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

Roland Füss* Markus Grabellus† Ferdinand Mager‡
Michael Stein§

Working Paper
This version: August 2015

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 noisy "ticker" news before scheduled macroeconomic announcements, is significantly related to the likelihood of price jumps and 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, which is resolved by macroeconomic news as "hard" facts.

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

*Corresponding author: 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, E-mail: roland.fuess@unisg.ch.

†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; E-mail: markus.grabellus@ebs.edu.

‡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, E-mail: ferdinand.mager@ebs.edu.

§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, E-mail: michael.stein@uni-due.de.

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 permanently flooded by a variety of information such as corporate earnings, macroeconomic announcements, and political news. As investors update their expectations about the economy and asset prices based on such information, it is of particular interest to know more about the relationship between asset returns and the quality of information that is provided by the news industry. This paper contributes to the literature on informational efficiency by analyzing how noisy information prior to public announcements affects price changes in asset markets at the time when this "hard" information is released.

Our study is based on a theoretical framework, which includes both the emergence of noisy information prior to macroeconomic announcements and the release of the public announcement itself. With a setup of information being considered as a composition of price-relevant signals and price-irrelevant noise, with the latter hindering inference about the former, our approach is related to Veronesi (2000) and Li (2005). Both authors refer to Detemple (1986) who employs a learning framework in the presence of incomplete information.

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) carried out studies about how noisy information affects price formation.[1] In contrast, our theoretical framework provides an explanation for changes in asset prices due to an increasing flow of noisy information. We define abnormal noise by an increase in the number of ticker information above the prior average information flow. The vast bulk of news (or news types) on the ticker has no systematic relation to jumps in the asset markets. Additionally, it cannot be interpreted as a source of jumps in an economically meaningful sense. However, interestingly, the abnormal amount of unspecific and noisy economic news flows before macroeconomic announcements itself explains the likelihood of jumps. Theoretically, we define the noise as information that is irrelevant to the price

[1]Diamond and Verrecchia (1981) propose an equilibrium model in which an individual trader utilizes prices as a source of partial information. Hence, they explicitly assume that a trader does benefit from the collected information of the other traders without regarding his own information as redundant. In such equilibrium, private incentives to collect information still exist, because only partial information of traders aggregates. More importantly, Diamond and Verrechia's (1981) partial aggregation equilibrium is explicitly derived in the presence of noise trading, i.e., in case of partial aggregation of many diverse sources of information in the price. The model provides an explanation of how information is incorporated into prices when only the partial revelation of prices is assumed.

of a risky asset, which arrives in addition to all of the relevant signals.

We 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 only focuses on specific information and, as such, it neglects the impact of noisy information. We show that, in addition to news surprises, the abnormal level of noise is an important source of price jumps in asset markets by arguing that the higher level of noise leads to increasing uncertainty. This makes it harder for market participants to infer signals from news flows prior to an announcement. It also makes it harder for them to derive judgments about the true price. The resulting relatively strong sticking to the prior, and thus, missing out on changes in the intrinsic value of asset prices, dissolves when the "hard" information is released and prices consequently adjust to a new equilibrium. In our empirical study, we demonstrate that this uncertainty increases the likelihood of price jumps, which are conditional on the release of material public information. Hence, such a price jump is not only stronger (weaker) when the surprise in the announcement is greater (lower) but also, when the preceding flow of noisy information increases (decreases).

Under different assumptions about the precision of information, our empirical study relates to Veronesi's (2000) dynamic asset pricing model. Theoretically, the author shows 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) showed that noisy information could lead to estimation errors, which increases volatility and risk premia.

Albagli, Hellwig, and Tsyvinski (2014) provide a model of corporate investment and risk-taking when aggregate information at financial markets consists of fundamentals and noise. In such a situation, the stock price not only reflects a noisy signal about the firm's value but also, a biased estimate of the firm's dividends. As a result, stock prices depart from the efficient market benchmark, which induces rent-seeking behavior among shareholders and market discipline fails. Albagli, Hellwig, and Tsyvinski (2013) place the noisy REE in an asset pricing environment and demonstrate how noisy information aggregation can help explain empirical asset pricing puzzles, i.e., large volatility in equity prices and large spreads on corporate default. Chen, Diltz, Huang, and Lung (2011) empirically study the efficiency of trading behavior in stock and option markets upon the arrival of noisy signals. Thereby, the authors defined buy and sell recommendations, which are derived from CNBC's Mad Money, as a proxy for noisy information. They conclude that option prices react more efficiently, i.e., less responsive, to noisy information than stock prices. This is due to the fact that informed traders dominate in option markets.

Our paper aims at a broader understanding of news flows and its impact on price jumps. We expand previous literature in several ways. Firstly, we develop a new variable to capture noise, which we label the *Information Density Indicator (IDI)*. This is independent 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, which is resolved through macroeconomic announcements classified as "hard" facts. Consequently, the aim of our paper goes beyond the link between macroeconomic news and price jumps. Secondly, while we do not define an explicit model of noisy rational expectations equilibrium, to the best of our knowledge, we are the first to empirically test a theoretical framework that explains the impact of noisy information on asset prices.[2] Our results show that an increasing flow of noisy information prior to the release of a public announcement raises the likelihood of a price jump. The results are robust to various test designs. Thirdly, 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 has analyzed co-jumps in several assets but—to the best of the authors' knowledge—failed to cover the case of 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 seem 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 linkage. We use macroeconomic data from the U.S., Germany and the Eurozone, which expands common data sources of previous jump literature.

[2]Note that the noisy rational expectation equilibrium (NREE) refers to noise trading where noise is *endogenously* reflected in the publicly available price. In contrast, our model of noisy information argues that the sheer amount of *exogenously* emerging, mainly price-irrelevant, public information leads to noisy signals.

Our test of the noisy information model provides important insights into price changes around public announcements. The empirical results imply that analysts' forecasts and other relevant signals can be diluted by noisy information and the price mechanism is distorted until the public information is released. It demonstrates that abnormal levels of news flows lead to a higher uncertainty prior to a scheduled announcement. Hence, our results have important implications for asset pricing, hedging strategies, portfolio diversification, and risk management.

The remainder of the paper is organized as follows: Section 2 refers to the noisy information framework that provides the theoretical foundation for explaining how increasingly noisy information leads to price jumps in asset markets. Section 3 presents the dataset, introduces the jump identification methodology, and shows descriptive statistics on intraday jumps. In Section 4, we formally introduce our information density indicator as a measure of abnormal noise. 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 different model and parameter specifications. Section 5 concludes.

2 Theoretical Framework

In a world where information and news flows have become increasingly dynamic, we propose to study the effects of both, hard facts that are delivered by scheduled macroeconomic announcements and the magnitude of the preceding news flows. We expect that some consensus or market expectations are already priced-in and, if the announcement does not contain any surprise, the prices will not move much. To disentangle and study the two effects, we propose a general market microstructure model for risky assets with information uncertainty and announcements effects.

