Trading European Central Bank Rumours on the EUR-USD Exchange Rate Market

Baback Roodbar[ab], Hugh Metcalf [a], Fabrizio Casalin [a]

Abstract

This paper investigates whether the release of market-relevant news in the form of rumours on Twitter can explain the excess of market volatility previously attributed to private information, speculation, and noise traders. We define a simple theoretical model to show that the systematic information content of such rumours should result in detectable price effects in macro-markets. We then pinpoint the arrival of 63 rumours of forthcoming ECB actions over a 420-day sample of one-minute spot EUR-USD rates, and show that there is a real-time, intraday increase in market volatility. This largely unexplored information set can potentially account for significant amounts of unexplained volatility in macro-markets and, therefore, identify a possible explanation of one of the most prominent puzzles in price discovery research.

Keywords: Informational Efficiency, Price Discovery, Exchange Rate Volatility

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[a] Newcastle University Business School, Barrack Road, NE1 4SE, Newcastle upon Tyne (UK).
[b] Corresponding author. Email: b.roodbar@ncl.ac.uk

1. Introduction

The excess volatility puzzle is one of the foremost unanswered questions in financial economics. The Efficient Market Hypothesis (EMH) has, in all its guises, offered theoretical and empirical backing to the notion that security prices vary as a result of new information arrival. A large number of studies, however, have shown that such flows of market-relevant information cannot fully explain the large volatility observed in financial markets. Many scholars have argued that such excess volatility can be explained by the existence of private information (see, among others, French and Roll 1989). A competing explanation comes from behavioural finance, and it is based on the idea of irrational investors as a solution to the 'excess volatility puzzle'. Within this school of thought, the existence of excess volatility is ascribed to the existence of noise, and to technical and speculative investors (see, among others, De Long et al. 1990). However, both these competing paradigms struggle to offer tangible evidence of the determinants of excess of volatility. 'Noise' and private information are, in fact, particularly difficult to pinpoint in time, source, scale and scope.

In this study, we define a tangible alternative source of excess financial market volatility, a part of the puzzle previously unaccounted for by economists but discerned by market participants. We focus on a new source of systematic informational flow that is relevant to macro-markets. The advent of social networks has enabled the identification of 'market rumours', although this has rarely been the subject of discussion within the price discovery literature. In fact, up until the introduction of Twitter and similar financial micro-blogging sources, such rumours, whilst known to market participants, were not available as a database to investigators. It is this, largely neglected, category of information which is of most interest to this study.[1]

More specifically, we pinpoint the source, timing, scale and scope of sixty-three financial market rumours relating to upcoming European Central Bank (ECB) policy actions and announcements over the period 29 September, 2013 to 08 May, 2015 and gauge their ability to explain the observed volatility in the Euro-US dollar market. We assert that such rumours are neither private at source nor noise in relevance. We define these market rumours as actionable information, broadcast on Twitter, by multiple market commentators. We suggest this is information to be considered for trade execution, provided that it leads to a probabilistic change

[1] Given the above discussion, the following statement still remains relevant today: 'If private information is at least in part ruled out, supporters of the Efficient Market Hypothesis must concede the existence of fundamental market information detected by market actors but not by economists.' (Andersen and Bollerslev, 1998):

in market participants' expectations of future ECB policy decisions, and therefore to a shift in market consensus. As long as a large enough number of market participants discern a particular rumour as having a high enough probability to occur, then a period of market volatility should be observable.

Our empirical results show that real-time price discovery in the foreign exchange markets are associated with the real-time arrival of ECB relevant rumours. More specifically, out of 63 ECB rumours under scrutiny, 25 exerted a significant and positive impact on foreign exchange volatility. The instantaneous increase in volatility during the first minute of rumour arrival was up to 211%, whereas the cumulative increase in volatility over a 60-minute window was as much as 2614%. This finding provides fundamental evidence that market-relevant rumours – conveying a potential change to future expectations of systematic risk factors – carry risk premium in macro-markets.

The findings presented in this study are of interest to academics, practitioners and policymakers. For academics, this previously undetected price formation process incrementally increases the proportion of excess volatility that can be explained. This is of wider salience given that ECB rumours are just one category of undetected rumour arrival. For practitioners, the implementation of a rumour trading strategy can yield significant profits. Sentiment-based trading algorithms have been successfully implemented (Tetlock 2007). A simple trading algorithm, which identifies and executes a directional trade based on fast-diffusing, large-scope (actionable) rumours could yield significant excess returns. For policy makers, particularly central banks, the monitoring of rumours is imperative given the sensitivity of markets during pre-announcement periods and the crucial relationship of investor expectations to desired market reaction to policy announcements. Policy makers may wish to correct market agents' interpretations of policy rumours, which if left unchecked may result in potentially disruptive volatility events.

The remainder of the paper is as follows. Section 2 provides a review of the literature and defines the theoretical framework that underpins the rationale for market rumours to be a source of information fundamental to the process of price formation in efficient markets. Section 3 provides details of market and information data. Section 4 sets out the methodology and assesses its robustness by means of Monte Carlo simulations. Section 5 discusses the empirical results, while Section 6 concludes.

2. Rumours and Price Formation: A Paradigm

The Efficient Market Hypothesis suggests that financial asset prices reflect all information relevant to the value of a given traded security. In its strongest form, the EMH dictates that relevant information, regardless of whether it is in the public domain, or held privately, will be reflected in market price. Given this assertion, asset price fluctuations should reflect the arrival of new information about relevant market events that have already occurred or are expected to occur in the future. This notion has resulted in a large body of research testing the informational efficiency of financial markets. A large number of studies have investigated the market impact of the arrival of macroeconomic news. One strand of this literature focuses on the directional change in asset prices following news arrival (Cutler et al. 1989, Menkhoff 2010, Berry and Howe 1994, Kurov and Stan 2018, and Altavilla et al. 2017). A second strand measures asset price volatility following news arrival (Andersen et al. 2000, Andersen and Bollerslev 1997, Chang and Taylor 2003, Bauwens et al. 2005, and Li et al. 2015). The latter is of greater relevance to this study.

At lower frequency, daily observations, French and Roll (1986), Barclay et al. (1990) and Ito et al. (1998) found that a relatively small amount of daily asset price volatility can be attributed to the arrival of new public information. They all conjecture the existence of private information among 'informed market agents', as the reason behind the remaining unexplained asset price volatility. However, any evidence of the existence of such private information is ambiguous, as opposed to being pinpointed in time with a given source.

The availability of higher frequency intraday data has yielded more insightful results. Andersen et al. (2000), Cutler et al. (1989), Menkhoff (2010), Andersen and Bollerslev (1997), and Chang and Taylor (2003) all found that a larger proportion of price variability can be attributed to the arrival of new information. There remains a consensus, however, that volatility attributable to the arrival of new public information is low when compared to that of their respective samples. Andersen and Bollerslev (1997), in particular, discovered a distinct periodic intraday volatility pattern where the magnitude of return variability is consistently correlated with variations in market activity. They suggested, in line with French and Roll (1986), that the greater variability in returns during periods of heightened market activity is evidence of price adjustments due to the existence of private information.[2] More recently,

[2] Periodic volatility patterns during periods of heightened market activity can also occur as a result of market microstructure factors such as systematic periods of increased order flows (Groß-Klußmann and Hautsch 2011).

scholars have increasingly focussed on studying the formation of prices prior to the arrival of new information. Bauwens et al. (2005), Andersen et al. (2007), and Groß-Klußmann and Hautsch (2011) have found heightened levels of volatility in stock, bond and currency markets prior to the arrival of new scheduled and unscheduled public information. Bauwens et al. (2005), have drawn upon these findings to give further empirical support to the notion that private information triggers price adjustments prior to market information becoming public. Despite this growing body of research, questions remain over the plausibility of the notion that a sizable majority of excess price variation occurs due to private information arrival. After all, by its nature, private information is likely to filter relatively slowly into price and not to produce large price deviations – as suggested by price discovery authors (see, among others, Anderson and Bollerslev 1997 and Bauwens et al. 2005). While it is fair to acknowledge the existence of private information and a resultant price formation process, the idea that information known by a limited number of individuals is the main – or one of the main determinants – of financial market volatility, is not entirely plausible.

The literature testing the informational efficiency of financial markets has traditionally divided new information into four broad categories. The first consists of the arrival of new scheduled public information. The second is the arrival of new unscheduled information. Both are generally about market events that have occurred in the past.[3] The third type consists of privately held information, which is assumed to circulate among a small group of 'in the know' market agents. Information of this type is generally about a market-relevant event due to take place in the future or which has already taken place, but of which the public are unaware.[4]

The fourth type consists of market rumours. The financial-market impact of this type of information has been explored to a lesser extent. This is in part due to the ambiguous nature of rumours and difficulty in acquiring timestamped historical datasets of rumour arrival. A substantial body of research has investigated the price effect of firm-specific rumours at daily frequency by considering takeover stories published in financial newspapers. Empirical results suggest that speculative stories of potential M&As published in the financial press result in significant changes in the price trends for the acquired firm's equity, during the pre-acquisition windows (see, among others, Pound and Zeckhauser 1990, Zivney et al. 1996, Gao and Oler

[3] The former has a pre-specified arrival time whereas the latter does not. Examples are macroeconomic data released by a government body, and the announcement of a profit warning.
[4] An example of private information would be insider knowledge of an upcoming takeover.

2012 and Chou et al. 2015, and Ahern and Sosyura 2015). However, the findings presented in this literature fail to show the real-time price formation effect of rumours. This is usually due to rumour datasets not containing timestamps to a high enough frequency. There is very limited research into the systematic influence of rumours on macro-markets. Oberlechner and Hocking (2004) have shown – using questionnaire and interview data – that traders implement currency market transactions based on informal communications with 'in the know' journalists and sources. The intuition is that market-relevant rumours carry an informational risk premium. Their intuition and survey findings are in line with the empirical results of this paper; however, in the absence of an empirical sample of timestamped market-relevant rumours, it is difficult to identify any associated real-time price discovery process.

The advent of social networks has made possible to track and timestamp the release of news and comments made by individual users, enabling researchers to investigate much stringent hypotheses on the link between rumours and financial markets. From a theoretical perspective Kosfeld (2005) builds on Banerjee's (1993) theoretical model to show that if the diffusion of a rumour is wide enough, through word of mouth, then such rumours can cause a significant 'price run-up'. The model builds on the assumption that rumours transmit more effectively in networks that are small and local rather than large and global. We would argue that this theoretical model can be expanded to include a more global outreach for a given rumour since the existence of social media outlets has been shown to lead to rapid rumour diffusion (Nekovee et al. 2007). From an empirical perspective, there is now a burgeoning strand of studies which exploits the possibility to timestamp comments from users on future firm-specific events such as earnings announcements, and matches their arrivals with price fluctuations (see, for example, Sprenger et al. 2014, Chen et al. 2014, Sul and Dennis 2017).

In addition, the parallel literature on the systematic influence of rumours on macro-markets is in its infancy, and mainly characterised by studies that focus on the detection of sentiment indices using social networks data (see, e.g., Renault 2017, and Siganov et al. 2017). We contribute to this nascent strand of research by focussing on the macroeconomic information content of ECB Twitter rumours and their link with the EUR-USD exchange rate. Our study is based on the intuition that the rapid global transmission enabled by networks like Twitter combined with the appetite of investors for insights on future policy stances of the ECB can create an environment in which systematic risk factors are at play – so that during rumour diffusion the market should command risk premia.

Rumours by their nature are difficult to pinpoint in time and rational expectations theory would suggest rumour information to be of little fundamental importance to the pricing of assets. It is therefore understandable that this type of information has remained overlooked in the past. We argue, however, that if rumours sufficiently alter the perceptions held by market participants of a given future market event, they become fundamental to the pricing mechanism.

We tackle this issue in the context of the strong form EMH, which asserts that an efficient financial market will price all available relevant information, public and private, about market events that have already occurred or are expected to occur in the future. Market rumours by their nature are information events predominantly indicating the size, scope, timing and probability of future market events.

The arrival of a market rumour could plausibly change the nature of investor forecasts of future events. Depending on the timing and quality of the source of a given rumour, market agents may reasonably alter the probability they attach to the possible outcomes of a specific future event and, as a result, may revise the pricing of assets with the expectation of reaping extra profits.

