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A Model to Quantify the Risk of Cross-Product Manipulation: Evidence from the European Government Bond Futures Market

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Abstract

Cross-product manipulation involves manipulating one financial product to profit from the subsequent reaction in a different but related product. In this paper, we develop a simple model that researchers and regulators can use to scan for the susceptibility of two markets to such misconduct. We also test the model empirically on a set of government bond futures contracts using a complete EUREX ultra-high-frequency dataset. Our findings show that cross-product manipulation is feasible across bond futures with different underlying maturities, issuers and contract expiry dates. The results suggest that cross-product manipulation might be widespread despite an increasing crackdown by regulators and prosecutors.

Keywords: Bond futures; fixed income; cross-product manipulation; cross-market manipulation; limit order book; market microstructure; ramping; related securities; spoofing; trading; trade surveillance

JEL codes: D4; F31; G1.

1 Introduction

Cross-product manipulation involves manipulation of one financial product with the intent to profit from the subsequent reaction in a different but related product. Several high-profile cases have been brought to light in recent years – suggesting that a worldwide regulatory crackdown only has started to scratch the surface of this form of financial market misconduct (AMF, 2019; DOJ, 2021; CFTC, 2022).

Many markets are closely related. Consequently, market participants follow developments in a wide range of related products for hedging and arbitrage purposes. Problematically, a manipulator may take advantage of this by, say, spoofing in one market and leaving a genuine resting order in another market that other traders are likely to monitor simultaneously. Among financial markets, the global fixed income market is extremely connected (Ilmanen, 1995; Sutton, 2000; Dahlquist and Hasseltoft, 2013) – making it particularly vulnerable. This is echoed in a document published by the UK financial regulator FCA (2018), stating that "some analysts [...] take a narrow approach, reviewing only the activity in the product which triggered the alert and not considering other trading in correlated products. Because many fixed income products are inter-connected, consideration of trading activity in correlated products - such as cash vs futures, or products with different durations - is an important element of effective surveillance."

The list of cross-product manipulation cases is growing, and high-profile examples include cross-product ramping and squeezing by Credit Suisse in the UK Gilt (government bond) market (FCA, 2014), cross-product pump-and-dump in European government bonds and bond futures by Morgan Stanley (AMF, 2019) and cross-product spoofing in US Treasury bond and bond futures contracts by NatWest (DOJ, 2021). Notably, this form of misconduct can involve both trade-based and order-based strategies.

Problematically, in the absence of whistle-blowing, cross-product manipulation is notoriously difficult to detect. As Stenfors et al. (2023) point out, a cross-product manipulator is significantly less likely to get caught as relatedness increases the number of manipulative pathways exponentially. This dramatically reduces the risk of detection and raises the challenges for regulators, lawmakers and compliance departments. Furthermore, there is neither a specific theory on cross-market manipulation, nor a successful tool or methodology for detection.

In this paper, we tackle this issue by developing a simple but robust model. The model has two crucial features. First, it quantifies the transmissibility between a potentially manipulative tactic in Product A (the source product) and the immediate reaction in Product B (the response product). Second, it quantifies how far in depth order volume matters for the transmissibility. The purpose of this is to assess whether two products could be susceptible to cross-product manipulation. We then test the model empirically on a set of European government bond futures contracts using a complete EUREX ultra-high-frequency dataset obtained via BEDOFIH.

Our findings show that cross-product manipulation is feasible across bond futures with different underlying maturities, issuers and contract expiry dates. However, creditworthiness, market liquidity, maturity difference, and depth play an essential role in the strength and direction of the transmission from the source to the response product. Overall, the results suggest that cross-product manipulation may be more widespread than hitherto brought to light by regulators and prosecutors.

Our paper addresses a specific form of price discovery and can, therefore, be read more generally in terms of its contribution to market microstructure literature on limit order books and limit order submission strategies (see, for instance, Barclay and Warner (1993); Chan and Lakonishok (1995); Fong and Liu (2010); Lo and Sapp (2010); Ranaldo (2004)). It is particularly related to work on financial market misconduct and abuse (Alexander and Cumming, 2020; Cumming et al., 2011, 2015) and order-based manipulation (Lee et al., 2013; Stenfors and Susai, 2021; Stenfors et al., 2023). Moreover, given the topicality of the subject matter at hand, recent publications by regulators and lawmakers also make up a bulk of the relevant literature (AMF, 2019; DOJ, 2021; CFTC, 2018, 2020, 2022; Securities and Exchange Surveillance Commission, 2018; Financial Services Agency, 2019).

The remainder of the paper is structured as follows. Section 2 provides an overview of cross-product manipulation from a theoretical and practical perspective. Section 3 describes the dataset and variables. Section 4 outlines the model and approach. Section 5 discusses the empirical results and Section 6 concludes.

2 Related cases and literature

2.1 Order-based cross-product manipulation

The rationale behind cross-product and cross-market manipulation can be explained through the lens of market micro-structure theory.

Market orders and transactions act as signals about market supply and demand, and provide hints about the likely future price direction in the short run. Limit order submissions and cancellations, despite not involving transactions *per se*, shape the depth and contours of a limit order book and also influence the expected price in the future. The following hypothetical scenario may serve as an illustration.

Suppose the market for Bond A on an electronic trading platform is made up of buy orders amounting to \$10 million at 120.00 and sell orders of \$10 million at 120.05. Assume then that a new trader enters the market with the desire to sell \$5 million at the highest possible price. Several limit order submission strategies are available. The trader could, for instance, split the sell order into a string of \$1 million orders. The logic behind order-splitting strategies and stealth trading is that a smaller order size is less likely to trigger a reaction by other traders (Barclay and Warner, 1993; Chan and Lakonishok, 1995; Chou and Wang, 2009; Engle et al., 2012). An alternative would be to submit the sell order deeper into the limit order book, say at 120.07, in the hope that a buyer of a large amount will emerge. However, the distance to the prevailing market price will have an influence on the probability of execution (Cao et al., 2009; Griffiths et al., 2000; Ranaldo, 2004). Either way, the purpose would be to prevent traders on the current bid side from cancelling their orders at 120.00 and resubmitting them at lower levels (due to free-option risk), or competing traders on the ask side from improving their sell orders at 120.05 (due to non-execution risk) (Fong and Liu, 2010; Liu, 2000). Thus, from a trader's perspective, a genuine limit order submission strategy involves a careful consideration of order size and aggressiveness with the aim to minimise the market impact and simultaneously maximise the probability of execution (Lo and Sapp, 2010).

The aim of an order-based manipulative strategy such as spoofing is essentially the opposite. It involves an assessment of appropriate order size and aggressiveness to trigger a market impact without any intent to execute the spoof orders at all. A spoofing strategy would consist of a combination of a genuine resting order and a spoof order. For instance, the trader may opt to submit a genuine sell order of \$5 million at 120.04. Then, a \$50 million (spoof) buy order is submitted at 119.97. The intent of the spoof order is a) that it will be cancelled and b) that it creates an artificial perception of supply and demand that is taken advantage of. Due to the large (spoof) order size, other traders might interpret the $50 million buy order at 119.97 as if the price of Bond A is likely to increase. Consequently, a successful spoof would mean that the genuine sell order of $5 million at 120.04 is filled. Immediately after that, the trader cancels the $50 million spoof buy order at 119.97, and the spoofing strategy is completed.

As the example above illustrates, spoofing is a low-cost and low-risk strategy compared to trade-based manipulative tactics such as ramping, which involves accumulating a trading position. Importantly, regardless of how large or how many the spoof orders are, they are never intended to be executed. Theoretically, this suggests that spoof orders are likely to be large (to induce a market reaction) but non-aggressive (to avoid execution). The purpose of submitting a spoof order is to cause other traders to react *as if* genuine price-moving information has entered the market, even though it is purely artificial. This is where spoofing goes beyond being a genuine trading strategy and, instead, becomes fraudulent or, as in some countries including the United States, explicitly illegal. Because it creates a false impression of the supply and demand in the market, spoofing can be seen as a form of market manipulation (Cumming et al., 2011, 2015).

Hitherto, algorithmic traders and major banks appear to be overrepresented in the regulatory cases and convictions related to spoofing (CFTC, 2018, 2020; Securities and Exchange Surveillance Commission, 2018; Financial Services Agency, 2019). A spoofer benefits from being able to quickly and repeatedly submit and cancel orders on exchanges or electronic trading platforms. Here, algorithmic traders have the edge over human traders. At the same time, large banks often act as primary dealers or market makers in a range of OTC products that have been shown to be susceptible to spoofing tactics. For instance, in 2020, US regulators fined JP Morgan a record $920 million for spoofing and manipulating precious metals and US Treasury futures contracts. Notably, the bank's activity had "involved hundreds of thousands of spoof orders" (CFTC, 2020).

