School of Finance

University of St.Gallen

SOMETHING IN THE AIR: INFORMATION DENSITY, NEWS SURPRISES, AND PRICE JUMPS

ROLAND FÜSS
MARKUS GRABELLUS
FERDINAND MAGER
MICHAEL STEIN

WORKING PAPERS ON FINANCE NO. 2015/17

SWISS INSTITUTE OF BANKING AND FINANCE (S/BF – HSG)

AUGUST 2015
THIS VERSION: APRIL 2016

Something in the Air: Information Density, News Surprises, and Price Jumps

Roland Füss[1], Markus Grabellus[2], Ferdinand Mager[3], Michael Stein[4]

Abstract

This paper introduces a new information density indicator to provide a more comprehensive understanding of price reactions to news and, more specifically, to the sources of jumps in financial markets. Our information density indicator, which measures the abnormal amount of news before scheduled macroeconomic announcements, is significantly related to the likelihood of price jumps and is independent of the magnitude of news surprises or pre-announcement trading activity. We therefore interpret this variable as a measure of additional uncertainty in the market, inducing diffuse beliefs among investors, which are resolved through macroeconomic news as "hard" facts.

Keywords: *Information flow*; *jump identification*; *macroeconomic announcements*; *price discovery process*; *price jumps.*
JEL Classification: $C58$, $F31$, $G12$, $G14$, $G15$

Acknowledgments

An earlier version of this paper circulated under the title "And it is Still Information That Drives Intraday Price Jumps in Financial Markets." For helpful comments, we are indebted to Daniel Andrei, Jonathan Batten, Maximilian Bredendiek, Thomas Gehrig, Sridhar Gogineni, Rasa Karapandza, Tobias Rühl, Josef Zechner, and the participants at the 62nd Midwest Finance Annual Meeting, the 49th Eastern Finance Annual Meeting, the 2015 ÖFG Workshop on Accounting, Information and Financial Crises, the 28th Australasian Finance and Banking Conference, and the Applied Financial Modelling Conference. The authors are grateful to Deutsche Börse AG for providing the MNI database.

[1]Swiss Institute of Banking and Finance (s/bf), University of St.Gallen, Rosenbergstrasse 52, CH-9000 St. Gallen, Switzerland and Research Associate at the Centre for European Economic Research (ZEW), Phone: +41 (0)71 224 7055, Fax: +41 (0)71 224 7088. roland.fuess@unisg.ch.

[2]Chair of Banking and Finance, Department of Finance and Accounting, EBS Business School, EBS Universität für Wirtschaft und Recht, Gustav-Stresemann-Ring 3, D-65189 Wiesbaden, Germany, +49 (0)611 7102 1271, Fax: +49 (0)611 7102 101271, markus.grabellus@ebs.edu

[3]Chair of Banking and Finance, Department of Finance and Accounting, EBS Business School, EBS Universität für Wirtschaft und Recht, Gustav-Stresemann-Ring 3, D-65189 Wiesbaden, Germany, Phone: +49 (0)611 7102 1256, Fax: +49 (0)611 7102 101256, ferdinand.mager@ebs.edu

[4]Corresponding Author: Department of Financial Market Econometrics, Faculty of Business Administration and Economics, University of Duisburg-Essen, Universitätsstrasse 12, D-45141 Essen, Germany, Phone: +49 (0)201 183 3821, Fax: +49 (0)201 183 4209, michael.stein@steinpage.com

1. Introduction

The fundamental question of how information impacts asset prices takes center stage in the financial literature on asset pricing (Fama (1965)). In financial markets, investors are constantly inundated by a variety of information, such as corporate earnings, macroeconomic announcements, and political news. The sheer mass of information makes it almost impossible to properly assess the importance of all the news for particular assets. Consequently, an abnormally high information flow can lead to imprecise signals. On the one hand, with higher information density, it becomes more likely that the proportion of noisy information increases. On the other hand, even if all information consists of fundamental news, an increase in information flow above a normal level can hinder efficient information processing. In both cases, noise obscures fundamentals and investors' expectations become more heterogeneous. Without disentangling the two effects, we define "noisy" information as imprecise price signals that lead to diffuse beliefs among market participants. Since investors update their expectations about the economy and asset prices based on such information, it is of particular interest how financial markets process information provided by the news industry, that is, how this information is incorporated into asset prices.

This paper contributes to the literature on informational market efficiency by analyzing how the level of information flow prior to public announcements affects the price process in asset markets at the time when "hard" information is released. We follow Detemple (1986), who employs a learning framework in the presence of incomplete information, as well as Veronesi (2000) and Li (2005), who provide a theoretical framework on the relationship between information quality and stock market returns. This literature regards external signals as consisting of (price-relevant) fundamentals and (price-irrelevant) noise. Noise impairs the inference about fundamentals, as it reduces precision. More precisely, if a signal becomes noisy, different assumptions on the precision of information are made and diffuse beliefs about the true state arise.[1]

We define abnormal information flow as an increase in the number of ticker information items above the prior average information flow. Precise signals would immediately trigger a price reaction

[1] Note that we use an exogenous measure of information density different from endogenous noisy return components, that is, market-specific frictions, such as liquidity-induced quote revisions.

under the assumption of informationally efficient markets, while noisy information would keep price changes bounded due to dispersion in investors' beliefs (Veronesi (2000)).[2] However, investors have differing access to news flow, and they differ in their ability to read out and price in signals. By learning from (observable) actions of other traders following increased news flow, the distribution of price expectations among market participants widens further. This additional uncertainty leads to a deferred price discovery process prior to macroeconomic announcements.

To analyze empirically how new information affects asset returns, we construct a measure that captures abnormal news flow before a public announcement. This information density indicator (IDI) measures the excess or abnormal level of information. It is calculated by subtracting the mean of incoming news items over a 25-minute period (from minute $t = -30$ to minute $t = -6$) from the amount of incoming news during the five minutes before an announcement. This deviation from the normal level of information flow is normalized by the sample standard deviation of news flows. Hence, IDI reflects the excess or abnormal level of information above the preceding news flow during the five-minute interval before the announcement. The size of the deviation indicates the strength of the news flow, which affects the dispersion of investor beliefs on fundamental value.

We then relate information density to (significant) price jumps, which occur conditional on scheduled macroeconomic announcements. Consequently, our estimation strategy includes both the emergence of noisy information in terms of diffuse beliefs prior to a news event and release of the public announcement. While the abnormal increase in information flow leads to imprecise signals, the macroeconomic announcements constitute quite precise, external signals. The use of price jumps rather than returns allows us to identify whether a holding-back of price changes prior to the announcement is evident and whether it unloads when "hard" facts are released. In other words, if prior to the release of a public announcement price-relevant signals are not overlaid with noise, this fundamental information would be instantaneously discovered in the price change. In contrast, if dispersion in investor beliefs increases, a resulting relatively strong adherence to the prior price expectation, and thus, missed changes in the intrinsic value of asset prices, dissolves when the "hard" information is released, and prices consequently adjust to a new equilibrium.

[2]The increase in volatility when information is perceived to be precise is confirmed by empirical studies (see, e.g., Hautsch, Hess, and Veredas (2011)).

Our empirical results show that higher abnormal information flow increases the likelihood of price jumps, which are conditional on the release of material public information. Hence, a price jump is more (less) likely when the preceding flow of abnormal information increases (decreases). Additionally, we find that abnormally high information density without “hard” news cannot be related to price jumps. However, the abnormal amount of specific and/or unspecific, and thus, noisy economic news flows, together with macroeconomic announcements, explains the likelihood of jumps. Our measure is further independent of the magnitude of news surprises and trading activity in the market. We interpret this result as the limited capacity of market participants to process the bulk of abnormal information flow, which lowers the precision of signals. In contrast, if the quality of information is high prior to scheduled news events, information is immediately incorporated in prices and price changes are bounded. It then follows that price jumps are less likely at the time of news releases.

We also contribute to the literature on information aggregation and the predictability of price jumps. For instance, Lee (2012) introduced a jump predictor test to identify the sources of jump intensity in individual stock returns. The author showed that macro- and micro-level information arrivals increase the likelihood of stock jumps within a short time horizon of 30 minutes. News surprises (as well as liquidity and volatility) are important sources of price jumps. However, previous literature mainly focuses on specific information, such as macroeconomic, firm-specific, or political announcements, and thus neglects the impact of noisy information (see, e.g., Almeida, Goodhart, and Payne (1998), Andersen, Bollerslev, Diebold, and Vega (2003), Andersen, Bollerslev, Diebold, and Vega (2007) and Hautsch, Hess, and Veredas (2011)). The majority of studies on the impact of information flows on market reaction use either the absolute amount of asset-specific ticker news or do not distinguish between fundamentals and noise. For instance, Clements and Todorova (2016) find a large impact of positive shocks in news arrivals on realized volatility of gold and oil futures. However, they use the pre-processed volume of information flow, which includes only asset-related news at weekly frequency. Hence, the average daily number of news items in their sample is significantly lower compared to our study.[3] Berry and Howe (1994) develop a measure

[3]Similar results are found by Kalev, Liu, Pham, and Jarnecic (2004), who use firm-specific announcements in their information flow measure to study the impact of variation in information flow on conditional volatility

of public information flow covering the absolute number of news items released by Reuters News Service on a half-hour basis from May 1990 to April 1991. While the authors find a moderate, positive impact on trading volume, the effect on price volatility is insignificant.

To gain more insight into the quality of information, another strand of literature analyzes the sentiment in aggregated news flows (see, e.g., Tetlock (2007) and Tetlock, Saar-Tsechansky, and Macskassy (2008)). For instance, Groß-Klußmann and Hautsch (2011) use an automated news analytic tool based on linguistic pattern recognition to discover the relevance, novelty, and direction of company-specific news. The authors show the importance of news classification in filtering out noise and identifying significant effects on returns, volatility, trading volume, and bid-ask spreads. We avoid using linguistic pattern recognition algorithms to capture sentiment or tone in our news items, because of the huge variety of macroeconomic news, the sheer amount of information, and the number of various international asset classes included in our data set. Due to the fact that a particular information item can have different or even opposing meanings for different assets, our broad data set makes it virtually impossible to properly utilize any asset-related sentiment indicator.

Under different assumptions about the precision of information, our empirical study is closely related to Veronesi's (2000) dynamic asset pricing model. This author shows theoretically that more precise information tends to increase the equity risk premium. Meanwhile, noisy signals have no impact on the risk premium, independent of investors' degree of risk aversion. In contrast, when exogenous signals become more precise, a positive relationship emerges between expected excess returns and conditional volatility. However, Li (2005) shows that noisy information could lead to estimation errors, which increases volatility and risk premia. While we make no assumption about the quality of the news flow, we consider the sheer amount of news arriving in the market as an indicator for the clouding of fundamental signals through diffuse beliefs, and corresponding trading actions across market participants.

This paper aims at a broader understanding of news flows and their impact on price jumps. Our information density indicator (IDI), which captures abnormal information flow, is indepen-

---

of stock returns.

dent of the magnitude of the macroeconomic surprise or pre-announcement trading activity, highly statistically significant, and of economic importance. We interpret this new variable as a measure of additional uncertainty in the market arising from diffuse beliefs among investors, which are resolved through macroeconomic announcements classified as “hard” facts. Consequently, the aim of our paper goes beyond the link between macroeconomic news and price jumps. To the best of our knowledge, we are the first to empirically test how noisy information, in terms of diffuse beliefs, affects the asset pricing process. Our results show that an increasing flow of information prior to the release of a public announcement raises the likelihood of a price jump. The results are robust to various test designs. We explicitly distinguish between jumps that can be related to only one macroeconomic announcement and jumps that are driven by simultaneous macroeconomic announcements. Previous literature analyzes co-jumps in several assets but—to the best of the authors’ knowledge—fails to address jumps that coincide with more than one macroeconomic announcement. If one distinguishes between multi-announcement jumps with and without conflicting news surprises, previous estimates on sources of price jumps appear to be conservatively underestimated. We base our analysis on bond and stock futures from the U.S. and German market with the FX rate as a linking factor. We use macroeconomic data from the U.S., Germany, and the Eurozone; this expands upon the common data sources used in the jump literature.

The remainder of this paper proceeds as follows: Section 2 addresses the information framework that provides the theoretical foundation for explaining how increasing amounts of information lead to price jumps in asset markets. Section 3 presents the data set, introduces the jump identification methodology, and shows descriptive statistics on intraday jumps. In Section 4, we formally introduce our information density indicator. Here, we analyze its role in predicting the likelihood of price jumps that are conditional on public announcements. We further test our results for robustness against a variety of model and parameter specifications. Section 5 sets forth our conclusions.

2. Information Flow and Asset Prices

This section provides the theoretical background for our empirical analysis regarding the impact that diffuse beliefs among investors, triggered by abnormal information flow, has on asset returns. We distinguish between preceding “noisy” news flows prior to and “hard” facts delivered at the point in time when scheduled macroeconomic announcements are released. To study the two effects, we propose a general market microstructure model for risky assets i with uncertainty and announcements effects. The model consists of two time periods: news flow occurs in $t-1$ before a scheduled public announcement reveals the hard facts at time t. At the beginning of $t-1$, price P is already conditioned on a forecast $F_{t-1,k}$ of the macroeconomic announcement of type k, $A_{t,k}$:

$$P_{t-1,i} = (P_{t-1,i} \mid E_{t-1}(A_{t,k})), \tag{1}$$

where $E_{t-1}(A_{t,k}) = F_{t-1,k}$. Under the assumption of an informationally efficient asset market, the price process is defined as $P_{t,i} = P_{t-1,i} + \varepsilon_t$ for any t. Accordingly, the expected price for the next period equals the price from the previous period:

$$E_{t-1}[P_{t,i} \mid F_{t-1,k}] = P_{t-1,i} = (P_{t-1,i} \mid E_{t-1}(A_{t,k})). \tag{2}$$

Since the forecast is not the only information that is relevant in the market, we naturally assume that several additional signals appear prior to macroeconomic announcements. We denote the information set available in the period $t-1$ as Ω_{t-1}. To formalize the effects news flow has on the price discovery process, we relate the price to the information set available in interval $t-1$ for each investor $n \in N$:

$$E_{n,t-1}[P_{t,i} \mid \Omega_{t-1}]. \tag{3}$$

The price expectation in the market based on the information set in $t-1$ is

$$E_{t-1}[P_{t,i} \mid \Omega_{t-1}] = \frac{1}{N}\sum_{n=1}^{N} E_{n,t-1}[P_{t,i} \mid \Omega_{t-1}] \tag{4}$$

with variance $V_{t-1}[P_{t,i} \mid \Omega_{t-1}]$. If new information arrives at the market, market participants will individually price in this news. The lower $V_{t-1}[P_{t,i} \mid \Omega_{t-1}]$, the more homogeneous the price expectations. However, the more dispersed the price expectations are, that is, the higher V_{t-1}, the harder it is for market participants to make inferences about price movements in the market and to realize any new intrinsic price movements. Veronesi (2000) attributes heterogeneous price expectations to diffuse beliefs among investors, who differ in their access to news flow and their ability to read out and price in signals.