Let us consider a scheduled macroeconomic announcement at time t, $A_{t,k}$. Trading occurs in any asset i, which can be affected by the beliefs about this fundamental value prior to its arrival as well as the actual value at the point in time when the "hard" information (announcement) is released. Market participants are equipped with inventory $I_{t-1,i}$, which should reflect their desired level of inventory I_i^*. If no new information arrives at the market, traders have no incentive to alter asset holdings, i.e. $E_{t-1}[\Delta I_{t,i}] = 0$.[3] As

[3]This assumes that most inventory adjustments with the objective to reduce risk, which arises from holding assets over the announcement period, have already taken place. For a discussion of risk premia

it can be assumed that prices are already conditioned on a forecast $F_{t-1,k} = E_{t-1,k}(A_{t,k})$ of the macroeconomic announcement, it follows that

$$P_{t-1,i} = (P_{t-1,i}|F_{t-1,k}). \tag{1a}$$

Under the assumption of an informational efficient asset market, the best forecast of the price for the next period is the previous price:

$$E_{t-1}[P_{t,i}|F_{t-1,k}] = P_{t-1,i} \tag{1b}$$

Nonetheless, traders are aware that the price may change according to unpredictable random disturbances $\varepsilon_{t,i}$:

$$P_{t,i} = P_{t-1,i} + \varepsilon_{t,i} \tag{1c}$$

However, since we often see an increasing amount of news coming to the markets before macroeconomic announcements are released, it is essential to not only consider the impact of the announcement itself but also the effects that news flows have on prices prior to an announcement. This information flow is denoted as ϕ_{t-1} and can contain price-relevant signals $\Theta_{t-1,i}$ for asset i, which affect its intrinsic value, $(P_{t-1,i}|\Theta_{t-1,i})$, as well as price-irrelevant elements, which are deemed to be, at least for asset i, informational noise $\zeta_{t-1,i}$. While this approach reflects the "signal equals fundamentals plus noise" argument as used in Detemple (1986) and subsequently in Veronesi (2000), our information set is defined analogously as signal plus noise specification. This leads us to the definition of a noisy price, based on the information flow:

$$E_{t-1}[P_{t,i}|\phi_{t-1}] = (P_{t-1,i}|\Theta_{t-1,i}) + \zeta_{t-1,i} \tag{2}$$

Given the dynamics of the news industry and financial markets, we can consider that the noise component varies considerably over time. We can define the precision of the signal to be $1/\zeta_{t-1,i}$. Thus, if $\zeta_{t-1,i}$ is large, we consider the quality of information to go down, i.e. the precision of the signal decreases and vice versa.[4] By incorporating the signal into

in the context of holding inventory, see, e.g., Savor and Wilson (2013, 2014)).

[4]Note that we explicitly focus on the effect of information quality, however, we refrain from analyzing how prices are affected by marginal costs of acquiring information and the degree of risk tolerance. If the marginal costs of information gathering are higher and the risk tolerance is lower, investors will acquire less precise information. We refer to Kim and Verrecchia (1991a) for a closer analysis of the impacts of these factors.

expectation formation, the posterior expectation can be derived from the forecast-based prior in a Bayesian manner:

$$\begin{aligned} E_{t-1}[P_{t,i}] &= (1-\pi_{t-1,i})E_{t-1}(P_{t,i}|F_{t-1,k}) + (\pi_{t-1,i})E_{t-1}(P_{t,i}|\phi_{t-1}) \\ &= E_{t-1}(P_{t,i}|F_{t-1,k}) + \pi_{t-1,i}(E_{t-1}(P_{t,i}|\phi_{t-1}) - E_{t-1}(P_{t,i}|F_{t-1,k})) \end{aligned} \tag{3}$$

with $\pi_{t-1,i} = \frac{1/\zeta_{t-1,i}}{1/(\sigma^2_{\varepsilon,i}+\zeta_{t-1,i})}$ being the weight of the price conjecture based on the observed news flow. In this setting, the precision of information, $1/\zeta_{t-1,i}$, is defined relative to the reciprocal of the sum of uncertainty, which arises from the normal variation in the price, $\sigma^2_{\varepsilon,i}$, and uncertainty, which arises from the noisiness of the signals $\zeta_{t-1,i}$. This relationship forms the weight $\pi_{t-1,i}$ of the signal-based price when traders update their prior beliefs based on the forecast.[5] As different investors may differ in their access to the news flow and their abilities to read out signals in the presence of noise, as well as in the ways of pricing-in these signals, it can be assumed that traders act according to their individual expectations. Thus, Equation (3) can be seen as an aggregated statement, which is averaged over all of the market participants.

Before we impose the effect of the announcement, we need to take into account that the updated expectations will affect the market and trigger the true value to change. Due to the fact that this revaluation by the market will typically take some time, we introduce time intervals into our model. Hence, we consider the intrinsic value $P_{t-\tau,i}$ at the immediate instant of time before the release of the announcement at $t-\tau$, which naturally is a function of recent relevant developments Θ_{t-1} incorporated in the news:

$$P^*_{t-\tau,i} = (P^*_{t-\tau,i}|\Theta_{t-1,i}) \tag{4.1}$$

However, the noise in the information that covers the relevant signals hinders the expectation to be closer to this new intrinsic value:

$$(P^*_{t-\tau,i}|\Theta_{t-1,i}) \neq E_{t-1}(P_{t,i}|\phi_{t-1}) \tag{4.2}$$

From these considerations, it is obvious that the more information is overlaid with noise,

[5]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 weight 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)). In our definition, the signal uncertainty $\sigma^2_{\omega,i}$ is directly represented by ζ_{t-1}, and also reflects time-varying uncertainty.

the more the expected price deviates from its new intrinsic value. If, on aggregate, market participants trade on the noisy information and thereby only partially price-in the new information, due to its reduced weight in the updating process, the market price at $t-\tau$ can be written as

$$P^{*}_{t-\tau,i} = E_{t-1}(P_{t,i}|\phi_{t-1}) \neq (P^{*}_{t-\tau,i}|\Theta_{t-1,i}). \tag{4.3}$$