Spoofing is not only difficult to detect. It may also be challenging to demonstrate malicious intent. However, what really widens the scope of manipulative possibilities is the universe of financial market products that open up doors to cross-product manipulation. It is widely known that numerous financial market assets, instruments and indices are closely connected and related. This presents traders with useful hedging opportunities. Problematically, it also makes markets more susceptible to cross-product and cross-market manipulation. Consider the previous hypothetical example of spoofing involving Bond A. The market is 120.00-120.05 with $10 million on each side of the electronic limit order book. A spoofer then enters the market and submits a genuine sell order of $5 million at 120.04. Now suppose there is a Bond B closely related to Bond A. Market participants are aware that the relatedness is high, so they tend to follow the developments in both markets in tandem. For simplicity, let us assume that the market for Bond B is 110.00-110.03 with $10 million on each side of the order book. An example of a cross-market spoof would involve submitting a buy order of $60 million at 109.98 for Bond B (the spoof order). Again, the best bid/ask price for Bond B remains unchanged at 110.00-110.03. However, other traders notice the substantial increase in demand from the bid side of Bond B, which is closely related to Bond A. As a result, they anticipate not only that the price of Bond B will increase but also the price of Bond A. A successful spoof would imply that the genuine order in Bond A gets executed, whereas the spoof order in Bond B is cancelled immediately thereafter.

An illustration of how order-based cross-product manipulation has played out in real-life is provided by a recent case by the US Department of Justice (DOJ). On 21 December 2021, NatWest pleaded guilty to fraud in the US and agreed to pay a $35 million fine (DOJ, 2021). The reason can briefly be summarised as follows.

Between January 2008 and May 2014, NatWest engaged in spoofing in the US Treasury (i.e. government bond) futures market. Separately, in 2018, NatWest traders also engaged in spoofing in the US Treasury cash market. According to the DOJ, NatWest traders placed "orders with the intent to cancel those orders before execution, attempting to profit by deceiving other market participants by injecting false and misleading information regarding the existence of genuine supply and demand in the market." The spoof orders were "designed to artificially push up or down the prevailing market price" and in some instances, the traders "took advantage of the close correlation between US Treasury securities and US Treasury futures contracts and engaged in cross-market manipulation by placing spoof orders in the futures market in order to profit from trading in the cash market."

Documents released by the DOJ provide the following example of cross-market manipulation. On 14 May 2014 at 12:33:44.593 p.m., a trader placed a spoof order to buy 210 Ultrabond futures contracts at $149.59375. The underlying asset of the CME Ultrabond future is a US Treasury bond with a remaining maturity of at least 25 years. The contract unit is a face value of maturity of $100,000, so 210 contracts are equivalent to $21,000,000. All spoof orders were cancelled 3.131

seconds later. In the meantime, the traders had filled genuine orders to sell $2,000,000 30-year US Treasury bonds. According to the DOJ, the intent behind the spoof orders was to "create the illusion of demand in the futures market, deceive other market participants, and artificially move the correlated cash market price higher."

As can be seen, single-product and cross-product manipulation are similar in terms of the attributes of the manipulative strategies and how they relate to the economic and psychological dynamics of the market. The key difference between single-product and cross-product manipulation is how the latter requires a consideration of the relatedness between the products and markets involved.

2.2 Trade-based cross-product manipulation

Spoofing and layering are order-based manipulation strategies that strive for a reaction or short-term momentum in the market that can be profited from by the manipulator. The intent is to move the market, but also to cancel the manipulative orders. By contrast, trade-based manipulation such as ramping, squeezing, pump-and-dump or triggering stop losses involve *genuine* buying or selling to cause the market price to move in certain direction (Allen and Gale, 1992; Stenfors, 2020). The manipulative element stems from the "intentional conduct that causes market prices to diverge from their competitive level" (Pirrong, 2017).

Like order-based manipulation, trade-based manipulation can involve a combination of products and markets. Consider the hypothetical example in the previous section concerning related bonds A and B. The market for Bond A is 120.00-120.05 with $10 million on each side of the limit order book. A manipulator then enters the market and submits a genuine sell order of $5 million at 120.04. The market for Bond B is 110.00-110.03 with $10 million on each side of the order book. Instead of submitting a spoof order inside the order book with the intent to cancel it, the manipulator could embark on a ramping strategy. Aggressively bidding above 110.00, or even buying at 110.03, might trigger other traders to lift the offer at 120.04 in Bond A – given that the products are closely related.

An illustration of how trade-based cross-product manipulation has played out in real-life is provided by a recent case by the French regulator Autorité des Marchés Financiers (AMF) (AMF, 2019). On 4 December 2019, the AMF fined Morgan Stanley €20 million for manipulating government French government bonds (OATs), Belgian bonds (OLOs) and French government bond futures contracts (FOATs). The reason can briefly be summarised as follows.

On 16 June 2015, between 09:29 and 09:44, Morgan Stanley purchased a significant number of FOATs and German government bonds futures contracts (Bund Futures (FGBLs) and Buxl Futures (FGBXs)) on EUREX. Immediately thereafter, at 09:44, Morgan Stanley sold 17 different OATs for €815 million and 8 OLOs for €340 million. The transactions for the cash bonds took place at MTS France, BrokerTec (an electronic trading platform) and MTS Belgium. According to AMF, Morgan Stanley had obtained "abnormal and artificial" price levels for the FOAT, OAT and OLO transactions. The regulator also argued that "the purpose of the FOAT acquisitions was to influence a price increase of this financial instrument, in order to cause an abnormal and artificial increase in the price of the OATs and OLOs, because of the correlation links between these instruments, immediately before they were sold." Further, the activity "constituted price manipulation through the use of a form of deception or contrivance" in part because it "had the effect of giving other participants a distorted picture of the state of the French sovereign bond market." However, according to AMF, the purpose of the activity in the German government bond futures (FGBL and FGBX) was not to manipulate the price of OATs. Hence, they were not included in the enforcement notice.

The Morgan Stanley case demonstrates that bonds or bond futures with different underlying *issuers* and *credit ratings* may be sufficiently related for cross-product manipulation attempts. However, an earlier case by the FCA illustrates that bonds of different *maturities* also may be susceptible.

On 20 March 2014, FCA fined Credit Suisse trader Mark Stevenson £662,700 for market abuse and prohibited him from any further work in the regulated financial services industry (FCA, 2014). The reason can briefly be summarised as follows.

On 10 October 2011, between 09:00 and 14:30, Stevenson bought £331 million of the UKT 8.75% 2017, a UK government gilt (below referred to as "the Bond"). The trading occurred on a day when the Bank of England announced that they would buy bonds from market makers as part of the central bank's quantitative easing programme. As a result, the central bank bond buying, which would take place between 14:15 and 14:45, was openly disclosed.

Stevenson accumulated a substantial position in the Bond during the day. This was partly done by outright purchases. An even larger proportion was bought through spread trades or switches involving related bonds. According to the FCA (2014), "Mr Stevenson deliberately traded in an aggressive style when purchasing the Bond which gave a false or misleading impression as to the price of the Bond and secured the price of the Bond at an abnormal or artificial level." The trading activity in the Bond was substantial in several respects. Stevenson's purchases accounted for 92% of the IDB market in the Bond on that day. The purchases represented around 2,700% of the average daily trading volume during the previous four months. Moreover, the Bond was illiquid compared to other related bonds. The average daily trading volume for the Bond amounted to £9 million during the previous five months. The closely related bonds averaged £74.5 million to £478.8 million.

[INSERT FIGURE 1 AROUND HERE.]

As seen in Figure 1, the activity by Stevenson caused the bond price [yield] to go up [down] compared to related bonds. According to the FCA, "Mr Stevenson's trading led to movements in the yield spread between the Bond and Comparator Bonds which were significantly outside their typical or normal ranges and the price levels for the Bond which resulted from this activity were abnormal. These abnormal price levels were also artificial, as there was no legitimate reason for the trading which led to the abnormal prices."

Although cross-product manipulation was not specifically mentioned in the Final Notice published by the FCA, two critical aspects stand out from this case that are crucial for our investigation. First, the case demonstrates that a manipulated price is easier to obtain when the product is illiquid or thinly traded. For cross-product manipulation, this implies that the *source* product is likely to be more liquid than the *response* product. Second, a manipulator can use related products for gearing (e.g. via spreads), while still maintaining relatively low market risk exposure. Referring to the previous example involving the two hypothetical bonds, a trader could, for instance, submit a spread order to sell \$100 million of Bond A and buy \$100 million of Bond A at 10.00 (120.00-110.00). Such a spread order or trade would be regarded as a part of a genuine trading, arbitrage or hedging strategy. However, if intended to create an artificial perception of supply or demand or to cause a market price to diverge from its competitive level, it would constitute market manipulation.

To sum up, there are numerous trade-based and order-based manipulation strategies. Most strategies can also involve more than one product or market, with possible combinations growing exponentially once all related products are considered. To continuously calculate which product combinations could be at risk to which manipulative tactics at which moment in time is an insurmountable task from a computation perspective. Nonetheless, in the following sections, we develop and test a simple one-size-fits-all model that can be used to "take the temperature" on any single- or cross-product combination to help determine its susceptibility to market manipulation.