We employ a standard Bayesian updating specification similar to Madhavan and Smidt (1991) to formalize how information is processed to update the prevailing price expectation based on the forecast. In period $t-1$, market participants update their forecast-based prior expectation when information arrives, with the updating strength dependent on signal precision:

$$\begin{aligned} E_{t-1}[P_{t,i} \mid (F_{t-1,k}, \Omega_{t-1})] &= (1-\pi_{t-1,i})E_{t-1}(P_{t,i} \mid F_{t-1,k}) + (\pi_{t-1,i})E_{t-1}(P_{t,i} \mid \Omega_{t-1}) \\ &= E_{t-1}(P_{t,i} \mid F_{t-1,k}) + (\pi_{t-1,i})\Big(E_{t-1}(P_{t,i} \mid \Omega_{t-1}) - E_{t-1}(P_{t,i} \mid F_{t-1,k})\Big) \end{aligned} \tag{5}$$

where $\pi_{t-1,i} = \frac{1/V(E_{t-1}[P_{t,i}|\Omega_{t-1}])}{1/(V(\varepsilon_{t-1})+V(E_{t-1}[P_{t,i}|\Omega_{t-1}]))}$ is the weight of the price conjecture derived from the observed news flow in the updating mechanism for the forecast-based prior beliefs. It is defined as the precision of the signal based on the news flow, $1/V(E_{t-1}[P_{t,i} \mid \Omega_{t-1}])$, relative to the reciprocal of the sum of uncertainties arising from normal variation in the price, $V(\varepsilon_{t-1})$, and variation in expectations due to information flow, $1/V(E_{t-1}[P_{t,i} \mid \Omega_{t-1}])$.[4]

We argue that the sheer amount of news items arriving at the market affects the degree of diffuse and widespread beliefs. In particular, an increase in information flow to an abnormal level will quickly extend the distribution of resulting price expectations among market participants. Li (2005) shows that this abnormal or noisy information can result in estimation errors, which further increases the range of diverse price expectations. These contrary expectations tend to offset each other, especially for major assets, where the number of informed and uniformed market participants is large.[5] Furthermore, when market participants price in the news *and* observe the trading actions of other traders to learn from the market reactions to news, beliefs become even more diffuse.[6]

The notion of the information content of prices and trading actions generally originates with

---

[4]Note that this corresponds to standard market microstructure models with, for example, $\tilde{P}_{t-1} = P^*_{t-1} + \omega_{t-1}$, where the private information signals of a true value P^*_{t-1} are denoted as ω_{t-1}. The weighting would result as $\pi_{t-1,i} = \frac{1/\sigma^2_{\omega,i}}{1/(\sigma^2_{\varepsilon,i}+\sigma^2_{\omega,i})}$, with the signal uncertainty $\sigma^2_{\omega,i}$ (see Madhavan and Smidt (1991) for a related setup). In our definition, the signal is public but noisy, and the uncertainty $\sigma^2_{\omega,i}$ is represented by $V(\varepsilon_{t-1})$, reflecting time-varying uncertainty.

[5]This argument is supported by Kim and Verrecchia (1994), who in the context of earnings announcements, question whether investors are fully and symmetrically able to interpret effects of news arriving at the market.

[6]This argument builds on Stoll and Whaley (1990), Chan, Chan, and Karolyi (1991) and Franses, van Ieperen, Kofman, Martens, and Menkveld (1997), who consider interactions between returns across assets or exchanges as measures of information transmission.

Diamond and Verrecchia (1981), who stress that "each trader conditions his estimate of the return both on his own private source of information and price, which in equilibrium serves as a 'noisy' aggregator of the total information observed by all traders." With the theoretical concept of rational expectations equilibrium (REE) in the presence of noise, Diamond and Verrecchia (1981), Admati (1985) and Kim and Verrecchia (1991a,b) examine how noisy information affects price formation. The partial aggregation equilibrium is explicitly derived in the presence of noise trading, that is, partial aggregation of many diverse sources of information in the price. In contrast, in our model, we argue that the sheer amount of exogenously emerging public information, either price-relevant fundamentals or price-irrelevant noise, leads to noisy signals.[7] As investors learn from price signals and draw conclusions from observing trading activities, a dynamic network of information transmission and information processing is formed, which further increases diffuse beliefs and the variation in expectations (see, e.g., Grossman and Stiglitz (1980)).[8] While a higher amount of information may lead to a higher amount of trading, the emergence of diffuse beliefs and signals clouded in trading noise may also lead to a holding back by investors due to increasing uncertainty.[9] Hence, as a consequence of dispersed expectations, price fluctuations are bounded above.

From Equation (5), it follows that $\pi_{t-1,i}$ is a function of Ω_{t-1}. Ω_{t-1} is defined in a range between abnormally low and abnormally high information flow, $\underline{\Omega_{t-1}} \leq \Omega^*_{t-1} \leq \overline{\Omega_{t-1}}$, with Ω^*_{t-1} indicating a normal level of information density. Accordingly, we can derive three scenarios:

1. The information flow is abnormally low, $\underline{\Omega_{t-1}}$, and $\pi_{t-1,i}$ converges towards 1: $E_{t-1}[P_{t,i} \mid F_{t-1,k}, \underline{\Omega_{t-1}}]_{\{\pi_{t-1,i}\to 1\}} = E_{t-1}(P_{t,i})$. In this unrealistic scenario, the best forecast for the price in t is the price from the previous period, as no new information is available to be priced in.

[7]In a more recent study, Albagli, Hellwig, and Tsyvinski (2014) provide a model of corporate investment and risk-taking when aggregate information in financial markets consists of fundamentals and noise. As a result, stock prices depart from the efficient market benchmark, which induces rent-seeking behavior among shareholders and market discipline fails. In contrast, our empirical analysis provides an explanation for changes in asset prices due to an abnormal flow of information that makes public signals less precise.

[8]Another effect that influences price discovery is the divergence of intrinsic values arising from news arrival. For example, if news diverges in terms of whether it is a good or a bad signal for each asset, the range of possibly resulting price expectations will be even larger. Hence, heterogeneous price expectations also arise when investors value assets differently across states (see Veronesi (2000)).

[9]The latter is also in line with Savor and Wilson (2013, 2014), who report risk premia effects by holding assets over announcement periods. The higher uncertainty surrounding macroeconomic announcements should amplify these risk premia, thereby limiting trading activity on the upside.

2. The information flow is normal, Ω^*_{t-1}, and $\pi_{t-1,i}$ lies in the interval between zero and 1: $E_{t-1}[P_{t,i} \mid F_{t-1,k}, \Omega^*_{t-1}]_{\{\pi_{t-1,i} \in]0,1[\}} = E_{t-1}(P_{t,i} \mid F_{t-1,k}) + (\pi_{t-1,i})\Big(E_{t-1}(P_{t,i} \mid \Omega^*_{t-1}) - E_{t-1}(P_{t,i} \mid F_{t-1,k})\Big)$. In this scenario, price expectations are updated according to the actual information provided by the news industry.
3. The information flow is abnormally high, $\overline{\Omega_{t-1}}$, and $\pi_{t-1,i}$ converges towards zero: $E_{t-1}[P_{t,i} \mid F_{t-1,k}, \overline{\Omega_{t-1}}]_{\{\pi_{t-1,i} \to 0\}} = E_{t-1}(P_{t,i} \mid F_{t-1,k})$. From the way price expectations are updated, more diffuse expectations lead to price expectations more anchored towards previous (forecast-based) expectations.

In period t, when the public announcement is released, the difference between the price based on the announcement and the updated price expectation based on Equation (5) affects the price process:

$$\begin{gathered}(P_t \mid A_{t,k}) - E_{t-1}[P_{t,i} \mid (F_{t-1,k}, \Omega_{t-1})] = \\ (P_t \mid A_{t,k}) - E_{t-1}(P_{t,i} \mid F_{t-1,k}) - (\pi_{t-1,i})\Big(E_{t-1}(P_{t,i} \mid \Omega_{t-1}) - E_{t-1}(P_{t,i} \mid F_{t-1,k})\Big).\end{gathered} \tag{6}$$

In the first scenario, there will be a strong price adjustment if $V(\varepsilon_{t-1})$ is large. However, this price change is driven exclusively by volatility and is independent of information flow. In contrast, in the second scenario, the deviation of the new equilibrium price from the predicted price is much smaller, because the price change is dampened by the updating based on information flow. However, if the difference between the intrinsic price based on the announcement and the forecast is large, there will be a strong adjustment in period t above the normal price fluctuation. Furthermore, if diffuse beliefs arise as in the third scenario, that is, $\pi_{t-1,i} = \frac{1/V(E_{t-1}[P_{t,i}|\Omega_{t-1}])}{1/(V(\varepsilon_{t-1})+V(E_{t-1}[P_{t,i}|\Omega_{t-1}]))}$ is small, there is less adjustment to signals contained in news flows prior to the announcement time t. Investors stick to the price based on the forecast, which will also lead to strong adjustments following the announcement, that is, when uncertainty is removed and the price discovery process is no longer, or at least to a much lesser extent, deferred by noise. Thus, there are two effects that will lead to divergence between the new intrinsic price and the expected price when the new "hard facts" arrive: On the one hand, the deviation of the actual announcement from the forecast impacts the price fluctuation. On the other hand, the divergence arises from the high information flow prior to the release of the macroeconomic announcement. From this, we conclude that abnormal information flows prior to announcements merely hinder the price discovery process and can be considered as additional uncertainty coming to the market.

While the divergence of announcement and forecast ($A_{t,k} - F_{t-1,k}$) is formally defined as announcement surprise, price expectations of market participants and their dispersion are not directly observable. Empirically, the abnormal information flow, $\overline{\Omega_{t-1}}$, is estimated by IDI. This is expressed as the deviation of news flow in $t-1$ from the average news flows over the previous five periods, standardized by its volatility. Hence, IDI measures the abnormal amount of information arriving at the market that causes diffuse beliefs and distorts the price discovery process. This distortion is resolved by a (significant) price change at the time of a precise signal, that is, when a public announcement is released.

Although we expect the diffuse beliefs to defer price discovery, there will still be some price fluctuations in the market. In Veronesi (2000), imprecise signals curb the equity risk premium independently of investors' risk aversion. We therefore take a conservative approach by considering price changes only beyond a certain threshold to estimate whether higher news flow prior to macroeconomic announcements leads to a deferred price discovery process and subsequently stronger adjustments. To accommodate this, we consider increases in information density prior to macroeconomic announcements. By so doing, we can estimate whether an abnormal news flow in $t-1$ indeed leads to strong price adjustments following the release of hard facts (announcement A_k) in t. Hence, we empirically test the third scenario, where more diffuse expectations arising from an abnormally high news flow, $\overline{\Omega_{t-1}}$, lead to price expectations more anchored towards previous (forecast-based) expectations. We analyze the price adjustment via jump methodology, that is, by considering only (statistically) significant price changes. This ensures a setup that is robust to pre-announcement drifts documented by Kurov, Sancetta, Strasser, and Halova Wolfe (2015) and Lucca and Moench (2015).[10] So we obtain an unbiased setup and comparability to existing studies in the macroeconomic announcement domain:[11]

[10]Kurov, Sancetta, Strasser, and Halova Wolfe (2015) report price drifts in the right direction for stock index and Treasury futures prior to announcements, and attribute this to leakage and proprietary data collection as sources of private information. This effect could reduce the probability of obtaining a jump and renders our approach of testing jumps conditional on macroeconomic announcements more conservative.

[11]See, e.g., Jiang, Lo, and Verdelhan (2011), who investigate sources of jumps in U.S. Treasury bonds in the presence of macroeconomic news based on announcement surprises and sudden shocks in volatility and

$$Jump_{t,i}|Announcement_k = f\left(\left(A_{t,k} - F_{t-1,k}\right), \overline{\Omega_{t-1}}\right), \tag{7}$$

3. Data and Jump Identification

In this section, we describe our data and the jump identification methodology. We then link the significant price jumps to macroeconomic announcements.

3.1. Data

The literature focuses almost exclusively on U.S. assets and U.S. macroeconomic news.[12] Besides the U.S. markets, we additionally include the German bond and equity markets as well as the EUR/USD exchange rate. We choose Germany to represent the European markets, as it has highly liquid bond and equity futures markets and the trading hours overlap with the U.S. markets.[13] As further sources of price jumps, we include macroeconomic news from Germany and the European Union. This allows us to analyze news (vs. non-news) related jumps across assets, regions, and different origins of macroeconomic announcements. Table 1 summarizes our data set of macroeconomic announcements.

<<< Table 1 about here >>>

For our analysis of the U.S. and German equity and bond markets, as well as the USD/EUR exchange rate, we collected raw tick-by-tick data for the S&P 500 E-Mini, the 10-year Treasury note, and the DAX and Bund futures, as well as for the EUR/USD spot rate. Futures for the bond and stock markets are more liquid than their underlying markets and lead their cash markets.[14] For the exchange rate, we choose spot market data from ICAP Electronic Broking Services (EBS).

---

liquidity.

[12] An exception is Chatrath, Dailing, Miao, and Ramchander (2014), who focus on four different exchange rates.

[13] We refrained from using single stocks for two reasons: First, the expected relationship between macroeconomic news and single stocks is less clear because of idiosyncratic firm characteristics. Second, due to lower liquidity, the time window to identify jumps needs to be larger, which increases potential dual causality problems. Based on 15-minute time intervals, Bradley, Clarke, Lee, and Ornthanalai (2014), for instance, focus on corporate information, such as analyst recommendations and earnings announcements, as well as management guidance, and their impact on jumps in equity prices.

[14] Chen, Diltz, Huang, and Lung (2011) also show that futures markets react more sensitively to news than the respective spot markets.