To complete our noisy information model, which takes into account the two effects that arise from noisy information and hard facts, we further introduce the arrival of a public announcement as another source of price impact. With $(P_{t,i}|A_{t,k})$ being the price that incorporates the release of the macroeconomic announcement, the new price reflects all of the information including the hard facts. With regard to the magnitude and direction of the price change, we can assume that the larger the surprise in the announcement, $A_{t,k}-F_{t-1,k}$, the higher the difference between the actual price, $(P_t|A_{t,k})$, and the expected price based on the forecast, $E_{t-1}(P_{t,i}|F_{t-1,k})$. As the direction of the announcement effect depends on the type of the macroeconomic variable, the news surprise should be positively correlated with the magnitude of the absolute price change:

$$|\Delta P_{t,i}| = f(A_{t,k} \underset{+}{-} F_{t-1,k}) \tag{5}$$

Regarding the influence of the preceding news flow, we have to take into account both the expectation dispersion $E_{t-1}(P_{t,i}|F_{t-1,k})-E_{t-1}(P_{t,i}|\phi_{t-1})$ and the weight of its factor within the process of expectation updating. However, for any given level of dispersion, a higher noise leads to a smaller effect of the news flow and *a posteriori* closer adjustment to the forecast-based expectation. This is due to the reduced weight of the information-based expectation when noise is high. Note that the stickiness of the price expectation indicates that, on aggregate, the price does not adapt to the new intrinsic price. Hence, the price discovery after the announcement should be stronger. For this to hold a significant change in the intrinsic value is not necessary. This is because the lower bound of this effect is zero, even if no signals are contained in the information. Therefore, we expect a positive impact of noise that is contained in the new information set on the magnitude of the price change. As the fractions $\Theta_{t-1,i}$ and $\zeta_{t-1,i}$ are not observable, we assume that the amount of relevant signals is naturally limited and an increase in $\phi_{t-1} = \Theta_{t-1,i} + \zeta_{t-1,i}$ is merely reflective of higher $\zeta_{t-1,i}$. Consequently, the expected influence of new information can be formalized as:

$$|\Delta P_{t,i}| = f\left(\left(\underset{+}{A_{t,k} - F_{t-1,k}}\right), \underset{+}{\phi_{t-1}}\right) \tag{6}$$

As a result of the effects arising from both, noisy information and scheduled macroeconomic announcements, the change in the price should be considerably strong, as market participants will adhere to take up the deferred adjustment to the intrinsic value as well as the price effect of the announcement surprise. This makes the study suitable for identifying jumps in prices in the presence of macroeconomic announcements.

Another reason to study price jumps is related to the result from our theoretical framework. Our results show that, in the presence of noise, it will be harder for representative traders to infer and act on signals. Thus, prices will be sticky until the uncertainty is resolved after the release of the announcement. However, as shown by Li (2005)), noisy information can also lead to estimation errors, thereby affecting risk premia and stock return volatility. In particular, the latter effect may be at work if prices are moved prior to the announcement. This reduces the stickiness of the price, and leads to a deviation for which we cannot make an assumption regarding size and direction. Another possibility for some prior adjustments might arise from risk-considerations when holding assets over announcement periods, as studied in Savor and Wilson (2013, 2014). Finally, this approach makes the analysis robust to possibly occurring partial adjustments and revelations. This is because adjustment of the price after the announcement can be seen as fully-revealing of all of the information that was in the market.

In order to obtain unbiased results, we control for further influences. To account for time-varying volatility and thus, to avoid possible estimation errors mentioned in the previous paragraph, we additionally consider $\sigma^2_{\varepsilon,t-1,i}$. Note that this reflects the randomness $\varepsilon_{t-1,i}$ in the price movements prior to the announcement. Furthermore, trading activity can also play a role. This is because many market participants, who are characterized by heterogeneous deals, may trade prior to an announcement. Hence, we further control for the deals, $d_{t-1,i}$, leaving the noise measure as reflective of the pure information effect. While Jiang, Lo, and Verdelhan (2011) use pure (il)liquidity measures and find that jump probabilities increase (decrease) with greater bid-ask spreads (order book depth), we measure trading activity without assuming that it indeed reflects liquidity, but rather controls for market activity. This is due to the fact that only by using trading activity and testing for its relationship with the noise in the market provides us with a viable control in line with the theoretical model: As we defined $E_{t-1}\left[\Delta I_{t,i}\right] = 0$ in cases where no new information arrives that would trigger an expected price change, there is no incentive to trade. If the measures for noisy information and trading activity are not positively correlated, this would provide evidence that our information density indicator does not, indeed, contain price-relevant information. Furthermore, if trading activity is high, we expect this to increase the probability of a price jump holding all other effects constant. Thus, the inclusion of the deals measure enables a further test of validity of our assumptions. This greatly enhances the reliability of testing our theoretical framework for the following reasoning: if noise and deals variables are both relevant and of the expected direction, we can conclude that the increase in trading should not be reflective of more relevant signals.

Taking into account several different macroeconomic announcements demands for their standardization. Since we are not primarily interested in the direction of the effects, we define the surprise indicator in absolute values. This leads us to the final specification:

$$Prob\left(Jump_{t,i}|Announcement_{t,k}\right) = f\left(\underset{+}{\left|A_{t,k} - F_{t-1,k}\right|}, \underset{+}{\phi_{t-1}}, \underset{+}{d_{t-1,i}}, \underset{+}{\sigma^2_{t-1,i}}\right) \tag{7}$$

Note that Equation (7) states the relationship between the level of noisy information and the likelihood rather than the size of a significant price change.[6] Technically speaking, a jump is defined as the difference between realized volatility and a realized bi-power variation at a specific point of time t (see Subsection 3.2 for a discussion on jump identification).

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.

[6]We follow previous literature using a probit model (see, e.g., Evans (2011) to examine whether news surprises and abnormal noise predicts jumps. Thus, we are interested in the likelihood of discontinuities in the pricing process, rather than in the resulting size. This is because, by definition, price jumps are price changes that are significant in size. In addition, we refrain from specifying an OLS regression model because we use standardized measures of announcement surprise and information density, rather than actual values. The latter hamper the interpretation of the economic significance of the coefficients.

3.1 Data

Existing literature almost exclusively focuses on U.S. assets and U.S. macroeconomic news.[7] Besides the U.S. markets, we additionally include the German bond and equity market as well as the EUR/USD exchange rate. We chose 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.[8] As further sources of price jumps we included 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 dataset 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. The futures for the bonds and stock markets are more liquid than their underlying markets and lead their cash markets.[9] For the exchange rate we choose spot market data from the EBS/ICAP. EBS/ICAP is the largest electronic trading platform for the major currency pairs that operates 24 hours per day. Its liquidity is higher than for the EUR/USD future.[10]

Our sample covers the six-year period from January 2006 to December 2011. We converted all of the data to Eastern Standard Time (EST) and accounted for the switch to Daylight Saving Time in the US 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, i.e.,

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

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

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

[10] Evans (2011) compared the EUR/USD futures market with the more liquid cash market for a selected sub-sample. He identified more jumps in the futures market but these were of similar size. The vast majority of the additional jumps were not related to U.S. macroeconomic news (Evans (2011), FN 6).