3 Data and variables

3.1 Data

This paper uses data from EUREX, the main trading venue for European government bond futures. The data has been obtained via BEDOFIH, and details every trade and volume change for EUREX securities and derivatives during 2020. Depth information is included to the 10th level for most products. We test the model on German, French and Italian benchmark government bond futures (see Table 1).

[INSERT TABLE 1 AROUND HERE.]

The selected products are related from several dimensions. First, they share the same currency (EUR). Second, FGBL, FOAT and FBTP have the same underlying maturity (around 10 years). Indeed, several studies have shown that the international co-movement between long-term bonds has been shown to be stronger than for short-term bonds (Jotikasthira et al., 2015; Kumar and Okimoto, 2011; Stenfors et al., 2022a). Third, FGBL and FGMB have the same underlying issuer (Germany) and, consequently, underlying credit risk. However, French bond yields often track the more liquid German bonds, which act as a benchmark for EUR-denominated bonds. The data set enables us to explore the susceptibility of cross-product manipulation across underlying contract maturities (e.g. 10-year German FGBL vs 5-year German FGBM) and across issuers of different creditworthiness (e.g. 10-year French FOAT vs 10-year Italian FBTP).

Furthermore, the paper considers activity on 2 March 2020, i.e. a week before the expiry of the Mar 20 futures contract. This is a period when both the Mar 20 and Jun 20 contract for each product is very liquid, which permits us also to analyse the relationship between different underlying contract expiry dates.[1] Table 2 provides an overview of the trading activity on 2 March 2020. As

[1] There are four bond futures contracts per year (Mar, Jun, Sep and Dec), and the nearest, second-nearest (and sometimes third-nearest) contracts are traded at any moment in time. The last trading day is two exchange days prior to the delivery day of the relevant maturity month. The delivery day is the tenth calendar day of the respective quarterly month, which means that the period studied includes the contract rollover. The fixing, expiry or rollover of a contract presents a manipulation risk on its own, and the importance of relatedness is arguably at a peak during this period.

can be seen, the European government bond futures market on EUREX is extremely large. For instance, more than €170 billion worth of the Mar 2020 10-year German Bund futures were traded, and over 4 million limit order book updates were generated.

[INSERT TABLE 2 AROUND HERE.]

3.2 Independent variables (the source product)

3.2.1 Imbalance score

The first part of a cross-product manipulation strategy involves altering an order book balance in one product (the *source product*) to create an artificial perception of supply and demand. This indicates a change in buying or selling pressure and thus foreshadows an imminent price movement. Book balance is the comparison of total volume on each book side. The *imbalance ratio*, x_n, is a common quantification of this imbalance.

$$x_n = \frac{\Sigma_{i=1}^{n} b_i - \Sigma_{j=1}^{n} a_j}{\Sigma_{i=1}^{n} b_i + \Sigma_{j=1}^{n} a_j} \tag{1}$$

where n is the number of price levels included in the calculation, and b_i and a_j are the bid and ask volumes at the ith and jth price levels, respectively.

x_n is bounded $[-1, 1]$ with most of its range occupied by low imbalance book states around zero. Traders are more inclined to react to potentially market-moving signals, which are reflected in strongly imbalanced book states, so we transform x_n to stretch out extreme imbalance ratios as follows.

$$I'_n = log\left(\frac{x_n - (-1)}{1 - x_n}\right) \tag{2}$$

The I'_n are distributed approximately normally, $N(0, \sigma_{I'_n})$ with $\sigma_{I'_n}$ generally reducing as n increases (see Figure 2). To allow the I'_n to be compared across different values of n, the I'_n were scaled to unit dispersion, resulting in the *imbalance score*, I_n.

$$I_n = \frac{I'_n}{\sigma_{I'_n}} \tag{3}$$

The transformation from x_n to I'_n is shown graphically in Figure 2, which shows a typical distribution of x_n for several selected values of n.

[INSERT FIGURE 2 AROUND HERE.]

The I_n are strongly collinear, so instead of including them directly in the model, we represent each as the net change to the imbalance score when the n^{th} price level is included.

$$dI_n = I_n - I_{n-1} \tag{4}$$

We describe the dI_n as *delta imbalance* values.

3.2.2 Bid-ask spread and volume proxy

The bid-ask spread and a volume proxy are included in the model because we suspect a wide spread or an imbalance score based on a relatively small total volume may affect the transmissibility of an imbalance signal to the receiving products.

The spread variable, s, is the centred difference between the best ask and bid prices, p_a p_b, respectively. s is not scaled to retain its cent scale.

$$s = (p_a - p_b) - \mu_s \tag{5}$$

Where μ_s is the mean spread observed over all book updates for a product.

Indicative volume, v, is the scaled and centred base 2 log of the total volume at or within five price steps of the best prices.

$$v' = log_2[\Sigma_{n=1}^{5}(b_n + a_n)] \tag{6}$$

$$v = \frac{v' - \mu_v}{\sigma_v} \tag{7}$$

Where μ_v and σ_v are respectively the mean and standard deviation of v'.

3.2.3 Sampling

The independent variables are calculated from source product book states at timestamps sampled according to the following process.

1. Determine the start and end timestamps of windows of unchanging best bid and ask prices.

2. Attribute an *extremum* sampling weight, $w_{e,i}$, to each book state, i. $w_{e,i} = \Sigma_{j=1}^{10} |I_{i,j}^*|$, where $I_{i,n}^* = I_{i,n}$ if $I_{i,n}$ establishes a new positive maximum or negative minimum imbalance score for imbalance depth n within its window of unchanging spread, and $I_{i,n}^* = 0$ otherwise.

3. Attribute a density sampling weight, $w_{d,i}$, to each book state, i. $w_{d,i}$ is the reciprocal of local point density in a space defined by the PCA transformation of the product's spread, indicative volume, and imbalance variables. PCA components sufficient to include 80% of the overall variation are included.

4. Randomly sample from the entire data set where the sampling probability for a given book state, i, is proportional to the product of its component sampling weights.

$$w_i = w_{e,i} \times w_{d,i} \tag{8}$$

The w_e biases the sampling towards the strongly imbalanced book states that are the focus of traders monitoring markets (see, in particular, Lo and Sapp (2010); Stenfors and Susai (2019)). The w_d sampling weight ensures that the model includes even rare combinations of spread, volume, and imbalances. The exclusion of book states that do not set new extreme imbalance scores tends to select events at the leading edge of a period of increased imbalance, and thus are likely to precede price responses to the imbalance. Figure 3 illustrates this leading-edge selection for selected I_n and the resulting w_e.

[INSERT FIGURE 3 AROUND HERE.]

As an illustration, the top four panels in Figure 3 show a selection of imbalance scores within a single period of unchanging spread in the Italian 10-year FBTP Jun 20 contract. The bottom panel shows the w_e summed across the selected imbalance scores at each order book state.

Reading the upper panels from left to right shows that the level 1 imbalance score drops initially, accumulating five new cumulative minimum values (green points) below zero (red line) before 13:39 on 2 March 2020. The other levels do not move as dramatically, and obtain only two such points in that time. Differences in the volumes considered by each imbalance score result in different book states being selected for each imbalance score. For example, although imbalance scores for $n = 1$, 3, and 7 all trend negative in the second half of the window, they take different paths and gain different numbers of sample points along the way. The $n = 9$ imbalance score echos the upward score drift between 13:39:05 and 13:39:10, but unlike the other levels, it moves above zero, marking several new cumulative maximum scores in doing so.

The lowest panel shows w_e, the absolute value of the selected imbalance scores at each order book state (including only the plotted imbalance levels for clarity). If multiple imbalance scores set a new maximum or minimum value on the same book state, a significant change was made close to the best price, and the resulting w_e can be large. If only a few imbalance scores reach new extrema, then the sum will include fewer terms and be lower, reflecting the less pervasive nature of the imbalance change. If many imbalance scores are included in a sum, but some are in opposing directions, then their sum will be reduced, reflecting the confused nature of the book imbalance.

The book state sampling method is applied independently within different time windows defined by stretches of unchanging best prices in the source instrument. These windows provide natural experimental units where the changing book depth is the main dynamic, allowing some isolation of the book imbalance signal from competing factors. Furthermore, as we require that a sampled book state and its price response must occur in sequence within the same window, the complication that the price response may be due to a shift in the source instrument's spread is avoided.

This design also naturally limits the imbalance-to-price-response delay to intervals short enough for the imbalance signal to remain a valid causal factor in the response. The longer the delay, the more the source instrument's depth changes and the more diluted the effect of the sampled imbalance becomes until it finally becomes irrelevant. This design takes the view that if the book depth has changed sufficiently to affect the best prices, then none of the imbalance signals observed prior to the change in best price remain valid causal factors for future price changes in the response security. This conservative restriction typically censors between 71% and 92% of price response observations, but it also biases observations towards imbalance-response pairs where the imbalance signal is most likely to be an important causal factor of the response. Figure 4 shows the distribution of the delay between sampled imbalance and observed price response or censoring.