ICAP/EBS is the largest electronic trading platform for the major currency pairs and operates 24 hours per day. Its liquidity is higher than that of the EUR/USD futures markets.[15]

Our sample covers the six-year period from January 2006 to December 2011. We converted all data to Eastern Standard Time (EST) and accounted for the switch to Daylight Savings Time in the U.S. and Europe. DAX and Bund futures are traded from 02:00 to 16:00 EST and a 10-year Treasury note is quoted from 18:00 to 16:00 EST, or 22 hours per day (in New York, Tokyo, and London). Meanwhile, the EUR/USD and S&P 500 E-Mini futures are traded 24 hours per day. For futures data, we use the contract closest to maturity and roll over when the next maturity contract becomes more actively traded. We transformed the raw data into equidistant five-minute return intervals, $r_j(i) = log(p_j/p_{j-1})$, where p_j denotes the price (measured in local currency) of the last trade in the j-th interval. We ignore opening returns to avoid contamination from overnight news. As is standard in this literature, we use the Market News International (MNI) database as the source for our information-flow indicator. MNI is the premier source for real time capital markets news. Hence, in comparison to other news providers such as Bloomberg or Reuters, the MNI database includes only financial market-related (i.e., economic) news; for our six-year observation period, it contains approximately 655,000 news entries.

3.2. Jump Identification

In recent years, much progress has been made in theoretical and empirical identification of price jumps (see, e.g., Lee and Mykland (2008); Tauchen and Zhou (2011)). A recent strand of empirical research links price jumps to macroeconomic announcements. Dungey, McKenzie, and Smith (2009) and Lahaye, Laurent, and Neely (2011) were among the first to empirically detect intraday jumps that coincide with macroeconomic announcements. To identify significant jumps, we apply jump detection techniques adopted from recent literature (e.g., Evans (2011)).[16] As originally introduced by Merton (1971) and now widely applied in research on jump identification

[15]Evans (2011) compares the EUR/USD futures market with the more liquid cash market for a selected subsample. He identifies more jumps in the futures market, but these are of similar size. The vast majority of the additional jumps are not related to U.S. macroeconomic news (Evans (2011), FN 6).

[16]Evans (2011) matched jumps in the U.S. bond and equity markets, as well as the Euro/U.S. dollar exchange rate with macroeconomic announcements from the U.S. He explains up to one-third of all jumps with macroeconomic announcements.

(e.g., Andersen, Bollerslev and Diebold (2007); Lee and Mykland (2008)), we assume a continuous time-jump diffusion process with a logarithmic price process, as follows:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + J(t)dq(t), \qquad 0 \leq t \leq T. \tag{8}$$

The logarithmic asset price consists of three components. The variable $\mu(t)$ describes a continuous locally bound variation process. $\sigma(t)$ is a strictly positive stochastic volatility process with a Wiener process $W(t)$. $J(t)$ refers to the respective jump size combined with a binomial counting process $q(t)$, which takes the value 1 when there is a jump at time t. Since we are not able to observe continuous sample paths for asset prices in reality, we divide the sample period into equidistant δ-periods of high-frequency returns. We then use discrete sample prices, a standard procedure in empirical research. Daily realized variation is captured in the sum of the corresponding $1/\delta$ high-frequency intraday squared returns, given in the non-parametric measure of the realized variation (RV):

$$RV_{t+1}(\delta) \equiv \sum_{i=1}^{1/\delta} r_{i\delta}^2. \tag{9}$$

The compounding return of the respective asset j is implied by $r_j(i) = log[S_j(t_i)/S_j(t_{i-1})]$, where $S_j(t_i)$ is the price of asset j at time t_i. Following Jacod and Shiryaev (2013) as well as Andersen, Bollerslev, Diebold, and Labys (2003), we assume that RV is a consistent estimator of total variance, including both the continuous component and jump component J:

$$RV_{t+1} = \int_t^{t+1} \sigma^2(v)dv + \sum_{t<v\leq t+1} J^2(v). \tag{10}$$

Equation (10) represents the continuous sample path and the jump component of the total return variation. When there are no jumps present, realized volatility equals the integrated variance. In the presence of jumps, realized volatility equals the integrated variance and the cumulative sum of the squared jumps. Note that integrated variance can be interpreted as the natural threshold for the bounded price changes existing in the pre-announcement phase due to diffuse beliefs. As introduced by Barndorff-Nielsen and Shephard (2004), the realized bipower variation (BV) captures the continuous price movement. This is defined as the scaled summation of the product of the respective adjacent absolute returns:

$$BV_{t+1}(\delta) \equiv \frac{1}{l-2} \sum_{i=1}^{1/\delta} \mid r_{t+i\delta} \mid\mid r_{t+(i-1)\delta} \mid, \tag{11}$$

where l defines the size of the rolling window. With the combination of realized volatility and realized bipower variation in Equations (10) and (11), the continuous and discontinuous components of the quadratic variations can be separated and the contribution of the jump component J can be extracted:

$$RV_{t+1}(\delta) - BV_{t+1}(\delta) \to \sum_{t<v\leq t+1} J^2(v). \tag{12}$$

Below, we apply the jump identification methodology introduced by Lee and Mykland (2008).[17] In so doing, we set our rolling window l to five trading days.[18] To test at time t whether a jump in the price data of the respective asset occurred, we use the following test statistic $L_j(i)$:

$$L_j(i) = \frac{r_j(i)}{BV_j(t_i)}. \tag{13}$$

Based on this test statistic $L_j(i)$, Lee and Mykland (2008) derived the following test statistic and corresponding critical value. The null hypothesis that there is no jump in price data in the interval t_{i-1} to t_i is rejected if

$$\frac{\mid L_j(i) \mid - C_{lj}}{S_{lj}} > 4.6001. \tag{14.1}$$

The constants C_{lj} and S_{lj} are given by the following equations:

$$C_{lj} = \frac{2log(l_j)^{1/2}}{c} - \frac{ln(\pi) + log(log(l_j))}{2c(2log(l_j))^{1/2}}, \tag{14.2}$$

$$S_{lj} = \frac{1}{c(2log(l_j)^{1/2}}. \tag{14.3}$$

The constant c is approximately equal to 0.7979 ($c \equiv \sqrt{2/\pi}$). The critical value is based on the 99th-percentile of a Gumbel distribution. We follow previous empirical papers on jump identification

[17]In several pre-tests, we compared different jump identification methodologies. With the approach that was suggested by Lee and Mykland (2008), the number of mis-specified jumps is minimized. This confirms the results of Hanousek, Kocenda, and Novotny (2012).

[18]We further applied alternative window sizes ranging from 3 to 20 days. At a window size of 5 trading days, the amount of spuriously identified jumps is minimized.

and choose a return frequency of five minutes to avoid most market microstructure noise (e.g., Evans (2011); Jiang, Lo, and Verdelhan (2011); Bongaerts, Roll, Rösch, Van Dijk, and Yuferova (2014)). This ensures that effects such as high-frequency trading, short-term anomalies, or bid-ask bounces do not contaminate our results.

3.3. Descriptive Statistics on Price Jumps

Table 2 provides summary statistics for the five-minute returns and significant jumps for each asset class. We find the most jumps for DAX futures (864), followed by 10-year Treasury note futures (797) and Bund futures (794), and a slightly lower count for S&P 500 E-Mini futures (670) and EUR/USD exchange rate (614).

<<< Table 2 about here >>>

Previous theoretical and empirical work (e.g., Barberis, Shleifer, and Vishny (1998); Veronesi (1999)) suggests that, on average, investors react more strongly to negative than to positive news. Moreover, our sample covers the subprime and Euro crises. Therefore, we expect to see more negative than positive jumps in the equity and bond markets. This asymmetry is confirmed by our results. It is most pronounced in DAX futures, where negative jumps outweigh positive ones by more than 90 percent. In the EUR/USD exchange rate, we see an almost identical number of positive (306) and negative (308) jumps.[19]

Since the jump detection procedure identifies jumps conditional on the underlying local volatility, markets with higher volatility should exhibit jumps of higher magnitude. On average, we see the largest absolute jumps in the more volatile equity markets, with (absolute) jump sizes of 0.53 percent (DAX) and 0.51 percent (S&P), while the smallest jumps are observed in the bond markets (U.S. Treasuries, 0.21 percent and Bunds, 0.16 percent), which also have the lowest volatility. As positive and negative jumps are of a similar size in each asset, we conclude—due to the mechanics of the jump identification procedure—that positive and negative jumps occur at comparable levels of local volatility. All maxima and minima in the five-minute intervals were identified as jumps.

[19]The EUR/USD exchange rate is a relative measure and the question whether a jump is positive or negative depends on the perspective. Therefore, the symmetry seems reasonable. We also checked whether positive and negative price jumps are differently affected by our IDI measure. However, we cannot find any differences neither in magnitudes nor in terms of sign or significance.

Figure 1 illustrates the intraday frequencies of jumps for our five assets. For all assets, we find pronounced peaks at 08:30 and 10:00 EST, when many U.S. macroeconomic announcements are released. In the U.S. Treasury futures, we observe a third peak at around 13:00 EST. The EUR/USD exchange rate (24-hour trading) also shows sparsely distributed jumps during illiquid trading times (e.g., during Asian trading hours). Although the S&P E-Mini is traded 22 hours per day, jumps are almost confined to the liquid trading times.

<<< Figure 1 about here >>>

3.4. Jumps Conditional on Macroeconomic Announcements

Table 3 shows the number of jumps for each asset that coincide with the various macroeconomic announcements within the five-minute return intervals.

<<< Table 3 about here >>>

In total, we include 51 macroeconomic announcements in our analysis (see Table 1). The selection of macroeconomic announcements is guided mainly by the literature (see, e.g., Balduzzi, Elton, and Green (2001); Andersen, Bollerslev, Diebold, and Vega (2003); Andersen, Bollerslev, Diebold, and Vega (2007)). However, we expand the set of announcements used in the literature and additionally include news from the European Monetary Union (EMU) and Germany. This is because jumps in the German assets, as well as the exchange rate, are often associated with news from the EMU and Germany. We also observe some jumps in U.S. assets, which can be linked to macroeconomic news from the EMU and Germany.[20]

Almost half (48.4 percent) of all jumps in U.S. Treasury futures can be linked to macroeconomic announcements, the highest ratio among all five assets. By far, the two most important announcements are *Initial Jobless Claims* and *Non-Farm Payrolls*.[21] They account for about one-third of

[20]Macroeconomic data from other European countries seem to play no role in explaining jumps in our five assets. In rare events, we can link statements (in particular from FED and ECB) to jumps in the markets, but with hardly any overlap to our sample periods. Note further that, since we use bond and equity futures indices in our empirical analysis, microeconomic fundamentals for individual stocks, such as earnings and analyst recommendations, can be neglected, which primarily drives unsystematic price jumps as shown by Lee (2012).

[21]To control for the dominant impact of these announcements on our main results, we re-run our analysis without these macroeconomic indicators in the robustness sub-section 4.4.

all macroeconomic announcements that can be related to significant jumps. Although the ratio of significant jumps with macroeconomic announcement is lower for S&P futures (29.0 percent) compared to U.S. Treasury futures, the results are similar in the sense that labor market-related news is most important.

German DAX futures react to macroeconomic news from the U.S., Germany, and the EMU. At 28.7 percent, the coincidence ratio is almost identical to that of S&P futures. In the DAX futures, more than half of all significant news is from Germany, with the most important ones being *Producer Price Index*, *Trade Balance*, and *Retail* and *Wholesale Prices*.[22] The coincidence ratio for Bund futures is approximately 39 percent, with U.S. announcements being slightly more important than German announcements.

For the EUR/USD currency pair, the results look similar to Bund futures. Approximately 41 percent of the jumps can be linked to macroeconomic announcements, with U.S. news being the most important. About 12 percent of the jumps are associated with German and EMU news, with the German ifo Business Climate Index alone accounting for 4 percent of the jumps. Table 4 shows the descriptive statistics on jumps corresponding to macroeconomic announcements and jumps that could not be linked to macroeconomic announcements. We see slightly higher means and standard deviations for announcement-driven jumps, but no clear pattern concerning extreme values across the different assets. However, minimum jumps in absolute values are always higher when there is no public announcement. This indicates that negative jumps, which are conditional on announcements, show lower absolute values compared to negative jumps when other news is released (such as firm-specific information) or important events occur, respectively. Skewness for jumps that are conditional on announcements tends to be more positive than for the non-announcement case.

<<< Table 4 about here >>>

[22]Labor market related news from Germany or the EMU rarely plays a role in explaining the jumps in the German Bund and DAX Futures. Markets seem to interpret them to a lower extent as predictors of the future state of the economy than U.S. labor market data.

4. Information Density, News Announcements, and the Likelihood of Jumps

4.1. Information Density Indicator

To operationalize the strength of the information flow, $\overline{\Omega_{t-1}}$, from Equation (7), and thus, to analyze the impact of information density before macroeconomic announcements arrive at the market, we develop a new variable, which we label *information density indicator (IDI)*. IDI measures the abnormal amount of news flow before the release of public announcements.[23] This indicator represents the relation between the amount of news items during the last five minutes before the announcement interval and the preceding news flow.[24] Formally, we define it analogously to the liquidity shock variable in Jiang, Lo, and Verdelhan (2011). Note that IDI captures only the sheer number of news items but not their relevance or quality. Thus, we consider as a measure for information shocks, the following:

$$IDI_{t-1} = \frac{News_{t-1} - \frac{1}{5}\sum_{i=2}^{6} News_{t-i}}{\sigma_{News}}, \tag{15}$$

where the mean of incoming news items ($News_{t-i}$) over five five-minute periods (from $t-2$ to $t-6$), $\frac{1}{5}\sum_{i=2}^{6} News_{t-i}$, is subtracted from the amount of incoming news during the five minutes before an announcement ($News_{t-1}$), standardized by the standard deviation over *six* five-minute intervals, σ_{News} (see Figure 2 for illustration purposes).[25] We use a five-minute interval to ensure that there is no overlap between the pure information flow and the precise signal, even though it is well-documented in the literature that most price adjustments to major announcements occur

[23] To capture a more general news flow effect on jumps, we tried various specifications of our measure. In so doing, we varied the construction of IDI depending on alternative specifications with regard to window size, and hence, the corresponding standardization. By construction, our IDI measure closely follows the news surprise and trading activity variables, for which we also define similar time intervals.

[24] Most announcements occur during the first half of the five-minute intervals, which leaves some time for the price process to correct "overshooting reactions" and reach their state of equilibrium. This renders our approach quite defensive in terms of measuring the jumps conditional on the expected effects, and leaves the pure impact on price discovery for analysis. We also assume that there are no effects coming from abnormal information flow immediately after the release of a public announcement, to omit biased estimates. This approach is robust to possibly remaining uncertainty not related to announcement uncertainty.