22 hours per day (in New York, Tokyo, and London). Meanwhile, the EUR/USD exchange rate and the S&P 500 E-Mini futures are traded all 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 ignored opening returns to avoid contamination from overnight news. As it is standard in this literature, we use the Market News International (MNI) database. MNI is the premier source for real time capital market related 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 the 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 that have been adopted from recent literature (e.g., Evans (2011)).[11] As originally introduced by Merton (1971) and now widely applied in research on jump identification (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 one 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

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

use the discrete sample prices, which is a standard proceeding in empirical research. The 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 (1987) as well as Andersen, Bollerslev, Diebold, and Labys (2003), we assume that RV is a consistent estimator of the total variance, including both the continuous and the 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, the realized volatility equals the integrated variance. In the presence of jumps, the realized volatility equals the integrated variance and the cumulative sum of the squared jumps.

As introduced by Barndorff-Nielsen and Shephard (2004), the realized bipower variation (BV) captures the continuous price movement. It is defined as the scaled summation of the product of the respective adjacent absolute returns:

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

where k defines the size of the rolling window. With the combination of the realized volatility and the 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:

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

In the following, we apply the jump identification methodology introduced by Lee and Mykland (2008).[12] In doing so, we set our rolling window k to five trading days.[13] To test at time t whether a jump in the price data of the respective asset occurred or not, we use the following test statistic $L_j(i)$:

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

Upon 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 the price data in the interval t_{i-1} to t_i is rejected if

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

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

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

$$S_{kj} = \frac{1}{c(2log(k_j)^{1/2}} \tag{14.3}$$

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 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 will not contaminate our results.

3.3 Descriptive Statistics on Price Jumps

Table 2 provides the summary statistics for the five-minute returns and the significant jumps for each asset class. We find the most jumps for the DAX futures (864), followed

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

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

by the 10-year Treasury note futures (797) and Bund futures (794) with almost the same number of jumps, and a slightly lesser count for S&P 500 E-Mini (670) and the EUR/USD exchange rate (614).[14]

<<< 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 crisis. 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 the 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.[15]

As the jump detection procedure identifies jumps conditional on the underlying local volatility, markets with higher volatility should exhibit jumps of higher magnitudes. 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 (US Treasury 0.21 percent and Bund 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.

Figure 1 illustrates the intraday frequencies of jumps for our five assets. For all of the assets, we find pronounced peaks at 08:30 and 10:00 EST, when many US macroeconomic announcements are released. In the US Treasury Futures, we observe a third peak at around 13:00 EST. The EUR/USD exchange rate (24 hours of trading) also shows sparsely distributed jumps during the illiquid trading times (e.g., during Asian trading hours).

[14] For a different sample period (1998-2006), Evans (2011) reported about 40 percent more jumps in the Treasury Futures than in the S&P Futures, using a similar jump detection procedure.

[15] As opposed to the other assets that are considered, the FX variable does not represent an absolute value asset. This is because the EUR/USD exchange rate is a relative valuation measure, making it reasonable that the asymmetry is weaker in this asset. Moreover, the question of whether a jump is positive or negative depends on the perspective. Even though the jump identification methodology is constructed to only detect absolute jumps, 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.

Although the S&P Future is traded 22 hours a 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 included 51 different macroeconomic announcements in our analysis (see Table 1). The selection of macroeconomic announcements is mainly guided by 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 that are used in previous literature and additionally include news from the 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 the U.S. assets, which can be linked to macroeconomic news from the EMU and Germany.[16]

Almost half (48.4 percent) of all jumps in the U.S. Treasury Futures can be linked to macroeconomic announcements which is the highest ratio among all five assets. By far, the two most important announcements are *Initial Jobless Claims* and *Non-Farm Payrolls*.[17] They account for about one third of all of the macroeconomic announcements that can be related to significant jumps. Although the ratio of significant jumps with macroeconomic announcement is lower for the S&P Futures (29.0 percent) compared to the U.S. Treasury futures, the results are similar in the sense that labor market related news is most important.

[16] Macroeconomic data from other European countries seem to play no role in explaining jumps in our five assets. In rare events, we could link political statements (in particular from Bernanke/FED and Trichet/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 analysts' recommendations, can be neglected, which primarily drives unsystematic price jumps as shown by Lee (2012).

[17] To control for a dominant impact of these announcements on our main results we re-run our analysis without these macroeconomic indicators in the robustness Sub-section 4.3

The German DAX Futures react to macroeconomic news from the U.S., Germany, and the EMU. With 28.7 percent, the coincidence ratio is almost identical to that of the S&P Futures. In the DAX Futures, more than half of all significant news is from Germany, with the most important ones being the *Producer Price Index*, *Trade Balance*, *Retail* and *Wholesale Prices*.[18] The coincidence ratio for the 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 the Bund Futures. Approximately 41 percent of the jumps can be linked to macroeconomic announcements with US news being the most important. About 12 percent of the jumps are associated to German and EMU news, with the German IFO Business Climate 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 the extreme values across the different assets. However, minimal 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 are released (such as firm-specific information) or important events occur, respectively. Obviously, the skewness for jumps that are conditional on announcements tends to be more positive than for the non-announcement case.

<<< Table 4 about here >>>

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

In this section, we describe our estimation model and introduce our measure for information density prior to macroeconomic announcements. We then present our empirical results and report various robustness checks.

[18]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.

4.1 Estimation Strategy

To analyze the role of *information density* ahead of macroeconomic announcements in explaining price jumps, let us recall from Section 2 the theoretical noisy information model:

$$Prob\left(Jump_{t,i}|Announcement_{t,k}\right) = f\left(\left|A_{t,k} \underset{+}{-} F_{t-1,k}\right|, \underset{+}{\phi_{t-1}},, \underset{+}{d_{t-1,i}},, \underset{+}{\sigma^2_{t-1,i}}\right), \qquad (15.1)$$

which can be restated for the empirical estimation in the following probit model specification:

$$\begin{aligned} Prob\left(J_{t,i}|Announcement_{k}\right) = f(&\alpha + \beta_{SUR}|SUR_{t,k}| + \beta_{IDI}IDI_{t-1} + \beta_{DLS}DLS_{t-1,i} \\ &+\beta_{VLA}VLA_{t-1,i}), \end{aligned} \qquad (15.2)$$

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 one when there is a jump and zero, otherwise, i.e. we are interested in whether the increase of noisy information affects the probability of a price jump. In the following, we discuss the chosen variables in detail.

$SUR_{t,k}$ (news surprise) and IDI_{t-1} (information density indicator) are our two *informational* variables. The former is the surprise in the macroeconomic announcement and the latter reflects the increased noise in the market prior to the release of an announcement. $DLS_{t-1,i}$ and $VLA_{t-1,i}$ control for the trading activity and volatility, respectively. As it is difficult to interpret the size of a jump with respect to the level of noise or news surprise, we refrain from deriving the marginal effects of our IDI measure on the absolute price jump from OLS estimation.