Figure 1a

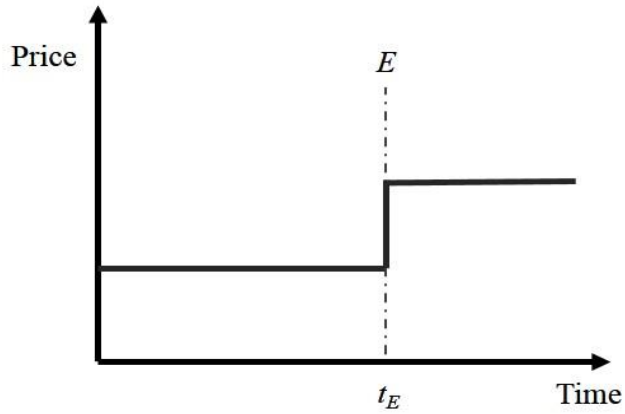
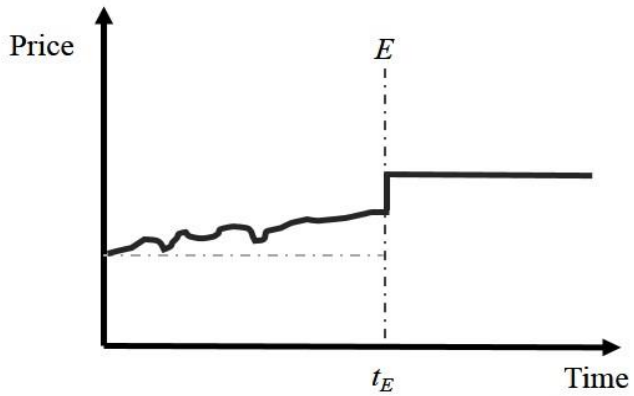


Figure 1a,b,c provide simple illustrations of price formation mechanisms leading up to a future event *E* in the presence of rumours. Figure 1a illustrates a semi-strong efficient market, where market agents react only to public information at the time of event *E*. The size, scope and probability of this event become known only at time t_E, and profits generated by the price adjustment would only be earned by those reacting immediately. In this case, the occurrence of event E can explain the full amount of volatility going on in the market. The price formation process illustrated in Figure1a is purely theoretical and not observable in financial markets.

A price formation process with increasing investor price forecast accuracy and private information diffusion is illustrated in Figure1b. Price variation is observed in this scenario up to event *E*.

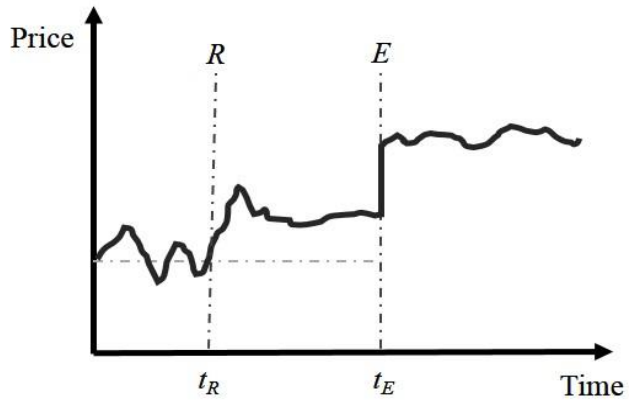
Figure 1b



The timing, size, scope and probability of a future event in a strong-form efficient market is partly known and priced by 'in the know' market agents. Market agents with the best forecasts or private information prior to event *E* will profit most. In this case, the occurrence of event *E* can account for only a fraction of the total market volatility, with fluctuations prior to event *E* which remain un-explained. This simple illustration does converge to the reality of financial market price formation.

In reality, however, Figure 1c is more representative of pre-event price formation. Price formation is a dynamic process where forecasts alter frequently due to continuous market information flows.

Figure 1c



The timing, size, scope and probability of upcoming event *E* changes based on heterogeneous forecasts and beliefs. Cumulative market participant forecasts form a market consensus, which at any given time determines price.

If the arrival of a rumour R sufficiently changes the forecasts of a large enough group of market agents to a new homogenous forecast, then a resultant volatility event may be expected. Given that market agents attach a certain probability to the rumour being true, they stand to profit by taking action based on the change to their forecasts. The profit may be contemporaneous at time t_R or based on a time advantage over market agents who react at time t_E. With the profit motive in mind, it is perfectly rational for market agents to change their position based on the probability they attach to the rumour being true. Such a probabilistic calculation is simply a risk-weighted trading decision, one that would be deemed rational in an efficient market. In this last case, the arrival of rumour R can account for the volatility prior to the arrival of event E.

While we frame our analysis in the context of the EMH, the modality previously described through which information arrives into the markets and affects the pricing of securities is also consistent with the so-called Policy Anticipation Hypothesis (PAH). The PAH puts forward the idea that market reactions to economic news are influenced by the expectations of investors who anticipate the response of monetary authorities to such news (see, e.g., Cook and Korn, 1991). Once we believe that rumours convey valuable information not yet known to the public, such rumours become part of the information set available to anticipate the ECB's policy stances, and therefore future movements in the EUR-USD market.

We provide below a more formal representation of the price formation process incorporating the arrivals of both official news and rumours that shows that rumours could, in principle, play a significant role in the pricing of securities.

To demonstrate this, we define I_t as a vector of all variables determining the exchange rate of a given currency pair prior to an event E. The outcome of such an event could alter the composition, magnitude and probability attached to any given element of vector I_t. We would, however, expect I_t to remain fixed between time 0 and t_E, without the arrival of unscheduled market-relevant information. This vector includes the known quantities of exchange rate determinants such as, the rate of inflation, trade balances and interest rate differential, as well as information about central bank announcements/actions, which determine investors' expectations about the future values of said variables. Further, we denote $\hat{I}_t$ as a vector containing the consensus estimates of all market participants of each element of I_t between time 0 and t_E. Equilibrium foreign exchange rate at any time $t \in [0; t_E]$ can be written as $FX_t =$

$\emptyset(I_t, \hat{I}_t)$. We can obtain the approximate change in the foreign exchange rate within this time window by linearizing $\emptyset$ and time differencing the result, so that:

$$\Delta FX_t \cong \emptyset_1' \Delta I_t + \emptyset_2' \Delta \hat{I}_t$$

where Δ is the difference operator between time 0 and t_E, and $\emptyset_1' = \frac{\partial \emptyset}{\partial I_t}$ and $\emptyset_2' = \frac{\partial \emptyset}{\partial \hat{I}_t}$. With the supposition that none of the foreign exchange rate determinants can change during the window, thus $\Delta I = 0$ and $\Delta FX = \emptyset_2' \Delta \hat{I}_t$. Any marginal effect on the exchange rate is given by an element of the vector $\emptyset_2'$, as a result of a change to a corresponding element of the market consensus vector $\hat{I}$. Changes to market consensus without material changes to vector *I*, detectable as excess volatility, can be deemed a repricing of risk by the market, due to either undetected information events or noise. We assert that a rumour event *R* can be seen as an undetected information event. Provided that *R* delivers information about the probability, scale, scope or timing of upcoming event *E*, and that it sufficiently alters market consensus elements of vector $\hat{I}$, a marginal effect on the exchange rate should be observable following the arrival of the rumour at time t_R. The magnitude of such a change should be proportional to $\emptyset_2' \Delta \hat{I}_t$ as a result of the arrival of *R*.

In Section 5.5, we show that this marginal effect is observable in terms of significant periods of exchange rate volatility following the arrival of ECB rumour information events.

3. Data description

3.1. Euro-US dollar exchange rate data

The Euro-US dollar currency market is the largest in the world by number of transactions per day. It opens 2200 GMT Sunday and is subject to a 24-hour trading day until 2200 GMT Friday. Pre-market (weekend) trading is available through some exchanges; however trading volume is relatively illiquid when compared to standard non-weekend trading (Chaboud et al. 2014). The market's opening hours overlap with geographic trading days in Tokyo, Sydney, Frankfurt, London and New York; the most active financial centres. This 24-hour trading day allows the investigation of price formation during the full weekly information cycle.

We source EUR-USD exchange rate data from Bloomberg professional services. We have chosen to utilise 1-minute interval exchange rate data to accommodate the investigation of post-rumour price formation in greater detail. The data supplied consists of exchange rate quotes for a period spanning from 29 September, 2013 to 08 May, 2015 (84 weeks, 420 days), totalling in 604,800 observations.[5] Quote data is available for weekend trading hours (2200 GMT Friday to 2200 GMT Sunday) however, we choose to omit these observations due to the reasons given above. Further, we omit trading half-days and major holidays during which trading is considerably less active. These omissions result in a final minute-by-minute data sample of 596,160 observations, from a total of 414 trading days, individually made up of 1440 1-minute intraday returns. We define intraday returns ($R_{t,n}$) in terms of trading day $t = 1,2, \ldots 414$ and minute interval $n = 1,2,\ldots,1440$. Where price is defined as $P_{t,n}$, minute by minute returns are calculated as follows:

$$R_{t,n} = \log(P_{t,n}) - \log(P_{t,n-1}) \qquad [1]$$

The collection of daily EUR-USD data is also required for inclusion in the baseline Flexible Fourier form regression to account for the highly persistent volatility factor as observed by Andersen and Bollerslev (1997). The inferred volatility in daily frequency observations of spot EUR-USD rate, as determined by EGARCH estimates, controls for the observable highly persistent volatility in exchange rate. A detailed discussion of this procedure will be outlined in Section 4. We source this daily data, spanning from 29 September, 2013 to 08 May, 2015 for a total of 420 observations, via Bloomberg professional services. Daily data (R_t) is then

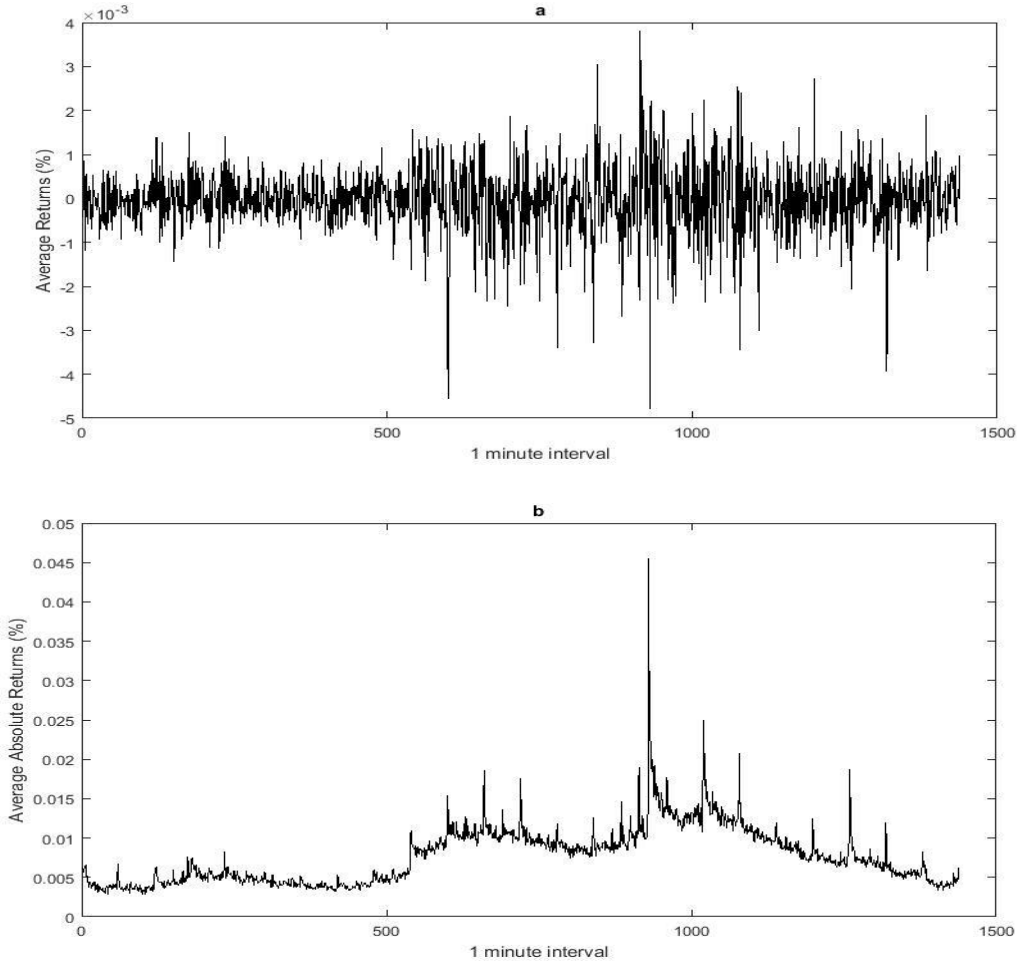
[5] We limit out sample to this period because in September 2015 Bloomberg signed a data agreement allowing it to include more financial market-relevant information first broadcast on Twitter. Prior to this, Bloomberg's inclusion of information found on Twitter was limited to official company disclosures broadcast by official company Twitter accounts.

filtered to omit related observations removed from our intraday sample (898 observations). Descriptive statistics for both daily and intraday frequency samples are presented in Table 1.

Table 1
Descriptive statistics for full sample daily and intraday minute-by-minute EUR-USD exchange rate returns.

	Mean	Median	St. Dev.	Skew	Kurtosis	Min	Max	Observations
R_t	$-4.55\text{x}10^{-4}$	$-1.45\ \text{x}10^{-4}$	0.0052	-0.138	2.84	-0.021	0.024	898
$R_{t,n}$	$-2.64\text{x}10^{-7}$	$3.05\text{x}10^{-9}$	$1.43\text{x}10^{-4}$	0.235	192.47	-0.0088	0.0094	596,160

Figure 2
(a) EUR-USD intraday 1-minute average (one trading day) raw returns $R_{.,n}$. (b) EUR-USD intraday 1-minute average (one trading day) absolute returns $|R_{.,n}|$.