[25] Figure 3, which shows rolling window estimates for the IDI measure ahead of macroeconomic announcements, also empirically indicates this pattern of increasing information density prior to an announcement.

within the first minute (see, e.g., Ederington and Lee (1993)). The second term in the nominator of Equation (15) measures the normal level of information flow in the respective preceding time period. Hence, it is the first term that specifies whether there is a deviation from normality, and the size of this deviation indicates the increase in information.

<<< Figure 2 about here >>>

Note that, in this example illustration, there is already some price movement before the announcement. From our theoretical model, we do not consider these movements to be large and they occur mainly randomly. Furthermore, we control for general movements and increased volatility. Hence, whether there are some price movements in between is not of major importance for our analysis, especially since we focus on jumps rather than price changes. Figure 3 also empirically indicates the pattern of increasing information density prior to an announcement. This figure shows the rolling window estimates for the evolution of the IDI measure for a one-hour period ahead of macroeconomic announcements ($t-12$ to $t-7$; $t-11$ to $t-6$; $\ldots$; $t-7$ to $t-2$). In the case of jumps, it increases substantially during the time period of one hour before an announcement, whereas it remains at about the same level in the case of no jumps.

<<< Figure 3 about here >>>

Table 5 shows descriptive statistics for the IDI measure. Conditional on macroeconomic announcements the mean IDI is higher in the case of jumps, for all five assets. The standard deviation of the IDI measure with and without a subsequent jump is about the same. This also applies to the min/max values. IDIs before jumps are highly negatively skewed, compared to IDIs without jumps, as shown by the distributions of IDI conditional on jumps and no jumps in Figure 4. This points to more observations with large IDI values, underpinned by slightly higher kurtosis.

<<< Table 5 about here >>>

<<< Figure 4 about here >>>

Figure 5 shows average IDI over a trading period of 24 hours. IDI does not exhibit pronounced peaks as with the jump frequencies across the trading day in Figure 1.[26]

<<< Figure 5 about here >>>

4.2. Estimation Strategy

To analyze the role of *information density* ahead of macroeconomic announcements in explaining price jumps, let us recall from Section 2 our theoretical framework, which can be restated for the empirical estimation in a probit model specification. If indeed an abnormal news flow prior to announcements defers the price discovery process, then it should increase the likelihood of a price jump when the hard facts are released. In addition, it is difficult to interpret the size of a jump with respect to the level of abnormal information or news surprise. Thus, we refrain from deriving the marginal effects of our IDI measure on the absolute price jump from OLS estimation. Since this effect should be unrelated to the magnitude of the news surprises, as well as to the general market structure prevailing, we also control for volatility and trading activity. Volatility affects the degree of expectation updating in our Bayesian setting. Higher volatility can reduce stickiness in the price process, while it can also increase changes in price expectations. Since our jump identification filter relies on local volatility to set the threshold for significant price movements, we expect the volatility effect to be rather small. Above, we argue that the price process is deferred by an abnormally high news flow, but we make no predictions about pre-announcement trading activity. However, for unbiased results, pre-announcement trading activity and abnormal news flow should be uncorrelated. The probit model takes the following form:

$$\begin{aligned} Prob\,(J_{t,i}|Announcement_k) = f(&\alpha + \beta_{SUR}|SUR_{t,k}| + \beta_{IDI}IDI_{t-1} + \beta_{DLS}DLS_{t-1,i} \\ &+\beta_{VLA}VLA_{t-1,i}), \end{aligned} \tag{16}$$

where *Prob* denotes the probability that a jump occurs conditional on a scheduled macroeconomic announcement. Our dependent variable is a binary indicator, which takes the value of 1 when

[26]Note that due to the construction of IDI, that is, the standard deviation is calculated over six five-minute intervals, while the mean represents the average over the first five intervals, the means in Table 5 and Figure 4 are upward-biased. However, when we consider all jumps that occur *without* an announcement, the mean and median are close to 0 and the standard deviation close to 1 with a positive skewness. This can be traced back to the very low variation in IDI for such situations.

there is a jump, and 0 otherwise, that is, we are interested in whether and how the increase in noisy information and the emergence of diffuse beliefs affects the probability of a price jump. In the following, we discuss the chosen variables in detail. IDI_{t-1} (information density indicator) and $SUR_{t,k}$ (news surprise) are our two *informational* variables. While the former reflects the increased information flow in the market prior to the release of an announcement, the latter is the surprise in the macroeconomic announcement. $DLS_{t-1,i}$ and $VLA_{t-1,i}$ control for trading activity and volatility, respectively.

Macroeconomic Surprise. The informational variable $|SUR_{t,k}|$ measures the surprise of the macroeconomic announcement k at time t. In line with Balduzzi, Elton, and Green (2001), Andersen, Bollerslev, Diebold, and Vega (2003), and Andersen, Bollerslev, Diebold, and Vega (2007), we define announcement surprise as follows:

$$SUR_{t,k} = \frac{A_{t,k} - F_{t-1,k}}{\hat{\sigma}_k}, \tag{17}$$

where $A_{t,k}$ is the actual value of the announcement k, $F_{t-1,k}$ is the market expectation of the announcement k indicated by the median forecast in the MNI database, and $\hat{\sigma}_k$ is the sample standard deviation of the news surprise, given by $A_{t,k} - F_{t-1,k}$.

Control Variables. Related to Mizrach and Neely (2008) and Jiang, Lo, and Verdelhan (2011), we use two variables to control for trading activity and volatility. The first variable DLS_{t-1} captures a sudden increase in the trading activity of the asset before the announcement:[27]

$$DLS_{t-1} = \frac{Deals_{t-1} - \frac{1}{5}\sum_{i=2}^{6} Deals_{t-i}}{\sigma_{Deals}}. \tag{18}$$

DLS_{t-1} measures the difference between the number of deals in the five-minute interval prior to the announcement ($t-1$) and the mean of deals over the intervals $t-6$ to $t-2$, divided by their standard deviation. The second control variable VLA_{t-1} represents the realized volatility in the interval of 30 minutes to the five minutes before the announcement:[28]

[27] Besides the deals variable (DLS), in our analysis, we further include the variable “transaction volume" (standardized similarly to DLS). Since DLS and transaction volume are highly correlated, we exclude the latter.

[28] 288 five minute intervals equal to 24 hours, which we use as window size.

$$VLA_{t-1} = \sigma(r_{t-1,t-6})\sqrt{288}. \tag{19}$$

The volatility measure of the market is calculated as the standard deviation of the five-minute log returns from $t-6$ to $t-1$, multiplied by the square root of the window size. Because our jump measure already controls for volatility level via the integrated variance, we expect only a moderate impact from this control variable on the likelihood of a jump.

Table 6 shows the correlation between our independent variables. Bravais-Pearson correlation coefficients range between -0.114 and +0.156. This indicates that multicollinearity neither seems to affect the inference statistics nor our estimation results. For most assets, the highest correlations are observed between SUR and VLA (0.087 to 0.148), with the exception of Treasury note futures, for which the linear dependency between volatility and IDI is 0.156. However, the correlation coefficients between IDI and News Surprise are 0.01 or less for all five assets.

<<< Table 6 about here >>>

Note that correlations near zero are good news not only in terms of econometrics but also, at this stage, they indicate that our model setup disentangles the different effects. For example, the low correlation between news surprise and information density indicator allows for a fully separate identification of these effects. Also, the orthogonality between the trading shock and information density indicators renders our model identification valid. This is because increased trading before an announcement is not necessarily driven by news, since higher news flows could defer price discovery, potentially limiting transactions. Finally, the low correlation between IDI and volatility indicates that there is no severe endogeneity problem. When macroeconomic announcements are perceived as more important (e.g., in volatile times or during times of crisis), news agencies might distribute more information in advance of announcements.[29] However, the correlation between IDI and realized volatility is close to zero, with the exception of Treasury note futures (0.156).

[29] See also Subsection 4.4 on robustness tests for a deeper discussion of the reverse causality problem. Note further that we see no distinctive pattern in the variation of jumps over our sample period or during more volatile market periods. This is probably attributable to the jump filter that relies on the local volatility to set the threshold for significant price movements.

4.3. Empirical Results

The estimation results for the probit model specifications according to Equation (16) are shown in Table 7. We begin with a parsimonious model by including only our main covariates *News Surprise* and *IDI*. We then add our control variables for *trading activity* and *volatility*. We report HAC-robust standard errors for all regressions, since our IDI measure is based on a rolling window approach.[30]

<<< Table 7 about here >>>

First, the intercept in all regressions of Table 7 is negative and highly significant. Economically speaking, this means that without taking into account news surprise, abnormal news flow, excess trading activity, and volatility, a price jump in the five asset markets is very unlikely. In contrast, for all five assets (and all model variations) the coefficients of IDI and the news surprise variable SUR are significant at the 1 percent level with a persistent positive sign, that is, the probability of a price jump increases with growing abnormal information density prior to the public announcement. This is in line with our theoretical hypotheses in Section 2. The magnitude of the *SUR* and *IDI* coefficients remains almost unchanged across the different model specifications, and only slightly decreases for the full specification, as expected.[31] For the full specification in Model XI, we observe the lowest *IDI* coefficient (0.104) for the FX market, which also applies to the *SUR* coefficient (0.114). The *SUR* and *IDI* coefficients are higher in the German and U.S. stock markets compared to the FX and bond markets. From this observation, and due to the fact that all measures are standardized, we conclude that news surprises and increasing abnormal information flow are more likely to trigger jumps in stock markets than in bond futures or FX markets. Finally, the results shown in Table 7 demonstrate that our IDI measure remains significant, even when we exclude the SUR measure or the control variables, or both. Hence, the likelihood of a jump not only depends

[30]We also tested our results with two-way clustered standard errors with announcement time and announcement type as cluster variables to account for intergroup correlation. Since we did not find qualitative differences in our results, we use HAC standard errors throughout our paper. To conserve space, we do not show the two-way clustered results here. However, they are available from the authors upon request.

[31]Because our estimates remain stable in size and significance over different model specifications, we also conclude that our results are not affected by a severe omitted variable bias.

on news surprises but also on abnormal information flow.[32]

The fact that IDI strongly corresponds with the probability of jumps allows us to interpret it as a valid measure to capture the level of noisy information, which leads to diffuse beliefs, prior to a public announcement. Note that otherwise, and under the assumption of weak-form information efficiency, we can expect that all price-relevant or news-related information would be immediately reflected in a price change. As a result, no price jumps would occur at the release of the macroeconomic announcement, even if we control for news surprises, since all relevant information were already incorporated in the asset price.

The trading activity variable, *Deals* (*DLS*), is also significant at the 1 percent level for all five assets in all model specifications. The results for the volatility measure, VLA, are more ambiguous. VLA is significant for the Treasury note and S&P futures but not for the EUR/USD exchange rate or the German Bund and DAX futures. Moreover, in the full specification of Model XI, volatility remains significant only for the EUR/USD exchange rate. This is not surprising, since *SUR*, as well as *IDI* and, more importantly, the jump identification methodology, are denoted as standardized measures, and thus already control for the current level of volatility. To sum up, our empirical results confirm the theoretical hypothesis that the occurrence of abnormal information flow prior to a public announcement significantly increases the probability of a price jump. Hence, there is strong empirical evidence for our hypothesis of the impact of noisy information and diffuse beliefs on the price discovery process.

4.4. Robustness Tests

This section sets forth a series of robustness checks. First, we apply a placebo test to control for whether IDI explains jumps that are unconditional to macroeconomic announcements. Therefore, we estimate the probit model specification for our data set from which we excluded all time intervals that coincide with macroeconomic announcements. The results are shown in Panel A of Table 8. We find that the information density indicator is not significant in any specification of this placebo test. This confirms our assumption that, if signals are not overlaid by a significant amount of

[32]Note that these results remain robust when we use absolute instead of abnormal information flow for our IDI measure.

abnormal information, the uncertainty in the market is lower, and thus, information precision is higher. However, our control variables for trading activity and volatility are highly significant and still explain the likelihood of jumps. We further re-run our regression model with a lagged, non-overlapping IDI over the time period of 7-to-12-minute intervals ($t-12:t-7$), that is, from 1 hour to the 35^{th} minute (see Figure 3). The regression results remain unchanged in significance and almost unchanged in magnitude. Only in the case of the S&P futures do we find weak significance for lagged IDI.[33]

<<< Table 8 about here >>>

Second, to test whether IDI is contaminated by dominant macroeconomic indicators and announcement times, we re-run the regressions without announcements on *initial jobless claims* and *non-farm payrolls* as well as the peaks in jumps at 08:30 and 10:00 EST (see Figure 1), when many important macroeconomic announcements (in particular job market related indicators) are scheduled.[34] This reduces our sample by about half. The results are reported in Table 8 Panel B. Our estimates remain robust, except for the EUR/USD market, where *IDI* is no longer significant.

Third, we address the question of how co-announcements might affect our estimation results.[35] We focus on co-announcements, that is, situations in which we see more than one macroeconomic announcement within the same five-minute interval. In these instances, two effects can be observed: either the news surprises go in the same direction and thereby reinforce themselves, which can trigger a jump, or the news surprises are conflicting. In the latter case, even large news surprises could be leveled out.[36] Table 8, Panel C shows the regression results for co-announcements without conflicting news surprises. As expected, our model remains robust. In Table 8, Panel D, we report the regression results for co-announcements only for conflicting news. Neither our information density indicator nor news surprises remain significant. In this sense, our overall regression results

[33]We also split our sample into subsamples of positive and negative news surprises. The estimation results remain robust for both subsamples. We see no substantial difference in the magnitude of the coefficients. To conserve space, the results are not reported here but are available from the authors upon request.

[34]We apply this robustness test even though we can detect no differences in the level of abnormal information flow prior to U.S. announcements.

[35]Note that the literature mainly disregards co-announcement effects.

[36]For bond futures and the EUR/USD exchange rate, we classify news surprises based on the interest rate effect. For stock market futures, we consider interest rate, as well as the cash flow effect.

reported above are a conservative estimate, as we do not exclude co-announcements with conflicting news. In Panel E, we show only the results for single announcements.[37] The results confirm the findings derived when we exploit the whole data set.

