Fast Trading and the Virtue of Entropy: Evidence from the Foreign Exchange Market

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Abstract

We examine the reaction of foreign exchange markets to macroeconomic news and uncover a positive and significant correlation between fast trading and the entropy of the distribution of exchange rate quotes in reaction to news. A larger share of fast trading increases the diversity of exchange rate quotes in the order book, measured by entropy, for given liquidity, order book depth and size of order flows. We also provide evidence that fast trading increases entropy, rather than merely reacts to it, using the reform of the WM Reuters fixing methodology in February 2015 as a natural experiment. While more entropy in exchange rate quotes means noisier information and arguably complicates price discovery from an individual trader's perspective, in the aggregate, as we show, more entropy actually brings traded prices closer to the random walk hypothesis, and improves indicators of market efficiency and quality of trade execution. We estimate that a 10 percent increase in entropy reduces the negative impact of macro news by over 60% for effective spreads, against over 40% for realized spreads and price impacts. Our findings suggest that the main mechanism by which fast trading may have desirable effects on market performance specifically hinges on enhanced diversity in exchange rate quotes, best captured by entropy.

Key words: High-Frequency Quoting, Asset Pricing, Macroeconomic News, Market Efficiency, Random Walk, Quality of Trade Execution

JEL classification: F31, G14, G15

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1 Introduction

High-frequency trading (HFT) is often blamed for occasionally disrupting markets with so-called “Flash crashes”. The concern is that HFT may have potential adverse effects on liquidity and volatility of financial markets (see e.g. Kirilenko and Lo 2013, Lee et al. 2013, Chaboud et al. 2014, Lewis 2014, Hasbrouck 2015, Dobrev and Schaumburg 2016). Somewhat surprisingly, out of a wealth of theoretical and empirical studies into the channels through which HFT impacts price formation and market thickness (see e.g. Brogaard et al. 2014, 2015, Chaboud et al. 2014, Latza et al. 2014, Biais et al. 2015, Foucault et al. 2016, among others), leading contributions, such as Hendershott, Jones and Menkveld (2011) and van Kervel and Menkveld (2019), have provided a more reassuring picture.

In this paper, we provide evidence that HFT tends to improve many indicators of quality of trade and market efficiency, but from a new angle. This evidence is in line with previous work on stock markets, suggesting that the pattern we uncover is not specific to foreign exchange. The question is therefore: how does HFT help?

We provide an empirical contribution to the answer, uncovering two key – hitherto neglected – facts, which point to a seemingly puzzling mechanism by which HFT may improve liquidity and market performance.

Here is what we do: consistent with standard methodology, we assemble a large sample of news and study the order book and trades around the release of each piece of news at high frequency. Differently from other studies, however, we do not focus on traded prices but on quoted prices and calculate their entropy, i.e. a measure of the diversity of their distribution.[1] Based on this, we show that HFT is associated with higher entropy in quoted prices, both of which have a positive impact on markets.

Here is the puzzle. Intuitively, high entropy (i.e. a rich, diverse distribution) in quoted prices makes information that traders can extract from the order book noisy. How can noise be good? A possible and plausible answer is: by creating noise, fast traders may prevent traders with a herd mentality from pushing prices in one direction.[2]

[1] To recall, exchange rate quotes or orders are instructions to buy or sell a certain quantity X of currency A against currency B at price Y. There are different types of orders. For instance, a market order is an order to buy or sell at the best available price. There are also stop-loss orders, limit orders, etc.

[2] We like to think of this mechanism using a historical parallel from World War II. Just before the Normandy Landings on 6 June 1944, the Allies engaged in a successful misinformation operation, sending coded messages via the BBC’s nightly radio broadcasts. Some of the coded messages were important information that British intelligence services wanted to convey to resistance movements in continental Europe. Others were complete nonsense and were only meant to create confusion among the Axis powers. Examples of coded messages include “John has a long moustache”, “Molasses tomorrow will bring forth cognac” and – perhaps the most famous of them all – “The long sobs of the violins fill my heart with a monotonous languor” which pre-announced D-Day. The idea here is that "too much information" is "useless information" and prompts the receiver not to react. In this

More specifically, HFT traders not only exploit arbitrage opportunities arising from their ability to place and execute orders over infinitesimal time intervals. They may also try to exploit their ability to process large volumes of information simultaneously, to direct and test the market with quotes at disparate prices, not necessarily in line with the market norm given available information. Correspondingly, algorithmic trading may rely on programs which generate either a structured and tidy flow of quotes, conditionally predictable once the market starts to move in response to news, or place seemingly erratic quotes. By way of example, a strategy known as "quote stuffing" consists in quickly entering and withdrawing a large number of trading orders in an attempt to flood the market and, in turn, create confusion and trading opportunities for fast traders (see e.g. Biais and Foucault 2014).[3] In many trading venues like e.g. NYSE, AMEX, and NYSE-Arca, the ratio of orders relative to actual transactions has exploded in the past decade, together with the increasing activity of high-frequency traders. As an example, Figure A in the online appendix shows that trades and quotes in US stocks on Nanex—a market data services firm—are of completely different orders of magnitude. As we will show below, this is also the case in our data on the exchange market.

The Shannon entropy, which is well-known in information theory since Shannon and Weaver (1949), provides a natural metric to quantify the structure of the order book. Intuitively, the Shannon entropy of a distribution can be understood as the extent of its diversity —maximal for a uniform distribution (see e.g. Brissaud 2005). Applied to the sequence of orders in reaction to news hitting the market, low entropy will result from distributions of order prices that are quite compact and concentrated. Conversely, entropy will be high when prices in the order book are diverse, spread out and erratic.[4]

case, the German army's efforts to decrypt the messages were impaired by the large number of irrelevant pieces of information they received. This levelled the informational playing field: both relevant and irrelevant states of the world had the same likelihood to occur, hence preventing agents to make decisions on the basis of the information in question. Granted, HFT does not work as the Allied commands of World War II. They do not coordinate their action. The parallel with HFT is that because it generates entropy and dispersion in quoted prices, market players have no focal point to converge upon. This basically reduces chances of one-sided trades and therefore limits market movements and volatility.

[3] Other fast trading strategies include "smoking", which consists in posting alluring limit orders to attract slow traders while executing trades on less generous terms, and "spoofing", which involves placing a large number of orders in the opposite direction to fast traders' true intentions in order to lure slower traders and move prices to the benefit of the fast traders. Over time, many of these practices have been deemed illegal.

[4] The concept of entropy was, in fact, originally used by physicists and mentioned for the first time in 1865 by German physicist Rudolf Clausius. It has been also used in information theory, computer science and, more recently, in economics and finance. Finance researchers use it to define portfolio selection and asset pricing strategies—in particular for options (see Zhou et al. 2013 for a review). Physicists have also used the concept of entropy in recent papers to study the time series properties of FX returns (e.g. Wang et al. 2012; Sosic et al. 2016). In particular, they find that entropy is higher in times of financial crises (e.g. the Asian crisis or the subprime crisis), which they consider as an indicator of higher "confusion" in FX markets—without outlining the economic mechanism through which entropy emerges in FX markets and discussing why it matters, however. We use here one of the interpretations of the concept of entropy, as defined by Brissaud (2005), p. 2: "For an observer outside the studied physical system, entropy represents the lack of information about the state of the system. But for the system itself, entropy represents information, positively counted".

We carry out our study on the foreign exchange market, focusing on the response to news. Our sample covers seven of the most liquid currency pairs (EURUSD, USDJPY, EURJPY, GBPUSD, EURGBP, USDCHF and EURCHF), sampled at the 100-millisecond frequency, with information on bid-ask spreads, volumes and direction of trades, over the first quarter of 2015. This dataset enables us to identify fast trades as those executed against a limit order within 200 milliseconds, i.e. faster than the reaction time of human beings of 250 milliseconds or more, in line with Latza et al. (2014).[5] Moreover, we build a dataset of about 150 announcements concerning macro, financial and policy decisions announcements relevant for the exchange market in 17 countries. We derive a standardized measure of the news content of each announcement building on the methodology of Andersen et al (2003). We calculate the entropy of the distribution of quoted prices following each announcement hitting the market over a 30 minutes window.

We show that the entropy of the distribution of exchange rate quotes is a good indicator to summarise the structure of the order book and its evolution in response to news. In particular, we document that entropy is significantly correlated with the share of fast trading in total trade.

It may be possible, however, that HFT tends to react to, rather than create, a more diverse distribution of exchange rate quotes as measured by entropy. To ascertain the direction of causality, we use a case study with features of a natural experiment—the reform of the WM Reuters fixing methodology on 15 February 2015, which lengthened the time interval over which official rates were calculated from 1 to 5 minutes. This reform was designed to avoid very short-term manipulations and targeted specifically large orders as well as high frequency quoting behaviour around the time of the fixing (i.e. 4 p.m. London time). Before the reform, legal action against large banks with the charge of rigging the market already caused large institutional traders to be wary of placing large orders during the fixing—essentially they were "out". Therefore, the reform should have impacted fast traders first and foremost. The results are suggestive: during the 1 minute fixing, we found a peak in entropy; after the reform and the extension to 5 minutes, it disappears. This is consistent with the view that the decline in entropy can be largely attributed to fast trading done outside large banks, such as HFT.

Next we produce evidence that while more entropy means noisier information—which, from an individual trader perspective, might translate into "confusion"—that added noise may have desirable effects from an aggregate perspective. In our findings, fast trading and entropy both cause prices to move more in line with the market-efficiency hypothesis, and improve indicators of quality of trade. Specifically, we find that a 10 percent increase in entropy reduces the adverse impact of macro news—adverse in the sense that prices move away from the random walk hypothesis—by

[5]Fast trading is a subset of algorithmic-generated trades. It partially overlaps with high-frequency trading, which includes trading strategies based on, inter alia, very large order submissions and cancellations. Latza et al. (2014) use London Stock Exchange data sampled at the millisecond level. They are therefore able to use a finer threshold of 50 ms, but found that it was not qualitatively different from a 100 ms threshold.

over 60% for effective spreads, against 40% for realized spreads and price impacts.

In our interpretation, entropy is the key channel by which this occurs, with a straightforward behavioural interpretation in the spirit of classic models such as Hong and Stein (1999). That fast traders post diverse quotes at no specific price levels arguably adds noise to fundamental information which, in principle, might complicate the problem of other individual traders. In other words, higher values of entropy (a more diverse distribution of exchange rate quotes) also imply slower information diffusion. But from a market-wide perspective, this additional noise may help offset existing distortions that move prices away from efficiency standards. By increasing the amount of information to be processed by traders, higher entropy in the distribution of quotes helps avoid one-sided concentration and mitigates overshooting, in turn bringing the pricing process closer to the prediction of classic theoretical models.

In addition to the aforementioned literature, our findings are relevant for the vast body of studies relating quantitative characteristics of trading (e.g. bid-ask spread, orders flows, etc.) to fast trading and microstructure features of markets (e.g. liquidity provision, price impact, market efficiency, etc.) as in e.g. Brogaard (2010), Brogaard et al. (2014), Easley et al. (2012). A number of studies—a leading example being Hendershott et al. (2011, 2013 and 2014)—find potentially positive effects of fast trading on market liquidity and performance, in terms of cost of trading and informativeness of quotes. Breedon et al. (2018) find that algorithmic traders withdrew liquidity and generated uninformative volatility in Swiss franc currency pairs in the wake of the removal of the cap on the Swiss franc on 15 January 2015. Van Kervel and Menkveld (2019) find that high-frequency traders initially lean against large institutional orders but eventually change direction and take position in the same direction for the most informed institutional orders. Our specific contribution is to show the key role played by the patterns of exchange rate quotes, and document how this varies with fast trading.

Our paper also speaks more broadly to the literature on the effects of high-frequency identified macro shocks, in particular monetary policy shocks. In particular, a growing body of studies, e.g. Kuttner (2001), Cochrane and Piazzesi (2002), Bernanke and Kuttner (2005), Gertler and Karadi (2015), Nakamura and Steinsson (2018) and Jarociński and Karadi (2018), have sought to exploit the fact that a large amount of monetary news is revealed in the immediate aftermath of scheduled monetary policy meetings. These studies typically construct monetary policy shocks using unexpected changes in interest rates over narrow time windows (e.g. 30 minutes) surrounding scheduled monetary policy announcements, as we do here on a broader set of macro news. Our paper puts the issue under the microscope to understand the mechanism and aims to identify how high frequency quoting patterns at the micro level influence the response of exchange rates to macro news, including monetary policy news.