Macroeconomic Surprise. The first informational variable $|SUR_{t,k}|$ measures the surprise of the macroeconomic announcement k at time t, $\left(A_{t,k} \underset{+}{-} F_{t-1,k}\right)$. According to our model and based on the rational expectation theory, only unexpected information has an impact on market prices. In line with Balduzzi, Elton, and Green (2001), Andersen, Bollerslev, Diebold, and Vega (2003), and Andersen, Bollerslev, Diebold, and Vega (2007), we define the announcement surprise as follows:

$$SUR_{t,k} = \frac{A_{t,k} - F_{t-1,k}}{\hat{\sigma}_k}, \tag{16}$$

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 $A_{t,k} - F_{t-1,k}$.

Information Density Indicator. To operationalize noise, $\zeta_{t-1,i}$, from Equation (2), and thus, analyze the impact of information density before macroeconomic announcements arrive at the market, we developed a new variable which we labeled *information density indicator (IDI)*. The IDI measures the abnormal amount of news flows before the release of public announcements.[19] It represents the relation of the amount of news items during the last ten minutes before the announcement interval and the preceding news flow.[20] Formally, we define it analogously to the liquidity shock variable in Jiang, Lo, and Verdelhan (2011). Note that the IDI measure only captures the sheer number of news items but not their relevance or quality, respectively. In our theoretical framework, we assumed that the unobservable amount of relevant signals is limited and so, the news flow is dominated by time-varying noise. Thus, the IDI can be considered as a measure for noise shocks:

$$IDI_{t-1} = \frac{News_{t-1} - \frac{1}{5}\sum_{i=2}^{6} News_{t-i}}{\sigma_{News}}, \tag{17}$$

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 ten minutes before an announcement ($News_{t-1}$), standardized by the sample standard deviation, σ_{News} (see Figure 2 for illustration purpose).[21] We define the period for the

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

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

[21]Figure 3, which shows rolling window estimates for the IDI measure ahead of macroeconomic an-

noise shock prior to the announcement as intervals of ten minutes rather than of five minutes to guarantee a more stable measure. The second term in the nominator of Equation (17) 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 of information. More precisely, in line with our definition of limited (if any) price-relevant signals in the news flow, our IDI variable measures the excess or abnormal level of noise.

<<< Figure 2 about here >>>

Note that, in this exemplary illustration, there is already some price movement before the announcement. From our theoretical model, we do not consider these movements to be large and mainly being randomly occurring. Furthermore, we control for general movements and increased volatility. Hence, whether there are some movements in between or not is not of major importance for our analysis, especially as we focus on jumps rather than price changes. Figure 3 also empirically indicates the pattern of increasing information density prior to an announcement. This 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. Whenever a macroeconomic announcement follows, the mean IDI is higher before the jumps compared to the announcements without 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. The IDIs before jumps are highly negatively skewed, compared to the IDIs without jumps. This points to more observations with large IDI values, which is also underpinned by a slightly higher kurtosis.

<<< Table 5 about here >>>

nouncements, also empirically indicates this pattern of increasing information density prior to an announcement.

Figure 4 shows the average IDI over a trading period of 24 hours. It does not exhibit pronounced peaks as we find them with the jump frequencies across the trading day in Figure 1.

<<< Figure 4 about here >>>

Control Variables. As in Mizrach and Neely (2008) and Jiang, Lo, and Verdelhan (2011), we use two variables to control the contribution of trading effects and volatility to price jumps.[22] The first variable DLS_{t-1} captures a deals shock in the trading of the asset before the announcement:

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

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. Thus, it serves as a measure capturing trading activity shocks.

The second control variable VLA_{t-1} represents the realized volatility in the interval 30 minutes until five minutes before the announcement:[23]

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

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.

Table 6 shows the correlation between our independent variables. Bravais Pearson's correlation coefficients range between -0.114 and +0.156. This indicates that multicollinearity does not seem to affect the inference statistics and our estimation results. For most of the assets the highest correlations are observed between News Surprise and Volatility (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 News Surprise and IDI are 0.01 or less in all five assets.

[22] Besides the deals variable (DLS), in our analysis, we further included the variable "transaction volume" (standardized similarly to DLS). Since DLS and transaction volume were highly correlated, we excluded the latter one.

[23] 288 five minute intervals equal to 24 hours, which we use as window size.

<<< Table 6 about here >>>

Note that the correlations near zero are good news not only in terms of econometrics but also, at this stage, it indicates that our model setup disentangles the different effects. For example, the low correlation between the surprise and information density indicator allows for a fully separate identification of these effects. Also, the low correlation between the trade shock and the information density indicator leaves our construction valid. This is because increased trading before an announcement is not driven by the news, as higher news flows should reflect higher noise and not price-relevant signals, which would induce transactions.

4.2 Empirical Results

The estimation results for the probit model specifications according to Equation (15.2) are shown in Table 7. We start with a parsimonious model by only including our main covariates—$NewsSurprise$ 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.[24]

<<< Table 7 about here >>>

First of all, 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 noise, 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 the news surprise variable SUR and our IDI measure are significant at the 1 percent level with a persistent positive sign, i.e. the probability of a price jump increases with growing abnormal noise 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. For the full specification in Model XI, we see the lowest IDI coefficient (0.104) for the FX market, which also applies to the SUR coefficient (0.114).

[24] 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. As 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.

The SUR and IDI coefficients are higher in the German and US stock markets compared to the FX and bond markets. From this, and due to the fact that all of the measures are standardized, we can conclude that news surprises and increasing abnormal noise is more likely to trigger jumps at stock markets than in bond futures or FX markets. Finally, the results of 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 on news surprises but also on abnormal information flow.

The fact that our information density indicator (IDI) corresponds highly with the probability of jumps allows us to interpret it as a valid measure to capture the level of noisy information prior to a public announcement. Note that otherwise, and under the assumption of the weak-form information efficiency hypothesis, we can expect that all of the 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 when we control for news surprises. This is because all relevant information is already incorporated in the asset price.

The trading variable, *Deals* (DLS), is also significant at the 1 percent level for all five assets in all of the 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.[25] Moreover, in the full specification of Model XI, volatility only remains significant for the EUR/USD exchange rate. This is not surprising, since the SUR, as well as the IDI measure and, more importantly, the jump identification methodology, are denoted as standardized measures and thus, already controls for the current level of volatility.[26] To sum up, the empirical results confirm the theoretical hypothesis that the occurrence of abnormal noise prior to a public announcement significantly increases the probability of a price jump. Hence, there is strong empirical evidence for the existence of the effects that are considered in our theoretical model of noisy information.