Fourth, we test whether *IDI* also explains the likelihood of co-jumps among asset prices. We expect that relatively higher numbers of co-jumps can be linked to announcements than single jumps, since they are caused by information rather than by similar liquidity in different markets (Bollerslev, Law, and Tauchen (2008)).[38] However, in explaining co-jumps, the role of the IDI measure is less clear. On the one hand, one could argue that news surprises should gain in relative importance to IDI. On the other hand, the explanation could be the abnormal level of information that facilitates the co-jumps in the first place. As in Lahaye, Laurent, and Neely (2011) we formally define a co-jump as follows:

$$Co-Jump_t = \prod_{k=1}^{K} I\left(|J_{tk}|\right), \tag{20}$$

where I is an indicator function that becomes positive if a jump arises in at least two of our five asset markets. To analyze the impact of news surprises and our information density indicator on co-jumps, we re-estimate Equation (16) as a multinomial probit model for SUR and IDI conditional on macroeconomic announcements. To guarantee sufficient observations and to avoid spurious accuracy, we grouped the co-jumps into three alternative groups with no jumps as the reference case ($y = 0$): only one jump as group 1 ($y = 1$), two and three co-jumps as group 2 ($y = 2$), and four and five co-jumps as group 3 ($y = 3$). The results are displayed in Table 9.

<<< Table 9 about here >>>

Both the SUR and IDI coefficients increase, when going from one jump only to two/three and four/five co-jumps (which are all highly significant). To explain co-jumps, IDI is not overshadowed by the importance of the macroeconomic surprise. Rather, it plays an increasing role in predicting

[37] Note that our main regression results in Table 7 include multi-announcement jumps with the same *IDI* (with and without jump) but naturally different news surprises. In the robustness test for single announcements, we explicitly avoid double counting *IDI* and, thus, rule out any sample selection bias.

[38] This is confirmed by our results (not reported here). Almost all co-jumps in five assets can be related to macroeconomic news.

the likelihood of co-jumps.[39] We attribute this finding to higher aggregate uncertainty in the presence of a higher level of noisy information, as cross-asset price discovery is increasingly hindered by contamination of relevant signals by information shocks.

Fifth, we add interaction terms between IDI and SUR, DLS and VLA to our model. Only for the assets EUR/USD FX and Bund futures could we detect significant coefficients for $IDI * DLS$, along with a weakly significant interaction for $IDI * VLA$ in Treasury futures. The result of insignificant interaction terms is particularly important for the combined effect between IDI and realized volatility. For instance, one could argue that news agencies distribute more information before a particular announcement, when market participants perceive that the announcement will have major impact on prices. Hence, the relationship between IDI and the size of the jump would arise due to the fact that IDI may be high when macroeconomic announcements are particularly important for asset prices (e.g., during highly volatile market periods or during the 2007/08 financial crisis). However, the results on interaction terms, together with the correlation analysis in Table 6, demonstrate that there is no severe endogeneity problem. This underpins our hypothesis that diffuse beliefs due to imprecise signals and higher uncertainty in the market arise from increased information flow. We also see no systematic patterns in information flow over the sample period. To further explore this issue, we first re-run model XI of Table 7 separately for the observations where SUR has values in the lowest and highest quartiles. The idea behind this estimation strategy is to show whether IDI is only a secondary effect of the news surprise impact; however, from the re-runs, we see no dependency between the two variables.

Finally, we test whether particular years or the 2007/08 financial crisis affect the impact of IDI on the likelihood of price jumps. To account for year effects and a potential impact of the financial crisis, we added dummies to our probit model. For the S&P, Treasury, and Bund futures, we find no significant effects. For the latter years in our sample, the year dummies for the FX market and the Bund futures are significant. However, our model remains robust, that is, IDI as well as our

[39]We also run the estimation with the trading activity and volatility control variables for all five assets, as well as in various combinations. The qualitative results (increasing coefficients for SUR and IDI) remain unchanged. Due to high multicollinearity among the control variables in the multi-asset case, we do not report the results here. However, they are available from the authors upon request.

news surprise and deals variables remain highly significant.[40]

5. Conclusions

Based on a theoretical framework, which includes both the emergence of diffuse beliefs due to noisy information prior to macroeconomic announcement and the release of the scheduled public announcement, we introduce an information density indicator (IDI). This allows us to empirically test the impact of news flows prior to macroeconomic announcements on price jumps. In its construction, IDI follows the liquidity shock variable of Jiang, Lo, and Verdelhan (2011) and measures the excess or abnormal level of information arriving in the market. We assume that an abnormal level of news flow prior to public announcements leads to diffuse beliefs that hinder the price discovery process.

By exploring a theoretical relationship between price jumps in financial markets and macroeconomic announcements, as well as other news, we follow a three-step estimation approach. In the first step, we identify jumps in five asset classes (U.S. and German bond and equity markets and the EUR/USD exchange rate), as proposed by Lee and Mykland (2008). In the second step, we systematically link the jumps to macroeconomic announcements from the U.S., Germany, and the EMU. Finally, we explore the role of information (information density prior to announcements and news surprise) in triggering price jumps, by simultaneously controlling for trading activity and volatility in a probit model specification.

Our empirical results show that our information density indicator is independent of the magnitude of news surprise and pre-announcement trading activity, is highly significant across all five assets, and withstands several robustness checks. Even in the case of co-jumps among our five assets, the IDI measure is not overshadowed by the news surprise variable in importance and plays an increasing role in predicting the probability of a co-jump. We interpret this finding as a sign of rather unspecific uncertainty in terms of diffuse beliefs, which is finally resolved by the arrival of "hard" news in the form of a public announcement. We attribute this finding to the limited ability of market participants to infer signals from news flows in the presence of noise, which hin-

[40]To conserve space, the results are not reported here but are available from the authors upon request.

ders price discovery. We also consider the placebo test result, that is, an increase in information alone without the arrival of an announcement does not trigger jumps, as strong evidence for the theoretically derived effect of a malfunctioning price discovery process prior to announcements. This is resolved only when hard facts hit the market. Price discovery after increases in news flow without a following announcement is more gradual.

These results have strong implications given the increasing amount of information in financial markets. Since exogenous noisy information clouds price-relevant information (if any is contained in the news flow, which is not a necessary condition in our model), analysts' forecasts and other relevant fundamental signals may be diluted. This distorts the price discovery process in the short-term and limits market efficiency ahead of macroeconomic announcements.

References

Admati, A. R. (1985): "A noisy rational expectations equilibrium for multi-asset securities market," *Econometrica*, 53(3), 629–657.

Albagli, E., C. Hellwig, and A. Tsyvinski (2014): "Risk-taking, rent-seeking, and investment when financial markets are noisy," Working Paper.

Almeida, A., C. Goodhart, and R. Payne (1998): "The effects of macroeconomic news on high frequency exchange rate behavior," *Journal of Financial and Quantitative Analysis*, 33(3), 383–408.

Andersen, T. G., T. Bollerslev, and F. X. Diebold (2007): "Roughing it up: including jump components in the measurement and forecasting of return volatility," *Review of Economics and Statistics*, 89(4), 701–720.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and P. Labys (2003): "Modeling and forecasting realized volatility," *Econometrica*, 71(2), 579–625.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2003): "Micro effects of macro announcements: Real-time price discovery in foreign exchange," *American Economic Review*, 93(1), 38–62.

——— (2007): "Real-time price discovery in global stock, bond and foreign exchange markets," *Journal of International Economics*, 73(2), 251–277.

Balduzzi, P., E. J. Elton, and T. C. Green (2001): "Economic news and bond prices: Evidence from the US treasury market," *Journal of Financial and Quantitative Analysis*, 36(4), 523–543.

Barberis, N., A. Shleifer, and R. Vishny (1998): "A Model of Investor Sentiment," *Journal of Financial Economics*, 49(3), 307–343.

Barndorff-Nielsen, O. E., and N. Shephard (2004): "Power and bipower variation with stochastic volatility and jumps," *Journal of Financial Econometrics*, 2(1), 1–37.

Berry, T. D., and K. M. Howe (1994): "Public information arrival," *The Journal of Finance*, 49(4), 1331–1346.

Bollerslev, T., T. H. Law, and G. Tauchen (2008): "Risk, jumps, and diversification," *Journal of Econometrics*, 144(1), 234–256.

Bongaerts, D., R. Roll, D. Rösch, M. A. Van Dijk, and D. Yuferova (2014): "The Propagation of Shocks Across International Equity Markets: A Microstructure Perspective," Research Paper, Erasmus School of Management.

Bradley, D. J., J. Clarke, S. S. Lee, and C. Ornthanalai (2014): "Information disclosure and intraday price discovery: Evidence from jumps," *Journal of Finance, forthcoming.*

Chan, K., K. C. Chan, and G. A. Karolyi (1991): "Intraday volatility in the stock index and stock index futures markets," *Review of Financial Studies*, 4(4), 657–684.

Chatrath, A., R. Dailing, H. Miao, and S. Ramchander (2014): "Currency jumps, cojumps, and the role of macroeconomic announcements," *Journal of International Money and Finance*, 40(2), 42–62.

Chen, C. R., D. Diltz, Y. Huang, and P. P. Lung (2011): "Stock and options market divergence in the presence of noisy information," *Journal of Banking and Finance*, 35(8), 2001–2010.

Clements, A. E., and N. Todorova (2016): "Information flow, trading activity and commodity futures volatility," *Journal of Futures Markets*, 36(1), 88–104.

Detemple, J. B. (1986): "Asset Pricing in a Production Economy with Incomplete Information," *Journal of Finance*, 41(2), 383–391.

Diamond, D. W., and R. E. Verrecchia (1981): "Information aggregation in a noisy rational expectations economy," *Journal of Financial Economics*, 9, 221–235.

Dungey, M., M. McKenzie, and V. Smith (2009): "Empirical evidence on jumps in the term structure of the US Treasury Market," *Journal of Empirical Finance*, 16(3), 430–445.

Ederington, L. H., and J. H. Lee (1993): "How markets process information: News releases and volatility," *The Journal of Finance*, 48(4), 1161–1191.

Evans, K. P. (2011): "Intraday jumps and US macroeconomic news announcements," *Journal of Banking and Finance*, 35(10), 2511–2527.

Fama, E. F. (1965): "The Behavior of Stock-Market Prices," *The Journal of Business*, 38(1), 34–105.

Franses, P. H., R. A. van Ieperen, P. Kofman, M. Martens, and A. J. Menkveld (1997): "Volatility Patterns and Spillovers in BUND Futures," *Journal of Financial Research*, 10, 459–482.

Gross-Klussmann, A., and N. Hautsch (2011): "When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions," *Journal of Empirical Finance*, 18(2), 321–340.

Grossman, S., and J. Stiglitz (1980): "On the Impossibility of Informationally Efficient Markets," *The American Economic Review*, 70(3), 393–408.

Hanousek, J., E. Kocenda, and J. Novotny (2012): "The Identification of Price Jumps," *Monte Carlo Methods and Applications*, 18(1), 53–77.

Hautsch, N., D. Hess, and D. Veredas (2011): "The impact of macroeconomic news on quote adjustments, noise, and informational volatility," *Journal of Banking & Finance*, 35(10), 2733–2746.

Jacod, J., and A. Shiryaev (2013): *Limit theorems for stochastic processes*, vol. 288. Springer Science & Business Media.

Jiang, G. J., I. Lo, and A. Verdelhan (2011): "Information shocks, liquidity shocks, jumps, and price discovery: Evidence from the US Treasury Market," *Journal of Financial and Quantitative Analysis*, 46(2), 527–551.

Kalev, P. S., W.-M. Liu, P. K. Pham, and E. Jarnecic (2004): "Public information arrival and volatility of intraday stock returns," *Journal of Banking & Finance*, 28(6), 1441–1467.

Kim, O., and R. E. Verrecchia (1991a): "Market Reaction to Anticipated Announcements," *Journal of Financial Economics*, 30(2), 273–309.

——— (1991b): "Trading volume and price reactions to public announcements," *Journal of Accounting Research*, 29(2), 302–321.

——— (1994): "Market liquidity and volume around earnings announcements," *Journal of Accounting and Economics*, 17(1), 41 – 67.

Kurov, A., A. Sancetta, G. H. Strasser, and M. Halova Wolfe (2015): "Price Drift before U.S. Macroeconomic News: Private Information about Public Announcements?," Working Paper.

Lahaye, J., S. Laurent, and C. J. Neely (2011): "Jumps, cojumps and macro announcements," *Journal of Applied Econometrics*, 26(6), 893–921.

Lee, S. S. (2012): "Jumps and information flow in financial markets," *Review of Financial Studies*, 25(2), 439–479.

Lee, S. S., and P. A. Mykland (2008): "Jumps in financial markets: A new nonparametric test and jump dynamics," *Review of Financial*, 21(6), 2535–2563.

Li, G. (2005): "Information Quality, Learning, and Stock Market Returns," *Journal of Financial and Quantitative Analysis*, 40(3), 595–620.

Lucca, D. O., and E. Moench (2015): "The Pre-FOMC Announcement Drift," *The Journal of Finance*, 70(1), 329–371.

Madhavan, A., and S. Smidt (1991): "A Bayesian model of intraday specialist pricing," *Journal of Financial Economics*, 30, 99–134.

Merton, R. C. (1971): "Optimum consumption and portfolio rules in a continuous-Time Model," *Journal of Economic Theory*, 3(4), 373–413.

Mizrach, B., and C. J. Neely (2008): "Information shares in the US Treasury Market," *Journal of Banking and Finance*, 32(7), 1221–1233.

Savor, P., and M. Wilson (2013): "How much do investors care about macroeconomic risk? Evidence from scheduled economic announcements," *Journal of Financial and Quantitative Analysis*, 48(2), 343–375.

——— (2014): "Asset pricing: a tale of two days," *Journal of Financial Economics*, 113(2), 171–201.

Stoll, H. R., and R. E. Whaley (1990): "The Dynamics of Stock Index and Stock Index Futures Returns," *Journal of Financial and Quantitative Analysis*, 25, 441–468.

Tauchen, G., and H. Zhou (2011): "Realized jumps on financial markets and predicting credit spread," *Journal of Econometrics*, 160(1), 102–118.

Tetlock, P. C. (2007): "Giving content to investor sentiment: The role of media in the stock market," *The Journal of Finance*, 62(3), 1139–1168.

Tetlock, P. C., M. Saar-Tsechansky, and S. Macskassy (2008): "More than words: Quantifying language to measure firms' fundamentals," *The Journal of Finance*, 63(3), 1437–1467.

Veronesi, P. (1999): "Stock market overreaction to bad news in good times: A rational expectations equilibrium model," *Review of Financial Studies*, 12(5), 975–1007.

——— (2000): "How does information quality affect stock returns?," *Journal of Finance*, 55(2), 807–837.