The paper is organized as follows. In the following section, we introduce our conceptual framework with a brief discussion of our empirical measure of the distribution of exchange rate quotes—the Shannon entropy. We then present a simple partial equilibrium model of asset pricing where this measure emerges as the natural metric of the information content of order books relevant to price formation. In Sections 4 we show that fast trading and the Shannon entropy of the distribution of quotes are systematically related empirically, and produce evidence that fast trading raises entropy, rather than reacts to it. In Section 5, we analyse how fast trading and entropy impact price formation, quality of trade execution and market efficiency. Section 6 concludes.

2 Entropy and the distribution of exchange rate quotes

In this section, we introduce our conceptual framework with a brief discussion of the Shannon entropy, which we propose as an empirical measure of the structure of trade. We then present a simple partial equilibrium model of asset pricing where this measure emerges as the natural metric to measure the information content of order books relevant to price formation.

At an intuitive level, entropy is typically introduced drawing on an example from information theory. A message is sent by an emitter through a channel and delivered to a receiver who attempts to infer which message was initially sent. Through the transmission process, the channel might have distorted the information initially available. Entropy measures the value of information that the message contains. If the message represents the realization of an event, the higher the number of possible events in the message, the higher the entropy; in particular, if in the message all events are equally likely, entropy is maximal. In contrast, in the case of events known with certainty, entropy equals 0. In other words, entropy is a measure of unpredictability of the set of states of the world described in the message.

In our context, we may think of entropy as characterizing uncertainty about the direction that a price process may take when some news hit the market. Entropy is higher, the higher the dispersion of beliefs about the implications of the news in question for the market price, thus the most disperse is the distribution of price quotes in the order book. A measure of this dispersion is the information content of entropy.

Formally, let p_i represent the probability that price i occurs in the sample's distribution of exchange rate quotes. By the definition of entropy by Shannon and Weaver (1949), we can write:

$$H\left(P_x, \text{time horizon}\right) = -\sum_i (p_i \log p_i).$$

As already mentioned, the Shannon entropy can be understood as the extent of the diversity of a statistical distribution. The negative log increases the weight given to rarer events because they carry more information (i.e they surprise when they occur). Entropy is hence maximal for uniform distributions and minimal for events known with certainty.

To visualize entropy, in Figure 1 we show the distribution of EURUSD quotes sampled at the one-minute frequency immediately after the announcement of two macro news. We select two case studies that contain a broadly similar number of quotes (about 7,000-9,000) for the same, most liquid, currency pair— to control for trade volume and liquidity. In the figure, each case study is synthetized by two scatter plots—the upper scatter plot shows quotes and volumes, while the lower one shows the distributions of the quotes. Contrast the two cases. In the case study to the left of the figure, the distribution of quotes is densely concentrated on a narrow range of prices within intervals smaller than 2 pips. In contrast, in the case study to the right of the figure, the distribution is spread out. Shannon entropy is low in the first case, high in the second.

These two case studies provide a preview of a key empirical result from our analysis: on average, the distribution with low entropy (to the left) corresponds to a low share of fast traders (14%). A higher share of fast traders (38%) characterizes the distribution to the right, with high entropy. We will see that this pattern is supported by extensive empirical analysis.

Why should entropy be relevant for market performance? A parsimonious way to elaborate on this question consists of drawing on the well known model by Hong and Stein (1999), henceforth HS. Departing from full rationality, these authors specify an economy with different types of agents trading claims on a risky asset, where prices are not fully revealing. Specifically, they postulate that "news watchers" are sequentially exposed to bits of information—or informative subinnovations of the fundamental. The key message from their analysis is that these traders will tend to "underreact to news", relative to the full information price under rational expectations.

HS postulates that news watchers only observe a small subset of innovations that the news convey but can acquire sequentially more subinnovations, according to a "rotation scheme." In the same spirit, we postulate that a news watcher gets information sequentually by observing the prices that are quoted in the order book over time. Individual orders may reflect both fundamental subinnovations and individual beliefs: the higher the dispersion of news and beliefs in the market, the higher the spread of the distribution, the less accurate the information on the innovation the trader can derive from an incomplete observation of the quote distribution.

Concretely, a trader will observe exchange rate quotes at specific price levels which vary by a few fractional pips, e.g. for the euro-dollar exchange rate, at 1.1558, 1.1559, 1.1560, 1.1561, 1.1562 USD/EUR, etc. By observing the orders that hit the market sequentially, the trader can update the frequency of each of these quotes—the longer she/he waits, the closer she/he will get to the market distribution. As in HS, the key trade-off is apparent: by waiting longer before posting her/his own order, our representative trader will observe a larger share of the distribution of quotes and thus acquire better information. However, by waiting longer, she/he may lose trading opportunities, i.e to buy or sell at a better price.[6]

We assume that, from past trades, the representative news watcher has a priori knowledge about the number of quotes that follow a piece of news, and has an priori idea of the share of the distribution of quotes she/he wants to observe before taking a position.[7] Let p_i denote the frequency of quotes at price level i, and α denote the share of the distribution of prices that the trader decides to observe a priori. After news hit the market, she/he will start to observe sequentially the orders that appear in the book. She/he will observe prices that are most frequently quoted, then move on to consider prices that are less frequently quoted—up to the point at which the frequency of the observed prices make up for α% of the total number of quotes he/she wants to observe before taking a position. Denoting z the number of quoted prices (subinnovations of information) that she/he observes, we can write the problem of the trader as:

$$z = \min \sum_{i=1}^{z} p_i \geq \alpha$$

Intuitively, the trader's problem is to find the number of quoted prices he/she needs to look at to extract sufficient information from the distribution of the quotes in question before trading. [8]

We can give a nicer concave shape to the optimization function, leveraging on the fact that $f(x) = x \ln(x)$ is strictly bijective over $[0, 1]$. The above minimization problem is thus equivalent to the following

$$z = \min \sum_{i=1}^{z} p_i \ln(p_i) \; \equiv \max - \sum_{i=1}^{z} p_i \ln(p_i)$$

The quantity $-\sum_{i=1}^{z} p_i \ln(p_i)$ is nothing else than the Shannon entropy. Crucial for our purpose is that z—the number of quotes optimally observed by the trader before taking action—is

[6] What is central in our analysis is to model the time it takes for our representative trader to process information, not the interaction between traders who process information.

[7] That traders know a priori the size of the order book is not an implausible assumption. It is common knowledge that the size of the order book hinges much on the time of the day (i.e. that trading in many pairs is typically much less active at night, i.e. during the Asian session). The size of the order book varies systematically conditional on the type of macro news (e.g. major monetary policy meeting decisions attract much more trading than releases of low-key data such as e.g. the unemployment rate).

[8] By way of example, imagine a situation in which 10,000 quotes are currently active on the market and spread over 10 different price levels or subinnovations (1 / 1.1 / 1.2/ . . . /1.9 for the USD/EUR pair, for instance). 3 price levels are overly attractive, with 3,000 quotes each. The remaining 1,000 quotes are evenly spread out among the 7 other price levels. In such a case, the trader processes 90% of the available quotes by looking at only 3 price levels. Now imagine that the same number of quotes and price levels are distributed completely uniformly. Each price level attracts 1,000 quotes, therefore representing 10% of the market. If the trader wants to cover 90% of the distribution of active quotes, he/she needs to look at 9 different price levels and integrate them into his/her decision. Because the quotes are much more dispersed, processing information becomes more complicated—the time needed for it is longer.

an increasing function of the Shannon entropy. Essentially, our z variable plays a similar role as the rate of information diffusion in Hong and Stein (1999), where traders are assumed to rotate in observing subinnovations about the fundamentals. In their context, z can be thought of as a proxy for the linear rate of information flow—higher values of z imply slower information diffusion. In our context, higher entropy means a richer dispersion of quotes to process before trading. Moreover, following the same steps as Hong and Stein, it can be shown that the difference between price p_j quoted by the trader observing the market and price p^* obtained in a fully revealing equilibrium —i.e. by synthesizing the entire distribution of quotes— is a function of Shannon entropy.

$$p^* - p_j = G\left(-\sum_{i=1}^{z} p_i \ln(p_i)\right)$$

By analogy with HS, higher values of entropy—higher values of z in HS— also imply slower information diffusion, insofar as entropy is a measure of the rate of information flow. And the difference between the fully revealing "fair" price and the trader's price is also a function of entropy. It should be clear here that our interpretation of entropy draws on models with cognitive bias, featuring divergence of opinions or beliefs among traders. In line with these models, the dispersion of exchange rate quotes results from a large number of a priori beliefs among market participants about the price process. However, in the case of algorithmic trading, the dispersion of exchange rate quotes is not necessarily driven by heterogeneous views about the interpretation of a fundamental shock—it may reflect an "absence of a view" about fundamentals, with fast traders posting diverse quotes to fit into their trading strategies. Observationally, of course, this would be equivalent to a large number of traders with different views.[9]

But this is where our approach is most effective in shedding light on the market micro-structure, with entropy defining an almost ideal metric to analyse how markets process information emanating from the distribution of exchange rate quotes. Market metrics that are standard in the literature, such as quoting spreads (i.e. the distance between the best and the worst ask, or the best and the worst bid), tend to weigh infrequent subinnovations, which arguably represent outliers, with potentially lower volumes and smaller probabilities of being executed. But what traders want to obtain is information about the structure of the entire distribution of quotes—paying more attention to prices that are most frequently quoted, and arguably reflect market-relevant subinnovations. We actually confirm this conjecture in the empirical section of the paper.

[9]In a model where price quotes are itself news, these may not necessarily be informative on the fundamentals.

3 Data

Our high-frequency data is for the first quarter of 2015. It covers important events such as the discontinuation of the EUR/CHF peg by the Swiss National Bank and the announcement and implementation of the European Central Bank's Asset Purchase Programme. Exchange rate quotes and transacted prices are taken from EBS, which is one of the two largest electronic platforms in the foreign exchange spot market (with Thomson Reuters). In particular, a large share of electronic spot trading for the two most liquid currency pairs, EURUSD and USDJPY is transacted through EBS. We have information on best bid and ask quotes, on volumes and on direction of trades. Data are sampled at the 100 millisecond (ms) frequency. We have data on seven liquid currency pairs (EURUSD, USDJPY, EURJPY, GBPUSD, EURGBP, USDCHF and EURCHF). We compute order flows, amounts traded and number of trades, as well as the Shannon entropy of exchange rate quotes for the pairs in question. We match each trade with the most recent quote at the same price of opposite direction, and compute the time difference between the trade and matched quote in question. When the time difference is below 200 milliseconds, trades are classified as "fast" since this threshold falls beyond the physical abilities of human beings in terms of speed of execution.

Our data on announcements are taken from FXStreet.[10] FXStreet provides information about the type of announcements, their realized, previous and forecasted values, as well as the corresponding time stamp (at the second level). We break announcements into five categories: real macroeconomic announcements (e.g. GDP, trade, unemployment data releases); financial announcements (bond auctions, capital flows, etc.); policy rate decisions by central banks; inflation-related announcements (HICP, consumer and producer price indices, etc.) and other relevant announcements (e.g. speeches from policy makers, international policy summits, etc.). Table 1 breaks down macroeconomic announcements by country and type, while Table 2 provides examples.

[Tables 1 and 2 about here]

We calculate expected values using the median of forecasts of professional forecasters, collected shortly before announcement of the macroeconomic data in question. Following Andersen et al. (2003), we measure the news content of the announcement by calculating the normalized difference between the realized value of a given macroeconomic indicator k and its value expected by market participants:

$$S_{i,t}^k = \frac{\Lambda_t^k - F_t^k}{\sigma^k}, \quad \nabla k \in I$$

where Λ_t^k is the value of the indicator k announced at time t, F_t^k is the expected value of the same

[10] The data were accessed in April 2016 from https://www.fxstreet.com/economic-calendar. FXstreet is a global online currency trading portal that offers real-time exchange rates, currency charts, news, market forecasts, technical analysis and currency conversion tools. Owned by Forexstreet S.L and registered in Barcelona, FXstreet is published for more than 50 countries and ranks within the world's top-ten online currency trading portals.

indicator, σ^k is the sample standard deviation of $\Lambda_t^k - F_t^k$, and I is the set of information indicators.