[INSERT FIGURE 4 AROUND HERE.]

3.3 Dependent variable (the response product)

The purpose of a cross-product manipulation strategy is ultimately to trigger a behavioural reaction by other traders in the *response product* that is advantageous to the perpetrator. The beneficial or profitable response can be proxied in different ways, e.g. through transactions (Lee et al., 2013), order cancellations (Stenfors and Susai, 2021) or price and volume shifts at the top of the book (Stenfors et al., 2023).

Our model uses changes in the "true price", p_t, as the response proxy, which is widely used in trade surveillance technology. p_t is defined as:

$$p_t = l \qquad for \quad p_b \leq l \leq p_a \tag{9}$$

$$= p_b \qquad for \quad l < p_b \tag{10}$$

$$= p_a \qquad for \quad l > p_a \tag{11}$$

where p_b and p_a are the best bid and ask prices respectively, and l is the last traded price.

The outcome variable in our model is the direction of the price change in the response product following the book state sampled in the source product. If there is no price change before the end of the window of stable spread in the source product, then no response is recorded and the sample is dropped from the data set (see Section 3.2.3).

4 The Model

The model seeks to quantify an associative link between a sampled book state and a price response following it to assess whether two products could be systematically susceptible to cross-product manipulation. Although time series, correlation-based approaches and TVP-VAR models are useful in studying the connectedness and transmission mechanism of shocks across financial markets (see, for instance, Diebold and Yılmaz (2009); Balcilar et al. (2021); Chatziantoniou et al. (2021); Stenfors et al. (2022b,a); Chatziantoniou et al. (2020); Gabauer et al. (2023)), they face significant challenges in this application. The multitude of possible unobserved causes for a price response, and the irregular spacing between book imbalance and price response eliminates or complicates the interpretability of many common time series approaches. Analysing correlations between price responses and each I_n within a product pair produces insights similar to those obtained from our model but does not allow for the inclusion of nuisance variables, nor does it as clearly isolate the marginal contribution of the n^{th} depth level.

We employ logistic regression on the delta imbalances, dI_n, and nuisance variables of spread and indicative volume, s and v, respectively. The binary outcome variable, p, is 1 if the observed price change is positive, and 0 otherwise. A separate model is fit for each product pair (cross-product), including self-pairs (single-product), and in each direction (i.e. the same product being source in one model and response in another) for a total of 64 separate models of the form below.

$$logit(p) = \beta_0 + \beta_s s + \beta_v v + \beta_I dI + \epsilon \tag{12}$$

where the β are the model coefficients, and $\epsilon \sim N(0, \sigma^2)$ is the residual error.

We define the *transmissibility* of the imbalance signal, η_i, as the difference between model m's mean absolute error (MAE), $\bar{e}_m$, from that of a null model that predicts random probabilities uniformly in the range $[0, 1]$, thus having null mean absolute error of 0.5.

$$\eta_m = 0.5 - \bar{e}_m \tag{13}$$

We expect that volume deeper in the book is less relevant to depth-driven trading decisions and, thus, less relevant to imbalance signal transmission. However, it is not obvious how quickly the relevance of the *depth* fades, nor how many levels should be included in each model. This number is likely to vary with volatility, trading rate, and spread amongst other aspects of market condition, resulting in different depth importance profiles for each model.

The construction of the dI_n as $dI_n = I_n - I_{n-1}$ allows separation of each depth level's influence and a principled step-wise process for variable selection in each model. The variable selection process starts with the base model of $logit(p) = \beta_0 + \beta_s s + \beta_v v + \epsilon$ then sequentially adds the dI_n from $n = 1$ to $n = 10$, recording the AIC value at each addition. The simplest model within 2 of the minimum AIC value is selected.

5 Empirical results

5.1 Transmissibility

The primary focus of the model is to quantify the association between a book imbalance in one product and a subsequent price change in another – this mechanism being necessary for a typical cross-product manipulation scenario.

Figure 5 shows the transmissibility of this imbalance signal between all pairs in the data set.

[INSERT FIGURE 5 AROUND HERE.]

Each panel collects one source product and one response product, and shows the four transmissibility values amongst them (Mar-Mar, Mar-Jun, Jun-Mar, Jun-Jun). The diagonal panels are shaded to indicate that the same product is source and response. For example, the top-left panel shows the transmissibility amongst the Italian 10-year FBTP contracts. Within each panel, the left-hand pair of points correspond to the March contract acting as the imbalance source (Mar-Mar, Mar-Jun), and the right-hand pair corresponds to the June contract as the source (Jun-Mar, Jun-Jun).

Non-zero transmissibility is observed both *within* product groups (shaded panels) and *across* product groups. Thus, the empirical results are in accordance with the expectation that major European government bond futures contracts could be susceptible to cross-product manipulation tactics because they are closely related. Notably, imbalance in the Germany 10-year FGBL Mar 20 contract appears to have a significant association with price movements in both contract maturities for the German 5-year FGBM and the French 10-year FOAT. This indicates that manipulation across products of *different maturities* (10-year and 5-year) (FCA, 2018) as well as *different issuers* (Germany and France) (AMF, 2019) appear to be feasible. Importantly, the German 10-year Bund future (FGBL) is one of the most liquid and widely monitored fixed income contracts worldwide – solidifying its role as a natural hedge but, unfortunately, also a likely source product in cross-product manipulation strategies.

The Italian 10-year FBTP product group appears to be isolated from the German 10-year FGBL and 5-year FGBM, and the French 10-year FOAT product groups. None of the latter three show strong transmission to Italian contracts (left-most column of panels), and the Italian contacts do not seem to have much transmission to the other three (top row of panels). However, amongst themselves, the FGBL, FGBM, and FOAT product groups appear to share significant interaction (lower-right group of nine panels). On the date from which this data was sourced (2 Mar 2020), the country credit ratings for Germany were AAA (stable) by S&P and Aaa (stable) by Moody's. The corresponding ratings for France were AA (stable) and Aa2 (stable), and for Italy BBB (negative) and Baa3 (stable). This is consistent with the Morgan Stanley case reported by AMF (2019) in that manipulation across products of different issuers and underlying credit risk is feasible as long as the *perceived creditworthiness* is relatively similar. Italian bond futures are clearly seen as outliers, which reduces their susceptibility to cross-product manipulation in combination with Germany and French government bond futures.

The transmissibility from Mar to Jun contracts (left-hand red point) exceeds in nearly all instances the transmissibility in the opposite direction (right-hand blue point). This suggests that manipulation across *contracts with different expiry dates* is feasible, but that the transmissibility from the more liquid to less liquid contract is greater than that from the less liquid to more liquid one. This is logical, given that the sampled date of 2 March 2020 is only four days away from the expiration date of the March contracts. As can be seen in Table 2, the traded volumes in the Mar 20 contracts vastly exceed those in the Jun 20 contracts. Just before the expiry, many traders and investors would be looking to roll their positions from the soon-to-be-expired contract to the following one. This known and strongly directional association between the two contracts should result in any hint of impending price movement in the March contract being quickly reflected in the June contract, but not the other way around. This is precisely what we see in the data.

5.2 Depth relevance

The secondary focus of the model is to explore how far in depth volume matters in regards to the transmission of an imbalance signal to another product. Orders very far from the best prices are not relevant to depth-driven, short-term trading decisions. However, it is not obvious how far is too far from the best prices to matter. Therefore, we examine the relevance of the marginal contribution to book imbalance made by the inclusion of volumes at the nth price level when the imbalance calculated from levels 1 to (n-1) is known.

Figure 6 shows the coefficients of every model, along with each model's η in the boxed numbers. Each panel displays a single model, i.e. one source product (one per row) and one response product (one per column). The diagonal panels are shaded to indicate that the same product is both source and response. For example, the top-left panel shows the Italian 10-year FBTP June-June model (single-product) and the top-right panel shows the Italian 10-year FBTP Jun to French 10-year FOAT March model (cross-product). The black horizontal bars within each panel indicate the 95% confidence intervals of the parameter coefficient estimates. The intercept parameter, β_0, is at the top, followed by the coefficients for spread, β_s, volume proxy, β_v, and each of the dI_n, β_I from level 1 to 10 progressing down the chart. Not all models include estimates for all dI_n due to the model selection process removing them from the model.

[INSERT FIGURE 6 AROUND HERE.]