Table 1: Macroeconomic Announcements

This table summarizes our data set of macroeconomic announcements. All timestamps are in Eastern Standard Time (EST). Advanced, preliminary, and final GDP announcements are pooled into one variable. ADP Payrolls started in May 2006. The Hudson Employment Index was discontinued in 2008. Pending Home Sales Index was released 13 times in 2010. Some EMU GDP and German Manufacturing Orders, Payroll Employment and Wholesale Prices data are missing.

Announcement	**No. of Observations**	**Announcement Time**	**Frequency**
Panel A: U.S. Announcements			
ADP Payrolls	68	08:15	Monthly
Business Inventories	72	10:00	Monthly
Chicago Purchasing Manager Index (PMI)	72	09:45	Monthly
Conference Board (CB) Consumer Confidence	72	10:00	Monthly
Construction Spending	72	10:00	Monthly
Consumer Price Index	72	08:30	Monthly
Durable Goods Orders	72	08:30	Monthly
Employment Cost Index	24	08:30	Quarterly
Existing Home Sales	72	10:00	Monthly
Factory New Orders	72	10:00	Monthly
Federal Open Market Committee (FOMC)	51	14:15	(Approx.) 6 Weekly
Gross Domestic Product	72	08:30	Monthly
Housing Starts	72	08:30	Monthly
Hudson Employment Index	26	06:00	Monthly
Industrial Production	72	09:15	Monthly
Initial Jobless Claims	313	08:30	Weekly
ISM Manufacturing	72	10:00	Monthly
ISM Non-Manufacturing	72	10:00	Monthly
Michigan Sentiment	72	10:00	Monthly
New Home Sales	72	10:00	Monthly
New York (NY) Empire State Index	72	08:30	Monthly
Non-Farm Payrolls	72	08:30	Monthly
Pending Home Sales Index	73	10:00	Monthly
Personal Income	72	08:30	Monthly
Producer Price Index	72	08:30	Monthly
Retail Sales	72	08:30	Monthly
Trade Balance	72	08:30	Monthly
Wholesale Inventories	72	10:00	Monthly
Panel B: EMU Announcements			
Economic Sentiment	72	05:00	Monthly
European Central Bank (ECB) Monetary Decision	73	07:45	(Approx.) Monthly
Gross Domestic Product	71	05:00	Monthly
Harmonized Index of Consumer Prices (HICP)	72	05:00	Monthly
Harmonized Index of Consumer Prices (HICP) - Flash	72	05:00	Monthly
Industrial Production	72	05:00	Monthly
Labor Cost	24	05:00	Quarterly
Producer Price Index	72	05:00	Monthly
Retail Sales	72	05:00	Monthly
Unemployment Rate	72	05:00	Monthly
Panel C: German Announcements			
Gross Domestic Product	48	02:00	6 Weekly
Harmonized Index of Consumer Prices (HICP)	72	02:00	Monthly
Harmonized Index of Consumer Prices (HICP) - Flash	72	Varies	Monthly
ifo Business Climate	72	04:00	Monthly
Import Prices	72	02:00	Monthly
Industrial Production	72	07:00	Monthly
Manufacturing Orders	70	06:00	Monthly
Payroll Employment	64	02:00	Monthly
Producer Price Index	72	Varies	Monthly
Retail Sales	72	Varies	Monthly
Trade Balance	72	Varies	Monthly
Wholesale Prices	67	02:00	Monthly
ZEW Survey	72	05:00	Monthly

Table 2: Summary Statistics for Intraday Jumps

This table shows summary statistics for the five-minute returns and the jumps of S&P 500 E-Mini futures, Treasury note futures, EUR/USD FX, DAX futures, and Bund futures. For the mean jump, the absolute value is reported. *N* indicates the number of returns, as well as the number of total, positive, and negative jumps. *Mean*, *Std.Dev.*, *Max*, and *Min* stand for arithmetic mean, standard deviation, maximum, and minimum value, denoted in percent.

	N	**Mean**	**Std.Dev**	**Max**	**Min**	**Skew**	**Kurtosis**
S&P Returns	436,665	0.00%	0.09%	4.32%	-2.96%	0.515	68.646
S&P Jumps	670	0.51%	0.67%	4.32%	-2.96%	0.723	8.714
S&P Positive Jumps	292	0.56%	0.50%	4.32%	0.14%	3.455	20.369
S&P Negative Jumps	378	-0.47%	0.37%	-0.14%	-2.96%	-3.411	19.148
Treasury Returns	419,487	0.00%	0.03%	2.24%	-1.62%	-0.776	214.386
Treasury Jumps	797	0.21%	0.27%	2.24%	-1.62%	-0.219	12.773
Treasury Positive Jumps	376	0.20%	0.15%	2.24%	0.07%	7.725	97.778
Treasury Negative Jumps	421	-0.22%	0.18%	-0.07%	-1.62%	-4.087	24.432
EUR/USD Returns	450,407	0.00%	0.04%	1.11%	-0.74%	0.109	18.069
EUR/USD Jumps	614	0.26%	0.29%	1.11%	-0.74%	0.276	2.674
EUR/USD Positive Jumps	308	0.27%	0.15%	1.11%	0.10%	2.502	11.925
EUR/USD Negative Jumps	306	-0.25%	0.11%	-0.11%	-0.74%	-1.429	5.678
DAX Returns	261,624	0.00%	0.12%	4.39%	-2.88%	0.100	39.993
DAX Jumps	864	0.53%	0.65%	4.39%	-2.88%	0.897	9.647
DAX Positive Jumps	294	0.56%	0.47%	4.39%	0.11%	4.489	30.872
DAX Negative Jumps	570	-0.52%	0.35%	-0.12%	-2.88%	-3.101	17.011
BUND Returns	262,920	0.00%	0.03%	1.36%	-1.48%	-0.218	59.856
BUND Jumps	794	0.16%	0.19%	1.36%	-1.48%	0.060	10.654
BUND Positive Jumps	352	0.16%	0.10%	1.36%	0.06%	5.737	61.376
BUND Negative Jumps	442	-0.16%	0.10%	-0.05%	-1.48%	-6.581	82.672

Table 3: Price Jumps and Macroeconomic Announcements

This table links jumps to macroeconomic announcements, that is, jumps conditional on public announcements (Jumps|Announcement). Since some announcement releases overlap, the aggregated amount of announcements coinciding with individual jumps is greater than the total number of jumps.

	S&P	**Treasury**	**EUR/USD**	**DAX**	**BUND**
Total Jumps	670	797	614	864	794
Jumps|Announcement	194	386	253	248	312
Coincidence Ratio	28.96%	48.43%	41.21%	28.70%	39.29%
Panel A: U.S. Announcements					
ADP Payrolls	6	14	6	5	11
Business Inventories	3	2	4	5	4
Chicago Purchasing Manager Index	6	9	4	10	6
CB Consumer Confidence	11	9	9	14	8
Construction Spending	13	24	12	22	15
Consumer Price Index	15	26	12	12	12
Durable Goods Orders	8	19	6	10	12
Employment Cost Index	5	9	3	4	4
Existing Home Sales	8	12	9	14	8
Factory New Orders	5	5	5	6	8
Federal Open Market Committee	20	28	26	13	13
Gross Domestic Product	8	17	5	11	12
Housing Starts	7	15	10	5	11
Hudson Employment Index	1				2
Industrial Production		1	2	1	3
Initial Jobless Claims	26	63	30	29	47
ISM Manufacturing	14	26	13	22	13
ISM Non-Manufacturing	4	8	3	7	8
Michigan Sentiment	3	8	4	10	7
New Home Sales	8	12	9	10	10
New York Empire State Index	5	16	4	8	10
Non-Farm Payrolls	38	58	41	39	46
Pending Home Sales Index	7	7	6	11	8
Personal Income	2	9	6	3	6
Producer Price Index	7	18	8	10	11
Retail Sales	5	27	9	5	18
Trade Balance	4	6	12	6	6
Wholesale Inventories	3		2	1	1
Panel B: EMU Announcements					
Economic Sentiment		1	1		3
ECB Monetary Decision	1	2	4	5	5
Gross Domestic Product			1		1
HICP				1	
HICP - Flash		1			5
Industrial Production			1	1	2
Labor Cost					2
Producer Price Index					3
Retail Sales					1
Unemployment Rate					1
Panel C: German Announcements					
Gross Domestic Product			1	1	
HICP - Flash	2	4	2	7	3
ifo Business Climate		1	12	4	18
Industrial Production	1				2
Manufacturing Orders			1	1	
Payroll Employment				1	2
Retail Sales			2		
ZEW Survey			4	2	7

Table 4: Summary Statistics for Jumps with and without Announcement

This table shows summary statistics for jumps linked to macroeconomic announcements (Jumps|Announcement) and jumps that cannot be linked to macroeconomic announcements (Jumps|Non-Announcement). N indicates the number of jumps. *Mean*, *Std.Dev.*, *Max*, and *Min* stand for arithmetic mean, standard deviation, maximum, and minimum value denoted in percent, respectively.

	N	**Mean**	**Std.Dev**	**Max**	**Min**	**Skew**	**Kurtosis**
S&P 500 E-Mini Futures							
Jumps|Announcement	194	0.55%	0.68%	4.32%	-1.49%	1.422	10.330
Jumps|Non-Announcement	476	0.50%	0.67%	3.81%	-2.96%	0.424	7.955
Treasury Note Futures							
Jumps|Announcement	386	0.21%	0.27%	2.24%	-0.78%	1.515	15.188
Jumps|Non-Announcement	411	0.21%	0.27%	0.65%	-1.62%	-1.753	10.078
EUR/USD Exchange Rate							
Jumps|Announcement	253	0.27%	0.30%	1.11%	-0.66%	0.393	2.818
Jumps|Non-Announcement	361	0.26%	0.29%	1.06%	-0.74%	0.188	2.569
DAX Futures							
Jumps|Announcement	248	0.58%	0.71%	3.93%	-1.95%	1.161	8.434
Jumps|Non-Announcement	616	0.51%	0.61%	4.39%	-2.88%	0.677	10.127
Bund Futures							
Jumps|Announcement	312	0.17%	0.19%	0.68%	-0.50%	0.102	2.713
Jumps|Non-Announcement	482	0.15%	0.18%	1.36%	-1.48%	0.031	16.082

Table 5: Descriptive Statistics of Information Density Indicator

This table reports descriptive statistics for the Information Density Indicator (IDI) conditional on subsequent macroeconomic announcements. Due to simultaneous announcements (within the same five-minute interval), the number of observations is higher than in Table 3.

	N	**Mean**	**Std.Dev**	**Max**	**Min**	**Skew**	**Kurtosis**
S&P 500 E-Mini Futures							
IDI|Jump	246	0.626	1.170	2.427	-1.974	-0.492	2.165
IDI|No Jump	3,462	0.226	1.196	2.449	-2.449	-0.101	1.923
Treasury Note Futures							
IDI|Jump	457	0.588	1.166	2.425	-2.254	-0.340	2.091
IDI|No Jump	3,251	0.210	1.200	2.449	-2.449	-0.069	1.919
EUR/USD Exchange Rate							
IDI|Jump	289	0.626	1.131	2.370	-2.310	-0.390	2.239
IDI|No Jump	3,419	0.260	1.204	2.449	-2.449	-0.105	1.908
DAX Futures							
IDI|Jump	481	0.670	1.140	2.427	-2.151	-0.434	2.238
IDI|No Jump	3,227	0.256	1.198	2.449	-2.449	-0.138	1.907
Bund Futures							
IDI|Jump	483	0.574	1.130	2.418	-2.310	-0.380	2.192
IDI|No Jump	3,225	0.262	1.193	2.449	-2.449	-0.112	1.917

Table 6: Correlation Matrix of Independent Variables

This table shows the Bravais-Pearson correlation coefficients between the covariates News Surprises and Information Density Indicator as well as the control variables for trading activity (Deals) and for Volatility.

	News Surprises	Information Density Indicator	Deals	Volatility
S&P 500 E-Mini Futures				
News Surprises	1			
Information Density Indicator	0.010	1		
Deals	0.008	-0.007	1	
Volatility	0.139	0.074	-0.130	1
Treasury Note Futures				
News Surprises	1			
Information Density Indicator	0.002	1		
Deals	0.024	0.084	1	
Volatility	0.097	0.156	-0.004	1
EUR/USD Exchange Rate				
News Surprises	1			
Information Density Indicator	0.006	1		
Deals	0.009	0.074	1	
Volatility	0.100	0.062	-0.110	1
DAX Futures				
News Surprises	1			
Information Density Indicator	0.003	1		
Deals	0.016	0.060	1	
Volatility	0.148	0.028	-0.076	1
Bund Futures				
News Surprises	1			
Information Density Indicator	0.004	1		
Deals	0.029	0.043	1	
Volatility	0.087	0.018	-0.114	1

Table 7: Abnormal Noise and Probability of Jumps

This table presents the coefficients from the probit regression for S&P 500 E-Mini futures, Treasury note futures, DAX futures, Bund futures, and the EUR/USD currency pair. The dependent variable is defined as price jump ($Y = 1$) and no price jump ($Y = 0$) conditional on a macroeconomic announcement according to Table 4. The models include the Information Density Indicator, News Surprise, as well as the two control variables, trading activity (Deals) and volatility level (Volatility). Models I-III show the parsimonious specifications by including only the main covariates News Surprise and IDI, while Models IV-VI include only the control variables Deals and Volatility. Variations of the full specification are shown in Models VII-XI. We report HAC-robust standard errors in parentheses. ***, ** and * indicate significant coefficients at the 1%, 5% and 10% levels, respectively.