The use of standardized news (in other words scaling the difference between the announced and expected values of indicator k by its respective standard deviation) facilitates comparison of exchange rate responses to different announcements. We should stress that, in most cases, announcement days are known in advance and surveys of market expectations are realized before macroeconomic data are released—news can be considered exogenous with respect to other economic developments. In extended specifications, we complement the set of standard macroeconomic announcements with the other relevant pieces of information mentioned above, such as outcomes of international meetings and speeches. There are no expected values for these pieces of information, so we relegate them to robustness checks.

Overall, our dataset comprises about 150 news and up to 1,223 observations (the same piece of news can impact different currency pairs). Descriptive statistics of our main variables of interest are shown in Table 3. The normalized surprise variable (as defined above) varies significantly in both directions, from -4.1 to 3.6 standard deviations. We can thus explore the market impact of news/shocks of different sizes. Following a news, there is a very high number of quotes in the order book—in our sample, we can have more than a million quotes over a 30 minutes window post-news. However, the number of actual transactions does not exceed 7,000. This confirms that the number of quotes and the number of transactions are of completely different orders of magnitude. Over the same time window, the log of entropy varies significantly; so does the share of fast traders, which varies significantly across currencies, as shown in Figure 2 below.

Figure 2 shows the distribution of the proportion of fast trades for different currency pairs in response to news. The boxplot indicates the 10th, 25th, 50th, 75th and 90th percentiles, respectively. It shows that the share of fast trades varies considerably between the different currency pairs, ranging from almost zero to 90 percent. Not all currency pairs attract fast trades to the same extent, in other words.

[Figure 2 about here]

4 Fast trading and entropy of the distribution of exchange rate quotes

Our first question concerns whether, in the data, there is any systematic relation between fast trading and the patterns of exchange rate quotes, as synthesized by the entropy of their distribution. To address this question, we estimate a log-log regression between the two variables, controlling for a wide set of controls used in the market microstructure literature, and including currency fixed effects. The regression model is as follows:

$$\log H_{j,t} = \alpha_j + \beta_F \log FT_{j,t} + OF_{j,t} + AmT_{j,t} + NumT_{j,t} + \epsilon_{j,t} \quad (1)$$

where $H_{j,t}$ is the entropy of exchange rate quotes measured over a 30 minutes horizon; $FT_{j,t}$ is the share of fast trading for currency pair j at time t, $OF_{j,t}$ the order flow, $AmT_{j,t}$ the amount traded and $NumT_{j,t}$ the number of trades; the residual is denoted as $\epsilon_{j,t}$. The results are presented in Table 4. The estimated coefficient β_F is significant at the 1% level and hovers around 0.2: an increase in fast trading activity by 10% is associated with a rise in entropy by 2%.

[Table 4 about here]

Observe that some of the regressors are not significant—including trading book depth, number of deals, number of quotes. Order book flow is significant, but small. Interestingly, order book depth is significant and negative—offsetting the effect of fast trading: entropy falls with order book depth. It is worth stressing that the inclusion of controls actually raises a bit the magnitude of the coefficient on the share of fast trading.

Table 4 provides evidence consistent with the view that, on average, fast traders are posting diverse quotes, increasing entropy. However, it can be argued that there is an endogenous relationship between entropy and fast trading. It may be possible that fast traders are attracted by a high diversity of quotes in response to news, to grab opportunities and act as middlemen, capturing bid-ask spreads as in the model of e.g. Jovanovic and Menkveld (2016). In this sense, high frequency traders may respond to entropy. Unfortunately, to our knowledge, there is no reliable instrument to control for endogeneity at the microstructure level.

To gain insights on this reverse causality problem, we consider a case study with features of a natural experiment. On February 15th, 2015, following an earlier scandal on fixing manipulation, WM Reuters decided to modify the way it computes the fixing of the exchange rate at 4 p.m. GMT (London time). Before the reform, fixing was computed over a 1-minute window. After the reform, the window in question was extended to 5 minutes. This reform was designed to avoid very short-term manipulations and targeted specifically large orders as well as high frequency quoting behavior around 4 p.m. Therefore, fast traders should have been amongst the first to be impacted by this methodological change. An important additional piece of information was that the reform was introduced well after large intermediaries were hit by legal action on charges of market manipulation. This legal action meant that all large banks were already quite wary and caution about trading around the fixing time.

[Figure 4 here]

Figure 4 presents the evolution of entropy before and after the reform, computing median entropy at 10-second intervals over 30 days before and after 15 February 2015. As is apparent from the figure and also from two statistical tests (difference in means and difference in medians), the fixing reform removed the peak in entropy observed before the reform and smoothed quoting patterns. As argued above, large financial intermediaries were already conspicuously absent from the market. This suggests that the fall in entropy can be presumably attributed to a drop in fast trading done outside banks, such as HFT.

The result from this case study suggests that it is fast trading activity that creates a more diverse distribution of exchange rate quotes, increasing entropy—inconsistent with an alternative view, that high entropy exogenous to fast trading attracts this class of market participants.

5 Fast trading, entropy and market efficiency

In this section, we investigate how fast trading and entropy affect the reaction of the foreign exchange market to macro news. We first define a set of key indicators of market efficiency and quality of trade execution that we employ as dependent variables in our regression analysis. Then we discuss our main results.

5.1 Empirical framework

5.1.1 Indicators of market efficiency

We measure market performance and quality of trade execution using standard indicators proposed in the literature—price efficiency, bid ask spread and price impact.

One may argue that volatility of exchange rates is a natural metric to study the market impact of fast trading. However, it is likely that some fast traders will generate volatility while others will seek to exploit it. In other words, volatility may tend to be endogenous with respect to fast trading activity. To circumvent this issue, the literature on high frequency trading, and especially the literature on high frequency quoting (see e.g. Conrad et al., 2015) has considered alternative metrics. One such metric is price efficiency. According to the market efficiency hypothesis, the price of financial assets should follow a random walk (see Fama 1970). Lo and MacKinley (1988, 1989) propose a variance ratio test, to estimate the distance of the price process from a random walk.[11] The main idea is that the variance of a random walk is linear in time intervals. Under the random walk hypothesis, the ratio between the short-term variance and the long-term variance per unit of time is equal to 1. Deviations from 1 would therefore provide evidence against the random walk hypothesis. Using the test statistic distribution provided by Lo and MacKinley (1989) for

[11]See Shiller and Perron (1985) for an analysis of statistical methods for testing the random walk hypothesis on financial markets.

heteroscedastic time processes, we estimate both the variance ratio statistic and its associated p-value (against the random walk hypothesis) immediately after announcement of macro news, by comparing the post 5-minutes unbiased variance estimator with the post-30 minutes one. The advantage of using the variance ratio as a metric of price efficiency is that immediate fast trading activity is pre-determined with respect to the variance ratio estimated over a 30 minutes window.

For a given time interval q and time horizon n, Lo and MacKinley (1989) define the following unbiased variance ratio test as measure of the log of the price process $X_0, X_1.., X_T$:

$$M_r(q) = \frac{\sigma_l^2(q)}{\sigma_c^2} - 1 \tag{2}$$

where $\sigma_l^2(q) = \frac{1}{m}\sum_{k=q}^{nq}(X_k - X_{k-q} - q\hat{\mu})^2$, $\sigma_c^2 = \frac{1}{nq-1}\sum_{k=1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2$, $m = q(nq - q + 1)(1 - \frac{q}{nq})$ and the mean drift in prices is measured as:

$$\hat{\mu} = \frac{1}{nq}\sum_{k=1}^{nq}(X_k - X_{k-1}) = \frac{1}{nq}(X_{nk} - X_0)$$

In the literature, some studies focus on the test statistic defined above as the dependent variable. But the variance ratio test is by essence two-sided. Therefore, we prefer to use the p-value associated with the test statistic instead, relying on the heteroscedastic robust asymptotic distribution proposed by Lo and MacKinley. The asymptotic distribution in question is:

$$M_r(q) \sim N[0, V(q)]$$

with $V(q) = \sum_{j=1}^{q-1}[\frac{2(q-j)}{q}]^2 \times \delta(j)$, where $\delta(j) = \frac{\sum_{k=j+1}^{nq}(X_k - X_{k-1} - \mu)^2 \times (X_{k-j} - X_{k-j-1} - \mu)^2}{[\sum_{k=1}^{nq}(X_k - X_{k-1} - \mu)^2]^2}$.

In addition to the variance ratio test, we consider other metrics traditionally used in the financial market microstructure literature, such as the effective spread, the realized spread and the price impact. The effective (half) spread is defined as:

$$es_{jt} = q_{jt}\frac{(p_{jt} - m_{jt})}{m_{jt}}$$

where q_{jt} is equal to +1 for buyer-initiated trades and -1 for seller-initiated trades, p_{jt} is the transaction price and m_{jt} is the prevailing quote midpoint.

The realized spread is computed as:

$$rs_{jt} = q_{jt}\frac{(p_{jt} - m_{jt+\tau})}{m_{jt}}$$

where $m_{jt+\tau}$ is the quote midpoint τ periods after the trade. The price impact is computed as:

$$pi_{jt} = q_{jt}\frac{(m_{jt+\tau} - m_{jt})}{m_{jt}}$$

All these metrics proxy for quality of trade execution; tighter spreads and lower price impacts are associated with lower execution costs and therefore better market functioning. Again, because these metrics are based on future prices, they are unlikely to be endogenous to contemporaneous fast trading activity.

Descriptive statistics for these variables are reported in the last three columns of Table 3. The random-walk test metric, the p-value of the variance ratio, is roughly equally distributed between significant results (below 10%) and non-significant results; the median of the p-value is 9%. Measures of quality of trade execution—effective spread, bid-ask spread—exhibit large outliers, which is not infrequent in the aftermath of a shock (large news in our case). The median value of the absolute bid-ask spread in the sample is around 30 pips, quite usual in normal times for FX traders, but due to large outliers, the mean exceeds 7 percentage points (our sample captures fully the first quarter of 2015, including significant events such as the announcement by the European Central Bank of the launch of its Asset Purchase Program on January 15th, the removal by the Swiss National Bank of the floor on the EURCHF on January 22nd, the EURUSD flash crash on March 18th, etc.). To mitigate concerns that these outliers may drive our results, we carry out robustness checks, by running regressions where the observations are winsorized below the 95th upper percentile of the absolute bid-ask spreads distribution. Results are robust to winsorization and are reported in the online appendix (see below).

5.1.2 Regression model

Our goal is to investigate the extent to which fast trading and entropy impact the reaction of the foreign exchange market to shocks to macroeconomic fundamentals. To this end, we regress the indicators of price efficiency and quality of trade execution defined above, on macroeconomic news (expressed in standard deviations), the log of fast trading activity/entropy, and an interaction term between these and macroeconomic news. Essentially, we build upon the specification of Andersen et al. (2003), who restrict their analysis to macroeconomic news, by augmenting the model with entropy and fast trading.

In the regression model, we also include a number of controls in the baseline estimates, such as order flows, in line with Evans and Lyons (2002), as well as liquidity, book depth, type of news, and other variables, in line with studies on market quality such as Conrad et al. (2015). Our dependent variables for price efficiency or execution quality (based on spreads) are all in absolute values (e.g. tighter spreads indicate lower costs of execution independently of their signs). By the same logic, we also measure the surprise component of macro indicators in absolute value, as we are not interested in asymmetric effects of downside or upside surprises, but on whether the surprise is large or small.

We consider first the fast-trading specification of our model. The equation we estimate for each currency pair j is:

$$|m_{j,t}| = \alpha_j + \beta_s \left|S^k_{j,t}\right| + \beta_{FT} \ln FT_{j,t} + \beta_I \ln FT_{j,t} \cdot \left|S^k_{j,t}\right| + controls + \varepsilon_{j,t} \tag{3}$$

where $|m_{j,t}|$ is either a price efficiency or an execution quality variable, $\left|S^k_{j,t}\right|$ the standardized news associated with the announced value of indicator k for country j at time, $lnFT_{j,t}$ is the log of fast trading activity over the period of interest, and the controls include order flows for currency j at time t, the amount traded, and the number of trades; α_j is a currency fixed-effect, and $\varepsilon_{j,t}$ is the residuals. In extensions of this baseline specification, we also control for the type of news.

We define the market reaction to macro news as $\frac{\partial|m_{j,t}|}{\partial\left|S^k_{j,t}\right|}$—for our baseline specification this will be

$$\frac{\partial\left|m_{j,t}\right|}{\partial\left|S^k_{j,t}\right|} = \beta_s + \beta_I \ln FT_{j,t}$$

Therefore, β_I is the semi-elasticity of the market reaction to macro news with respect to fast trading.