A coefficient estimate bar crossing the vertical dashed line marking zero indicates lack of evidence to support the hypothesis that the coefficient value is *not* zero. Where an estimate bar lies to the right of the zero line, an increase in its parameter's value will increase the model's estimate of the probability of a positive price response. If the the bar lies to the left, then an increase in the parameter reduces the model's probability estimate. The magnitude of the change in probability estimate depends on both the value of the coefficient and the values of the other parameters, making direct interpretation of the coefficients difficult. However, as a simple example consider the result for the 10-year French FOAT March vs. the Germany 5-year FGBM June (bottom row, 5th panel). When all parameters for the 10-year French FOAT March are held at their median values, changing the dI_3 parameter from its lower to upper quartile values will change the predicted probability of a positive price change in Germany 5-year FGBM June from 44% to 77%, while doing the same for dI_1 only changes the predicted probability from 57% to 68%. In practical terms, this means that the German bond futures market could be highly sensitive to spoof order submitted at level 3 of the French bond futures market. This finding is concerning, as it suggests that cross-product manipulation might be feasible in fixed income markets with *different* issuers (and credit rating), *different* maturities and *different* contract expiry dates.

The significant variation in coefficient estimates between models indicates that factors specific to individual source-response security pairings play a significant role. These external factors relate to the degree fo relatedness between a pair, and so are summarised by the η_m of each pair. Figure 7 shows how the coefficients for each independent variable change with η. A LOESS approximation and its 95% confidence interval (shaded) are overlaid on each variable.

[INSERT FIGURE 7 AROUND HERE.]

Figure 7 shows that despite the clear variation between models there are common themes for models with non-zero transmission. In general, the spread and volume proxy coefficients remain close to zero regardless of η, indicating that – at least for this collection of liquid and actively traded instruments – their values are irrelevant for assessing transmissibility. By contrast, (with the possible exception of $n = 10$) the coefficients for the dI_n variables show a positive association with η. This indicates that the more transmission a product pairing has, the greater the importance of the imbalance at *all* depths, albeit with each depth level having a different importance.

To illustrate the relative importance of each dI_n, Figure 8 plots the precision-weighted mean coefficient values for each independent variable taken from models having $\eta \geq 0.05$. Models with $\eta < 0.05$ are excluded to remove the influence of product pairings that show no transmission.

[INSERT FIGURE 8 AROUND HERE.]

As expected from Figure 7, the mean coefficients in Figure 8 for spread and the volume proxy are very small, indicating relatively small effect on transmission probability. Additionally, the gradual reduction in the dI_n coefficient values beyond $n = 3$ is in accordance with the general understanding that imbalances due to volume deep in a book are less indicative of an imminent price movement, and hence of less relevance to transmissibility than imbalances observed closer to the best prices.

The values for the dI_1 and dI_2 coefficients show a marked difference between single-product imbalance transmission (blue points) and cross-product transmission (red points). This provides an insight into the differing drivers of single- and cross-product imbalance transmission. In both cases, the top-of-book imbalance is less important than imbalance contributed by volumes at levels 2 to 4. However, top-of-book imbalances (dI_1) appear to have no effect at all on cross-product transmission, while their effect is significant for single-product transmission. The single- and cross-product coefficients for dI_2 are closer together than those for dI_1, but remain notably distinct. After dI_3 the single- and cross-product coefficients are broadly the same.

The results do not imply that European fixed-income futures are immune to cross-product manipulation tactics at the top of the book or that the model is unable to capture a crucial feature in trading psychology. Rather, it confirms that this is a liquid and efficient market where a range of factors may determine prices. Volume changes at the top of the book in a *related* product may or may not count as immediately relevant. What is immediately relevant, however, are volume changes at the top of the book in the *same* product – as well as substantial shifts in supply and demand at a few levels within the order book of the *same and related* products. From a practical perspective, this highlights why cross-product manipulation can be notoriously difficult to detect. Monitoring and surveillance would not only need to involve a huge list of product combinations. The process also requires order book data that is not necessarily required to test for susceptibility of single-product manipulation.

6 Conclusions

During the last decades, global financial markets have evolved dramatically. Financial innovation and technological development have spurred the creation of new financial instruments, new trading venues and the adoption of more sophisticated risk management practices. Markets have also become more interconnected – more lately as a result of electronic trading platforms and algorithmic trading and execution becoming established in a wider range of products and markets.

Hedging and arbitrage opportunities – in many cases accompanied by more stiff competition — has undoubtedly helped to lower transaction costs and enhance market efficiency and the price discovery process. Unfortunately, however, the process also appears to have generated new risks to financial stability (e.g. flash crashes which are challenging to stop) and sophisticated strategies to commit financial market fraud (e.g. cross-product manipulation which is notoriously difficult to detect).

In this paper, we have taken initial steps to address the latter issue by designing and testing a simple model that can be used by a wide range of stakeholders (e.g. regulators, exchanges, financial institutions and surveillance technology providers) to scan for the risk of manipulation between two markets or products. The model not only generates a snapshot of whether a product combination could be susceptible to cross-product manipulation. It also quantifies the importance of changes at different levels of the order book in the source product for a subsequent price reaction in the response product.

Using a complete EUREX ultra-high-frequency data set, we test the model empirically on 8 single-product and 56 cross-product combinations of European government bond futures contracts. Three empirical findings are notable. First, consistent with the literature, cross-product manipulation is feasible across products of different maturities (5-year and 10-year) and different issuers (Germany and France). Second, manipulation across products of different issuers and underlying credit risk seems feasible as long as the perceived creditworthiness is relatively similar (Germany and France), but not when involving an outlier (Italy). Third, manipulation across contracts with different expiry dates is feasible and will likely involve a liquid source product and less liquid response product (i.e. March 2020 and June 2020, rather than vice versa). Studying the order book depth of the source product, we find that levels 2 to 4 are most relevant for both single- and cross-product combinations. Deeper into the order book, the impact of volume imbalances gradually fades. Interestingly, level 1 imbalances only have an impact on single-product transmission.

Recent discoveries and cases by regulators worldwide indicate that cross-product manipulation may involve various order types, strategies and markets. Unfortunately, our findings suggest these only represent the tip of an iceberg. Related products in markets where the level of relatedness and connectedness is high, such as fixed income, interest rate derivatives and commodities, are likely to be particularly vulnerable. Our simple model is not capable of discovering *actual* cross-product manipulation. Still, it can provide a snapshot of where regulators, exchanges, financial institutions and surveillance technology providers should start to look.

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Table 1: Government bond futures contracts overview

Contract	Remaining term in years	Issuer	Contract size
Long-Term Euro-BTP Futures (FBTP)	8.50 to 11.00	Republic of Italy	€100,000
Euro-Bund Futures (FGBL)	8.50 to 10.50	Federal Republic of Germany	€100,000
Euro-Bobl Futures (FGBM)	4.50 to 5.50	Federal Republic of Germany	€100,000
Euro-OAT Futures (FOAT)	8.50 to 10.50	Republic of France	€100,000

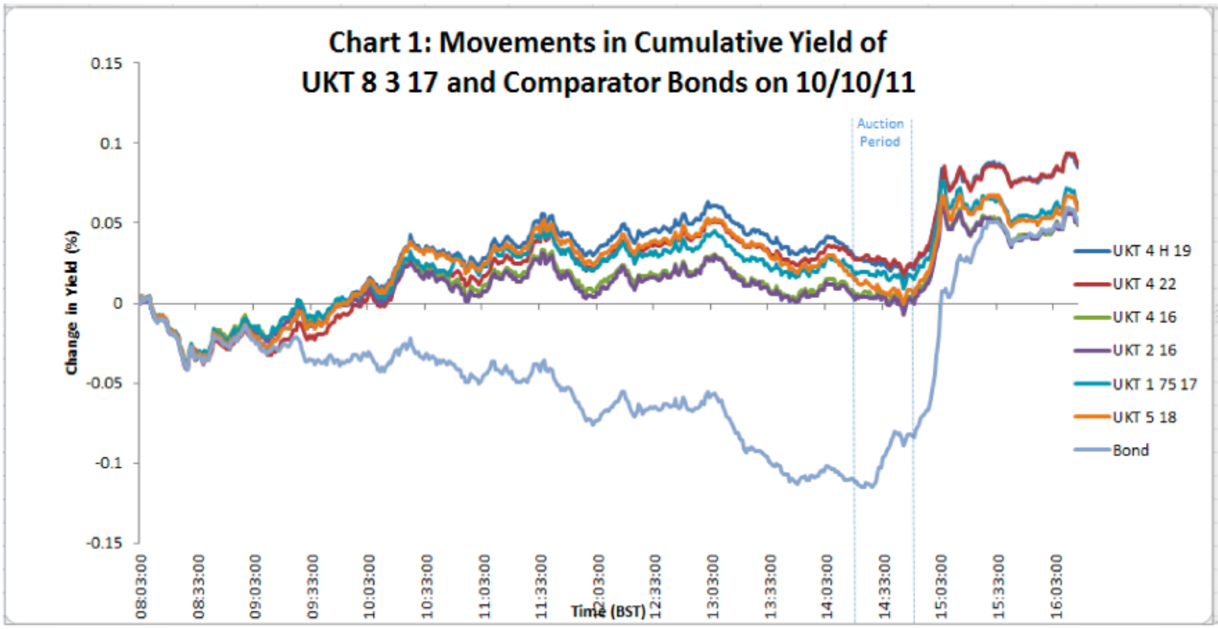
Source: EUREX (2023)