[25] We also added interaction terms between IDI and SUR, DLS and VLA to our model. Only for the assets EUR/USD FX and Bund Futures we could detect significant coefficients for IDI*DLS. We further re-run our regression model with a lagged, non-overlapping IDI ($t-12:t-7$). The regression results remained unchanged in significance and almost unchanged in magnitude. Only in the case of the S&P futures, we found weak significance for the lagged IDI. To conserve space, the results are not reported here but are available upon request from the authors.

[26] The coefficient of deals (DLS) exceeds the one of IDI for all assets. This can be traced back to the construction of the IDI measure, where the information flow prior to the announcement is measured over a ten-minute interval rather than a five-minute interval as in the case of deals. This leads to a larger IDI variable and therefore to a smaller coefficient.

4.3 Robustness Tests

In this section we carry out a series of robustness checks. Firstly, we apply a placebo test to control whether the information density indicator (IDI) also explains jumps that are unconditional to macroeconomic announcements. Therefore, we estimate the probit model specification for our dataset from which we excluded all of the 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 information is not overlaid by a significant amount of noisy information, the uncertainty in the market is lower, and thus, the information precision is higher. However, our control variables for trading activity and volatility are highly significant and still explain the likelihood of jumps.

<<< Table 8 about here >>>

Secondly, to test whether our IDI measure is contaminated by dominant macroeconomic indicators and announcement times, we re-run the regressions without 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. 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 our IDI measure is no longer significant.

Thirdly, we address the question of how co-announcements might affect our estimation results.[27] We focus on co-announcements, i.e., situations when 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 into 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.[28] 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 are significant anymore. In this sense, our overall regression

[27] Note that previous literature mainly disregarded co-announcement effects.

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

results that are reported above are a conservative estimate, as we did not exclude the co-announcements with conflicting news. In Panel E, we only show the results for single announcements.[29] The results confirm the findings derived when we exploit the whole dataset.

Fourthly, we test whether our IDI measure also explains the likelihood of co-jumps among asset prices. We expect that relatively more co-jumps can be linked to announcements than single jumps as they are caused by information rather than by similar liquidity in different markets (Bollerslev, Law, and Tauchen (2008)).[30] 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, it could be the abnormal level of noise 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-estimated Equation (15.2) as 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 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 >>>

As we can see, 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). When it comes to explaining co-jumps, our IDI measure is not overshadowed by the importance of the

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

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

macroeconomic surprise. Instead, it plays an increasing role in predicting the likelihood of co-jumps.[31] We attribute this finding to a higher aggregate uncertainty in the presence of a higher level of noisy information, as the cross-asset price discovery is increasingly hindered by the contamination of relevant signals by noise shocks.

Finally, we test whether particular years or the 2007/08 financial crisis affect the impact of the IDI measure on the likelihood of price jumps. To account for year effects and a potential impact of the financial crisis we added year 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 is still robust, i.e. the IDI as well as our news surprise and deals variables remain highly significant.[32]

5 Conclusions

Based on a theoretical framework, which includes both the emergence of noisy information prior to macroeconomic announcement and the release of the scheduled public announcement itself, 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, the measure follows the liquidity shock variable of Jiang, Lo, and Verdelhan (2011) and measures the excess or abnormal level of noise.

In line with previous literature, we consider these information sets arriving at the market as a composition of price-relevant signals and price-irrelevant noise, where the latter prevents inference about the former. Assuming limits to relevant signals, we define abnormal noise by an increase in the amount of ticker information. The innovation in the modeling of noise as an exogenous information shock and representing it with a shock measure served us well in identifying the role of noise prior to announcements. Furthermore, the IDI opens up one direction to take into account the increasing bulk of information in the market.

By exploring a theoretical relationship between price jumps in financial markets and macroeconomic announcements, as well as other news, we followed a three-step estimation

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

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

approach. In the first step, we identify jumps in five assets 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 (news surprise and information density prior to announcements) in triggering price jumps by simultaneously controlling for trading activity and volatility in a probit model specification.

The 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 of our five assets, and withstands several robustness checks. Even in the case of price co-jumps among our five assets, the IDI measure dominates 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, which is finally resolved by the arrival of "hard" news in terms of a public announcement. This finding is attributed to the limited possibilities for market participants to infer signals from news flows in the presence of noise, which hinders price discovery. We also consider the placebo test result, i.e., an increase in noise alone without the arrival of an announcement does not trigger jumps, as a strong evidence for the theoretically derived effect of a malfunctioning price discovery process prior to announcements. This is resolved only when the hard facts hit the market, so that the price discovery after news increases without announcement in the following can be assumed to be more gradual in nature.

These results have strong implications when considering the increasing availability and presence of information in financial markets. As exogenous noisy information clouds price-relevant information (if any is contained in the news flow, which is not a necessary condition in our model setup), analysts' forecasts and other relevant fundamental signals may be diluted. This distorts the price discovery process and ultimately, challenges the assumptions on efficient markets.

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 (2013): "Dynamic dispersed information and the credit spread puzzle," Working Paper.

——— (2014): "Risk-taking, rent-seeking, and investment when financial markets are noisy," Working Paper.

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.

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.*

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.

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.

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.

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

Jacod, J., and A. N. Shiryaev (1987): "Limit theorems for stochastic processes," .

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.

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.

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 non-parametric 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.

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.

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

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 dataset 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: US 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 the 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 percentage.

	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 the jumps to macroeconomic announcements, i.e. the jumps conditional on the public announcements (Jumps|Announcement). As some of the 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: US 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 the summary statistics for jumps linked to macroeconomics 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 percentage.

	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 Deals and 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 the 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 IDI measure, News Surprise, as well as the two control variables trading activity (Deals) and volatility level (Volatility). Models I-III show the parsimonious specifications by only including the main covariates News Surprise and IDI, while Models IV to VI only include the control variables Deals and Volatility. Variations of the full specification are shown in Models VII to XI. We report HAC-robust standard errors in parenthesis. ***, ** and * indicate significant coefficients at the 1%, 5% and 10% level, 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)	(0.05)	(0.059)	(0.052)	(0.048)	(0.0)
News Surprises	0.179***		0.179***				0.190***	0.173***	0.177***		0.180***
	(0.04)		(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)	(0.03)				(0.03)	(0.029)		(0.03)	(0.03)
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)	(0.03)	(0.04)	(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)		(0.03)	(0.031)		(0.03)	(0.03)	(0.03)
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)	(0.04)	(0.06)	(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)	(0.04)	(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		-0.09	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)	(0.05)	(0.048)	(0.057)	(0.056)	(0.053)	(0.058)
News Surprises	0.122***		0.22***				0.228***	0.220***	0.215***		0.223***
	(0.036)		(0.039)				(0.04)	(0.04)	(0.04)		(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 = 2927)											
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)	(0.07)	(0.071)	(0.067)	(0.072)
News Surprises	0.217***		0.219***				0.222***	0.224***	0.220***		0.223***
	(0.037)		(0.038)				(0.04)	(0.038)	(0.04)		(0.04)
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 the IDI Measure**