The regression model for fast trading is the same as above, whereas the log of fast trading activity over the period of interest $\ln FT_{j,t}$ is replaced with entropy $H_{j,t}$:

$$|m_{j,t}| = \alpha_j + \beta_s \left|S^k_{j,t}\right| + \beta_{FT} \ln H_{j,t} + \beta_I \ln H_{j,t} \cdot \left|S^k_{j,t}\right| + controls + \varepsilon_{j,t} \tag{4}$$

where $H_{j,t}$ is the entropy of the distribution of quotes, measured over a 30 minutes window after the news. Again, the β_I coefficient represents the semi-elasticity of market quality measures with respect to entropy conditional on macroeconomic news.

5.2 Results

5.2.1 Price efficiency

Our first set of results concerns the question of whether a higher share of fast trading and/or higher entropy is detrimental to price efficiency, as measured by the statistical deviation of the price process from a random walk. The OLS estimates of our fast trading and entropy equations (3) and (4) are shown in Tables 5 and 6. In either table, the dependent variable is the heteroscedastic-robust *p*-value of the variance ratio test. Column (1) reports our baseline, while columns (2)-(4) include order flows, liquidity measures and control for news type. All estimates include currency fixed effects. Errors are robust to heteroscedasticity.

Results for our OLS estimates of the fast-trading equation (3) are shown in Table 5. The coefficient for the surprise component of news is highly significant and negative—large surprises lower the p-value of the variance ratio test. In other words, "large news" cause the price process to deviate from the random walk hypothesis, and introduce price persistence as well as worsens the quality of trade execution (typically by increasing spreads). However, and here is a key result, the interaction coefficient between fast trading and the magnitude of the economic surprise is of the opposite sign, i.e. positive, and significant at the 1% level: a large share of fast trading attenuates the adverse impact of large macro news on exchange rate price efficiency.

[Table 5 about here]

This is a key empirical finding. To visualize it, in Figure (3) we plot the average price impact of news over a 30 minutes window, against the share of fast trading, by currency pair and type of news. Besides one clear outlier, the US dollar response to policy interest rate news, the rest of the observations are characterised by a *negative* relation between the share of fast trading and price impact. A high proportion of high frequency trading tends to reduce the response of prices to news. Why this is the case is what we will further discuss below.

[Figure 3 about here]

Results for our OLS estimates of the entropy equation (4), in turn, are shown in Table 6. The coefficient for the surprise component of news is also negative—large surprises lower the p-value of the variance ratio test—but now significant only at the 10-15 percent level. Nonetheless, the interaction coefficient between entropy and the magnitude of the economic surprise has again the opposite sign relative to the effect of news—and its effect is also significant only at the 10-15% level. High entropy tends to attenuate the adverse impact of large macro news on exchange rate price efficiency.

[Table 6 about here]

5.2.2 Quality of trade execution

We now discuss our OLS estimates of model equations (3) and (4), where quality of execution metrics (in absolute terms) are regressed on the surprise component of macroeconomic news and either the share of fast trading or entropy. For each quality of execution variable, we report the regression without controls and with the full set of controls. As above, currency fixed effects are included in each specification, and standard errors are robust to heteroscedasticity.

[Table 7 about here]

The results for the fast trading equation are shown in Table 7. As in Table 5, the coefficient on macro news is significant at the 1% level of confidence and positive for the execution quality variables—large macro surprises deteriorate execution quality (i.e., they are associated with wider spreads). Once again, however, the interaction coefficient between the share of fast trading and macro news is systematically of the opposite sign of the direct effect of macro news, and significant up to the 1% level of confidence. A larger share of fast trading attenuates the adverse impact of large macro news on quality of execution. The effect is economically sizeable. A 10% increase in the share of fast trading in market activity reduces the impact of macro news by 9% for the effective spread, 7% for the realized spread and 15% for the price impact.[12]

[Table 8 about here]

Results obtained from model equation (4), where we replace the share of fast trading with entropy, are also in line with the above. Across execution quality variables, the coefficient for macro news tends to be positive, which indicates that large macro surprises deteriorate execution quality (i.e. lead to wider spreads), but not consistently significant at the standard level. In contrast, the coefficient of entropy is positive and highly significant. The interaction coefficient between entropy and macro news is negative and significant at the 5% level when we include the full set of controls. This indicates that entropy tends to attenuate the adverse impact of macro news on the execution quality variables.

It is worth stressing that even the magnitude of the coefficients for entropy is broadly in line with those obtained for the share of fast trading, after taking into account the fact that the elasticity between the share of fast trading and entropy is estimated to be on the order of 0.2. So, intuitively, one should expect a ratio of 5 between the two coefficients, as is roughly the case here. Figure 5 summarizes the results for the two specifications. In line with this, we estimate that a 10 percent increase in entropy reduces the negative impact of macro news by over 60% for effective spreads, against over 40% for realized spreads and price impacts.

[Figure 5 about here]

As an important check and placebo test, we run the model using as dependent variable a different measure of dispersion of quotes, the quoting spread—defined as the average of the spread between the best and worst asks and between the best and worst bids. Table 9 presents estimates for different market quality metrics. In these regressions, the interaction terms between macro news and the quoting spread is not significant. This is highly relevant, because, together with the rest of our results, it confirms the view that fast trading affects market performance via its effect on the structure of the order book, rather than pure outliers which may not be that relevant for traders. This result clarifies and strengthens the case for using entropy as the relevant summary

[12] These estimated impacts are based on the estimated coefficients of model equation (3) discussed above, taking into account both the direct effect of fast trading on trade quality execution metric, as well as the interaction between fast trading and normalized news.

measure of patterns in exchange rate quotes.

Finally, as additional robustness checks we obtained estimates with winsorized observations, where we removed the upper 5th percentile of the distribution of absolute bid-ask spreads observations. We also obtained estimates where we used our measure of entropy in levels, rather than in logarithms. In both cases, our results remained robust (see the corresponding tables in the online appendix).

[Table 9 about here]

5.3 Discussion

Overall, our findings lend support to the hypothesis that fast trading impacts market reaction to macro news through its effect on quoting patterns, highlighting a so far understudied transmission channel. A large share of high frequency trading dampens overreaction to news, reduces price persistence and brings prices more in line with a random walk—hence closer to the prediction of the efficient market hypothesis.

Our results would hence suggest that the fact that fast traders may end up posting diverse quotes at no specific price levels ends up having desirable effects on market performance—arguably offsetting existing distortions that move prices away from efficiency standards. One possible mechanism is that high entropy in the distribution of exchange rate quotes increases the amount of information to be processed by market participants. And in light of the classical analysis by Hong and Stein (1999), underlying our discussion in Section 2, this may contribute to slow down markets and reduce their reaction to macro news. [13] The seemingly erratic pattern of exchange rate quotes posted by fast traders appears to counteract any tendency of other traders to overreact to news and helps avoid one-sided concentration. Put differently, by creating what could be regarded as noise, fast trades may prevent traders with a herd mentality from pushing prices in one direction.

6 Conclusion

Our findings matter for policy and research. From a policy perspective, they suggest that an increasing diversity of exchange rate quotes associated with fast trading is not necessarily damaging for market performance. It is actually beneficial in our estimates. This is a point deserving further

[13] This also connects to the literature on the delayed overshooting puzzle uncovered by Froot and Thaler (1990) who observed that gradual portfolio adjustment could explain why some investors are slow in responding to changes in fundamentals, perhaps because these investors need some time to think about trades before executing them, or because they simply cannot respond quickly to recent information; see Bachetta and van Wincoop (2010) and (2018) for more recent discussions.

attention in discussions about the optimal regulatory regime for fast trading. From a research perspective, future work should complement the findings reviewed here with an analysis of possible nonlinearities and reconsider the role of entropy in situations of market stress. Finally, our paper speaks more broadly to the literature on the effects of high-frequency identified macro shocks, notably monetary policy shocks. It suggests that micro-market conditions, especially high frequency quoting patterns, are crucial aspects of the mechanism underlying the transmission —and interpretation— of macro shocks to exchange rates, including those stemming from monetary policy.

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7 Statistic appendix

7.1 Data

We use FX street to extract macroeconomic news, as well as market expectations associated with the news in question. Because we want to focus on news with market impact, we extracted news classified by FXStreet as “important”. This represents more than 150 macroeconomic announcements over 17 countries. We focus on the most liquid currency pairs, as high-frequency trading is usually limited on illiquid markets. These pairs are: EURUSD, USDJPY, EURJPY, USDCHF, EURCHF, GBPUSD, EURGBP. Note that we have much less currency pairs than countries because we take news from several euro area members.

Overall, our dataset comprises up to 1,223 observations (the same piece of news can impact different currency pairs). We present the descriptive statistics of our main variables of interest in Table 3.

Using FXStreet data, we were able to retrieve the time stamp indicating when announcements were released. For each piece of news concerning the country of issuance of a particular currency (for instance, for a macro announcement in the UK, we look at GBPUSD and EURGBP), we compute in the following 30 minutes different metrics: random-walk test, average effective spread, bid-ask spread, average quotes entropy, average share of fast trading, etc. Then we obtained for each dyad (news, currency pair) a series of variables with market quality metrics, share of fast trading and entropy averaged over a 30 minute-window. Our dataset is restricted to observations with the said announcements. We therefore have a cross-sectional data set, not a panel data set. This rules out estimation problems arising from e.g. clustered standard errors or serial auto-correlation.

The typical trade-off for choosing a window of observations is to have a long enough time period to capture most of the impact of announcements on the market, but short enough to avoid confounding the impact of a particular announcement with other pieces of information. For this reason, we chose 30 minutes as a time window. Besides, this allows us to implement the random walk test, which is usually done in the literature by computing a short variance over 5 minutes and a long one over 30 minutes.

7.2 Random-walk test

Following Lo and MacKinley (1989), we define three parameters:

- The sample time of log prices. Even though our observations are sampled at 100ms intervals, it makes little sense to look at log returns over such a small interval. We therefore sample the data at 5-second intervals.
- Long and short horizons—set at 30 and 5 minutes, respectively.
- The "n" and the "q" parameters (as defined by Lo and MacKinley 1989)—set, respectively, to 6 (30 minutes/5 minutes) and 60 (5 minutes/5 seconds).

From there, we compute the unbiased random walk statistic as explains in the text. The p-value test is two-sided.

7.3 Quality of execution metrics

We present the computations of the quality of execution spreads in section 5.1.1. Typically, we compute the spreads at the 100 ms frequency based on the best bid and the best ask, unless otherwise mentioned (one exception is the quoting spread, which is based on the average spread between the best and worst bid and the best and worst ask). We then take the average of these metrics in the 30 minutes following the macro announcements.

7.4 Share of fast trading

To compute the share of fast trading over a certain time frame, we match all trades with their corresponding quote (same price, volume and opposite trading side). We then look at the time difference between quotes and trades and define as fast trading those executed below 200 ms (bearing in mind that the average reaction time of a human being is above 250 ms).

7.5 Entropy

To compute the entropy of the distribution of quotes, we consider all quotes active in the market in the 30-minute period following a macroeconomic announcement. From this distribution, we compute the Shannon entropy using the formula presented in section 2.