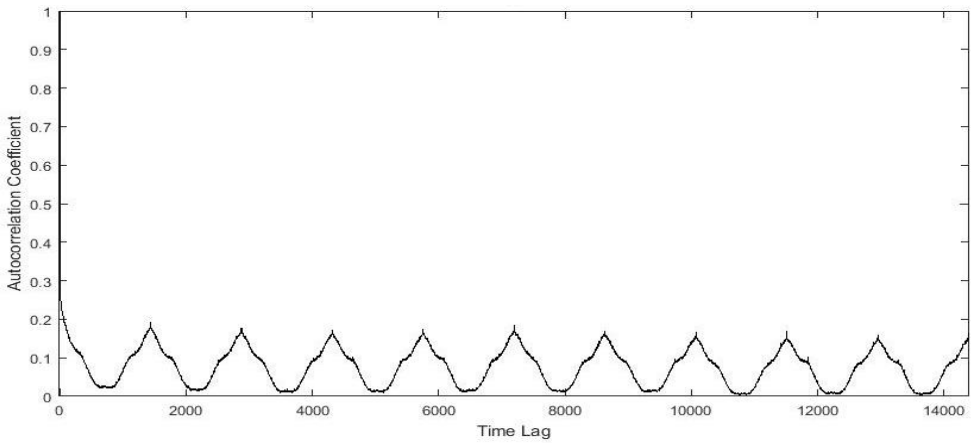


3.2. Intraday patterns of the Euro-USD series

It is clear from Table 1 that with a skewness of 0.235 and kurtosis of 192.47 the EUR-USD minute-by-minute raw returns are not normally distributed across the sample. This is consistent with previous studies by Chaboud et al. (2014) and Andersen and Bollerslev (1998), who make use of intraday currency 1-minute and 5-minute data respectively. Furthermore, it can be

observed that when sample returns are averaged for the trading day, there are distinguishable increases in return variability during specific times of the trading day. This greater variability is somewhat apparent, although centred around zero, for raw returns but is profoundly clear for absolute returns. This unique feature of intraday data was initially identified by Andersen and Bollerslev (1997a) and has been consistently observed by a number of other scholars (see, e.g., Bauwens et al. 2005, and Chaboud et al. 2014). Figure 2 illustrates the average interval raw and absolute returns across the trading day.

Figure 3
Ten day correlogram for absolute EUR-USD returns $|R_{t,n}|$.



The regular intraday pattern observed for absolute returns suggests persistent spikes in volatility at regular times for the trading day across the sample. These spikes in price variability coincide with prominent geographical financial centres opening and with their respective scheduled public information releases of macroeconomic data and Central Bank news. This study defines the trading day as commencing 2200 GMT when the average absolute 1-minute returns are low relative to the trading day. There are small periodic increases in absolute returns as Asian financial centres begin their respective trading days. There is a notable rise to a higher level of 0.011% for the Frankfurt opening, and a further rise to 0.016% for the start of the London trading day. There are further spikes in absolute returns at 0900 GMT (660th interval) and 1000 GMT (720th interval) which represent regular macroeconomic data releases. The most distinctive feature of the daily pattern is that of the 930th trading interval at which point absolute returns spike to 0.046%. This represents East Coast US financial centres opening and the release of scheduled macroeconomic data such as the US employment report. Further distinguishable spikes represent a second scheduled release of macroeconomic data, US stock

markets closing, and times during which the Federal Open Market Committee (FOMC) releases information.

The intraday pattern in absolute returns discussed above has been reported to result in a persistent U-shaped autocorrelation effect throughout the sample (see, e.g., Andersen and Bollerslev 1998, and Bauwens et al. 2005). We report similar findings in Figure 3, which depicts the 10-day correlogram for absolute returns. Standard volatility models, developed by design for analysis of lower frequency daily, weekly and monthly data, are not appropriate given the persistent autocorrelation in observations (Payne 1996). This is the principal reason we offer for selecting the methodology outlined in Section 4.

3.3. Information event data

There are two sources of financial market information for this study: Bloomberg professional services and Twitter. Information events sourced via the former facilitate the inclusion of times during which scheduled and unscheduled public information arrive. For scheduled events, a unity value is included as a dummy variable for the event window commencing at the minute the information is released via Bloomberg. The inclusion of said event windows allows for the testing of the paper's main hypothesis while controlling for any volatility jumps attributable to scheduled public information events. From Bloomberg professional services, we collect timestamped data for 20 categories of scheduled public information releases, totalling 429 events of this type for the period 29 September, 2013 to 08 May, 2015. Further, 250,000 unscheduled public information arrivals (news headlines) are collected via Bloomberg for the same period. The times of such news headlines are cross-referenced with our sample of timestamped rumours, controlling for any period during which unscheduled information arrival clashes with a rumour event window.

Details of public information data are provided in Table 2. For the purpose of this study, we collate scheduled public information in twenty categories, FOMC rate decisions, ECB rate decisions, FOMC meeting minutes release, speeches given by prominent ECB and FOMC Committee members, US employment reports, Category 1 economic data (US GDP, US CPI, US ISM manufacturing data, US consumer confidence, German ZEW economic confidence data, German IFO economic confidence data and Eurozone CPI) and Category 2 economic data (US retail sales data, US Durable Goods, US Manufacturing PMI, German Employment Report, European PMI manufacturing, German Industrial Production and German Factory Orders).

Table 2
Scheduled public information arrival for period September 29, 2013 to May 08, 2015.

Announcement	Regular Time (GMT)[6]	Bloomberg Relevance Indicator[7]	Number of Observations
FOMC Rate Decision	1900/1800	97.6	13
ECB Rate Decision	1245	97.7	18
FOMC Minutes	1930/1830	97.6	12
ECB Speakers	Various	N/A	46
FOMC Speakers	Various	N/A	52
US Employment Report	1330	99.2	20
US CPI (Cat 1)	1330/1230	94.4	19
US GDP (Cat 1)	1330/1230	96.8	19
US ISM (Cat 1)	1500/1400	96.0	19
German ZEW (Cat 1)	1000	98.3	19
German IFO (Cat 1)	0900	96.6	19
Eurozone CPI YoY (Cat 1)	1000	95.3	19
US Consumer Confidence (Cat1)	1330/1230	95.2	19
US Durable Goods (Cat 2)	1330/1230	92.1	19
US Retail Sales (Cat 2)	1330/1230	91.3	19
US Manufacturing PMI (Cat 2)	1445/1345	90.0	19
German Employment Report (Cat 2)	0855	90.0	19
Eurozone Manufacturing PMI (Cat 2)	0800 to 0900	90.0	19
German Industrial Production (Cat 2)	0700 or 1100	93.2	20
German Factory Orders (Cat 2)	0700 or 1100	91.5	20

We set up a domain where market-relevant rumours can be pinpointed in time by using Twitter. It is important to note, at this point, the definition, and thus selection criteria, of 'market-relevant rumours' for this research. Our selection criteria are based on the source (non-incumbent, informal source) and 'actionability' of a rumour (therefore market relevance). Firstly, we define a rumour as unofficial or uncorroborated information pertaining to the outcome of a future systematic risk event. It is therefore, the credibility, formality and incumbency of the source of this information which is fundamental to the 'rumour' definition. We select rumours broadcast by commentators not formally associated with the policy-making institutes. Any commentator that is associated with the ECB in any formal capacity is considered to be releasing formal information, not rumour. The source of the rumour must also

[6] It is worth noting that for Eastern Standard Time (New York) the change to daylight saving time occurs sooner and ends later than in Western Europe. This can cause some disparity when observing US related information events. We control for these disparate periods when constructing public information dummy variables.

[7] A relevance indicator provided by Bloomberg determines the constituent economic data events included in the latter two categories.

be a non-incumbent information distributor for the information content to be considered rumour. For example, Reuters and Bloomberg are government-authorised first-distributors of an array of market data and information (see, among others Li et al. 2015). Information released through their respective Twitter accounts is associated with this authorisation and therefore considered unambiguous. We therefore omit information released from these accounts and focus on 'in the know' market commentators. 'In the know' is defined by the recognition (number of followers) such commentators have on the social media platform Twitter. This following may be due to the credibility of past rumour broadcasts.[8]

Secondly, we define the 'actionability' of a rumour based on the scope of the content, time of arrival and diffusion among commentators. We select rumours with large enough scope to be potentially relevant for market agents active in macro-markets. The selection of ECB policy related rumours makes this criteria attainable. The arrival of the rumour must take place prior to the relevant policy announcement. Finally, the rumour must be sufficiently absorbed by enough market commentators to be considered 'actionable'. We measure this by the number of times the rumour is repeated or requoted.

Preliminary analysis of the EUR-USD market shows that of the largest 25 absolute returns for our sample, 10 occur concurrently with the arrival of news associated with the ECB (see Table 3). It is, therefore, appropriate that we focus on highly relevant market rumours relating to forthcoming ECB actions or changes in remit. Such highly relevant market rumours are appropriate examples of actionable information discerned by market actors but not yet investigated by economists. Rumours of this type are quoted as 'ECB sources' stories. These rumours are regularly reported by 'in the know' financial market commentators via Twitter. ECB-sources stories are particularly prevalent within a one-week window of the ECB's Governing Council meeting that takes place on a monthly basis. We can gauge the popularity of an ECB-sources story by the number of times the quoted rumour is repeated. It is relatively simple to search Twitter archives for the phrase 'ECB sources'. We select ECB rumour events where the quoted story is repeated by more than 20 'in the know' financial market commentators. We then perform an advanced search for the full quoted story, e.g. 'ECB Sources: ECB is working on a discussion paper to execute government bond buying', and pinpoint the time of the first broadcast of the quote. In total, we collect times for the first

[8] A study of the reasons behind said credibility is not carried out in this paper; however, this could prove an interesting area for further research.

broadcast of 63 ECB rumour events. Details of the 63 'ECB sources' events are given in the appendix.

All such broadcasts are timestamped to within one-minute accuracy, which alleviates the difficulty of pinpointing the arrival of a rumour in time. Moreover, the unique nature of Twitter as a broadcasting mechanism is that commentators are not subject to stringent financial regulatory body mandates and in-house substantiation filtration systems. This fundamentally differentiates Twitter from incumbent financial news broadcasters such as Bloomberg and Reuters.

Financial market-relevant information broadcast via Twitter is now so important to market agents that in September 2015, Bloomberg signed a data agreement with Twitter allowing it to incorporate more financially relevant information found on the social media platform (see, e.g., Renault 2017, and Bloomberg 2015). Prior to this Bloomberg had limited the inclusion of financial information, found on Twitter, to official company filings approved by the Securities and Exchange Commission. For this reason, we have limited our sample to end in May 2015.

4. Methodology

To infer any meaningful exchange rate volatility effect due to the arrival of new information, we need to account for the intraday pattern in absolute returns found in the previous section. We make use of the Andersen and Bollerslev's (1998) empirical model as it is the most closely aligned with our aim of detecting exchange rate return variability linked with the arrival of new information. This model has been developed specifically for the purpose of controlling for the diurnal pattern persistent in intraday data. By design, the model is flexible and can be adapted to control for latent daily volatility clustering, low-frequency calendar effects and the arrival of heterogeneous public information other than the principal rumour information in question. The model has been applied by several scholars to study the volatility effects of the arrival of new information on equity, currency, bonds and their respective futures markets (see, e.g. Bauwens et al. 2005, Andersen and Bollerslev 1998, Bollerslev et al. 2000, and Andersen et al. 2000).

In order to 'smooth' out intraday periodicity we must consider two scales of time; day *t* and interval *n* within day *t*. Thus, $R_{t,n}$ is the market return at interval *n* of day *t* (e.g. 2200 GMT would be *n* = 1 for a given day, *t*). The model can be specified as follows:

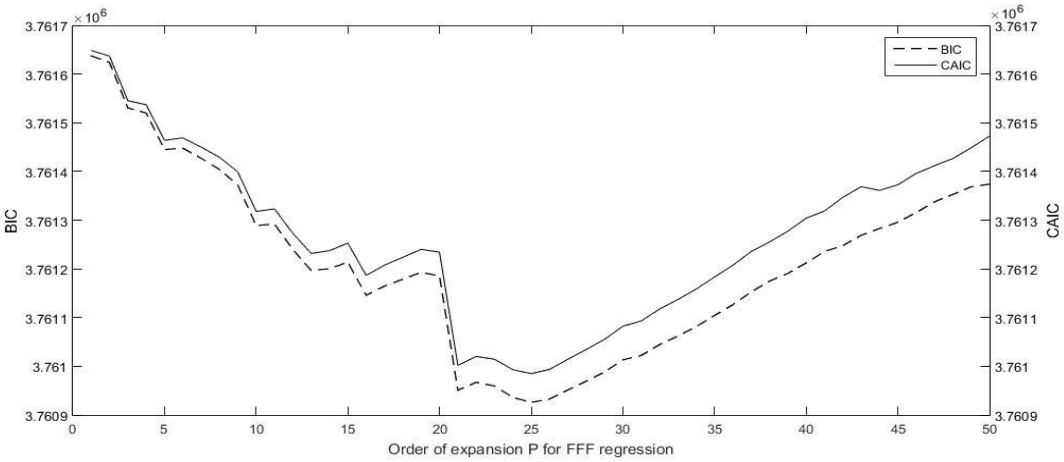
$$R_{t,n} - \bar{R}_{t,n} = \sigma_{t,n} \cdot s_{t,n} \cdot Z_{t,n} \qquad [2]$$

where $\bar{R}_{t,n}$, is the expected market return, which is defined as a sample mean of 1-minute returns. $Z_{t,n}$, is a normally distributed error term with mean zero and unit variance, whereas the term $s_{t,n}$ captures the intraday periodicity and heterogeneous public information arrival, as well as ECB rumour events. Finally, $\sigma_{t,n}$ captures a latent volatility component at intra-day frequency which is computed by means of the following formula:

$$\hat{\sigma}_{t,n} = \hat{\sigma}_t / N^{1/2} \qquad [3]$$

where *N* is the number of intervals in each day (1440) and $\hat{\sigma}_t$ is daily volatility estimated by applying GARCH models to the EUR-USD series.

