A-D Statistic | A-D Critical Value (1%) |
|---|---|---|---|---|---|
|  | Index | 0.00 | 0.00 | 10.31 | 1.09 |
|  | Futures Return | 0.00 | 0.00 | 2.69 | 1.09 |
| Sugar | Spot Change | 0.00 | 0.00 | 9.05 | 1.09 |
|  | Commercials | 0.00 | 0.00 | 2.82 | 1.09 |
|  | Financials | 0.00 | 0.00 | 3.87 | 1.09 |
|  | Index | 0.00 | 0.00 | 13.05 | 1.09 |
|  | Futures Return | 0.00 | 0.00 | 2.48 | 1.09 |
| Soybean meal | Spot Change | 0.00 | 0.00 | 12.39 | 1.08 |
|  | Commercials | 0.00 | 0.00 | 1.42 | 1.08 |
|  | Financials | 0.00 | 0.00 | 1.33 | 1.08 |
|  | Index | 0.01 | 0.05 | 1.26 | 1.08 |
|  | Futures Return | 0.00 | 0.00 | 3.13 | 1.08 |
| Wheat | Spot Change | 0.00 | 0.00 | 8.13 | 1.09 |
|  | Commercials | 0.00 | 0.00 | 3.07 | 1.09 |
|  | Financials | 0.00 | 0.00 | 3.80 | 1.09 |
|  | Index | 0.00 | 0.00 | 5.02 | 1.09 |
|  | Futures Return | 0.00 | 0.00 | 5.17 | 1.09 |

## A.4 Lead-lag relationship between the spot and the futures market in the sample

In the structural model setting for Equation 2, unidirectional causality is assumed from the spot to the futures price. While this assumption aligns with some empirical studies and Pradhan, Hall, and du Toit (2021), I recognise that the lead-lag relationship is a well-established area of research, and its complexity is highlighted by studies on its time-dependency, such as Zhang, Pan, Yang, and Pu (2022) and Shao, Yang, Shao, and Stanley (2019).

To validate this assumption, I examine the relationship between spot and futures prices within the sample used in this paper, which includes 12 agricultural commodities with weekly frequency. Given the non-Gaussian nature of the sample distribution, I apply an alternative identification approach using non-Gaussianity by employing Independent Component Analysis (ICA) within the SVAR model to determine the causal ordering among variables Moneta, Entner, Hoyer, and Coad (2013) Bonhomme and Robin (2009). To follow the methodology developed by Shimizu, Hoyer, Hyvärinen, Kerminen, and Jordan (2006), I adopt LiNGAM algorithms publicly available in Github.

$$Y = \begin{bmatrix} \Delta S_t \\ \Delta F_t \end{bmatrix}.$$

The matrix equation can be represented as:

$$Y = BY,$$

where $B$ is a $2 \times 2$ matrix defines the causal interrelationships between the spot market and the futures market. The following is the estimated B matrix for each commodity.

**Commodity: Soybean oil**

$$\begin{bmatrix} 0 & 0 \\ 0.812 & 0 \end{bmatrix}$$

**Commodity: Corn**

$$\begin{bmatrix} 0 & 0 \\ 0.886 & 0 \end{bmatrix}$$

**Commodity: Cocoa**

$$\begin{bmatrix} 0 & 0 \\ 0.725 & 0 \end{bmatrix}$$

**Commodity: Cotton**

$$\begin{bmatrix} 0 & 0 \\ 0.851 & 0 \end{bmatrix}$$

**Commodity: Feeder cattle**

$$\begin{bmatrix} 0 & 0 \\ 0.424 & 0 \end{bmatrix}$$

**Commodity: Coffee**

$$\begin{bmatrix} 0 & 0 \\ 0.816 & 0 \end{bmatrix}$$

**Commodity: Hard Red wheat**

$$\begin{bmatrix} 0 & 0 \\ 0.915 & 0 \end{bmatrix}$$

**Commodity: Live cattle**

$$\begin{bmatrix} 0 & 0 \\ 0.471 & 0 \end{bmatrix}$$

**Commodity: Lean hogs**

$$\begin{bmatrix} 0 & 0.564 \\ 0 & 0 \end{bmatrix}$$

**Commodity: Soybeans**

$$\begin{bmatrix} 0 & 0 \\ 0.914 & 0 \end{bmatrix}$$

**Commodity: Sugar**

$$\begin{bmatrix} 0 & 0 \\ 0.894 & 0 \end{bmatrix}$$

**Commodity: Soybean meal**

$$\begin{bmatrix} 0 & 0 \\ 0.715 & 0 \end{bmatrix}$$

**Commodity: Wheat**

$$\begin{bmatrix} 0 & 0 \\ 0.869 & 0 \end{bmatrix}$$

Except for the feeder cattle, the ICA-algorithm-based VAR estimation supports the unidirectional causality from the spot to the futures market, which underpins the model setting for the spot price expressed by Equation 2. Feeder cattle, live cattle, and lean hogs in the livestock categories exhibit substantially lower causal effects compared to the other commodities, as their estimated coefficients are below 0.6.

# B Structural Form estimation

## B.1 Validity of the Labelling

This section provides all the $R^2$ of the regression results explained in section 3.1 but regarding the spot price, the financial speculator, and index factors. The result for the commercial-financial and the residual factors are reported in the section 3.1.