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**	**Model VII**	**Model VIII**	**Model IX**	**Model X**	**Model XI**
Panel A: S&P 500 E-Mini Futures (n = 3,263)											
Intercept	-1.612***	-1.530***	-1.668***	-1.500***	-1.541***	-1.612***	-1.702***	-1.694***	-1.698***	-1.629***	-1.745***
	(0.045)	(0.036)	(0.049)	(0.035)	(0.044)	(0.045)	(0.050)	(0.059)	(0.052)	(0.048)	(0.000)
News Surprises	0.179***		0.179***				0.190***	0.173***	0.177***		0.180***
	(0.039)		(0.039)				(0.039)	(0.042)	(0.038)		(0.039)
IDI		0.138***	0.139***				0.143***	0.137***		0.138***	0.140***
		(0.029)	(0.030)				(0.030)	(0.029)		(0.030)	(0.030)
Deals				0.222***		0.221***	0.226***		0.226***	0.228***	0.228***
				(0.035)		(0.037)	(0.038)		(0.037)	(0.037)	(0.037)
Volatility					0.053**	0.076***		0.025	0.051*	0.061**	0.042
					(0.023)	(0.023)		(0.029)	(0.023)	(0.024)	(0.023)
Panel B: Treasury Note Futures (n = 3,263)											
Intercept	-1.253***	-1.163***	-1.311***	-1.274***	-1.354***	-1.524***	-1.470***	-1.483***	-1.637***	-1.533***	-1.650***
	(0.038)	(0.030)	(0.040)	(0.032)	(0.049)	(0.052)	(0.044)	(0.055)	(0.058)	(0.053)	(0.059)
News Surprises	0.191***		0.194***				0.199***	0.179***	0.177***		0.182***
	(0.038)		(0.035)				(0.036)	(0.035)	(0.036)		(0.037)
IDI		0.144***	0.146***				0.127***	0.129***		0.105***	0.109***
		(0.024)	(0.024)				(0.025)	(0.024)		(0.025)	(0.025)
Deals				0.331***		0.330***	0.325***		0.330***	0.325***	0.325***
				(0.031)		(0.030)	(0.031)		(0.030)	(0.030)	(0.030)
Volatility					0.501***	0.518***		0.391***	0.475***	0.459***	0.413***
					(0.081)	(0.088)		(0.083)	(0.089)	(0.089)	(0.091)
Panel C: EUR/USD Exchange Rate (n = 3,263)											
Intercept	-1.451***	-1.434***	-1.510***	-1.610***	-1.353***	-1.641***	-1.728***	-1.453***	-1.707***	-1.655***	-1.723***
	(0.043)	(0.034)	(0.046)	(0.040)	(0.060)	(0.066)	(0.054)	(0.066)	(0.071)	(0.067)	(0.071)
News Surprises	0.101***		0.103***				0.113***	0.109***	0.111***		0.114***
	(0.038)		(0.039)				(0.043)	(0.040)	(0.043)		(0.044)
IDI		0.143***	0.144***				0.104***	0.146***		0.102***	0.104***
		(0.027)	(0.027)				(0.028)	(0.027)		(0.028)	(0.028)
Deals				0.547***		0.547***	0.538***		0.548***	0.537***	0.538***
				()0.037)		(0.037)	(0.037)		(0.037)	(0.036)	(0.037)
Volatility					-0.035	0.045		-0.090	0.022	0.016	-0.009
					(0.074)	(0.08)		(0.076)	(0.081)	(0.081)	(0.083)

Table 7 continues on the next page.

Table 7 continued.

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX	Model X	Model XI
Panel D: DAX Futures (n = 2,927)											
Intercept	-1.441***	-1.340***	-1.516***	-1.323***	-1.339***	-1.400***	-1.567***	-1.535***	-1.530***	-1.454***	-1.593***
	(0.044)	(0.034)	(0.047)	(0.033)	(0.048)	(0.050)	(0.048)	(0.057)	(0.056)	(0.053)	(0.058)
News Surprises	0.217***		0.223***				0.228***	0.220***	0.215***		0.223***
	(0.040)		(0.039)				(0.040)	(0.040)	(0.040)		(0.041)
IDI		0.154***	0.159***				0.151***	0.158***		0.144***	0.150***
		(0.027)	(0.028)				(0.028)	(0.028)		(0.028)	(0.028)
Deals				0.245***		0.245***	0.240***		0.244***	0.241***	0.240***
				(0.028)		(0.028)	(0.028)		(0.028)	(0.028)	(0.028)
Volatility					0.041*	0.048**		0.014	0.025	0.044*	0.019
					(0.023)	(0.024)		(0.024)	(0.026)	(0.024)	(0.025)
Panel E: Bund Futures (n = 2,927)											
Intercept	-1.342***	-1.223***	-1.393***	-1.307***	-1.152***	-1.329***	-1.523***	-1.339***	-1.470***	-1.364***	-1.509***
	(0.042)	(0.032)	(0.044)	(0.034)	(0.064)	(0.065)	(0.047)	(0.070)	(0.071)	(0.067)	(0.072)
News Surprises	0.217***		0.219***				0.222***	0.224***	0.220***		0.223***
	(0.037)		(0.038)				(0.040)	(0.038)	(0.040)		(0.040)
IDI		0.120***	0.122***				0.111***	0.123***		0.108***	0.112***
		(0.026)	(0.026)				(0.027)	(0.026)		(0.027)	(0.027)
Deals				0.321***		0.322***	0.319***		0.320***	0.320***	0.319***
				(0.028)		(0.028)	(0.029)		(0.029)	(0.028)	(0.029)
Volatility					-0.054	0.051		-0.133	-0.018	0.037	-0.034
					(0.132)	(0.137)		(0.135)	(0.141)	(0.137)	(0.141)

Table 8: Robustness Tests of Information Density Indicator

This table presents several robustness tests on Information Density Indicator (IDI) for the coefficients from probit regressions for S&P 500 E-Mini futures, Treasury note futures, DAX futures, Bund futures, and the EUR/USD currency pair. Panel A shows the results for the placebo test. The dependent variable is defined as no price jump ($Y = 0$) and price jump ($Y = 1$) *un*conditional on a macroeconomic announcement according to Table 4. Consequently, these placebo models exclude the surprise indicator, but include IDI, as well as the two control variables, trading activity (Deals) and volatility level (Volatility). The regressions in Panel B test whether IDI is contaminated by dominant macroeconomic indicators and announcement times. Excluding important announcements reduces the sample by about half. Panel C tests whether the estimation results are affected by the occurrence of co-announcements without conflicting news, while Panel D controls for conflicting results only. Panel E shows test results when only a single announcement is released at a specific date. We report HAC-robust standard errors in parentheses. ***, **, and * indicate significant coefficients at the 1%, 5%, and 10% levels, respectively.

	S&P 500 E-Mini Futures	**Treasury Note Futures**	**EUR/USD Exchange Rate**	**DAX Futures**	**Bund Futures**
Panel A: Placebo Test					
Intercept	-3.238***	-3.294***	-3.371***	-2.960***	-3.062***
	(0.016)	(0.017)	(0.021)	(0.016)	(0.018)
IDI	-0.014	-0.005	0.009	0.003	0.02
	(0.013)	(0.014)	(0.014)	(0.012)	(0.013)
Deals	0.092***	0.137***	0.161***	0.127***	0.089***
	(0.017)	(0.01)	(0.019)	(0.012)	(0.015)
Volatility	0.110***	0.318***	0.260***	0.061***	0.287***
	(0.005)	(0.018)	(0.018)	(0.004)	(0.015)
N	398,977	411,142	412,588	227,450	228,655
Panel B: Without Peaks in Jump Activity					
Intercept	-2.313***	-2.274***	-2.002***	-1.903***	-1.998***
	(0.099)	(0.103)	(0.109)	(0.094)	(0.114)
News Surprise	0.168***	0.108	0.063	0.195***	0.223***
	(0.062)	(0.065)	(0.066)	(0.06)	(0.059)
IDI	0.184***	0.123***	0.157***	0.194***	0.140***
	(0.055)	(0.045)	(0.042)	(0.046)	(0.041)
Deals	0.318***	0.316***	0.564***	0.271***	0.327***
	(0.053)	(0.038)	(0.05)	(0.037)	(0.036)
Volatility	0.185***	1.047***	0.171	0.102**	0.658***
	(0.042)	(0.154)	(0.111)	(0.041)	(0.208)
N	1,756	1,784	1,798	1,437	1,455
Panel C: Co-Announcement Jumps without Conflicting News					
Intercept	-1.418***	-1.378***	-1.869***	-1.438***	-1.437***
	(0.11)	(0.114)	(0.173)	(0.122)	(0.155)
News Surprise	0.179**	0.220***	0.220***	0.198***	0.240***
	(0.078)	(0.072)	(0.089)	(0.082)	(0.083)
IDI	0.182***	0.109**	0.117**	0.188***	0.241***
	(0.058)	(0.048)	(0.059)	(0.057)	(0.057)
Deals	0.145	0.312***	0.664***	0.274***	0.340***
	(0.104)	(0.063)	(0.08)	(0.063)	(0.062)
Volatility	0	0.387**	0.213	-0.007	-0.105
	(0.055)	(0.187)	(0.21)	(0.056)	(0.344)
N	638	647	643	624	622

Table 8 continues on the next page.

Table 8 continued.

	S&P 500 E-Mini Futures	**Treasury Note Futures**	**EUR/USD**	**DAX Futures**	**Bund Futures**
Panel D: Co-Announcement Jumps with Conflicting News Only					
Intercept	-1.332***	1.057***	-1.734***	-1.126***	-1.257***
	(0.152)	(0.17)	(0.245)	(0.144)	(0.174)
News Surprise	0.126	0.076	-0.075	0.112	0.156
	(0.113)	(0.096)	(0.137)	(0.104)	(0.114)
IDI	-0.117	-0.054	-0.119	0.072	-0.067
	(0.083)	(0.066)	(0.096)	(0.072)	(0.075)
Deals	-0.008	0.326***	1.185***	0.005	0.286
	(0.13)	(0.069)	(0.171)	(0.081)	(0.088)
Volatility	-0.024	0.258	-0.176	-0.013	-0.051
	(0.063)	(0.239)	(0.239)	(0.048)	(0.174)
N	415	420	424	394	394
Panel E: Jumps Without Co-Announcements					
Intercept	-1.994***	-1.901***	-1.703***	-1.783***	-1.371***
	(0.071)	(0.078)	(0.085)	(0.077)	(0.116)
News Surprise	0.207***	0.196***	0.110**	0.257***	0.221***
	(0.052)	(0.05)	(0.055)	(0.054)	(0.066)
IDI	0.166***	0.111***	0.107***	0.133***	0.118***
	(0.041)	(0.035)	(0.035)	(0.037)	(0.045)
Deals	0.292***	0.313***	0.423***	0.272***	0.319***
	(0.047)	(0.037)	(0.044)	(0.036)	(0.05)
Volatility	0.076***	0.489***	-0.018	0.047	-0.11
	(0.029)	(0.117)	(0.098)	(0.033)	(0.24)
N	2,197	2,194	2,187	1,896	1,031

Table 9: Multinomial Probit Model of Co-Jumps

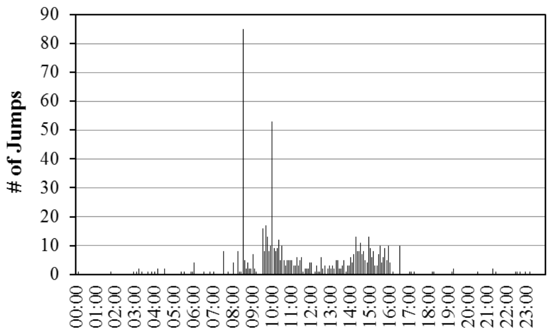
This table reports the estimation results of the multinomial probit model for the likelihood of one and multiple price jumps. To guarantee a sufficient number of coordinated price jumps, we build three categories: one jump ($y = 1$), two and three jumps ($y = 2$), as well as four and five jumps ($y = 3$), with $y = 0$ as the reference group. The total number of observations is $n = 2,927$. To conserve space, we do not show the coefficients for the controls "deals" and "volatility." HAC-robust standard errors are presented in parentheses. *** indicates statistical significance at the 1% level.

	One Jump	**Two or Three Jumps**	**Four or Five Jumps**
Intercept	-1.700***	-1.886***	-2.417***
	(0.059)	(0.063)	(0.085)
News Surprise	0.276***	0.287***	0.362***
	(0.054)	(0.054)	(0.068)
IDI	0.106***	0.197***	0.213***
	(0.034)	(0.038)	(0.049)
N (jump)	342	277	128

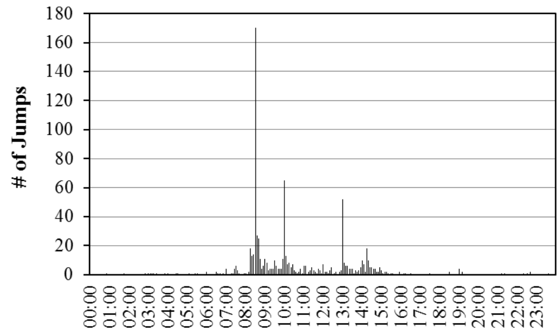
Figure 1: Intraday Frequencies of Price Jumps

This figure plots the absolute intraday frequency of price jumps for the five asset markets, S&P 500 E-Mini, Treasury note, DAX, and Bund futures, as well as EUR/USD FX spot rate, on the y-axis for corresponding five-minute time intervals (in EST) on the x-axis. Price jumps are estimated according to Equations (13) and (14.1).