Figure 4
Bayesian and Consistent Akaike Information Criterion calculated for Flexible Fourier Form (FFF) regression where order of expansion P takes values from 1 to 50.



In order to fully specify a functional model from the general representation outlined in eq.[2], the components are log-transformed and squared. This allows for the isolation of the term $s_{t,n}$ as the sole explanatory component of a normalised and debased 1-minute EUR-USD volatility process:

$$2\ln\left[\left|R_{t,n} - \bar{R}_{t,n}\right|\right] - \ln \hat{\sigma}_{t,n}^2 = c + 2\ln s_{t,n} + \varepsilon_{t,n} \qquad [4]$$

The final model is defined by Andersen and Bollerslev (1998) as two-step Flexible Fourier Form (FFF) regression. The first step requires appropriate estimates of the sample mean, $\bar{R}_{t,n}$, a GARCH estimate of the latent daily volatility component $\hat{\sigma}_t$ and the specification of the public information, intraday pattern and rumour event components of $s_{t,n}$. The second step is the ordinary least squares (OLS) estimation of the FFF model provided below in its final form:

$$2\ln\frac{\left|R_{t,n} - \bar{R}_{t,n}\right|}{\hat{\sigma}_t/N^{1/2}} = c + \delta_{0,1}\frac{n}{N} + \delta_{0,2}\frac{n^2}{N} + \sum_{k=1}^{D}\lambda_k I_k(t,n) + \sum_{p=1}^{P}\left(\delta_{c,p}cos\frac{p2\pi}{N}n + \delta_{s,p}sin\frac{p2\pi}{N}n\right) + \varepsilon_{t,n} \qquad [5]$$

where the unknown parameters to estimate are $c, \delta_{0,1}$, $\delta_{0,2}$, $\delta_{c,p}$, $\delta_{s,p}$, and λ_k, with p = 1, …, P and k = 1, .., D. The $\sum_{p=1}^{P}\left(\delta_{c,p}cos\frac{p2\pi}{N}n + \delta_{s,p}sin\frac{p2\pi}{N}n\right)$ sinusoidal parameter (Fourier series) controls for the intraday seasonality component of each day t of N intervals (1440). This allows for linear estimation of the volatility impact attributable to public information and rumour events k, for interval n, on day t, represented by $I_k(t,n)$. Normalising constants n/N and n^2/N are linear and quadratic trends within each day, where n =1, …, 1440. P determines the order of expansion (pitch) of the sinusoidal components in the trigonometric variable. An order of

expansion of 4–8 has been implemented in previous adoptions of this model (Andersen and Bollerslev 1997b; Bollerslev et al. 2000). The order of expansion (P) appropriate for the FFF regression implemented with one-minute frequency data used in this analysis is likely to deviate from the above studies, given their use of 5-minute data. We determine the appropriate order of expansion by calculating the Bayesian and Consistent Akaike Information Criterion for eq.[5] where P ranges from 1 to 50. The results of model comparison provided in Figure 4 shows that the optimum value for the order of expansion of the Fourier series is P = 25. The periodic pattern can be converted to absolute returns, exclusive of dummy variables, as follows:

$$\left|R_{t,n} - \bar{R}_{t,n}\right| = N^{-1/2} \cdot \hat{\sigma}_t \cdot \exp\left(\frac{\hat{c} + \hat{\delta}_{0,1}\frac{n}{N} + \hat{\delta}_{0,2}\frac{n^2}{N} + \sum_{p=1}^{P}\left(\hat{\delta}_{c,p} cos\frac{p2\pi}{N}n + \hat{\delta}_{s,p} sin\frac{p2\pi}{N}n\right)}{2}\right) \cdot \exp\left(\hat{\varepsilon}_{t,n}/2\right) \qquad [6]$$

A comparative illustration is provided in Figure 5 between 1-minute average trading day realised absolute returns and fitted absolute returns implied by the FFF model and calculated in eq.[6]. Charts a, b and c demonstrate the improvement in fit when the tuning parameter P is increased from 6 to 12 and then to 25 – with the latter being the optimal order of expansion.

OLS estimation of the FFF regression outlined above will provide consistent parameter estimates for information and rumour events, given correct specification of the sinusoidal term according to Andersen and Bollerslev (1998). The heteroscedasticity correction and log transformation in the first step of the sequential FFF approach enhance the efficiency of linear parameter estimates for public information and rumour event dummies in the second step. We double-check that this is the case by simulating 1000 trials of the "absolute returns series as specified by eq.[5]" using the Monte Carlo approach. We find all parameter estimates (OLS) in the second step FFF regression to be normally distributed, including all 25 $\delta_{c,p}$ and $\delta_{s,p}$ coefficients. This simulation exercise suggests that the finite sample properties of the above OLS estimates do not depart from the standard asymptotic properties.[9] For the daily sample period, 29 September, 2013 to 08 May, 2015, we observe large exchange rate fluctuations (Figure 6a) particularly for the latter part of the 414 day, sample period. We model such periods of heightened volatility by means of an exponentially weighted EGARCH(1,1) specification that we fit to the daily EUR-USD returns series. Such specification turns out to be the best equipped to capture the direction and persistence of volatility shocks in the daily sample. Figure 6b depicts the estimated daily volatility obtained.

[9] The empirical results from the above Monte Carlo simulations are available from the authors upon request.

Figure 5

Comparative illustration: Fit of the Fourier component, with tuning parameter P=6, 12 and 25, of the FFF model to the average absolute one-minute EUR-USD returns across the 24-hour trading day. (a) Fit of the Fourier component with tuning parameter P = 6 of the FFF model to the average absolute one-minute EUR-USD returns across the 24-hour trading day. (b) Fit of the Fourier component with tuning parameter P = 12 of the FFF model to the average absolute one-minute EUR-USD returns across the 24-hour trading day. (c) Fit of the Fourier component with tuning parameter P = 25 of the FFF model to the average absolute one-minute EUR-USD returns across the 24-hour trading day.

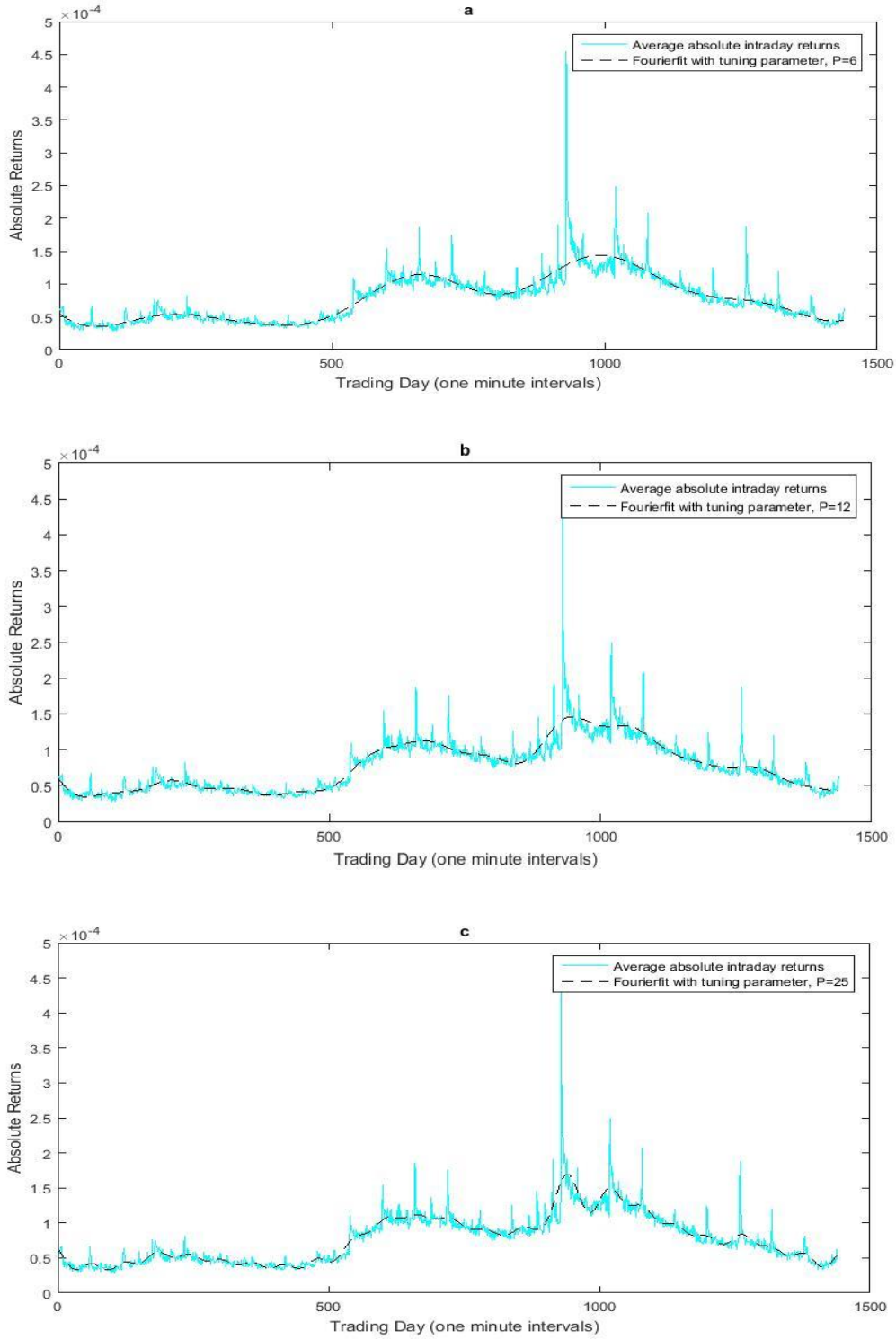
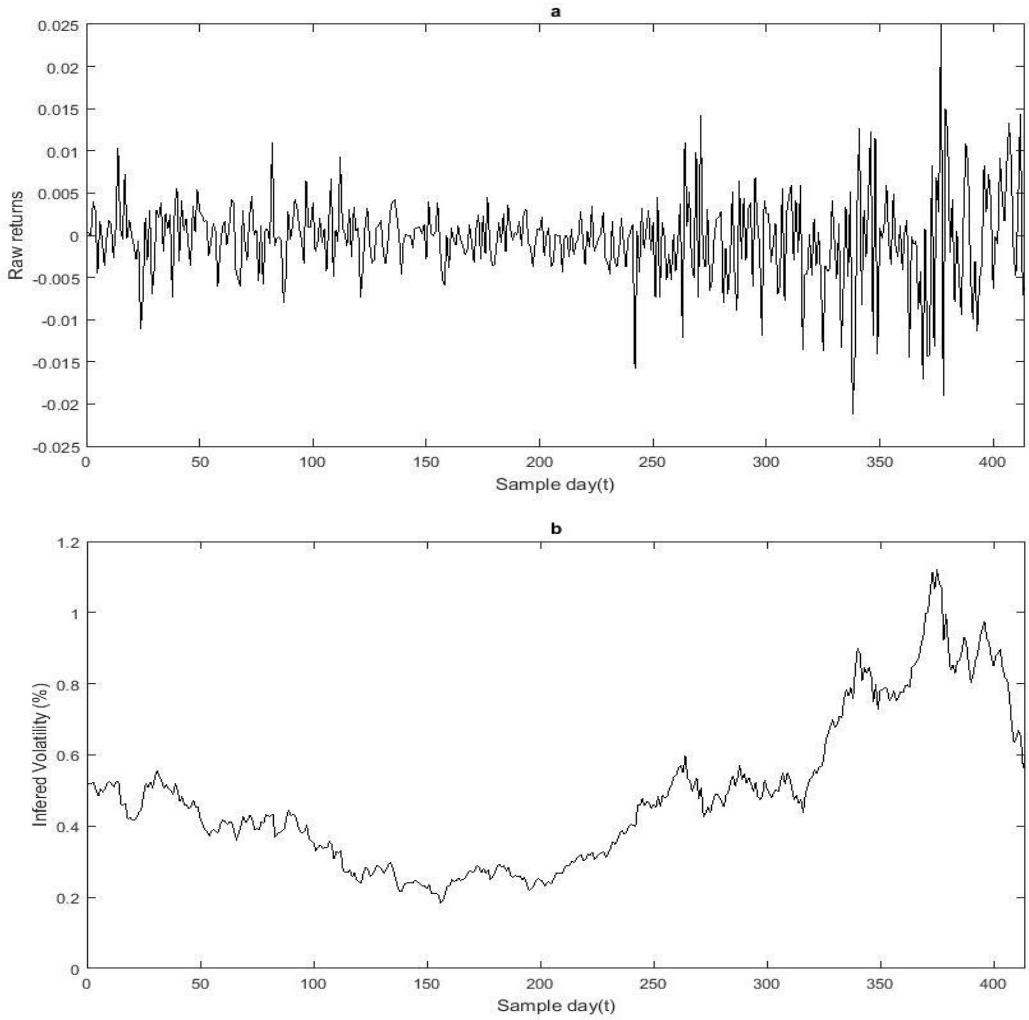


Figure 6
(a) Raw daily returns for 414-day period from 29 September, 2013 through 08 May, 2015. (b) Conditional standard deviation inference from an EGARCH(1,1) model for daily EUR-USD returns for 29 September, 2013 through 08 May, 2015.