Table 2: Market overview (2 March 2020)

Contract	Book updates	Trades	Traded volume	Mean (median) trade size	Value (mio EUR)
FBTP Mar 20	691,200	52,948	190,687	3.6 (2)	27,725
FBTP Jun 20	65,363	8,748	25,567	2.9 (1)	3,729
FGBL Mar 20	4,364,532	120,191	965,050	8 (3)	171,599
FGBL Jun 20	1,106,744	23,215	143,831	6.2 (2)	25,180
FGBM Mar 20	1,144,754	23,441	542,036	23.1 (6)	73,634
FGBM Jun 20	304,945	5,702	74,495	13.1 (4)	10,146
FOAT Mar 20	2,820,576	41,479	249,121	6 (3)	42,082
FOAT Jun 20	410,772	7,765	17,376	2.2 (1)	2,981

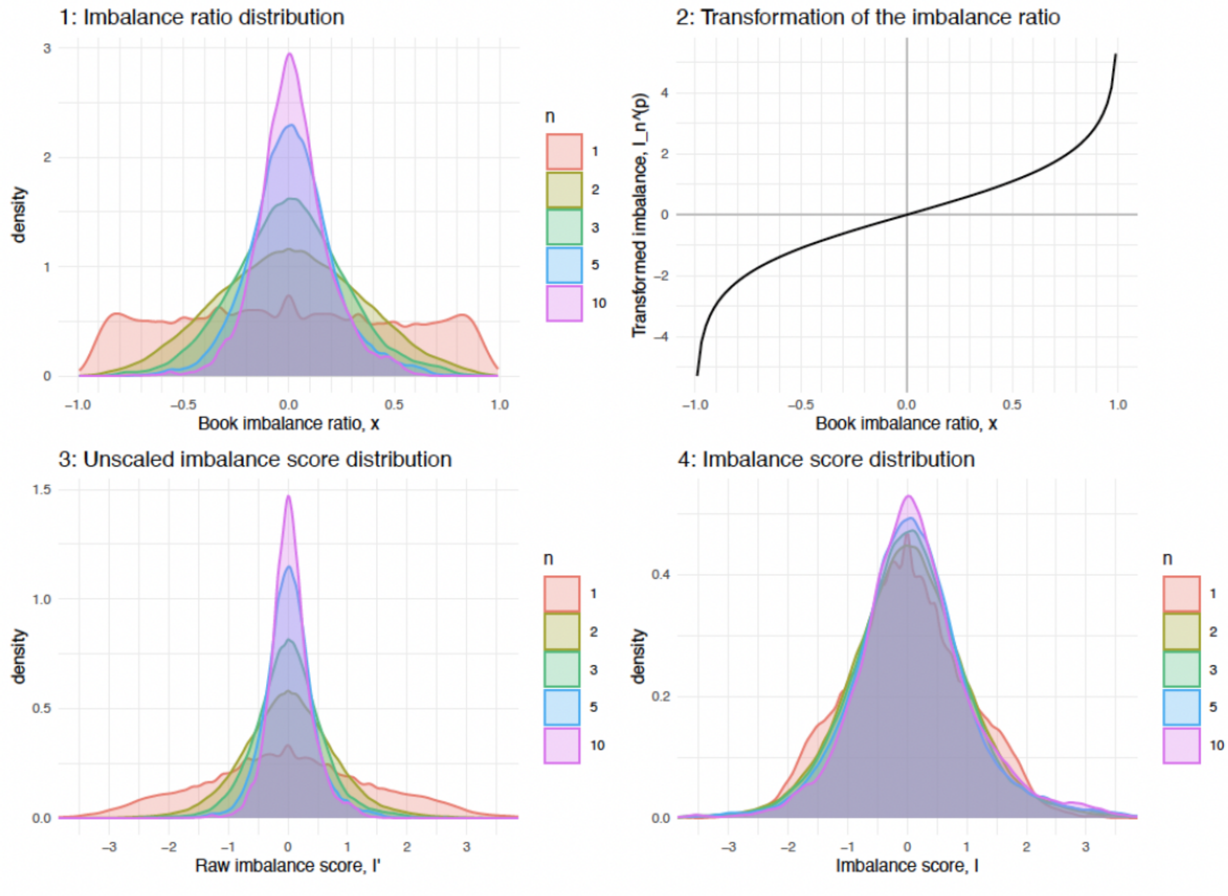
Source: EUREX and authors' calculations.

Figure 1: Squeezing/ramping of a Gilt (UK government bond) and related bonds



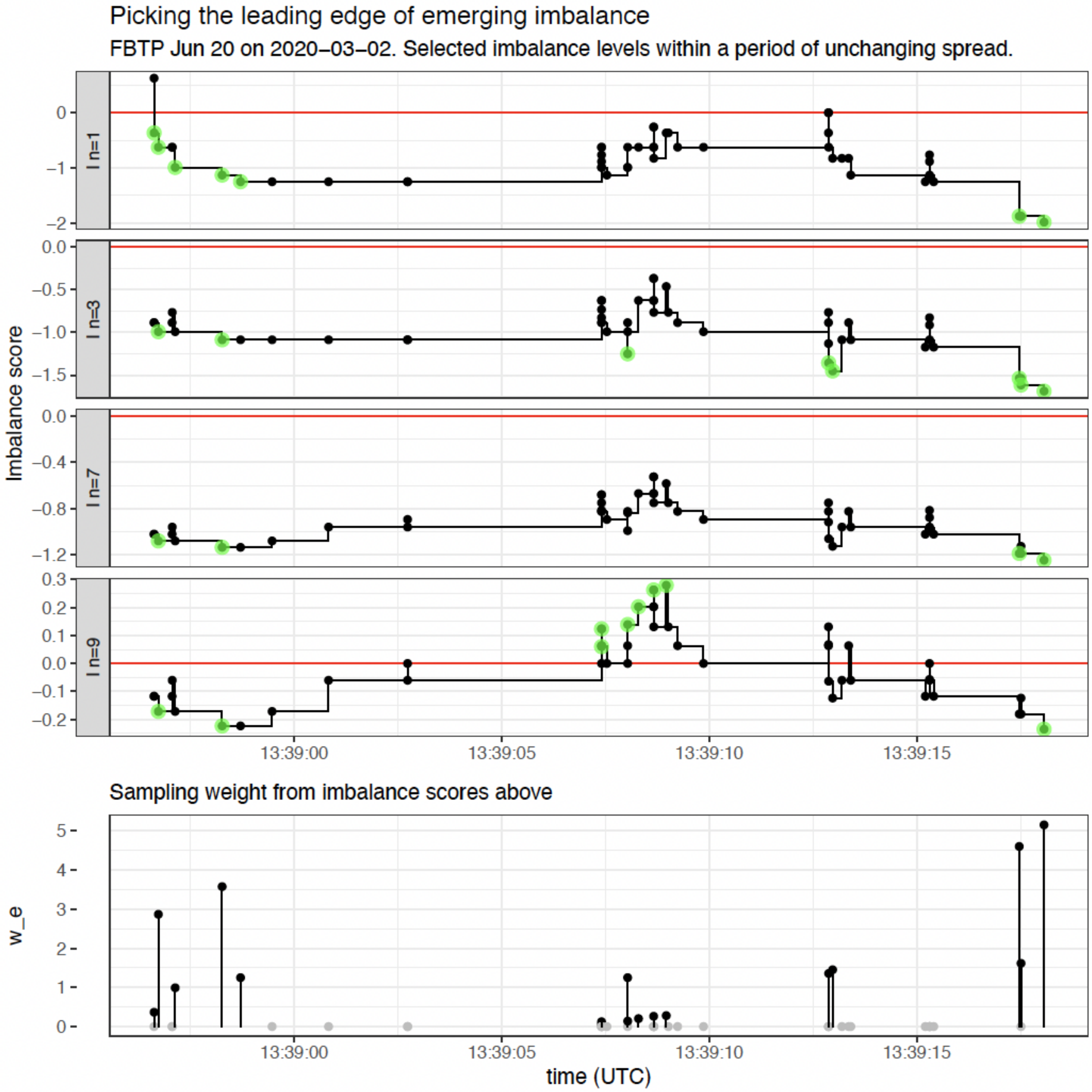
Source: FCA (2014)

Figure 2: Transformation to standardised, unbound imbalance score (FBTP Mar 20)