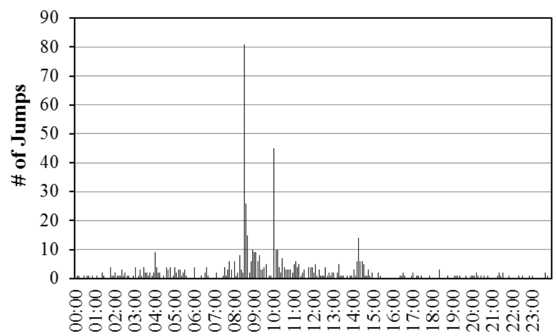
S&P 500 E-Mini futures



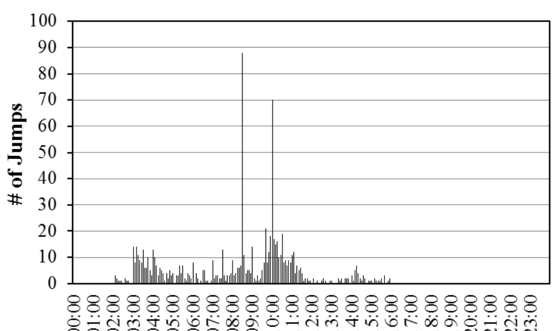
Treasury Note futures



EUR/USD Exchange Rate



DAX Futures



Bund Futures

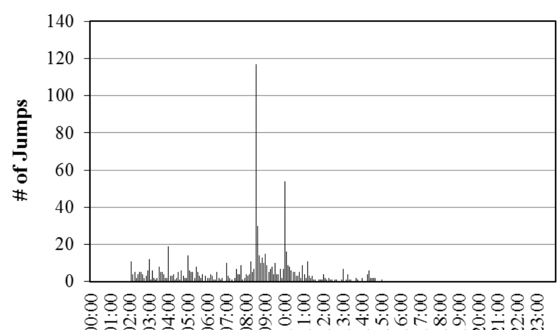
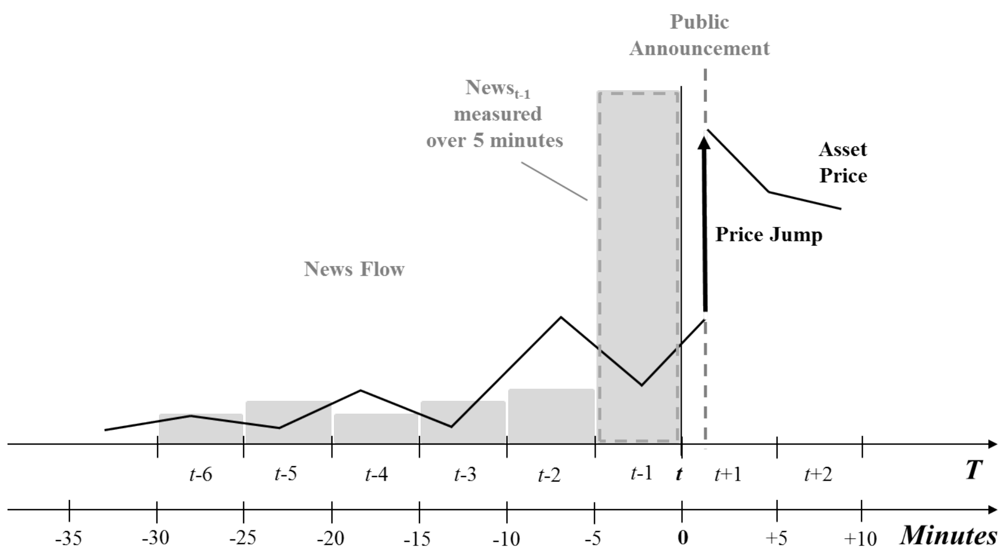


Figure 2: Illustration of the Information Density Indicator

This figure illustrates the construction of the Information Density Indicator (IDI) according to Equation (15). Panel A shows the increase in information flow (grey bars) prior to a public announcement (vertical grey dotted line), while Panel B shows the case where no abnormal news flow occurs. As defined in (15), we define $t-1$ as the five-minute interval prior to the announcement. Most of the announcements are released at the beginning of the five-minute interval $t+1$, that is, immediately after t; thus, we estimate, in line with most jump literature, prices in the five-minute interval after the scheduled time of the public announcement.

Panel A: *Abnormal* news flow in $t-1$



Panel B: *Normal* news flow in $t-1$

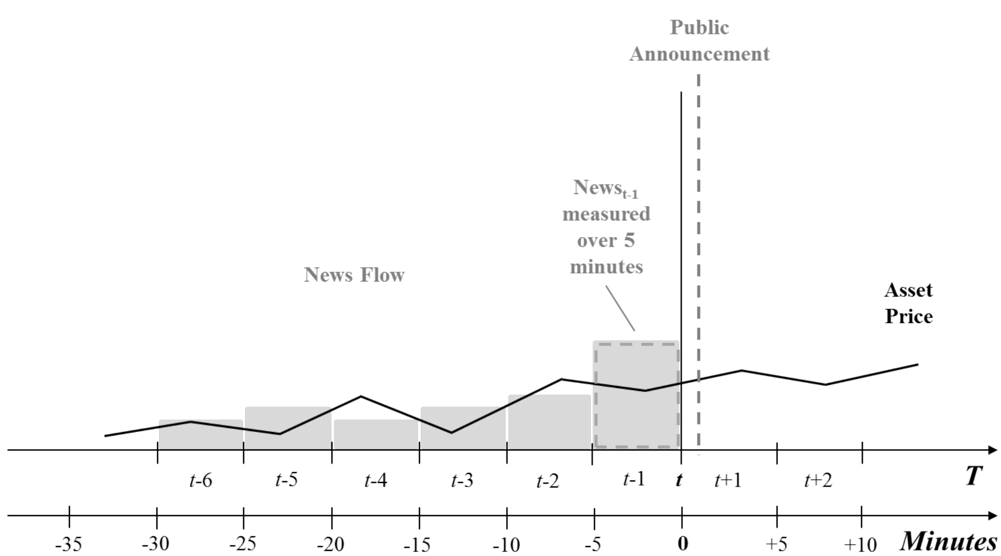
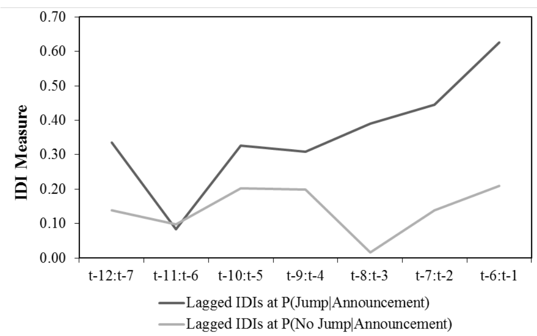
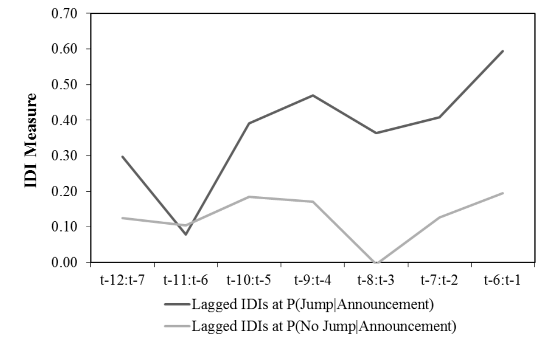


Figure 3: Alternative Lagged Information Density Indicators

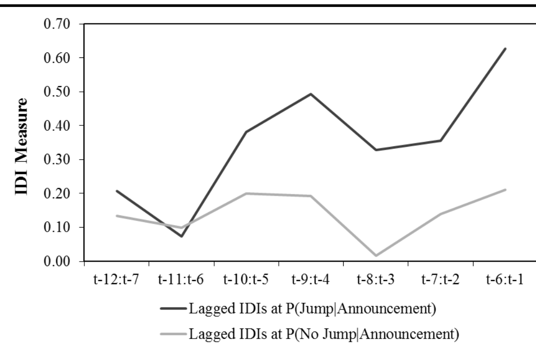
This figure shows alternative lagged Information Density Indicators (IDIs) separated by jump and no-jump occurrences. For instance, $t-6$ to $t-1$ and $t-12$ to $t-7$ indicate the time period of 1 to 6 five-minute intervals (from 5^{th} minute to half an hour) and the time period of 7-to-12-minute intervals (from one hour to 35^{th} minute) prior to the announcement. The development of the estimated rolling-window IDI measures prior to a scheduled public announcement is shown for the cases with (dark grey line) and without (light grey line) jumps.

S&P 500 E-Mini futures | **Treasury note futures**

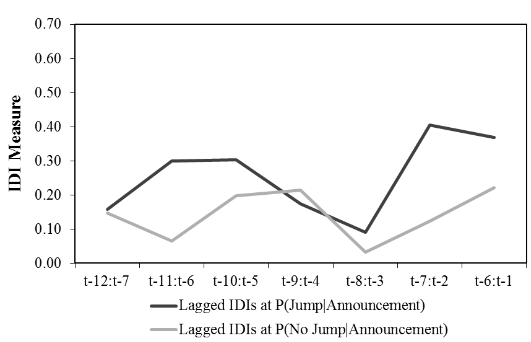




EUR/USD



DAX futures | **Bund futures**



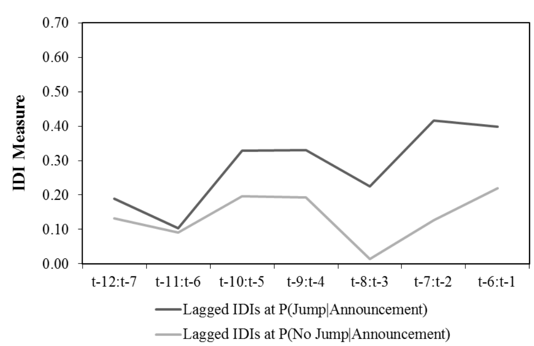
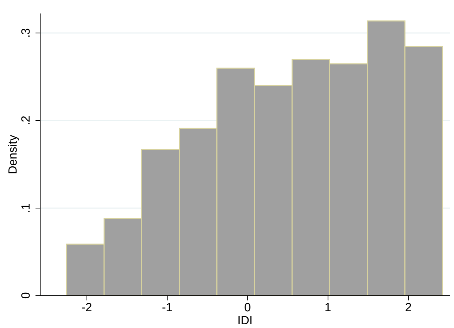


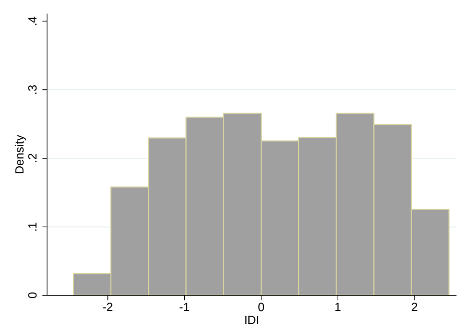
Figure 4: Distribution of Information Density Indicator

This figure shows the distribution of the information density indicator (IDI) separated by jump and no-jump occurrences conditional on subsequent macroeconomic announcements. x- and y-axis plot the normalized values of IDI and their relative frequency, respectively. For all five assets, IDI is highly negatively skewed for jumps conditional on macroeconomic announcements, while IDI without jumps follows a uniform distribution, which confirms the relationship between abnormal information flow and jumps.

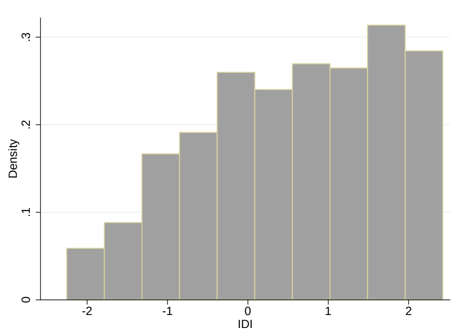
IDI|Jump	IDI|No Jump

E-Mini S&P 500 Futures





Treasury Note Futures



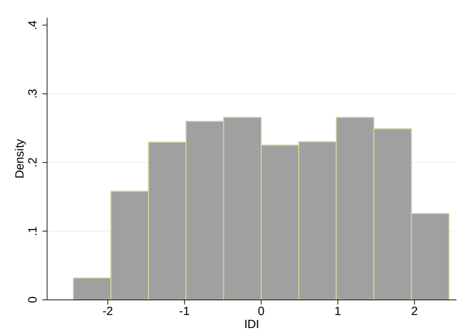


Figure 4 continued.

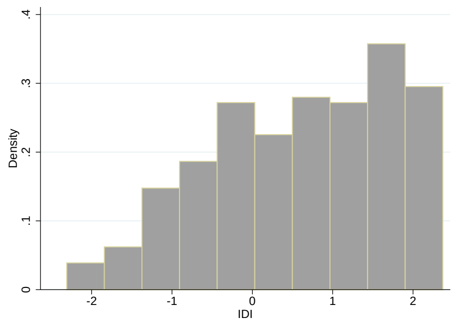
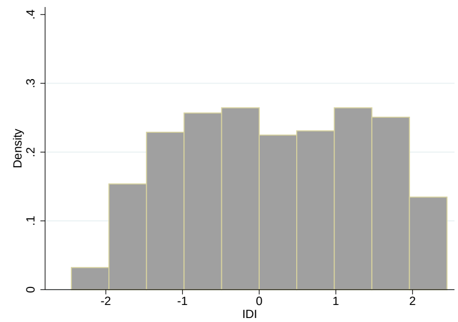
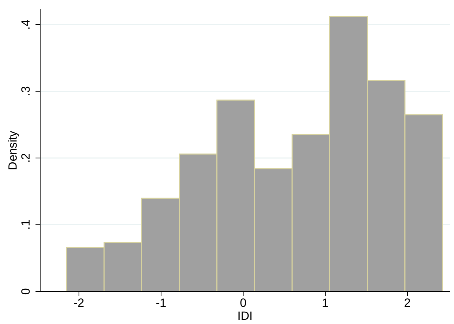
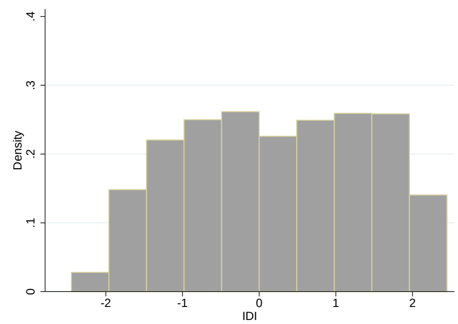
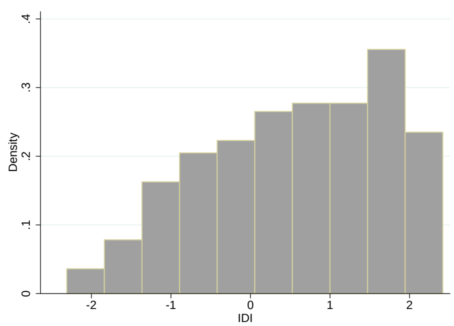
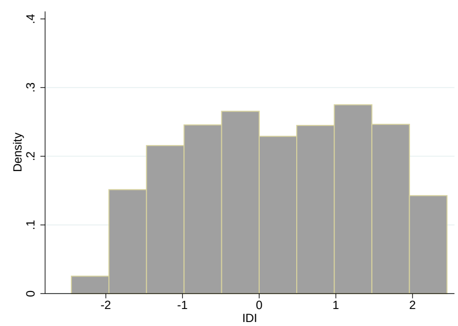
IDI|Jump	**IDI|No Jump**
EUR/USD	
	
DAX Futures	
	
Bund Futures	
	

Figure 5: Average Intraday Patterns of Information Density Indicator

This figure plots the average intraday values (in EST) of the information density indicator (IDI) in the considered time period. The amount of news is defined as economically relevant information, which we allow, according to our definition of diffuse beliefs, to be either related or unrelated to both asset prices and macroeconomic announcements. Positive (negative) values of IDI indicate an abnormal information flow above (below) a normal level. Note that the average value of IDI is above zero due to its construction, where the five-minute interval for $t-1$ prior to the public announcement is subtracted from the mean over the previous 25 minutes from $t-2$ to $t-6$. This deviation is normalized by the standard deviation over the previous 30 minutes from $t-1$ to $t-6$ according to Equation (15).