This table presents several robustness tests on our IDI measure 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 the IDI measure, as well as the two control variables trading activity (Deals) and volatility level (Volatility). The regressions in Panel B test whether the IDI is contaminated by dominant macroeconomic indicators and announcement times. Excluding important announcements reduces the sample about the 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 parenthesis. ***, **, and * indicate significant coefficients at the 1%, 5%, and 10% level, 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: **Multinominal Probit Model of Co-Jumps**

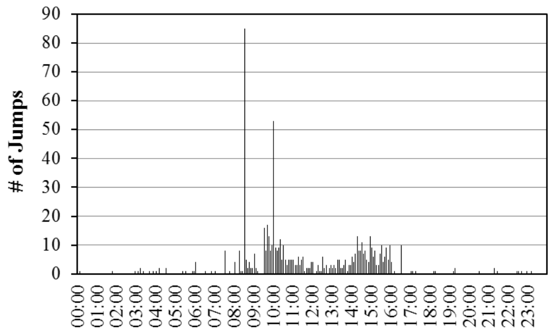
This table reports the estimation results of the multinomial probit model for the likelihood of one and multiple price jumps. To guarantee a sufficient number of coordinated price jumps, we build three categories: one jump ($y = 1$), two and three jumps ($y = 2$), as well as four and five jumps ($y = 3$), with $y = 0$ as the reference group. Total number of observations $n = 2927$. To conserve space we do not show the coefficients for the controls "deals" and "volatility". HAC robust standard errors are presented in parenthesis. *** indicates statistically significance at the 1% level.

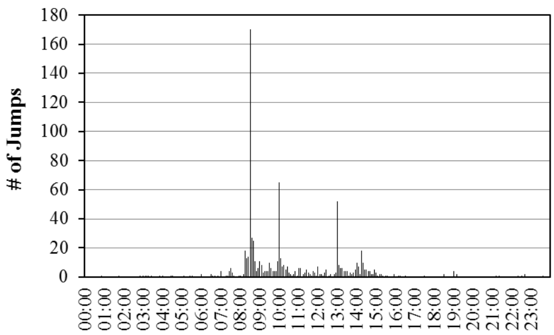
	One Jump	**Two or Three Jumps**	**Four or Five Jumps**
Intercept	-1.700***	-1.886***	-2.417***
	(0.059)	(0.063)	(0.085)
News Surprise	0.276***	0.287***	0.362***
	(0.054)	(0.054)	(0.068)
IDI	0.106***	0.197***	0.213***
	(0.034)	(0.038)	(0.049)
N (jump)	342	277	128

Figure 1: **Intraday Frequencies of Price Jumps**

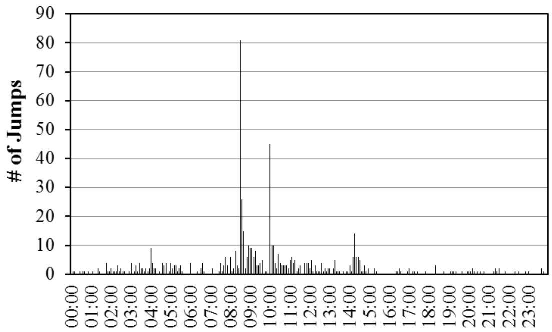
This figure plots the absolute intraday frequency of price jumps for the five asset markets, S&P 500 E-Mini, Treasury Note, DAX, and Bund Futures, as well as EUR/USD FX spot rate, on the y-axis for corresponding five-minute time intervals (in EST) on the x-axis. The price jumps are estimated according to Equations (11) and (12).

S&P 500 E-Mini Futures	**Treasury Note Futures**

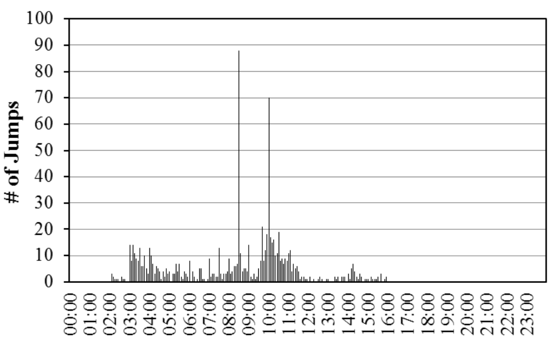




EUR/USD Exchange Rate



DAX Futures	**Bund Futures**



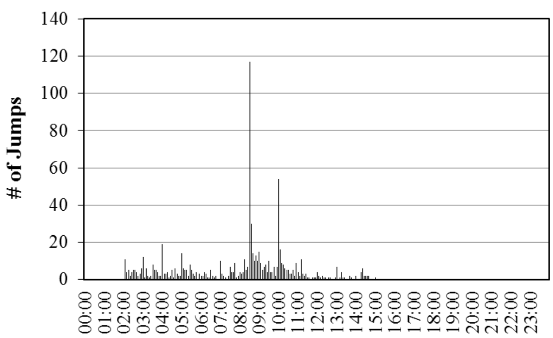
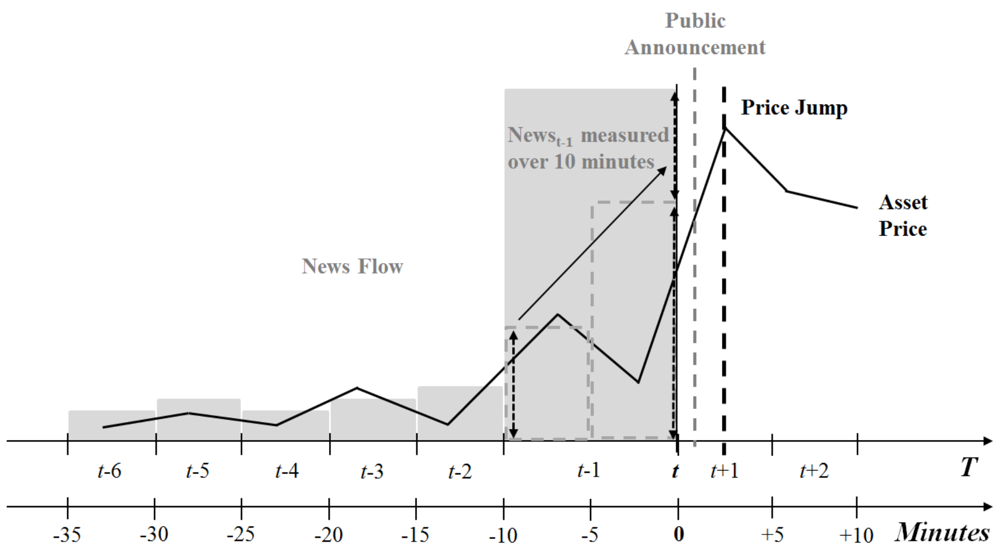


Figure 2: **Illustration of the Information Density Indicator (IDI)**

This figure illustrates the construction of the Information Density Indicator (IDI) according to Equation (17). Panel A shows the increase in noisy information (grey bars) prior to a public announcement (vertical grey dotted line), while Panel B shows the case when no abnormal news flow occurs. In comparison to the definition of the variable "Deals" in Equation (18), we define $t-1$ as a ten-minute interval prior to the announcement. Because most of the announcements are released at the beginning of the five-minute interval $t+1$, i.e. closely after t_0, we estimate, in line with most jump literature, prices in the five-minute interval after the public announcement to guarantee a more stable measure as well as a more conservative approach.