Overall, in the light of the supporting evidence from the Akaike and Bayesian Information Criterion for the first-step procedure for eq.[5], along with additional results of the Monte Carlo simulation of the second step procedure, we conclude the FFF model is an appropriate tool for the purpose of this study.

5. Empirical findings

5.1. Preliminary analysis

We begin by tabulating the 25 largest absolute one-minute returns over the full sample period. We then cross-reference the times and dates of these abrupt changes in exchange rate with our sample of the public and actionable information data set. The same matching exercise was followed by Fleming and Remolona (1999), Andersen, Bollerslev and Cai (2000) and Bollerslev, Cai and Song (2000) in their analyses of return variability in stock, bond and currency markets in response to public information arrival. Their results show, in consensus, that the largest 25 absolute returns of their respective markets of interest occur during times of public information arrival. We carry out the same exercise for our data set and find that of the 25 largest absolute returns, 21 occur during times of public information arrival. These last, together with their matched information/rumour event, are reported in Table 3.

Twenty of the largest jumps in exchange rate can be attributed to scheduled public information and one to the unscheduled announcement of the approval of an economic assistance package for Greece. These 21 events were corroborated, certified and reported by the accredited newswire Bloomberg. Such information has in the past been referred to as fundamental financial market information; relevant, 'rational' public market information reported by an authorised newswire. Four of the 25 largest absolute EUR-USD returns for our full sample period occurred during times of 'actionable' information arrival. Three of these events were rumours of forthcoming ECB action reported by 'in the know' commentators broadcasting on Twitter. The fourth was the reporting of the arrival of Russian troops in Crimea by independent Twitter users.

While this matching exercise is somewhat subjective, the results reported in Table 3 suggest that 'actionable' rumours discerned by market agents could have a sizable impact on market price. These matching results provide the basis for the hypothesis that the availability of Twitter as a medium for rumour diffusion would enable economists to identify a form of ambiguous – yet actionable – information that can be associated with significant fluctuations in market prices. We conclude this to be substantial preliminary support for the hypothesis that market rumours – i.e., information previously not discerned and categorised as private information or mis-identified as not fundamental – are of value to traders and they are a constituent factor of market price formation.

Table 3
Largest absolute 1-minute returns for EUR-USD spot exchange rate market from 29 September, 2013 through 08 May, 2015. For each of the 25 largest absolute returns, we indicate the information/rumour event, which may have contributed to returns.

Absolute Returns (%)	Timestamp (GMT)	Return Interval	Information/Rumour event
0.942	03/04/2015 1330	930	US Employment Report
0.878	07/11/2013 1245	885	ECB Rate Decisions
0.875	18/03/2015 2004	1384	FED Press Conference
0.823	06/03/2015 1331	931	US Employment Report
0.786	22/01/2015 1344	944	ECB Press Conference
0.761	22/01/2015 1340	940	ECB Press Conference
0.617	18/03/2015 1800	1260	FED Rate Decision
0.587	06/02/2015 1330	930	US Employment Report
0.571	20/02/2015 1735	1175	Euro group decide to extend financial assistance to Greece
0.564	18/03/2015 2005	1385	FED Rate Decision
0.535	05/12/2014 1330	930	US Employment Report
0.479	12/03/2015 1230	930	US Retail Sales
0.422	18/02/2015 1900	1260	FOMC Minutes
0.421	03/10/2014 1330	930	US Employment Report
0.404	04/09/2014 1245	885	ECB Rate Decisions
0.388	22/01/2015 1345	945	ECB Press Conference
0.375	07/02/2014 1330	930	US Employment Report
0.367	18/03/2015 2003	1383	FED Rate Decision
0.363	04/12/2014 1732	1172	ECB Sources (Twitter): German ECB members opposed to new balance sheet language
0.356	17/09/2014 1900	1260	FED Rate Decision
0.344	06/11/2014 1333	933	ECB Press Conference
0.342	28/02/2014 1000	720	Rumours of Russian troops in Sevastopol emerge on Twitter
0.340	20/11/2013 1520	1040	ECB Sources (Twitter): Governing council considering negative deposit rate of 0.1%
0.339	21/01/2015 1435	995	ECB Sources (Twitter): QE proposal calls for roughly €50 billion in bond buying per month
0.338	29/10/2014 1800	1260	FED Rate Decision

5.2. Intraday periodicity

The highly persistent intraday volatility pattern evident in one-minute absolute returns illustrated in Figure 2 is consistent with the findings of previous studies based on intraday data. For instance, Andersen and Bollerslev (1998), Bollerslev et al. (2000) and Bawuens et al. (2005) all found evidence of intraday periodicity of this type for five-minute interval data and adopted the FFF regression approach to control for this. Their selection of smaller sets of tuning parameters (8, 4, 6 and 4 respectively) is appropriate for lower frequency five-minute data.[10]

[10] Andersen and Bollerslev (1998) is the only study to include parameter results of the cosinor element of the FFF regression. They find all but one of the sinusoidal parameters, the fourth sine variable, to be significant.

Table 4
Coefficient estimates for constant, normalising constants and Fourier components of the FFF regression of eq.[5]. Results set out for the complete FFF regression (inclusive of public information and ECB rumour event dummies), and for the same regression with both rumour and public information events excluded.

Parameter	FFF regression	t-Stat	Rumours excluded	t-Stat	Periodic pattern Only	t-Stat
c	14.26	3.772	14.32	3.779	14.974	3.905
δ0,1	-116.8	-5.155	-117.2	-5.163	-121.5	-5.290
δ0,2	0.081	5.136	0.081	5.144	0.084	5.271
δc,1	-13.42	-5.851	-13.45	-5.852	-13.83	-5.947
δs,1	-1.874	-35.28	-1.864	-35.03	-1.815	-33.71
δc,2	-3.090	-5.389	-3.103	-5.401	-3.226	-5.547
δs,2	0.057	2.033	0.054	1.927	0.043	1.531
δc,3	-1.744	-6.837	-1.744	-6.827	-1.796	-6.946
δs,3	0.536	26.56	0.537	26.55	0.514	25.11
δc,4	-0.793	-5.517	-0.796	-5.529	-0.843	-5.784
δs,4	-0.758	-45.66	-0.762	-45.81	-0.717	-42.63
δc,5	-0.514	-5.571	-0.518	-5.600	-0.492	-5.255
δs,5	-0.057	-3.911	-0.051	-3.476	-0.041	-2.766
δc,6	-0.333	-5.166	-0.329	-5.092	-0.348	-5.315
δs,6	-0.057	-4.239	-0.058	-4.289	-0.084	-6.150
δc,7	-0.187	-3.898	-0.186	-3.879	-0.195	-4.015
δs,7	-0.080	-6.290	-0.079	-6.177	-0.052	-4.084
δc,8	-0.105	-2.813	-0.105	-2.802	-0.104	-2.746
δs,8	0.113	9.270	0.111	9.082	0.104	8.477
δc,9	-0.157	-5.211	-0.158	-5.245	-0.155	-5.065
δs,9	-0.002	-0.178	-0.006	-0.470	-0.016	-1.298
δc,10	-0.117	-4.664	-0.120	-4.782	-0.133	-5.222
δs,10	0.023	1.985	0.025	2.143	0.034	2.872
δc,11	-0.105	-4.850	-0.105	-4.867	-0.104	-4.774
δs,11	0.058	5.153	0.056	4.912	0.034	2.962
δc,12	-0.071	-3.731	-0.072	-3.801	-0.082	-4.249
δs,12	-0.067	-6.024	-0.065	-5.841	-0.055	-4.826
δc,13	-0.096	-5.652	-0.094	-5.539	-0.107	-6.186
δs,13	0.012	1.095	0.013	1.158	0.012	1.069
δc,14	-0.056	-3.571	-0.056	-3.576	-0.032	-2.010
δs,14	0.015	1.351	0.012	1.101	0.008	0.762
δc,15	0.012	0.853	0.012	0.821	-0.016	-1.101
δs,15	-0.077	-7.131	-0.075	-6.897	-0.082	-7.457
δc,16	-0.051	-3.752	-0.052	-3.794	-0.045	-3.271
δs,16	0.032	2.955	0.032	2.927	0.043	3.946
δc,17	-0.004	-0.286	-0.002	-0.175	0.009	0.678
δs,17	0.034	3.194	0.035	3.284	0.042	3.822
δc,18	0.037	2.986	0.037	2.960	0.031	2.476
δs,18	-0.011	-1.024	-0.012	-1.083	-0.037	-3.430
δc,19	-0.018	-1.506	-0.019	-1.566	-0.039	-3.210
δs,19	0.050	4.686	0.049	4.570	0.065	6.018
δc,20	0.010	0.863	0.010	0.889	0.029	2.434
δs,20	-0.032	-3.055	-0.032	-3.028	-0.027	-2.515
δc,21	0.063	0.511	0.061	5.333	0.050	4.259
δs,21	-0.015	-1.440	-0.016	-1.499	-0.034	-3.161
δc,22	0.025	2.243	0.026	2.337	0.021	1.869
δs,22	0.021	1.999	0.022	2.113	0.035	3.312
δc,23	0.065	5.799	0.064	5.768	0.066	5.865
δs,23	-0.049	-4.652	-0.049	-4.684	-0.048	-4.508
δc,24	0.180	16.34	0.180	16.35	0.182	16.32
δs,24	0.024	2.260	0.024	2.246	0.021	1.955
δc,25	0.042	3.835	0.041	3.746	0.036	3.218
δs,25	-0.003	-0.325	-0.004	-0.364	-0.001	-0.064

For the purpose of this study, we find a tuning parameter of 25 to be the most appropriate for the one-minute frequency EUR-USD returns sample, as outlined in Section 4. In Table 4 we set out parameter estimates for the intraday periodicity control component of the FFF regression of eq.[5]. The second and third column report the parameter estimates for the full FFF regression inclusive of rumour and public information dummy variables. The remaining columns report parameter estimates obtained when the rumour event dummy variables and when the rumour and public information event dummy variables, respectively, are excluded from the FFF regression[11]. The results show that most of the fifty sinusoidal parameter estimates are significant and perform well in controlling for the highly persistent intraday periodicity in absolute EUR-USD returns. As with findings presented by Andersen and Bollerslev (1998), some Fourier series parameter estimates are insignificant. The inclusion of such terms is, however necessary for better smoothing of the intraday periodic component.[12] Most notably, results in Table 4 show that the inclusion of rumour and public information dummy variables reduces the number of significant sinusoidal parameters and the respective size of their coefficient estimates. Andersen and Bollerslev (1998), Andersen et al. (2000) and Bauwens et al. (2005) have all suggested and supported the idea that intraday periodicity is a manifestation of price variability resulting from the existence of private information. From these results, we can conclude that the inclusion of a relatively small number of rumour event variables is able to absorb some volatility dynamics previously captured by the intraday periodic components.

[11] The R^2 for FFF regression, rumours excluded and periodic pattern only are 0.0953, 0.0941 and 0.0895 respectively.

[12] For example, the inclusion of the insignificant ninth sine parameter ($\delta s,9$) facilitates the inclusion of the subsequent significant sinusoidal parameters.

5.3. Volatility response structure

Macroeconomic public information and rumour events occur infrequently in our sample period relative to the large number of 596,160 EUR-USD return observations. We observe 63 rumour events and control for 20 categories of macroeconomic announcements the summation of which is 492 observations of information events. The relative infrequency of such events and persistent noise in high frequency intraday data – as noted in Sections 3.2 and 4 – make coefficient point-estimation of independent events and corresponding time intervals following the events implausible (Andersen and Bollerslev 1997). The inclusion of an FOMC rate decision event as a 1-minute dummy variable in eq.[5], for example, would result in an insignificant coefficient estimate given the aforementioned infrequency of such an event. To control for this feature of our dataset, one option is to extend event dummy variables to a longer time horizon, say 60 minutes following the event instead of 1 minute. This solution would improve the chances of getting significant coefficient estimates. These last, however, would provide only a broad-brush picture of the immediate impact of information arrival on the volatility of exchange rate. In this case, the coefficient estimates would only suggest some impact on volatility during the 60-minute event window. Empirical estimates of eq.[5] with 60-minute dummy variables capturing rumour events are reported in Table 6.