Table B.19: **The explanatory power of the spot price factor**
The table below shows $\mathbf{R}^2$ values of regressions of dependent variables in *dependent* row on the spot price factor.

| *Dependent* | **Spot Price Difference** | **Commercial Hedgers Position** | **Financial Speculators Position** | **Index Traders Position** | **Futures Return** |
|---|---|---|---|---|---|
| Soybean oil | 0.9994 | 0.3137 | 0.2693 | 0.0728 | 0.6780 |
| Corn | 1.0000 | 0.3897 | 0.2964 | 0.0589 | 0.7831 |
| Cocoa | 0.9997 | 0.2728 | 0.2098 | 0.0650 | 0.5385 |
| Cotton | 0.9996 | 0.1867 | 0.1684 | 0.0101 | 0.7144 |
| Feather cattle | 0.9993 | 0.0741 | 0.1152 | 0.0233 | 0.1759 |
| Coffee | 0.9999 | 0.5219 | 0.5168 | 0.0838 | 0.6606 |
| Hard Red wheat | 0.9996 | 0.3410 | 0.2591 | 0.0592 | 0.8289 |
| Live cattle | 0.9996 | 0.1767 | 0.1974 | 0.0312 | 0.2310 |
| Lean hogs | 0.9997 | 0.3551 | 0.3298 | 0.0346 | 0.2475 |
| Soybean | 0.9997 | 0.5220 | 0.4478 | 0.1248 | 0.8275 |
| Sugar | 0.9999 | 0.3362 | 0.2741 | 0.0000 | 0.7868 |
| Soybean meal | 0.9994 | 0.3547 | 0.3526 | 0.0058 | 0.5303 |
| Wheat | 0.9996 | 0.2330 | 0.1669 | 0.0409 | 0.7434 |

Table B.20: **The explanatory power of the Financial Speculator Factor**
The table below shows $\mathbf{R}^2$ values of regressions of dependent variables in *dependent* row on the Financial Speculator Factor.

| *Dependent* | **Spot Price Difference** | **Commercial Hedgers Position** | **Financial Speculators Position** | **Index Traders Position** | **Futures Return** |
|---|---|---|---|---|---|
| Soybean oil | 0.0015 | 0.6038 | 0.7210 | 0.0007 | 0.0181 |

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| *Dependent* | **Spot Price Difference** | **Commercial Hedgers Position** | **Financial Speculators Position** | **Index Traders Position** | **Futures Return** |
|---|---:|---:|---:|---:|---:|
| Corn | 0.0039 | 0.6494 | 0.6609 | 0.1924 | 0.0183 |
| Cocoa | 0.0010 | 0.0539 | 0.1514 | 0.0332 | 0.2101 |
| Cotton | 0.0038 | 0.8269 | 0.7931 | 0.1271 | 0.0221 |
| Feather cattle | 0.0019 | 0.5332 | 0.8940 | 0.0011 | 0.0317 |
| Coffee | 0.0002 | 0.4087 | 0.4646 | 0.0406 | 0.0367 |
| Hard Red wheat | 0.0014 | 0.4613 | 0.7345 | 0.0007 | 0.0070 |
| Live cattle | 0.0000 | 0.7685 | 0.6247 | 0.1417 | 0.1726 |
| Lean hogs | 0.0015 | 0.6731 | 0.4854 | 0.0943 | 0.0545 |
| Soybean | 0.0045 | 0.4562 | 0.5896 | 0.0138 | 0.0150 |
| Sugar | 0.0003 | 0.6132 | 0.5761 | 0.0647 | 0.0033 |
| Soybean meal | 0.0001 | 0.2477 | 0.3196 | 0.0423 | 0.0003 |
| Wheat | 0.0086 | 0.5999 | 0.8281 | 0.0352 | 0.0519 |

Table B.21: **The explanatory power of the Index Trader Factor**
The table below shows $\mathbf{R}^2$ values of regressions of dependent variables in *dependent* row on the Index Trader Factor.

| *Dependent* | **Spot Price Difference** | **Commercial Hedgers Position** | **Financial Speculators Position** | **Index Traders Position** | **Futures Return** |
|---|---:|---:|---:|---:|---:|
| Soybean oil | 0.0006 | 0.0140 | 0.0012 | 0.9024 | 0.0007 |
| Corn | 0.0001 | 0.0779 | 0.0219 | 0.9054 | 0.0045 |
| Cocoa | 0.0040 | 0.0997 | 0.0002 | 0.8928 | 0.0024 |
| Cotton | 0.0018 | 0.0965 | 0.0155 | 0.9709 | 0.0036 |
| Feather cattle | 0.0107 | 0.0799 | 0.0048 | 0.9959 | 0.0362 |
| Coffee | 0.0025 | 0.1138 | 0.0314 | 0.9321 | 0.0151 |
| Hard Red wheat | 0.0002 | 0.0725 | 0.0027 | 0.9181 | 0.0002 |
| Live cattle | 0.0036 | 0.1155 | 0.0064 | 0.9602 | 0.0011 |
| Lean hogs | 0.0001 | 0.0546 | 0.0231 | 0.9479 | 0.0050 |
| Soybean | 0.0039 | 0.0818 | 0.0139 | 0.9055 | 0.0063 |
| Sugar | 0.0000 | 0.0347 | 0.0013 | 0.9989 | 0.0001 |
| Soybean meal | 0.0008 | 0.0569 | 0.0102 | 0.9150 | 0.0008 |
| Wheat | 0.0002 | 0.0323 | 0.0183 | 0.9557 | 0.0020 |