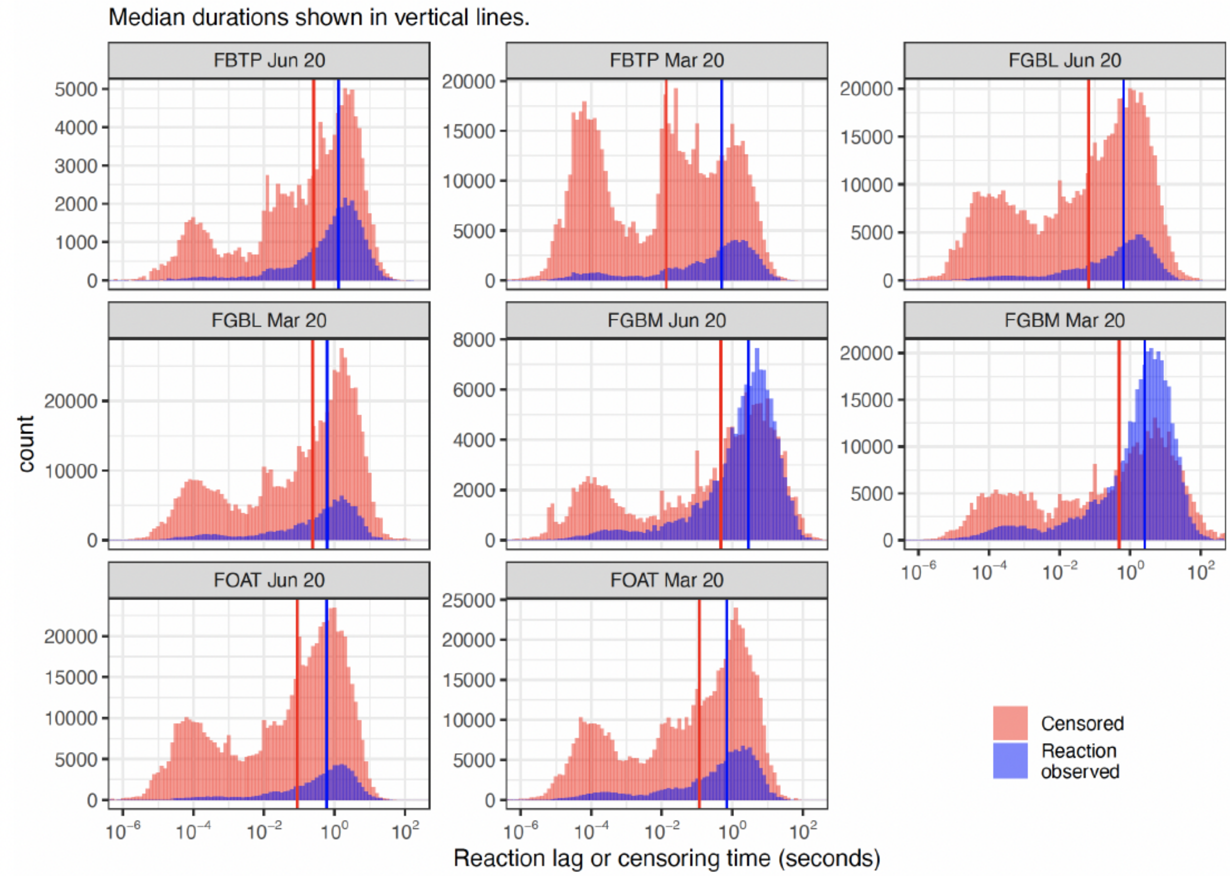
Source: EUREX and authors' calculations

Figure 3: Book state sample weighting



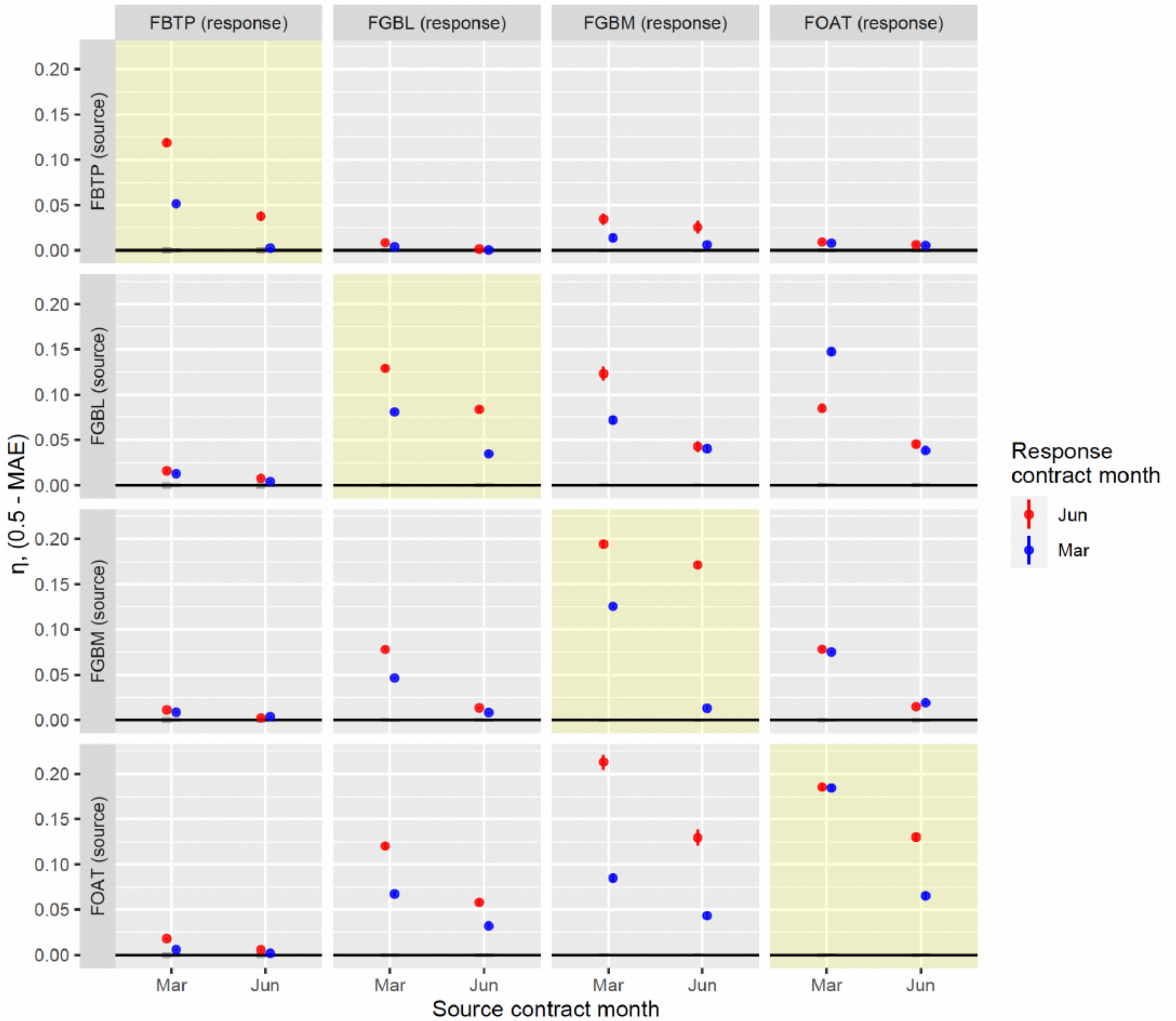
Source: EUREX and authors' calculations

Figure 4: Delay between sampled book state and price response or censoring



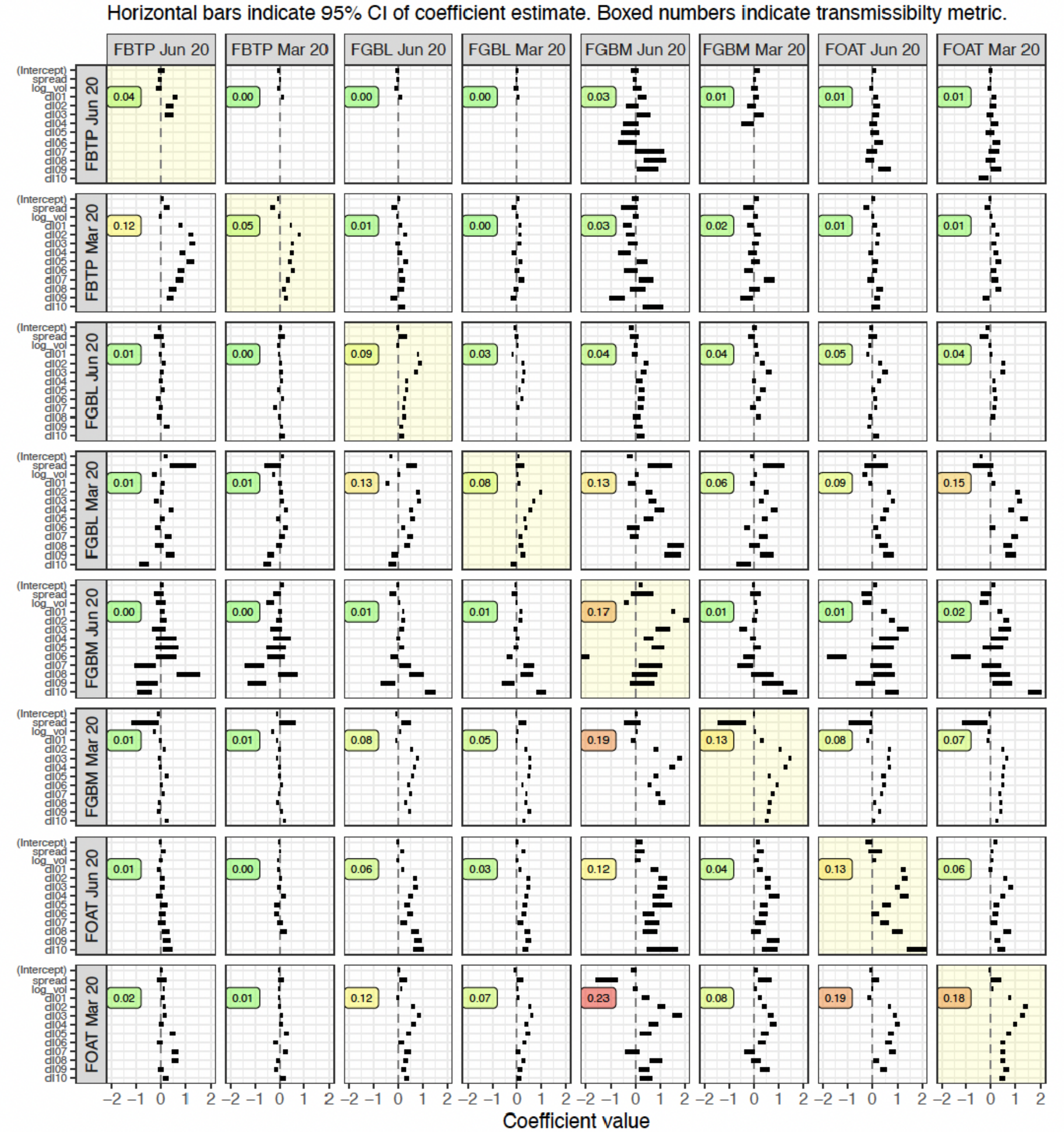
Source: EUREX and authors' calculations

Figure 5: Transmissibility of an imbalance signal