Andersen and Bollerslev (1997) have proposed an alternative methodology to gain better insight into the instantaneous and cumulative impact of information events on price variability. They propose that volatility response in exchange rates following information arrival can be proxied with an average volatility pattern across all such events. They calibrate this pattern by fitting a third-order polynomial to volatility observations during announcement event windows. The fitted volatility response pattern is then included in the FFF regression as an explanatory variable to calculate the degree to which absolute returns during the event "load onto" this pattern. The implication of this is that, for each information event k and subsequent N_k time intervals, the $I_k(t,n)$ term in eq.[5] is replaced with a calibrated volatility response pattern $\gamma(i)$ where $i = 0,1,2 \dots, N_k$. Given that this volatility response pattern is pre-determined, an estimated coefficient λ_k loading onto this pattern during event k, enables the calculation of the immediate volatility impact of an information event. The immediate volatility response in absolute returns (from eq.[6]) is given by $\exp(\hat{\lambda}_k \cdot \gamma(0)/2) - 1$, whereas the same response for the subsequent time intervals is given by $\exp(\hat{\lambda}_k \cdot \gamma(i)/2) - 1$. The cumulative response in absolute returns for the full event window is calculated as:

$$M(k) = \sum_{i=0}^{N_k} \left[\exp\left(\frac{\hat{\lambda}_k \cdot \gamma(i)}{2} \right) - 1 \right] \quad [7]$$

While Andersen and Bollerslev (1997) adopt a single volatility response pattern for macroeconomic information arrival, we calibrate four volatility response patterns specific to the type of macroeconomic information event and calibrate a further volatility response pattern specific to rumour event windows. The intuition is that the volatility response pattern following information arrival differs depending on the speed of information arrival as well as the type of information content. For instance, during macroeconomic events such as the ECB rate decision where a press conference is held, information arrival is incremental. This is contrary to macroeconomic data release, where information arrival is immediate.

We calibrate volatility response patterns specific to ECB rumour events, ECB rate decision events, FOMC rate decision events, slow-release public information events (FOMC minutes, FOMC and ECB prominent speakers) and fast-release public information events (US Employment report, US GDP, US CPI, US ISM manufacturing data, US consumer confidence, German ZEW economic confidence data, German IFO economic confidence data, Eurozone CPI, US retail sales data, US Durable Goods, US Manufacturing PMI, German Employment Report, European PMI manufacturing, German Industrial Production and German Factory Orders).

The four volatility response patterns for macroeconomic announcements are calibrated by fitting a third-order polynomial to the dummy variables attached to the event windows for the four categories of macroeconomic information. The polynomial restricts the volatility response window to 60 minutes for all macroeconomic information releases, except the ECB and FOMC rate decisions, for which the response window is extended to 120 minutes to accommodate the lengthy press conference that follows the decision announcement.

The third-order polynomials calibrated for the volatility response following ECB (eq.[8]) and FOMC rate decisions (eq.[9]) are provided below:

$$\gamma(i) = 5.577[1 - (i/120)^3] - 0.127\left[1 - (i/120)^2\right]i + 0.00301[1 - (i/120)]i^2 \quad [8]$$

$$\gamma(i) = 8.856[1 - (i/120)^3] - 0.228\left[1 - (i/120)^2\right]i + 0.00412[1 - (i/120)]i^2 \quad [9]$$

where $i = 0,1,2 \ldots ,120$. We then specify the third-order polynomials calibrated for the volatility response following slow-release public information events (eq.[10]) and fast-release public information events (eq.[11]) as follows:

$$\gamma(i) = 3.850[1 - (i/60)^3] - 0.218\left[1 - (i/60)^2\right]i + 0.00733[1 - (i/60)]i^2 \qquad [10]$$

$$\gamma(i) = 4.527[1 - (i/60)^3] - 0.326\left[1 - (i/60)^2\right]i + 0.0100[1 - (i/60)]i^2 \qquad [11]$$

where $i = 0,1,2 \ldots ,60$.

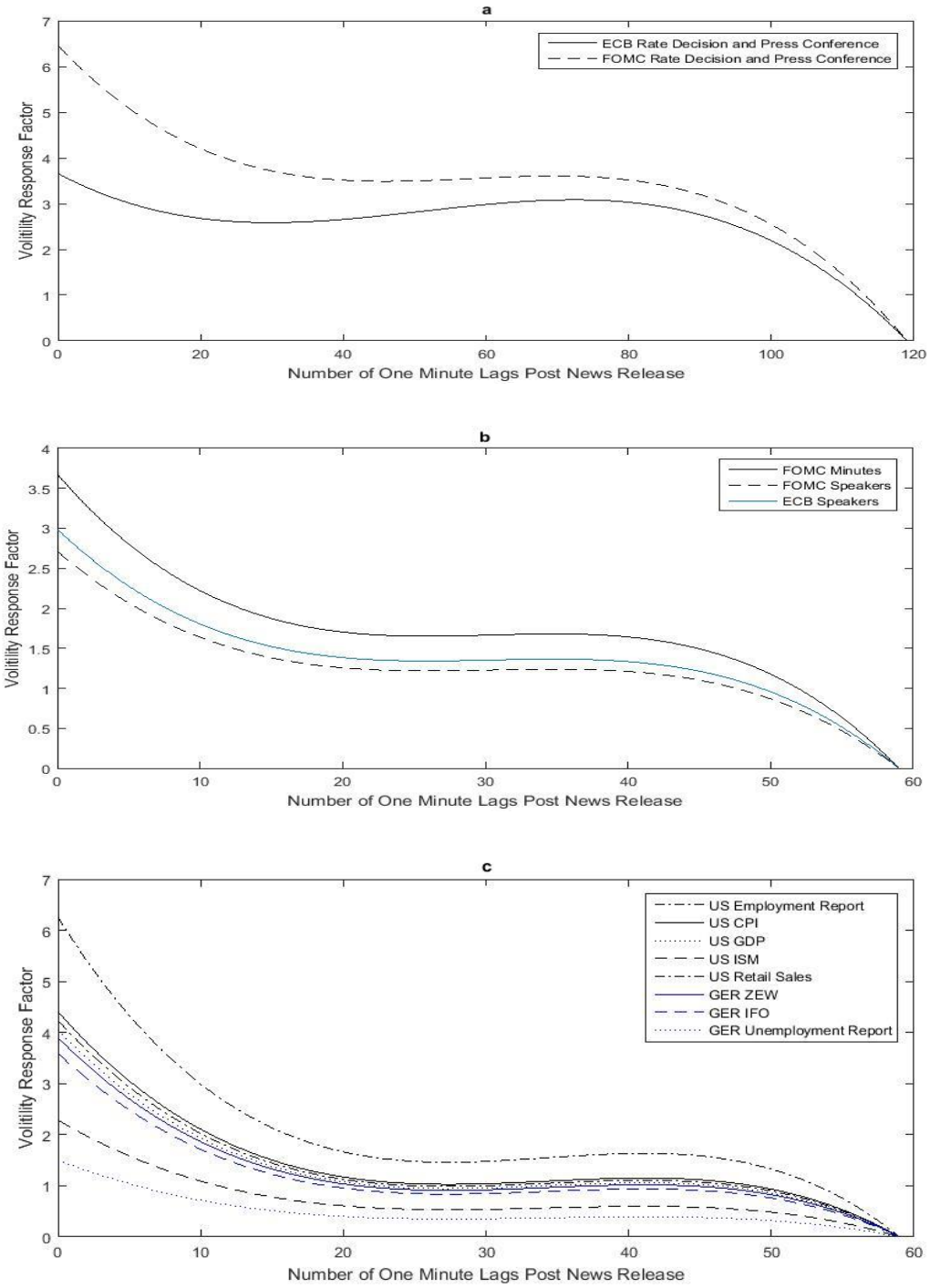
The volatility response pattern for ECB rumour event windows is calibrated through a higher 7th-order polynomial fitted to all parameters of eq.[5] relevant for ECB rumour event windows. The choice of higher-order polynomial allows for more flexibility in capturing greater fluctuations in the volatility pattern throughout rumour event windows. Intuitively, the ambiguous nature of market rumours could in fact result in a less cohesive price formation process. From experimentation and evidence presented in Figure 8 we can see that, contrary to 'fundamental' macroeconomic events, the volatility response following rumour events does not decay consistently across the event window. There is a distinct decrease, followed by an increase in volatility response for five 1-minute intervals following the arrival of a rumour before volatility begins to decay again. A higher-order polynomial allows for better calibration of this distinct pattern. The 7th-order polynomial calibrated for the volatility response following ECB rumour events (eq.[12]) is specified as follows:

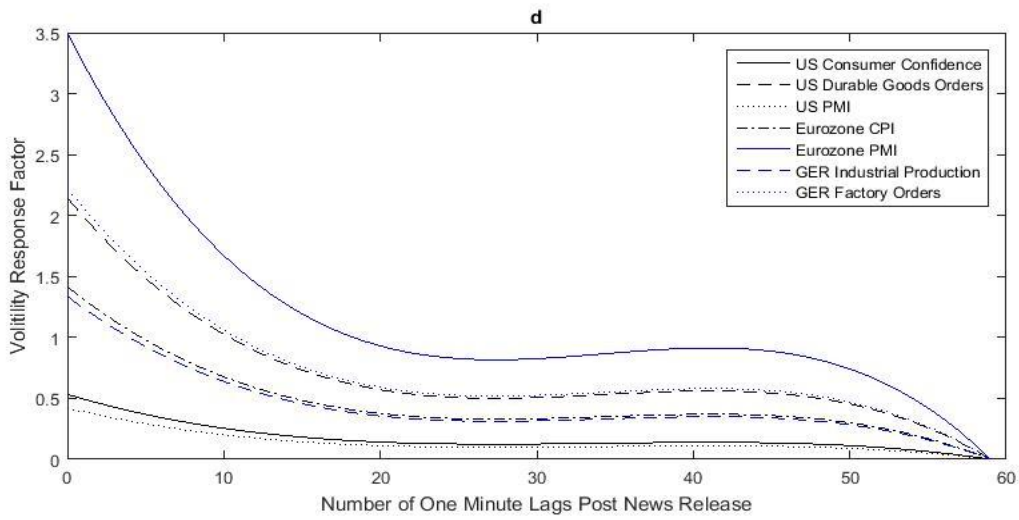
$$\gamma(i) = 2.75e^{-10}i^7 - 6.60e^{-8}i^6 + 6.25e^{-6}i^5 - 2.98e^{-4}i^4 - 0.0075i^3 + 0.096i^2 - 0.52i + 0.19 \qquad [12]$$

where $i = 0,1,2 \ldots ,60$.

Figure 7

(a) Estimated volatility response pattern for FOMC and ECB rate decision event windows. (b) Estimated volatility response pattern for slow-release public information events. (c and d) Estimated volatility response pattern for fast-release public information events.





5.4. Public information announcement effect

Figure 7 illustrates the shape of the estimated volatility-response patterns calculated as $\hat{\lambda}(k,i) = \hat{\lambda}_k \cdot \gamma(i)$ for each of the 20 macroeconomic public information announcements. Figure 7a illustrates the volatility-response patterns following ECB and FOMC rate decisions, where their different scale is determined by the degree to which absolute returns during such events load onto the decay structures of eqs.[8]-[9]. Figure 7b depicts the volatility-response patterns following slow-release macroeconomic announcements. Also, in this case, such patterns are determined by the degree to which absolute returns during such events load onto decay structure of eq.[10]. Figure 7c and 7d display the response patterns for the fast-release macroeconomic data announcements where the volatility-decay structure is specified in eq.[11]. The volatility persists at a higher level and for a longer time horizon during ECB and FOMC rate decisions. For slow-release public information, the immediate volatility response is smaller but decays at a slower rate. The volatility response to fast-release economic data announcements, is more immediate but volatility decays at a far faster rate.

Table 5 reports the empirical estimates of the loading coefficient $\hat{\lambda}_k$ for all 20 macroeconomic information announcements. Such coefficients are OLS estimates of eq.[5] where the $I_k(t,n)$ dummy variable refers to the predetermined volatility-response patterns associated with the relevant type of macroeconomic information, as determined by eqs.[8]-[11]. All but two of the 20 public information announcements are significant at the 5% level. The announcements are ranked by order of largest instantaneous impact on absolute returns, calculated as $\exp\left(\hat{\lambda}_k \cdot \gamma(0)/2\right) - 1$.

Table 5
Public information arrival effects on the volatility of 1-minute EUR-USD exchange rate returns.