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



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

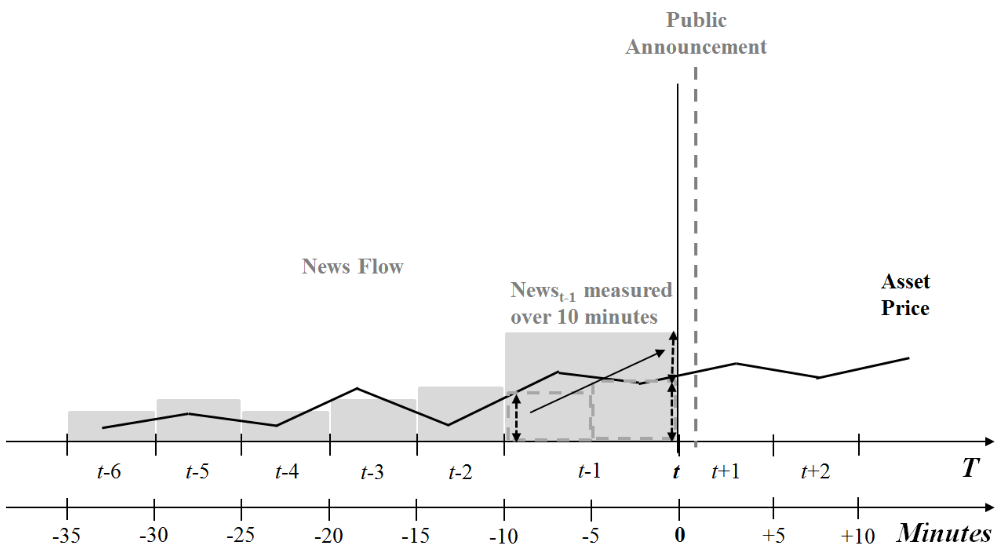
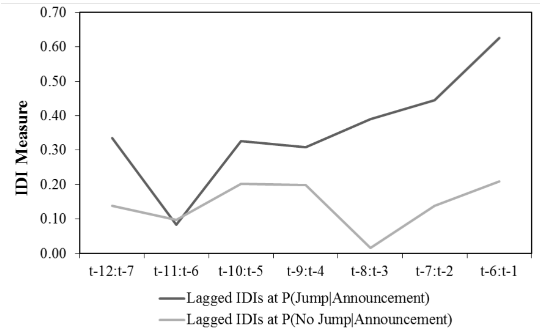
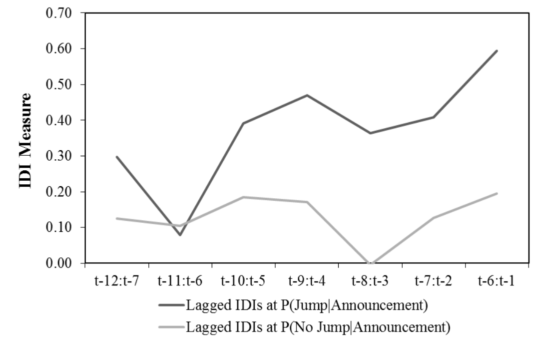


Figure 3: **Alternative Lagged Information Density Indicators**

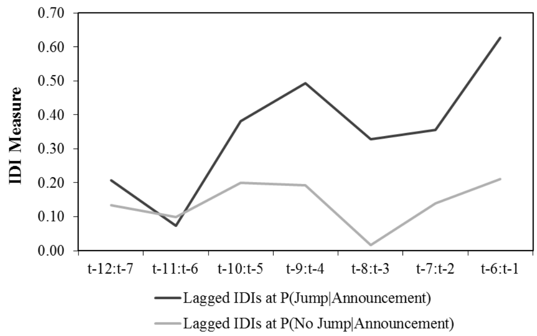
This figure shows alternative lagged Information Density Indicators (IDI) separated by jump and no-jump occurrences. For instance, $t-6$ to $t-1$ and $t-12$ to $t-7$ indicate the time period of one to six five-minute intervals (from 5^{th} minute to half an hour) and the time period of seven to twelve-minute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

S&P 500 E-Mini Futures	**Treasury Note Futures**

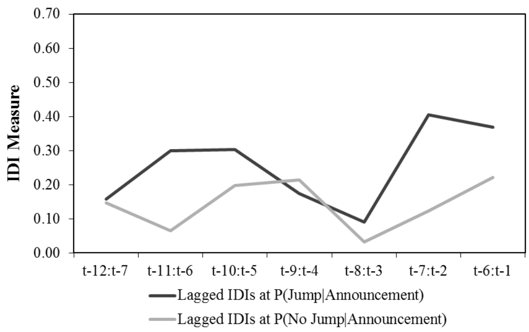




EUR/USD



DAX Futures	**Bund Futures**



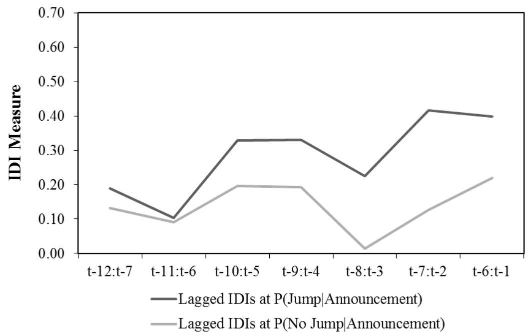


Figure 4: **Average Intraday Patterns of Information Density Indicator (IDI)**

This figure plots the average intraday values (in EST) of the information density indicator (IDI) in the considered time period. Noisy news is defined as economically relevant information which is completely unrelated to both asset prices and macroeconomic announcements. Positive (negative) values of the IDI measure indicate a noise level above (below) a normal amount of noise. Note that the average value of IDI is above zero due to the fact that we use a ten-minute interval for $t-1$ prior to the public announcement and standardize this value by subtracting the mean and standard deviation over the previous 25 minutes from $t-2$ to $t-6$ according to Equation (17).