Table 1: Number of Macro Announcements – Country Breakdown (First Quarter of 2015)

	Financial	**Prices**	**Interest rates**	**Macroeconomy**	**Speeches, meetings and summits**
Autralia	3	4	6	28	7
Canada	2	6	3	21	1
Euro area	105	176	12	616	71
Hong Kong	0	0	0	1	0
India	0	0	1	0	0
Japan	10	18	4	80	7
Russia	0	5	1	14	0
South Africa	0	0	0	1	0
Switzerland	0	8	4	38	4
United Kingdom	8	10	0	32	9
United States	204	88	5	924	224

Source: FX Street

Table 2: Examples of Macroeconomic Announcements for Selected Countries

Financial	**Prices**	**Interest rates**
Italy : 10-y Bond Auction	Austria : Producer Price Index (MoM)	Australia : RBA Interest Rate Decision
Italy : 5-y Bond Auction	Austria : Wholesale Prices n.s.a (MoM)	Australia : RBA Monetary Policy Statement
Japan : Foreign bond investment	Belgium : Consumer Price Index (MoM)	European Monetary Union : Targeted LTRO
Spain : 12-Month Letras Auction	Canada : Industrial Product Price (MoM)	Russia : Interest rate decision
Spain : 2-y Bond Auction	European Monetary Union : Producer Price Index (MoM)	Switzerland : SNB Interest Rate Decision

Macroeconomy	**Speeches, meetings and summits**
Australia : Construction Work Done	Japan : BOJ Deputy Governor Nakaso Speech
Canada : Housing Starts s.a (YoY)	Japan : BoJ Monetary Policy Meeting Minutes
Switzerland : UBS Consumption Indicator	Switzerland : SNB Chairman Jordan Speech
United States : NAHB Housing Market Index	United States : Fed's Bullard speech
United States : Pending Home Sales (MoM)	United States : FOMC Member Powell Speech

Source: FX Street

Table 3: Descriptive Statistics

	Normalized surprise	Log Reaction time	Log Entropy	Order book flow	Order book depth	Trading book depth
# of obs	368	1211	1223	1223	1223	1223
Mean	0.05	0.73	1.35	-4.97	123.08	0.10
Std	1.05	0.57	0.10	53.54	127.81	0.24
Min	-4.12	0.00	1.09	-758.65	0.56	0.00
25%	-0.50	0.26	1.29	-2.73	28.92	0.00
50%	0.00	0.59	1.35	0.07	84.63	0.02
75%	0.74	1.10	1.41	3.11	178.62	0.10
Max	3.60	3.05	1.69	279.00	996.21	3.14

	Number of quotes	Number of deals	Var Ratio Pvalue	Abs. Effective Spread	Abs. Bid-Ask Spread
# of obs	1223	1223	1223	1220	1223
Mean	273163	474	0.24	3.19	7.54
Std	212783	664	0.29	5.17	13.18
Min	3914	1	0.00	0.00	0.05
25%	90795	76	0.00	1.53	0.12
50%	220600	236	0.09	1.84	0.29
75%	421757	642	0.41	3.20	13.45
Max	1199774	6936	1.00	115.95	144.91

Source: authors' computations

Table 4: Elasticity of Entropy with respect to Fast Trading

	Entropy (log) **No controls**	**Entropy (log)** **Order flows and depth**	**Entropy (log)** **Microstructure**	**Entropy (log)** **Type of news**
Share of fast traders (log)	0.146*** (0.0)	0.194*** (0.0)	0.199*** (0.0)	0.200*** (0.0)
Order-book flow		0.000** (0.02)	0.000*** (0.0)	0.000*** (0.0)
Order book depth		-0.200*** (0.0)	-0.191* (0.06)	-0.202** (0.05)
Trading book depth		0.006 (0.68)	0.017 (0.64)	0.016 (0.64)
Number of quotes			-0.000 (0.93)	0.000 (0.95)
Number of deals			-0.001 (0.73)	-0.001 (0.72)
News type: inflation				0.002 (0.84)
News type: macroeconomics				-0.010* (0.08)
News type: other CB announcements				0.013+ (0.12)
Intercept	1.331*** (0.0)	1.337*** (0.0)	1.336*** (0.0)	1.343*** (0.0)
R2	0.407	0.458	0.458	0.462

Robust p-values in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, $^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (1), including currency fixed effects with robust standard errors. Baseline OLS estimates are reported in column (1), while columns (2)-(4) include controls for order flows, liquidity measures and dummies for news type. All regressions include currency fixed effects.

Number of observations: 1,211

Table 5: Estimated Impact of Macro News and Share of Fast Trading on Price Efficiency

	Variance ratio test (pvalue) **No controls**	**Variance ratio test (pvalue)** **Order flows and depth**	**Variance ratio test (pvalue)** **Microstructure**	**Variance ratio test (pvalue)** **Type of news**
Normalized fundamental surprise	-0.101*** (0.0)	-0.091*** (0.0)	-0.095*** (0.0)	-0.095*** (0.0)
Share of fast traders (log)	-0.140*** (0.01)	-0.258*** (0.0)	-0.210* (0.06)	-0.210* (0.06)
Norm. surprise x log FT share	0.107*** (0.0)	0.097*** (0.0)	0.103*** (0.0)	0.103*** (0.0)
Order-book flow		-0.000 (0.89)	0.000 (0.51)	0.000 (0.51)
Order book depth		0.028 (0.92)	0.454 (0.24)	0.455 (0.24)
Trading book depth		0.203** (0.03)	0.201 (0.33)	0.201 (0.34)
Number of quotes			-0.000+ (0.13)	-0.000+ (0.13)
Number of deals			-0.003 (0.82)	-0.003 (0.83)
News type: inflation				0.117*** (0.0)
News type: macroeconomics				0.118*** (0.0)
News type: CB announcements				-0.000 (0.36)
Intercept	0.328*** (0.0)	0.351*** (0.0)	0.353*** (0.0)	0.235*** (0.0)
R2	0.044	0.065	0.071	0.071

Robust p-values in parentheses: $***p < 0.01,\ **p < 0.05,\ *p < 0.1,\ ^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (3) where errors are robust to heteroscedasticity and where the p-values of the variance ratio tests are regressed on the surprise component of macroeconomic announcements and the share of fast trading measured over a 30 minutes window.

Baseline OLS estimates are reported in column (1), while columns (2)-(4) include controls for order flows, liquidity measures and dummies for news type controls. All regressions include currency fixed effects.

Number of observations: 1,223

Table 6: Estimated Impact of Macro News and Entropy on Price Efficiency

	Variance ratio test (pvalue) **No controls**	**Variance ratio test (pvalue)** **Order flows and depth**	**Variance ratio test (pvalue)** **Microstructure**	**Variance ratio test (pvalue)** **Type of news**
Normalized fundamental surprise	-0.597* (0.09)	-0.490+ (0.14)	-0.491+ (0.14)	-0.491+ (0.14)
Entropy (log)	-0.905*** (0.0)	-1.061*** (0.0)	-1.021*** (0.0)	-1.020*** (0.0)
Norm. surprise x log entropy	0.433* (0.09)	0.350+ (0.15)	0.353+ (0.15)	0.352+ (0.16)
Order-book flow		0.000 (0.65)	0.000 (0.34)	0.000 (0.34)
Order book depth		-0.205 (0.31)	0.139 (0.69)	0.140 (0.69)
Trading book depth		0.208** (0.01)	0.199 (0.24)	0.199 (0.24)
Number of quotes			-0.000 (0.24)	-0.000 (0.24)
Number of deals			-0.001 (0.92)	-0.001 (0.92)
News type: inflation				0.554*** (0.0)
News type: macroeconomics				0.555*** (0.0)
News type: other CB announcements				0.000*** (0.0)
Intercept	1.480*** (0.0)	1.716*** (0.0)	1.665*** (0.0)	1.109*** (0.0)
R2	0.054	0.081	0.084	0.084

Robust p-values in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, $^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (4) where errors are robust to heteroscedasticity and where the p-values of the variance ratio tests are regressed on the surprise component of macroeconomic news and the log of entropy measured over a 30 minutes window. Baseline OLS estimates are reported in column (1), while columns (2)-(4) include controls for order flows, liquidity measures and dummies for news type controls. All regressions include currency fixed effects.

Number of observations: 1,223

Table 7: Estimated Impact of Macro News and Share of Fast Trading on Quality of Trade Execution

	Effective spread No controls	**Effective spread Full set of controls**	**Realized spread No controls**	**Realized spread Full set of controls**	**Average price impact No controls**	**Average price impact Full set of controls**
Normalized fundamental surprise	1.198** (0.02)	1.177** (0.02)	0.994* (0.09)	1.003* (0.1)	1.974** (0.05)	1.921* (0.06)
Share of fast traders (log)	1.351* (0.06)	1.565*** (0.01)	1.945*** (0.0)	1.930** (0.03)	1.066** (0.03)	-0.347 (0.67)
Surprise x Share of fast traders (log)	-1.005*** (0.01)	-0.983*** (0.01)	-0.743* (0.08)	-0.776* (0.07)	-1.451** (0.04)	-1.547** (0.03)
Order-book flow		-0.002 (0.75)		-0.005 (0.35)		-0.001 (0.78)
Order book depth		13.654+ (0.14)		5.692 (0.44)		-0.154 (0.97)
Trading book depth		-2.433*** (0.01)		-0.366 (0.8)		-2.579* (0.08)
Number of quotes		-0.001*** (0.01)		-0.001+ (0.1)		-0.001** (0.02)
Number of deals		0.160** (0.03)		0.086 (0.38)		0.377*** (0.0)
News type: inflation		-1.100 (0.41)		-2.564 (0.21)		-1.320 (0.24)
News type: interest rate		0.600 (0.85)		1.635 (0.55)		6.982** (0.05)
News type: macroeconomics		-0.184 (0.89)		-1.338 (0.52)		0.276 (0.8)
News type: other CB announcements		-0.000 (0.28)		-0.000*** (0.0)		-0.000*** (0.0)
Intercept	10.592*** (0.01)	10.893*** (0.0)	3.590*** (0.01)	4.303* (0.07)	11.576*** (0.0)	10.498*** (0.0)
R2	0.28	0.291	0.364	0.373	0.28	0.286

Robust p-values in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, $^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (3) where errors are robust to heteroscedasticity and where quality of trade execution metrics in absolute terms are regressed on the surprise component of macroeconomic announcements and share of fast trading. For each quality of trade execution variable, we report the regression without controls and with the full set of controls. All regressions include currency fixed effects.

Number of observations: 1,211

Table 8: Estimated Impact of Macro News and Entropy on Quality of Trade Execution

	Effective spread No controls	**Effective spread Full set of controls**	**Realized spread No controls**	**Realized spread Full set of controls**	**Average price impact No controls**	**Average price impact Full set of controls**
Normalized fundamental surprise	7.301+ (0.15)	8.483** (0.02)	4.154 (0.31)	5.736** (0.04)	4.944+ (0.17)	6.070* (0.09)
Entropy (log)	17.132** (0.02)	24.624*** (0.0)	16.860*** (0.0)	22.082*** (0.0)	15.341*** (0.0)	19.287*** (0.0)
Norm. surprise x Entropy (log)	-5.471+ (0.15)	-6.227** (0.02)	-3.162 (0.3)	-4.236** (0.05)	-3.638+ (0.19)	-4.481* (0.1)
Order-book flow		-0.013* (0.05)		-0.010** (0.03)		-0.006*** (0.01)
Order book depth		20.915** (0.04)		19.196*** (0.0)		-0.616 (0.81)
Trading book depth		-0.657 (0.5)		2.351** (0.03)		2.981+ (0.14)
Number of quotes		-0.002*** (0.0)		-0.001*** (0.0)		-0.000*** (0.0)
Number of deals		-0.017 (0.81)		-0.148** (0.04)		-0.081 (0.42)
News type: inflation		-9.346*** (0.0)		-9.823*** (0.0)		-6.931*** (0.0)
News type: macroeconomics		-8.431*** (0.0)		-8.344*** (0.0)		-6.073*** (0.0)
News type: other CB announcements		0.000*** (0.0)		0.000*** (0.0)		0.000*** (0.0)
Intercept	-15.587* (0.09)	-17.776*** (0.0)	-19.138*** (0.01)	-18.167*** (0.0)	-14.169*** (0.0)	-13.005*** (0.0)
R2	0.387	0.63	0.225	0.359	0.244	0.269

Robust p-values in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, $^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (4) where errors are robust to heteroscedasticity and where quality of trade execution metrics in absolute terms are regressed on the surprise component of macroeconomic announcements and the log of entropy. For each quality of trade execution variable, we report the regression without controls and with the full set of controls. All regressions include currency fixed effects.