Public information announcements	**Coefficient** $\hat{\lambda}_k$	**t-Stat**	**Instantaneous increase in volatility (%)**	**Effect on daily cumulative absolute returns (%)**
FOMC Rate Decision	0.729	36.55	2423.563	49.36
US Employment Report	1.382	19.82	2183.577	19.35
US CPI (Cat 1)	0.973	9.981	805.590	6.619
US Retail Sales (Cat 2)	0.935	10.78	730.839	9.602
US GDP (Cat 1)	0.894	9.155	656.767	8.890
German ZEW (Cat 1)	0.861	8.860	602.211	8.349
FOMC Minutes	0.955	22.42	528.481	6.675
ECB Rate Decision	0.656	21.49	523.766	35.53
German IFO (Cat 1)	0.792	8.188	501.201	5.737
Eurozone Manufacturing PMI (Cat 2)	0.772	7.973	474.424	5.510
ECB Speakers	0.776	9.454	345.261	6.619
FOMC Speakers	0.704	9.268	287.847	4.693
US ISM (Cat 1)	0.505	4.928	213.608	3.819
German Factory Orders (Cat 2)	0.491	5.214	203.625	2.364
US Durable Goods (Cat 2)	0.474	4.838	192.256	3.513
German Employment Report (Cat 2)	0.332	3.426	111.979	1.772
Eurozone CPI YoY (Cat 1)	0.313	3.216	102.876	1.349
German Industrial Production (Cat 2)	0.295	3.137	95.057	1.541
US Consumer Confidence (Cat1)	0.118	1.191	30.526	0.707
US Manufacturing PMI (Cat 2)	0.093	0.897	23.406	0.512

To provide an example, the estimated FOMC rate decision loading coefficient implies that $\exp(\hat{\lambda}_k \cdot \gamma(0)/2) = \exp((0.729 \cdot 8.856)/2) = 25.23$ – this is tantamount to an approximately 2423% $((25.23 - 1) \cdot 100)$ instantaneous increase in the 1-minute absolute returns following FOMC rate decisions. The cumulative impact as outlined in eq.[7] would be 678.64. Given that 1-minute average absolute returns, during the 1800 to 2000 GMT time 120-minute horizon for FOMC rate decisions, are approximately equal to 0.008% and that average cumulative absolute returns for the trading days in our sample equal 11%, on days when FOMC rate decisions take place there is an average increase of approximately $(678.64 \cdot 0.008)/11 = 49.36\%$ in cumulative absolute returns.

The results presented in Table 5 show that public announcements – ‘fundamental’ to the price formation process by proponents of the Efficient Market Hypothesis – do have a considerable immediate and cumulative impact on price variability. The relative infrequency of such events, however, means that a very small proportion of overall sample volatility can be attributed to such events. Nonetheless, these results show that the FFF regression model in use is able to capture the effects of macroeconomic announcement events, and therefore it can be used as useful term of comparison for the results of the next section.

5.5 ECB rumours arrival effects

We take two approaches in identifying the impact of ECB rumour events on the volatility of EUR-USD absolute returns. The first is to model each ECB rumour event as a 60-minute dummy variable in eq.[5]. Here the $I_k(t,n)$ dummy variables (for k = 1, .., 63), included in the full FFF regression take unity value for rumour event k for the sixty minutes after rumour arrival. In this case, the macroeconomic event dummy variables also take unity value for their respective event windows. The coefficient estimates $\hat{\lambda}_k$ for this approach captures the degree to which volatility is affected during the full 60-minute rumour event window. The second approach consists of including each ECB rumour event as the 60-minute volatility response pattern as specified by eq.[12]. In this case, also the macroeconomic control variables are modelled through their volatility responses as specified by eqs.[8]-[11]. The coefficient estimates $\hat{\lambda}_k$ for this second approach captures the degree to which absolute returns, during each rumour event window, load onto the pre-specified volatility response pattern.

Table 6 provides empirical results for the first approach. The rumour events are ranked by the magnitude of their coefficient estimates attached to the 60-minute dummy variables. Of the 63 rumour events, 25 events result in a significant increase in the volatility of absolute returns. The largest increase is associated with the arrival of a rumour stating that the ECB Governing Council has drawn up a proposal which calls for quantitate easing to the magnitude of €50 billion on a monthly basis. To provide an example, the coefficient estimate of 3.475 for this rumour, implies an $\exp(3.475/2) - 1 = 209.05\%$ increase in the volatility of absolute returns for the respective event arrival.

The results presented in Table 6 show that the significant rumour events have a positive shock on absolute returns. In line with expectations, all of these rumours produce a positive impact on volatility, with no rumour having a significant and negative impact.

The above analysis based on the use of dummy variables provides little insight into how the volatility process during the event window evolves. We therefore move on to the second approach outlined that should allow greater insight into the immediate and ensuing volatility impact of rumour events.

Table 6
Rumours of ECB action: effects on the volatility of 1-minute EUR-USD exchange rate measured as absolute returns for a 60-minute event window. Details given for coefficient estimates of the 25 ECB rumour events found to be statistically significant.

ECB rumour events	Coefficient $\widehat{\lambda_k}$	t-Stat	Inferred increase in volatility (%)
ECB Sources: QE proposal calls for roughly €50 billion in bond buying per month	3.475	4.745	209.054
ECB Sources: Governing council considering negative deposited rate of 0.1%	3.102	4.237	173.531
ECB Sources: Existential threat to Euro if fiscal policy reform is not tackled	3.061	4.181	169.986
ECB Sources: Governing council may not have reached lower bound on key rate	2.894	3.953	156.389
ECB Sources: Central bankers to challenge Draghi on leadership style	2.644	3.611	138.006
ECB Sources: Governing council likely to refrain from new measures for next few months	2.609	3.563	135.594
ECB Sources: Said to allow 24 hours to make smaller ABS purchases	2.598	3.549	134.883
ECB Sources: New ECB action next week is unlikely	2.514	3.434	129.317
ECB Sources: ECB raising ELA for Greek banks to €71 billion	2.110	2.882	105.663
ECB Sources: ECB and Treasury building emptied under security concern	2.096	2.862	104.906
ECB Sources: Rate change unlikely. LTRO not on top of the communication agenda	2.079	2.839	104.021
ECB Sources: ECB to accept Greek bonds as collateral if deal is reached	2.026	2.759	101.293
ECB Sources: ECB won't accept Greek bond swap and wants full repayment	2.017	2.755	100.860
ECB Sources: ECB has approved additional €400 billion for Greek banks as emergency liquidity	1.860	2.540	93.239
ECB Sources: ECB cites barriers to QE. Need to let old measures work	1.799	2.456	90.418
ECB Sources: ECB to allow Greek banks ELA up to €60 billion	1.723	2.352	87.047
ECB Sources: Bundesbank still striving to put limits on ECB QE	1.716	2.344	86.765
ECB Sources: Bundesbank sources say they are willing to accept significant stimulus package	1.652	2.180	84.038
ECB Sources: Weidmann opposed to today's rate cut	1.574	2.113	80.810
ECB Sources: No major policy change expected in January	1.537	2.099	79.335
ECB Sources: ECB buying Spanish short dated covered bonds	1.401	2.091	74.108
ECB Sources: Markets over interpreting possibility of QE. No consensus but intense debate	1.385	2.068	73.543
ECB Sources: Preparing package of measures, including cuts to all 3 rates for June meeting	1.324	1.976	71.312
ECB Sources: Governing council prefer additional time to assess current measures	1.277	1.972	69.672
ECB Sources: G.C discussing ABS purchases worth up to €500 billion which could start this year	1.268	1.970	69.351

Table 7 reports empirical results of the loading coefficient $\hat{\lambda}_k$ for rumour events k. The coefficient estimates are based on OLS estimation of eq.[5] where the $I_k(t,n)$ variables refer to the predetermined volatility response patterns associated with the ECB rumour event windows, as specified in eq.[12]. Of the 63 event windows following ECB rumour arrival, 20 events are found to have significant loading coefficient $\hat{\lambda}_k$.

The rumour events are ranked by order of biggest instantaneous impact on absolute returns calculated as $\exp(\hat{\lambda}_k \cdot \gamma(0)/2) - 1$. To provide an example, the estimated loading coefficient for the ECB rumour, 'ECB Sources: QE proposal calls for roughly €50 billion in bond buying per month', implies $\exp(\hat{\lambda}_k \cdot \gamma(0)/2) = \exp((3.692 \cdot 0.615)/2) = 3.11$. This is equivalent to an approximately 211% $((3.11 - 1) \cdot 100))$ instantaneous increase in the 1-minute absolute return interval following the arrival of this rumour.

The cumulative impact obtained by applying eq.[7] is as large as 134.95. Given that 1-minute average absolute returns during the 1430 to 1530 GMT event window for this rumour are approximately equal to 0.013% and that average cumulative absolute returns for the trading days in our sample equals 11%, the arrival of this ECB rumour has an average increase of approximately $(134.95 \cdot 0.013)/11 = 15.95\%$ in cumulative absolute returns.

The twenty rumour events found to significantly load onto the volatility response patterns of eq.[12] are the same as those found to have the most significant coefficients in Table 6 – when the rumour event window was a basic 60-minute dummy variable for each event. This would suggest that rumour events with the biggest volatility impact load onto the predetermined volatility response pattern more effectively.

Figure 8 depicts the shape of the estimated volatility response patterns calculated as $\hat{\lambda}(k,i) = \hat{\lambda}_k \cdot \gamma(i)$ for the 5 ECB rumour event windows with the biggest loading coefficients. Such patterns are dependent on the degree to which absolute returns during ECB rumour events load onto the decay structures given by eq.[12].

The volatility decay structure following rumour arrival is more complex than that of macroeconomic information. There are instantaneous jumps in the volatility of absolute returns in the first minute interval following rumour arrival.

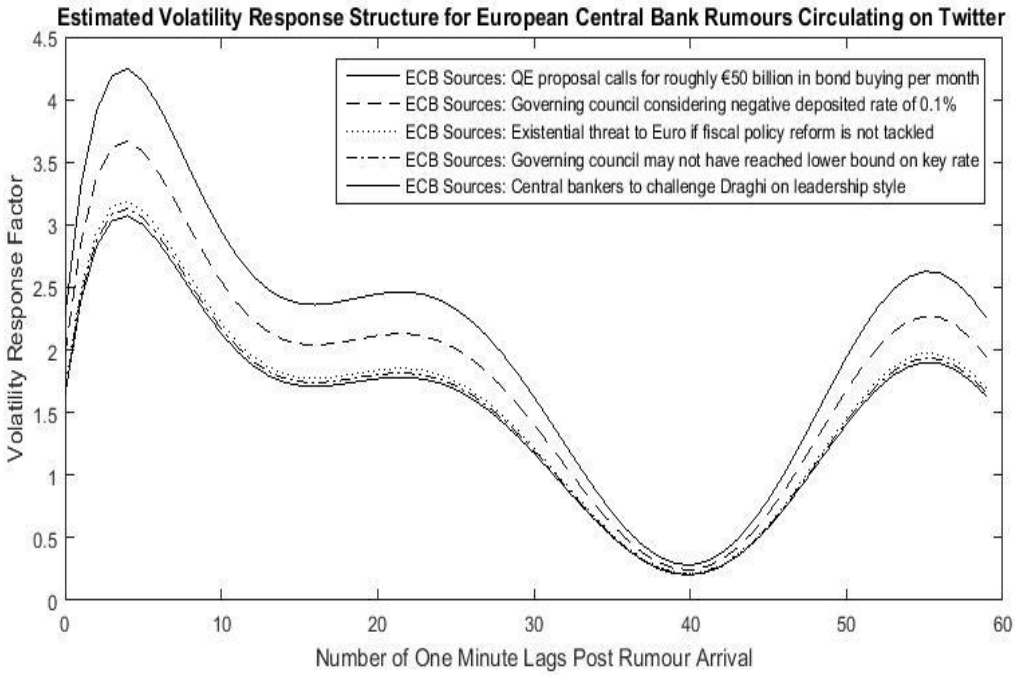
Table 7
Rumours of ECB action: effects on the volatility of 1-minute EUR-USD exchange rate as measured by absolute returns. Details given for the 20 rumour events which have significant 'loading' coefficient $\hat{\lambda}_k$ estimates for the volatility decay structure specified by eq.[12].

ECB rumour events	Coefficient $\hat{\lambda}_k$	t-Stat	Instantaneous increase in volatility (%)	Increase in daily cumulative absolute returns (%)
ECB Sources: QE proposal calls for roughly €50 billion in bond buying per month	3.692	4.544	211.199	15.949
ECB Sources: Governing council considering negative deposited rate of 0.1%	3.190	3.926	166.647	13.166
ECB Sources: Existential threat to Euro if fiscal policy reform is not tackled	2.775	3.415	134.711	10.415
ECB Sources: Governing council may not have reached lower bound on key rate	2.720	3.347	130.774	9.363
ECB Sources: Central bankers to challenge Draghi on leadership style	2.671	3.287	127.350	9.796
ECB Sources: Governing council likely to refrain from new measures for next few months	2.624	3.230	124.089	9.523
ECB Sources: Said to allow 24 hours to make smaller ABS purchases	2.512	3.092	116.500	8.894
ECB Sources: New ECB action next week is unlikely	2.249	2.768	99.674	7.519
ECB Sources: ECB raising ELA for Greek banks to €71 billion	2.185	2.688	95.760	6.689
ECB Sources: ECB and Treasury building emptied under security concern	2.184	2.688	95.712	6.685
ECB Sources: Rate change unlikely. LTRO not on top of the communication agenda	2.177	2.680	95.318	6.656
ECB Sources: ECB to accept Greek bonds as collateral if deal is reached	2.154	2.650	93.904	4.535
ECB Sources: ECB won't accept Greek bond swap and wants full repayment	2.110	2.597	91.333	6.359
ECB Sources: ECB has approved additional €400 billion for Greek banks as emergency liquidity	2.086	2.567	89.919	5.292
ECB Sources: ECB cites barriers to QE. Need to let old measures work	2.067	2.544	88.829	4.274
ECB Sources: ECB to allow Greek banks ELA up to €60 billion	2.067	2.539	88.793	6.646
ECB Sources: Bundesbank still striving to put limits on ECB QE	1.935	2.382	81.313	5.620
ECB Sources: Weidmann opposed to today's rate cut	1.911	2.351	79.961	4.672
ECB Sources: No major policy change expected in January	1.895	2.332	79.063	5.876
ECB Sources: Bundesbank sources say they are willing to accept significant stimulus package	1.792	2.206	73.510	3.498

Such jumps are then followed by a sharp increase in volatility that reaches its peak at the 6th one-minute interval. At this point, volatility declines gradually before increasing again following the 40th one-minute interval. For flexibility, by design, the 7th order polynomial set

out in eq.[12] does not reach zero. This is justified given that volatility persistence is evident, in Figure 8, up to the 60th minute and beyond.