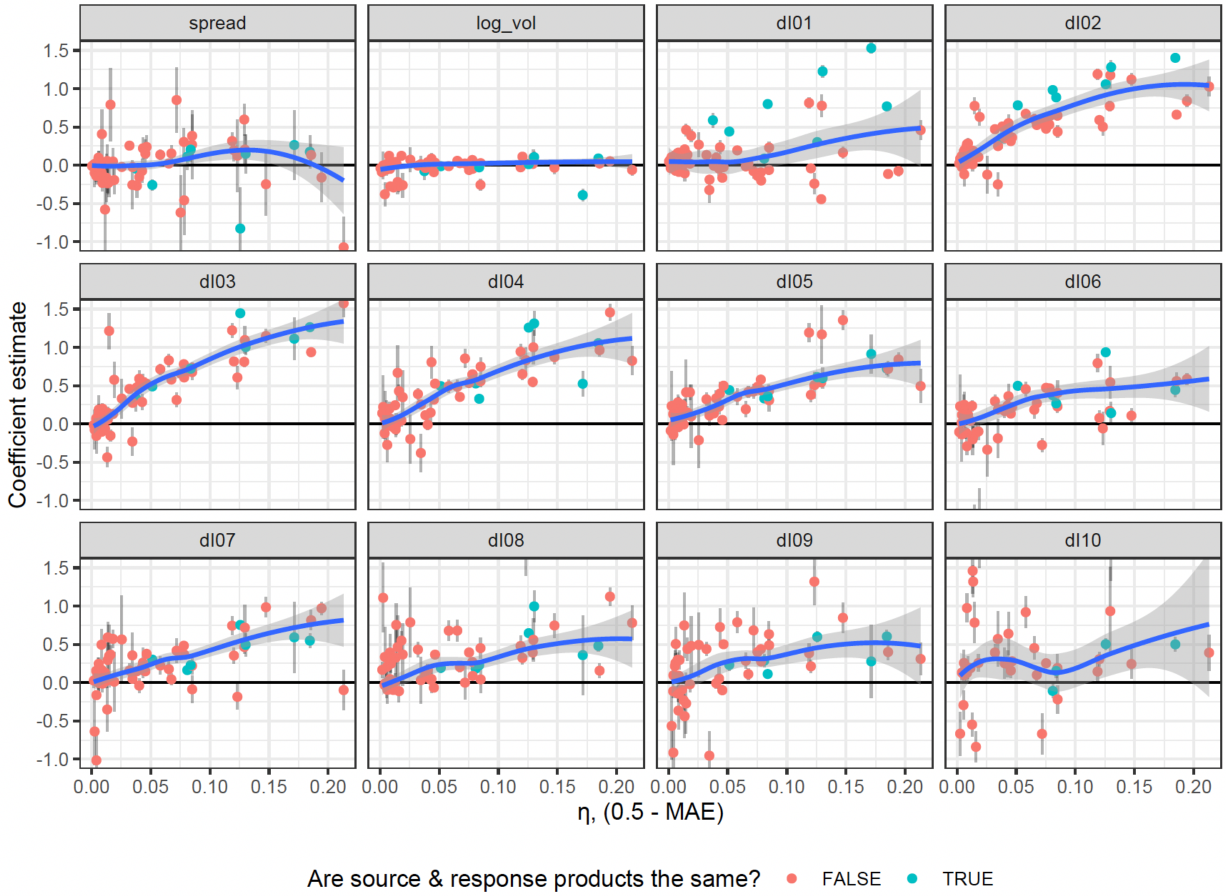
Source: EUREX and authors' calculations

Figure 6: Transmission model coefficients



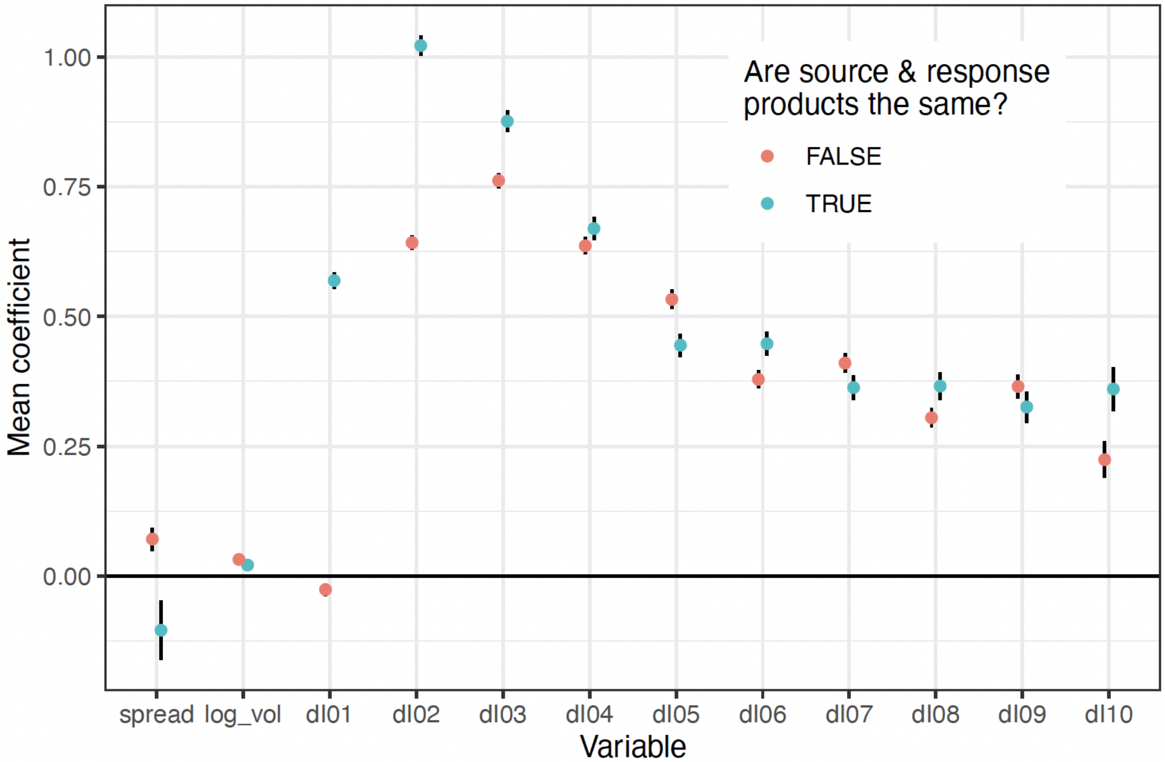
Source: EUREX and authors' calculations

Figure 7: Coefficients by transmissibility



Source: EUREX and authors' calculations

Figure 8: Averaged coefficients by transmissibility



Source: EUREX and authors' calculations