Number of observations: 1,223

Table 9: Estimated Impact of Macro News and Quoting Spread on Quality of Trade Execution

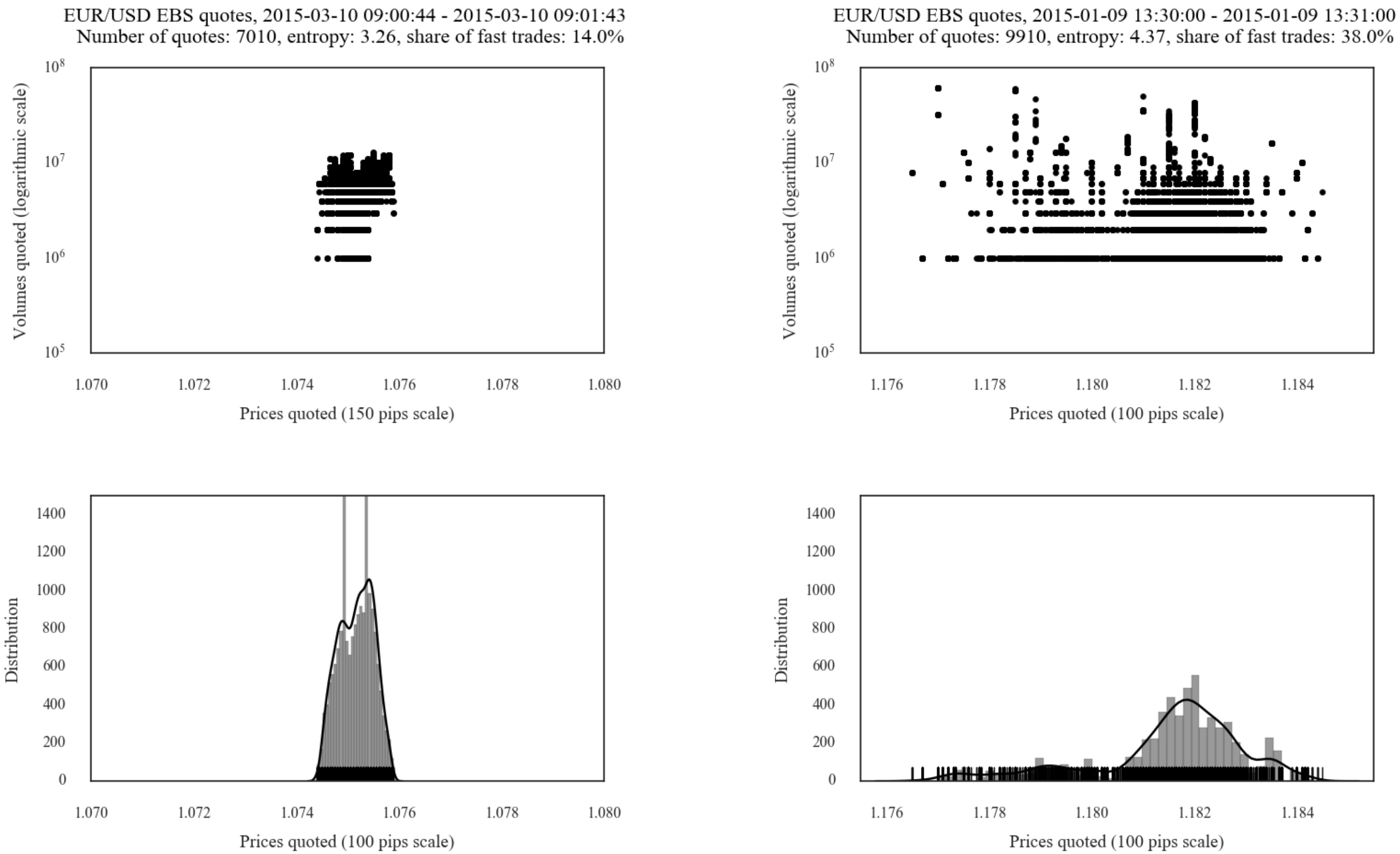
	Effective spread	**Effective spread**	**Realized spread**	**Realized spread**	**Average price impact**	**Average price impact**
Normalized fundamental surprise	-0.137 (0.54)	-0.013 (0.95)	-0.061 (0.8)	0.024 (0.92)	-0.040 (0.91)	-0.138 (0.69)
Quoting spread	0.226*** (0.0)	0.208*** (0.0)	0.220*** (0.0)	0.211*** (0.0)	-0.061* (0.06)	-0.070** (0.03)
Norm. Surprise x Quoting spread	0.053 (0.29)	0.003 (0.95)	-0.005 (0.94)	-0.054 (0.44)	0.065 (0.45)	0.053 (0.55)
Order-book flow		0.013 (0.32)		0.008 (0.39)		0.004 (0.41)
Order book depth		-27.388+ (0.2)		-25.114* (0.09)		4.475 (0.5)
Trading book depth		5.231* (0.09)		0.541 (0.81)		-0.770 (0.72)
Number of quotes		-0.002* (0.06)		-0.001* (0.05)		-0.000 (0.3)
Number of deals		0.220** (0.04)		0.084 (0.33)		0.128+ (0.12)
News type: inflation		2.036*** (0.0)		0.360 (0.27)		1.995*** (0.0)
News type: macroeconomics		2.682*** (0.0)		1.617*** (0.0)		2.680*** (0.0)
News type: other CB announcements		-0.000+ (0.12)		-0.000* (0.06)		-0.000 (0.9)
Intercept	7.859*** (0.0)	4.718*** (0.0)	3.903*** (0.0)	1.977*** (0.0)	6.897*** (0.0)	4.675*** (0.0)
R2	0.313	0.49	0.147	0.264	0.186	0.207

Robust p-values in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, $^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (4) where errors are robust to heteroscedasticity and where quality of execution metrics in absolute terms are regressed on the surprise component of macroeconomic announcements and the quoting spread (i.e the average of the spread between the best and worst ask, and the best and worst bid). For each quality of execution variable, we report the regression without controls and with the full set of controls. All regressions include currency fixed effects.

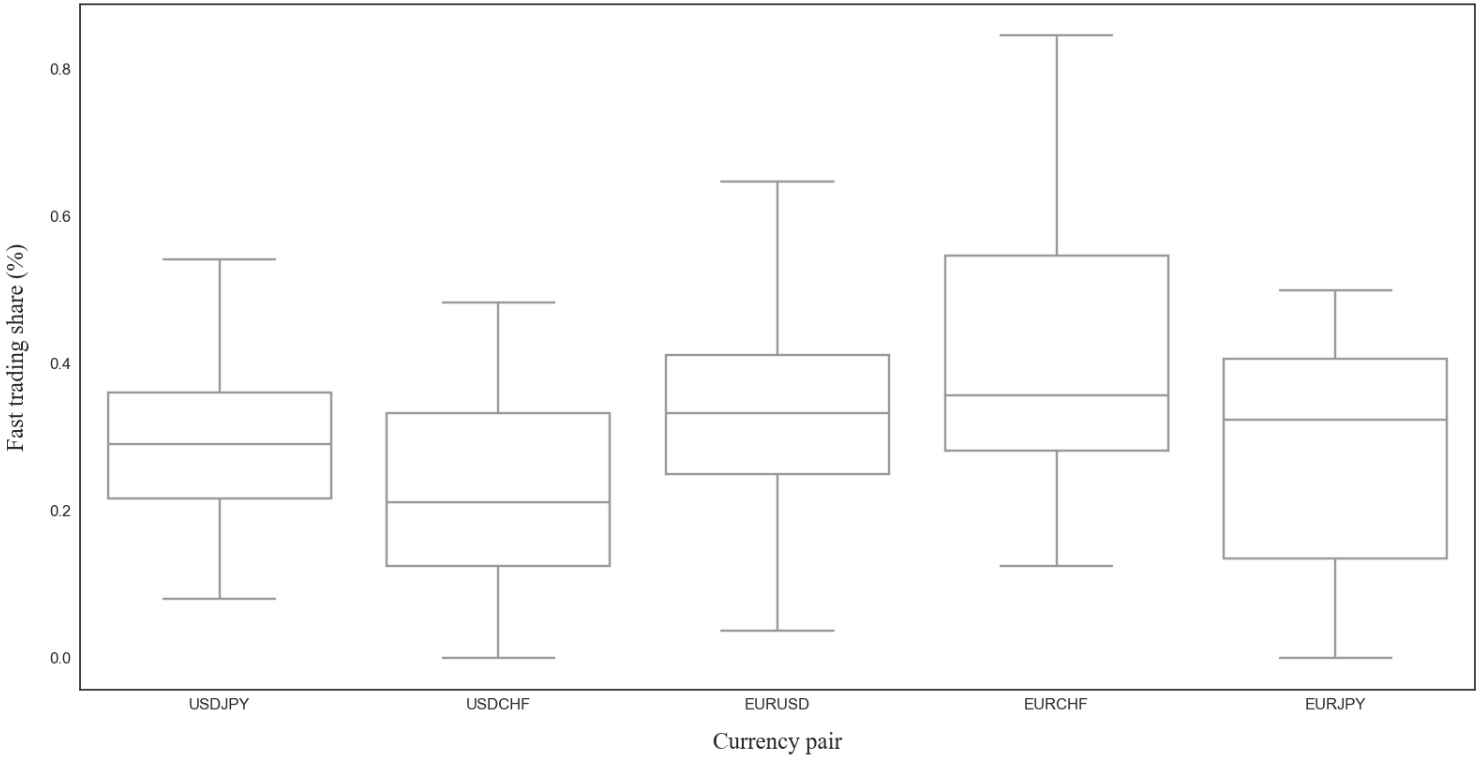
Number of observations: 1,211

Figure 1: Entropy and Quoting Patterns: EURUSD Case Study



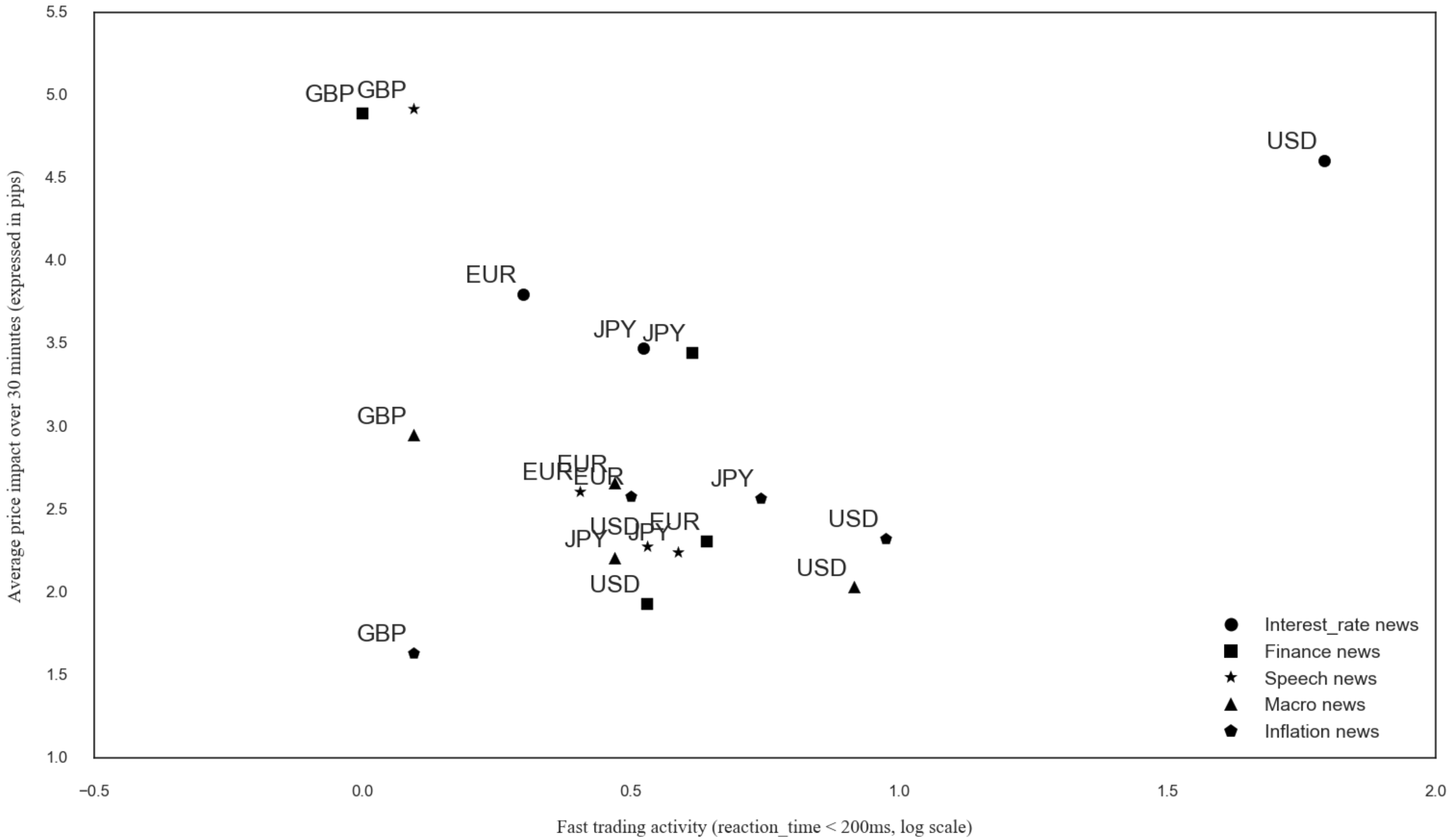
Note: The figure shows 1-minute quotes for the EURUSD on two different days, with low and high values of entropy (on the left- and right-hand side of the figure, respectively). The upper quadrant shows scatter plots of prices and volumes quoted, while the lower quadrant shows the respective distributions of exchange rate quotes. We use the same scale for both the vertical and horizontal axes.

Figure 2: Distribution of the Share of Fast Trading for Selected Currency Pairs



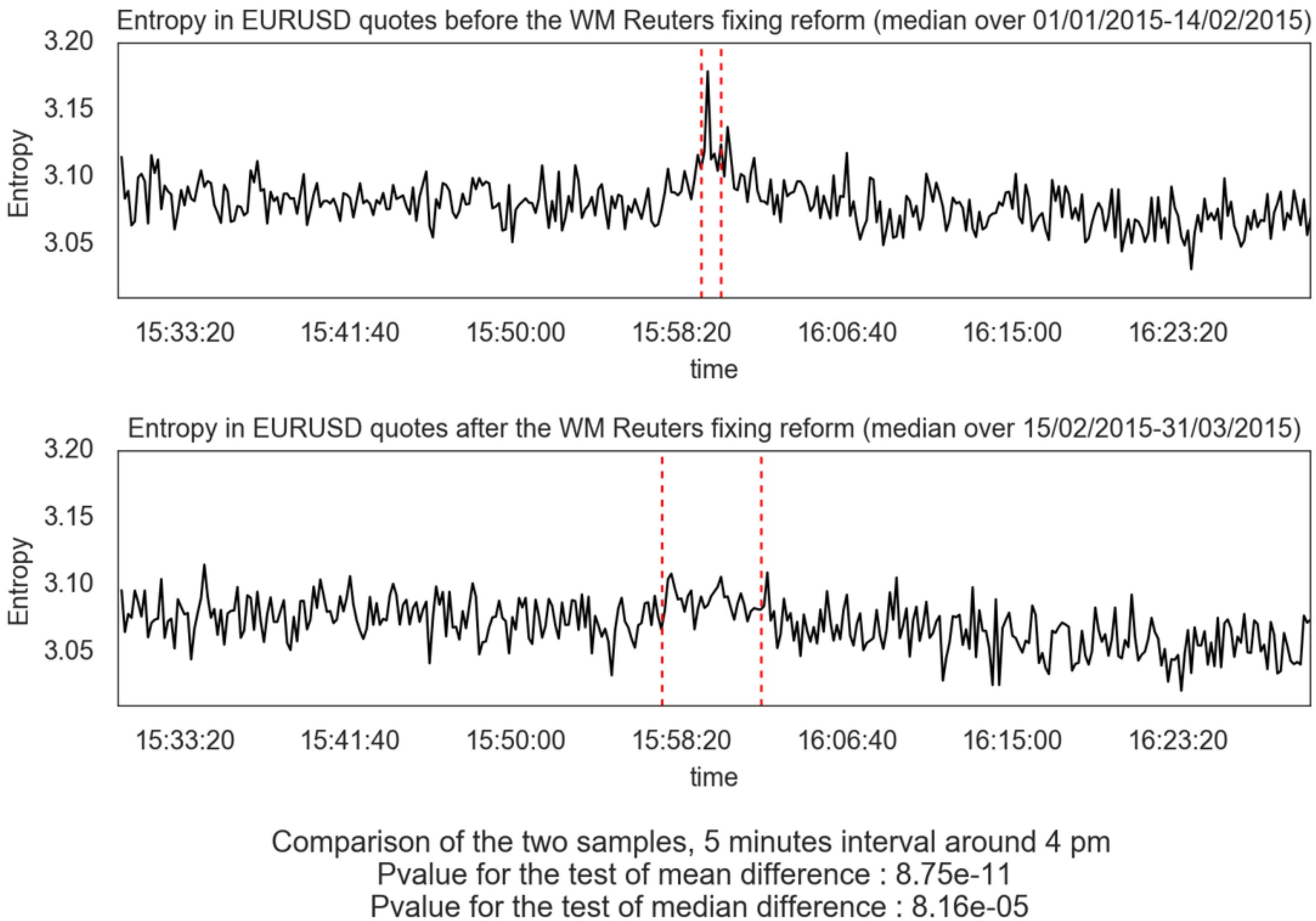
Note: This figure shows the distribution of the share of fast trading for different currency pairs. The boxplot lines indicate the 10th, 25th, 50th, 75th and 90th percentiles, respectively.

Figure 3: Price Impact and Share of Fast Trading, per News Type and Country



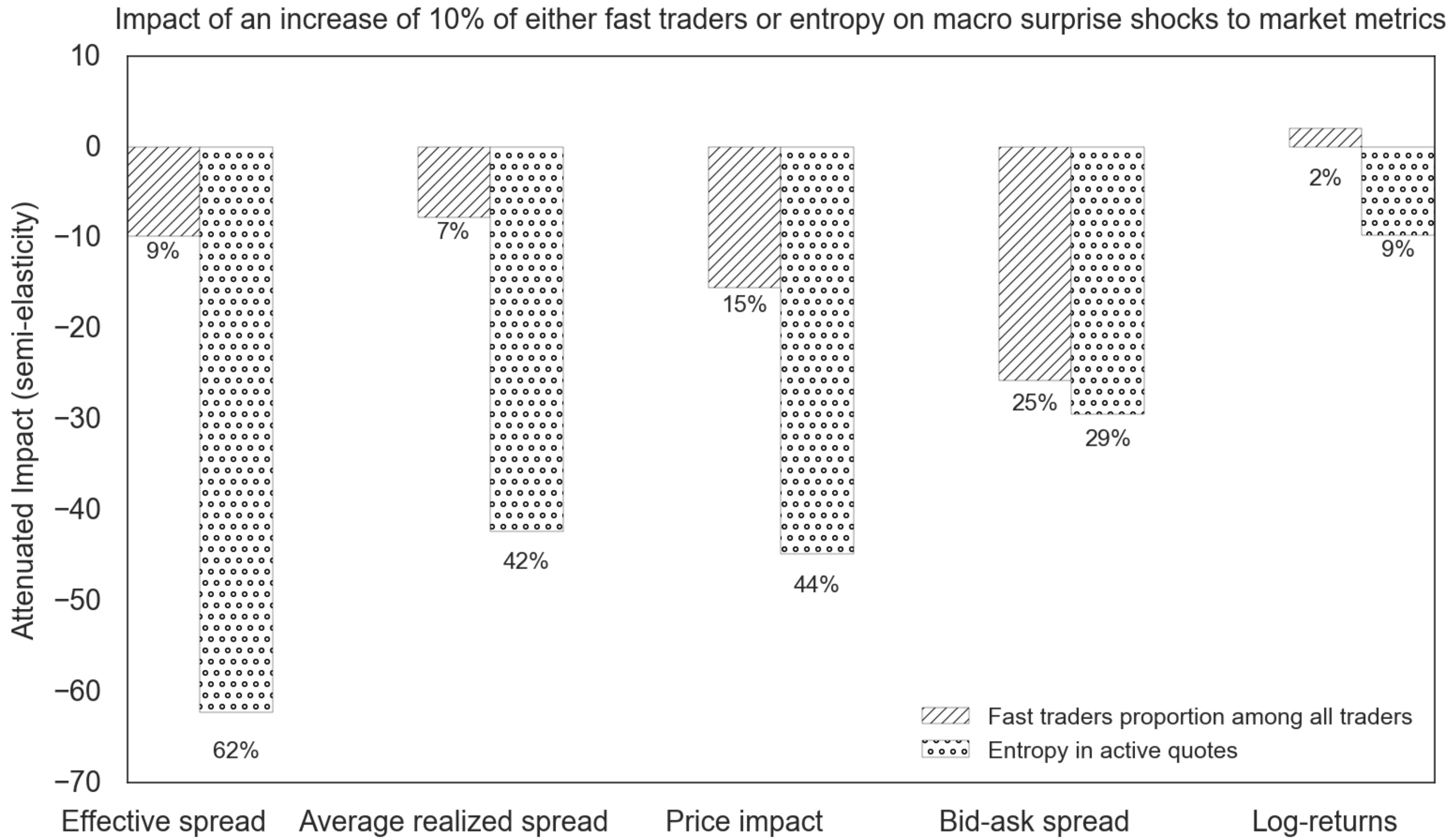
Note: The figure plots the average price impact against the share of fast trades for all announcements and base currencies, over a 30 minutes window.

Figure 4: Variation of Median Entropy, before and after the WM Reuters Fixing Reform of February 15th 2015



Note: This figure presents the variation of median entropy, before and after the WM Reuters fixing reform (computed at 10 second-intervals over 30 days for each sample) in a one-hour window centered around 4 p.m. (GMT). The time window for computing the fixing is represented as red dashed lines.

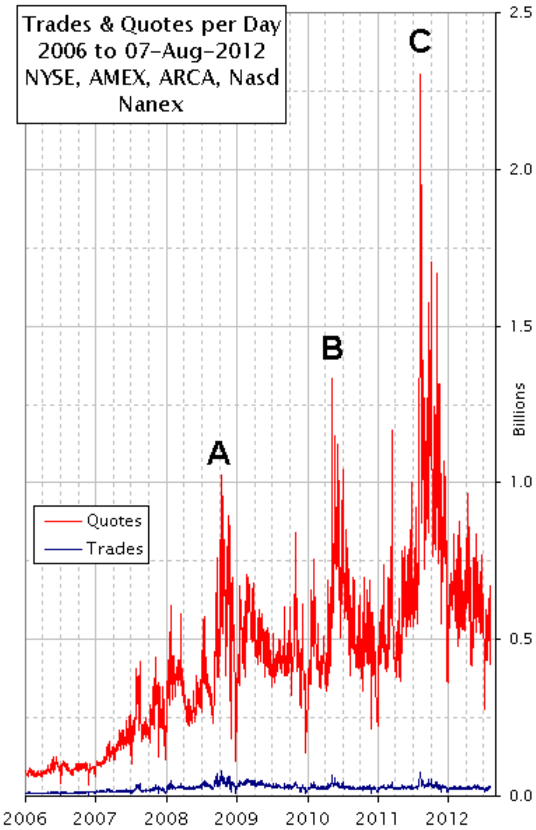
Figure 5: Economic Magnitude of the Dampening Effect on News: Fast Trading vs. Entropy



Note: The figure compares the economic magnitude of the dampening effect of fast trading vs. entropy on the market reaction to news computed from the estimates obtained from model equations (3) and (4). The effect is computed using the direct effects of fast trading and entropy, respectively, along with their interacted effect with news.

A Online Appendix

Figure 6: Actual Transactions and Quotes in US stocks on Nanex



Note: Source: Nanex

Table 10: Elasticity of Entropy with respect to Fast Trading (winsorized observations)

	Entropy (log) **No controls**	**Entropy (log)** **Order flows and depth**	**Entropy (log)** **Microstructure**	**Entropy (log)** **Type of news**
Share of fast traders (log)	0.145*** (0.0)	0.196*** (0.0)	0.202*** (0.0)	0.204*** (0.0)
Order-book flow		0.000** (0.02)	0.000*** (0.0)	0.000*** (0.0)
Order book depth		-0.218*** (0.0)	-0.198** (0.05)	-0.207** (0.04)
Trading book depth		0.009 (0.53)	0.020 (0.6)	0.019 (0.59)
Number of quotes			-0.000 (0.82)	-0.000 (0.92)
Number of deals			-0.001 (0.71)	-0.001 (0.7)
News type: inflation				0.002 (0.81)
News type: macroeconomics				-0.009+ (0.12)
News type: other CB announcements				0.012+ (0.16)
Intercept	1.331*** (0.0)	1.337*** (0.0)	1.336*** (0.0)	1.342*** (0.0)
R2	0.404	0.458	0.458	0.462

Robust p-values in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, $^{+}p < 0.2$

Note: The table reports OLS estimates of the model equation (1), including currency fixed effects with heteroscedastic robust standard errors. Baseline OLS estimates are reported in column (1), while columns (2)-(4) include controls for order flows, liquidity measures and dummies for news type. Data were winsorized by removing the top 5th percentile of the distribution of absolute bid-ask spreads. All regressions include currency fixed effects.

Number of observations: 1,1161

Table 11: Estimated Impact of Macro News and Share of Fast Trading on Price Efficiency (winsorized data)

	Variance ratio test (pvalue) **No controls**	**Variance ratio test (pvalue)** **Order flows and depth**	**Variance ratio test (pvalue)** **Microstructure**	**Variance ratio test (pvalue)** **Type of news**
Normalized fundamental surprise	-0.090*** (0.01)	-0.081** (0.01)	-0.084*** (0.01)	-0.084** (0.01)
Share of fast traders (log)	-0.128** (0.01)	-0.248*** (0.0)	-0.188* (0.1)	-0.188* (0.1)
Norm. surprise x Share of fast traders (log)	0.099*** (0.0)	0.089*** (0.0)	0.096*** (0.0)	0.095*** (0.0)
Order-book flow		-0.000 (0.94)	0.000 (0.52)	0.000 (0.52)
Order book depth		0.050 (0.86)	0.441 (0.25)	0.442 (0.25)
Trading book depth		0.193** (0.03)	0.225 (0.27)	0.224 (0.27)
Number of quotes			-0.000+ (0.17)	-0.000+ (0.17)
Number of deals			-0.005 (0.7)	-0.005 (0.71)
News type: inflation				0.113*** (0.0)
News type: macroeconomics				0.114*** (0.0)
News type: other CB announcements				-0.000 (0.24)
Intercept	0.318*** (0.0)	0.341*** (0.0)	0.340*** (0.0)	0.226*** (0.0)
R2	0.039	0.06	0.066	0.066

Robust p-values in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, $^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (3) where errors are robust to heteroscedasticity and where the p-values of the variance ratio tests are regressed on the surprise component of macroeconomic announcements and the share of fast trading measured over a 30 minutes window.

Baseline OLS estimates are reported in column (1), while columns (2)-(4) include controls for order flows, liquidity measures and dummies for news type controls. Data were winsorized by removing the top 5th percentile of the distribution of absolute bid-ask spreads. All regressions include currency fixed effects.

Number of observations: 1,161

Table 12: Estimated Impact of Macro News and Entropy on Price Efficiency (winsorized data)

	Variance ratio test (pvalue) **No controls**	**Variance ratio test (pvalue)** **Order flows and depth**	**Variance ratio test (pvalue)** **Microstructure**	**Variance ratio test (pvalue)** **Type of news**
Normalized fundamental surprise	-0.654* (0.06)	-0.553* (0.09)	-0.557* (0.1)	-0.558* (0.1)
Entropy (log)	-0.937*** (0.0)	-1.104*** (0.0)	-1.061*** (0.0)	-1.061*** (0.0)
Norm. fundamental surprise x Entropy (log)	0.480* (0.06)	0.401* (0.1)	0.407* (0.1)	0.407+ (0.1)
Order-book flow		0.000 (0.59)	0.000 (0.33)	0.000 (0.34)
Order book depth		-0.169 (0.4)	0.152 (0.66)	0.152 (0.66)
Trading book depth		0.197** (0.02)	0.207 (0.23)	0.207 (0.23)
Number of quotes			-0.000 (0.3)	-0.000 (0.31)
Number of deals			-0.002 (0.84)	-0.002 (0.84)
News type: inflation				0.571*** (0.0)
News type: macroeconomics				0.571*** (0.0)
News type: other CB announcements				0.000* (0.06)
Intercept	1.518*** (0.0)	1.769*** (0.0)	1.713*** (0.0)	1.142*** (0.0)
R2	0.057	0.084	0.087	0.087

Robust p-values in parentheses: $***p < 0.01,\ **p < 0.05,\ *p < 0.1,\ ^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (4) where errors are robust to heteroscedasticity and where the p-values of the variance ratio tests are regressed on the surprise component of macroeconomic news and entropy measured over a 30-minute horizon. Baseline OLS estimates are reported in column (1), while columns (2)-(4) include controls for order flows, liquidity measures and dummies for news type controls. Data were winsorized by removing the top 5th percentile of the distribution of absolute bid-ask spreads. All regressions include currency fixed effects.

Number of observations: 1,161

Table 13: Estimated Impact of Macro News and Share of Fast Trading on Quality of Trade Execution (winsorized data)

	Effective spread No controls	**Effective spread Full set of controls**	**Realized spread No controls**	**Realized spread Full set of controls**	**Average price impact No controls**	**Average price impact Full set of controls**
Normalized fundamental surprise	0.365 (0.33)	0.262 (0.39)	0.437 (0.27)	0.512 (0.21)	0.598 (0.32)	0.764 (0.21)
Share of fast traders (log)	2.292 (0.22)	6.056** (0.01)	2.806** (0.04)	3.786** (0.03)	1.451** (0.01)	0.628 (0.67)
Normsurprise x Share of fast traders (log)	-0.608 (0.22)	-0.391+ (0.19)	-0.637+ (0.13)	-0.639* (0.08)	-0.669+ (0.11)	-0.980** (0.03)
Order-book flow		-0.008 (0.31)		-0.006 (0.33)		-0.004 (0.22)
Order book depth		15.577+ (0.19)		14.218* (0.1)		-4.559 (0.26)
Trading book depth		1.237 (0.43)		2.239+ (0.12)		0.252 (0.88)
Number of quotes		-0.002** (0.03)		-0.001** (0.03)		-0.000 (0.45)
Number of deals		-0.176 (0.24)		-0.128 (0.32)		0.166+ (0.17)
News type: inflation		1.690*** (0.0)		0.091 (0.82)		1.703*** (0.0)
News type: macroeconomics		2.312*** (0.0)		1.315*** (0.0)		2.513*** (0.0)
News type: other CB announcements		-0.000 (0.28)		-0.000+ (0.1)		0.000+ (0.11)
Intercept	6.951*** (0.0)	4.003*** (0.0)	2.843*** (0.0)	1.406*** (0.0)	6.128*** (0.0)	4.216*** (0.0)
R2	0.329	0.523	0.174	0.266	0.201	0.221

Robust p-values in parentheses: $***p < 0.01,\ **p < 0.05,\ *p < 0.1,\ ^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (3) where errors are robust to heteroscedasticity and where quality of trade execution metrics in absolute terms are regressed on the surprise component of macroeconomic announcements and share of fast trading. For each quality of trade execution variable, we report the regression without controls and with the full set of controls. Data were winsorized by removing the top 5th percentile of the distribution of absolute bid-ask spreads. All regressions include currency fixed effects.

Number of observations: 1,161

Table 14: Estimated Impact of Macro News and Entropy on Quality of Trade Execution (winsorized data)

	Effective spread No controls	**Effective spread Full set of controls**	**Realized spread No controls**	**Realized spread Full set of controls**	**Average price impact No controls**	**Average price impact Full set of controls**
Normalized fundamental surprise	7.151+ (0.17)	8.271** (0.03)	3.142 (0.45)	4.661+ (0.11)	5.150+ (0.16)	
Entropy (log)	16.753** (0.03)	24.237*** (0.0)	15.613*** (0.01)	20.535*** (0.0)	15.501*** (0.0)	
Norm. x Entropy (log)	-5.373+ (0.18)	-6.075** (0.03)	-2.370 (0.46)	-3.393+ (0.13)	-3.785+ (0.18)	
Order-book flow		-0.013* (0.06)		-0.009** (0.04)		
Order book depth		20.889** (0.04)		19.059*** (0.0)		
Trading book depth		-0.500 (0.6)		2.293** (0.03)		
Number of quotes		-0.002*** (0.0)		-0.001*** (0.0)		
Number of deals		-0.024 (0.74)		-0.143** (0.05)		
News type: inflation		-9.144*** (0.0)		-9.069*** (0.0)		
News type: macroeconomics		-8.269*** (0.0)		-7.712*** (0.0)		
News type: other CB announcements		0.000+ (0.16)		0.000** (0.04)		
Intercept	-15.054+ (0.11)	-17.414*** (0.0)	-17.479** (0.01)	-16.780*** (0.0)	-14.391*** (0.0)	
R2	0.39	0.633	0.226	0.36	0.252	

Robust p-values in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, $^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (4) where errors are robust to heteroscedasticity and where quality of trade execution metrics in absolute terms are regressed on the surprise component of macroeconomic announcements and the log of quotes entropy. For each quality of trade execution variable, we report the regression without controls and with the full set of controls. Data were winsorized by removing the top 5th percentile of the distribution of absolute bid-ask spreads. All regressions include currency fixed effects.

Number of observations: 1,161

Table 15: Estimated Impact of Macro News and Entropy on Price Efficiency (Entropy in Level)

	Variance ratio test (pvalue) **No controls**	**Variance ratio test (pvalue)** **Order flows and depth**	**Variance ratio test (pvalue)** **Microstructure**	**Variance ratio test (pvalue)** **Type of news**
Normalized fundamental surprise	-0.470* (0.06)	-0.388+ (0.1)	-0.390+ (0.11)	-0.390+ (0.11)
Entropy	-0.233*** (0.0)	-0.271*** (0.0)	-0.262*** (0.0)	-0.262*** (0.0)
Norm. fundamental surprise x Entropy	0.118* (0.07)	0.095+ (0.12)	0.097+ (0.12)	0.097+ (0.12)
Order-book flow		0.000 (0.76)	0.000 (0.36)	0.000 (0.36)
Order book depth		-0.199 (0.33)	0.183 (0.59)	0.184 (0.59)
Trading book depth		0.208** (0.01)	0.201 (0.24)	0.201 (0.24)
Number of quotes			-0.000+ (0.19)	-0.000+ (0.2)
Number of deals			-0.001 (0.9)	-0.001 (0.9)
News type: inflation				0.434*** (0.0)
News type: macroeconomics				0.435*** (0.0)
News type: other CB announcements				0.000 (0.79)
Intercept	1.163*** (0.0)	1.339*** (0.0)	1.305*** (0.0)	0.869*** (0.0)
R2	0.054	0.081	0.085	0.085

Robust pvalues in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, $^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (4) where errors are robust to heteroscedasticity and where the p-value of the variance ratio test are regressed on the surprise component of macroeconomic news and the level of entropy measured over a 30 minutes window. Baseline OLS estimates are reported in column (1), while columns (2)-(4) include controls for order flows, liquidity measures and dummies for news type controls. All regressions include currency fixed effects.

Number of observations: 1,223

Table 16: Estimated Impact of Macro News and Entropy on Quality of Trade Execution (Entropy in Level)

	Effective spread No controls	**Effective spread Full set of controls**	**Realized spread No controls**	**Realized spread Full set of controls**	**Average price impact No controls**	**Average price impact Full set of controls**
Normalized fundamental surprise	5.883+ (0.15)	6.345** (0.02)	3.459 (0.27)	4.257** (0.04)	3.917+ (0.14)	4.717* (0.07)
Entropy	4.621** (0.03)	6.279*** (0.0)	4.511*** (0.0)	5.629*** (0.0)	3.915*** (0.0)	4.867*** (0.0)
Norm.surprise x Entropy	-1.539+ (0.15)	-1.618** (0.02)	-0.922 (0.27)	-1.095** (0.04)	-1.001+ (0.16)	-1.212* (0.08)
Order-book flow		-0.012* (0.06)		-0.009** (0.03)		-0.005** (0.02)
Order book depth		19.919** (0.05)		18.305*** (0.0)		-1.458 (0.58)
Trading book depth		-0.644 (0.51)		2.377** (0.03)		2.938+ (0.15)
Number of quotes		-0.002*** (0.0)		-0.001*** (0.0)		-0.000*** (0.0)
Number of deals		-0.018 (0.8)		-0.150** (0.04)		-0.076 (0.45)
News type: inflation		-6.397*** (0.0)		-7.177*** (0.0)		-4.554*** (0.0)
News type: macroeconomics		-5.494*** (0.0)		-5.711*** (0.0)		-3.705*** (0.0)
News type: other CB announcements		-0.000** (0.04)		-0.000*** (0.0)		0.000 (0.86)
Intercept	-10.481+ (0.15)	-11.891*** (0.0)	-13.969*** (0.01)	-12.888*** (0.0)	-8.711*** (0.0)	-8.258*** (0.0)
R2	0.399	0.631	0.234	0.36	0.243	0.267

Robust pvalues in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, $^{+}p < 0.2$

Note: The table reports OLS estimates of model equation (4) where errors are robust to heteroscedasticity and where quality of trade execution metrics in absolute terms are regressed on the surprise component of macroeconomic announcements and the level of entropy. For each quality of trade execution variable, we report the regression without controls and with the full set of controls. All regressions include currency fixed effects.

Number of observations: 1,223