Figure 8
Five rumour events with the largest volatility response factor are graphed below.



All in all, the empirical findings detailed in this section show that there is a significant increase in the volatility of EUR-USD rate for 60-minute event windows during which ECB rumours arrive and circulate on Twitter. The rumour events with the biggest volatility impact follow quite similar volatility response patterns, producing jumps in absolute returns as large as 211% and increases in cumulative daily absolute returns as large as 15%. These findings point to the existence of a form of actionable market information able to explain a significant share of the large volatility in the EUR-USD spot exchange rate.

As a further test of our central hypothesis, we carry out empirical estimates of eq.[5] for a split sample of days with rumour and days without rumour. Due to the existence of days with multiple rumours, this is tantamount to 58 days (83,520 observations) with rumours and 356 days (512,640) without rumours. The R^2 for the sample with and without ECB rumours is calculated to be 0.1032 and 0.0933 respectively. This is tantamount to a 10.61% improvement in explaining excess volatility with the discernment of ECB rumours.

6. Conclusions

This study identifies market-relevant rumours as a form of public information that has been largely overlooked by price discovery literature. We present a new database of previously undetected public information that is able to explain a substantial share of the excess volatility observed on foreign exchange markets. We therefore assert that such rumours are actionable information as – by changing market consensus upon broadcast – they have substantial impact on the volatility of the EUR-USD exchange rate. More specifically, we pinpoint the arrival of 63 rumours of forthcoming ECB action, as broadcast via Twitter, to within 1-minute accuracy. We show that 25 of such rumours have a pronounced impact on the volatility of 1-minute EUR-USD exchange rate returns for a 420-day sample period. The instantaneous increase in volatility during the first minute of rumour arrival is up to 211%, while the cumulative increase in volatility over a 60-minute window is as much as 2614%.

The findings of this paper demonstrate the existence of financial market-relevant information seemingly discerned by market agents but overlooked by economists. The identification of rumour information events as a determinant in the price formation process offers new opportunities to understand the proportion of volatility in financial markets left unexplained by the arrival of scheduled and unscheduled public information as broadcast via incumbent financial market news sources such as Bloomberg and Reuters. Furthermore, the hypothesis attributing market volatility to private information can be, to some extent, scaled down in the light of the existence of market rumours previously misidentified as private information that can, in fact, be classified as public information.

Our empirical results highlight a number of implications for both central banks and market regulators. The existence of such 'actionable information' suggests that an unofficial channel of communication exists between central banks and market participants. This may be a transmission mechanism through which sensitive information can be incrementally passed onto the market in order to prevent overwhelming volatility events. Alternatively, the existence of such rumours may be in direct violation of the central banks' intent, in which case the acknowledgement and repudiation of such rumours is of vital importance for the central bank. For the market regulator there are implications in terms of informational efficiency. It is plausible to argue that the existence of 'actionable rumours' via Twitter increases the informational efficiency of financial markets. The network of 'in the know' market commentators provides market participants with a source of free market-relevant information

at the point of delivery – the same type of information that is often highly expensive to retrieve in real time via incumbent newswires. In principle, such a reduction in the cost of information might mitigate informational asymmetries, making informed trading less costly and therefore reducing the role of speculative trading. This assertion remains valid, with the caveat that rumours are indeed actionable and not ‘noise’. The efficient distinction between ‘actionable rumours' and ‘noise’ can depend on the market agent’s ability to discern reliable ‘in the know’ commentators. Further, the lack of regulatory jurisdiction over Twitter needs to be addressed given the degree to which information disseminated through Twitter can impact market prices, as we have shown in this paper. The deliberate distribution of false market-relevant news via Twitter may result in significant volatility events beneficial to the distributor.

There are significant opportunities for further research supported by the findings of this study and the rumour dataset identified in our empirical analysis. For instance, uncertainty and risk perception measures could be used as a control variable to investigate the relative importance of rumours. Bilgin et al. 2018 and Gozgor et al. 2016 show that uncertainty measures such as the VIX, partisan conflict and global economic policy uncertainty indexes contribute in a non-linear manner to the price formation process in commodity markets. The transmission of rumours into price may also be monetary policy or business cycle dependent, in which case an investigation in line with the aforementioned literature could prove productive. Another avenue for further research would involve the investigation of the credibility of rumour broadcasters over time. The results could provide a novel metric for testing the long-term efficiency of markets under the adaptive market hypothesis.

References

Ahern, K.R., & Sosyura, D. (2015). Rumor has it: Sensationalism in financial media. *Review of Financial Studies*, *28*(7), 2050–2093.

Altavilla, C., Giannone, D., & Modugno, M. (2017). Low frequency effects of macroeconomic news on government bond yields. *Journal of Monetary Economics*, *92*, 31–46.

Andersen, T.G., & Bollerslev, T. (1998). Deutsche mark–dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies. *Journal of Finance*, *53*(1), 219–265.

Andersen, T.G., & Bollerslev, T. (1997a). Heterogeneous information arrivals and return volatility dynamics: Uncovering the long-run in high-frequency returns. *Journal of Finance*, *52*(3), 975–1005.

Andersen, T.G., & Bollerslev, T. (1997b). Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance*, *4*(2), 115–158.

Andersen, T.G., Bollerslev, T., & Cai, J. (2000). Intraday and interday volatility in the Japanese stock market. *Journal of International Financial Markets, Institutions and Money*, *10*(2), 107–130.

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

Andersen, T.G., Bollerslev, T., Diebold, F.X., & Vega, C. (2007). Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics*, *73*(2), 251–277.

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

Balduzzi, P., Elton, E.J., & Green, T.C. (2001). Economic news and bond prices: Evidence from the US Treasury market. *Journal of Financial and Quantitative Analysis*, *36*(04), 523—543.

Banerjee, A.V. (1993). The economics of rumours. *Review of Economic Studies*, *60*(2), 309–327

Barclay, M.J., Litzenberger, R.H., & Warner, J.B. (1990). Private information, trading volume, and stock-return variances. *Review of Financial Studies*, *3*(2), 233–253.

Bauwens, L., Omrane, W.B., & Giot, P. (2005). News announcements, market activity and volatility in the euro/dollar foreign exchange market. *Journal of International Money and Finance*, *24*(7), 1108–1125.

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

Bloomberg. Bloomberg adds enhanced custom alerts and tools to its Twitter offering. [Press release]. (16 September 2015). Available

at: https://www.bloomberg.com/company/announcements/bloomberg-and-twitter-sign-data-licensing-agreement/.

Bollerslev, T., Cai, J., & Song, F.M. (2000). Intraday periodicity, long memory volatility, and macroeconomic announcement effects in the US Treasury bond market. *Journal of Empirical Finance*, *7*(1), 37-55.

Bomfim, A.N. (2003). Pre-announcement effects, news effects, and volatility: Monetary policy and the stock market. *Journal of Banking & Finance*, 27(1), 133–151.

Campbell, J.Y., Lo, A., & MacKinlay, A.C. (1997). *The econometrics of financial markets* Princeton, N.J: Princeton University Press..

Chaboud, A.P., Chiquoine, B., Hjalmarsson, E., & Vega, C. (2014). Rise of the machines: Algorithmic trading in the foreign exchange market. *Journal of Finance*, *69*(5), 2045–2084.

Chang, Y., & Taylor, J. S. (2003). Information arrivals and intraday exchange rate volatility, *Journal of International Financial Markets, Institutions and Money*, *13*(2), 85–112.

Chou, H.I., Tian, G.Y., & Yin, X. (2015). Takeover rumours: Returns and pricing of rumoured targets. *International Review of Financial Analysis*, *41*, 13–27.

Conrad C., & Lamla M. (2010). The high-frequency response of the EUR-US dollar exchange rate to ECB communication. *Journal of Money, Credit and Banking*, *42*(7), 1391–1417.

Cook, T., & Korn, S. (1991). The reaction of interest rates to the employment report: The role of policy anticipation. *Economic Review*, 3–12.

Cutler, D.M., Poterba, J.M., & Summers, L.H. (1989). What moves stock prices? *Journal of Portfolio Management*, *15*(3), 4–12.

De Long, J.B., Shleifer, A., Summers, L.H., & Waldmann, R.J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703–738.

Dickey, D.A., & Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427–431.

Engle, R. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. *Journal of Economic Perspectives*, 157–168.

Fama, E. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, *25*(2), 383–417.

Faust, J., Rogers, J. H., Wang, S. Y. B., & Wright, J. H. (2007). The high-frequency response of exchange rates and interest rates to macroeconomic announcements. *Journal of Monetary Economics*, *54*(4), 1051–1068.

Fleming, M., & Remolona, E. (1999). Price formation and liquidity in the US treasury market: The response to public information. *Journal of Finance*, *54*(5), 1901–1915.

French, K.R., & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics*, *17*(1), 5–26.

Gao, Y., & Oler, D. (2012). Rumors and pre-announcement trading: Why sell target stocks before acquisition announcements? *Review of Quantitative Finance and Accounting*, *39*(4), 485–508.

Gropp, R., & Kadareja, A. (2012). Stale information, shocks, and volatility. *Journal of Money, Credit and Banking*, *44*(6), 1117–1149.

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

Hailiang Chen, H., De, P., & Hwang, B. H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies*, 27(5), 1367–1403.

Harju, K., & Hussain, S.M. (2011). Intraday seasonalities and macroeconomic news announcements. *European Financial Management*, *17*(2), 367-390.

Ito, T., & Lin, W.L. (1992). Lunch break and intraday volatility of stock returns: An hourly data analysis of Tokyo and New York stock markets. *Economics Letters*, *39*(1), 85–90.

Ito, T., Lyons, R.K., & Melvin, M.T. (1998). Is there private information in the FX market? The Tokyo experiment. *Journal of Finance*, *53*(3), 1111–1130.

Kosfeld, M. (2005). Rumours and markets. *Journal of Mathematical Economics*, *41*(6), 646–664.

Kurov, A., & Stan, R. (2018). Monetary policy uncertainty and the market reaction to macroeconomic news. *Journal of Banking and Finance 86*, 127–142

Kuttner, K.N. (2001). Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. *Journal of Monetary Economics*, *47*(3), 523–544.

Li, W., Wong, M.C., & Cenev, J. (2015). High-frequency analysis of macro news releases on the foreign exchange market: A survey of literature. *Big Data Research*, *2*(1), 33–48.

Lo, A.W. (2004). The adaptive markets hypothesis. *Journal of Portfolio Management*, *30*(5), 15–29.

Lucca, D.O., & Moench, E., 2015. The Pre-FOMC announcement drift. *Journal of Finance*, *70*(1), 329–371.

Lyons, R.K. (2001. *The microstructure approach to exchange rates* (Vol. 12). Cambridge, MA: MIT Press.

Menkhoff, L. (2010). High-frequency analysis of foreign exchange interventions: What do we learn? *Journal of Economic Surveys*, *24*(1), 85–112.

Mitchell, M.L., & Mulherin, J.H. (1994). The impact of public information on the stock market. *Journal of Finance*, *49*(3), 923–950.

Nekovee, M., Moreno, Y., Bianconi, G., & Marsili, M. (2007). Theory of rumour spreading in complex social networks. *Physica A: Statistical Mechanics and its Applications*, *374*(1), 457–470.

Oberlechner, T., & Hocking, S. (2004). Information sources, news, and rumours in financial markets: Insights into the foreign exchange market. *Journal of Economic Psychology*, *25*(3), 407–424.

Payne, R. (1996). *Announcement effects and seasonality in the intra-day foreign exchange market* (No. dp238). Financial Markets Group.

Pound, J., & Zeckhauser, R. (1990). Clearly heard on the street: The effect of takeover rumours on stock prices. *Journal of Business*, 291–308.

Renault, T. (2017). Intraday online investor sentiment and return patterns in the U.S. stock market. *Journal of Banking and Finance 84*, 25–40.

Riordan, R., Storkenmaier, A., Wagener, M., & Zhang, S.S. (2013). Public information arrival: Price discovery and liquidity in electronic limit order markets. *Journal of Banking and Finance*, 37(4), 1148–1159.

Siganos, A., Vagenas-Nanos, E., & Verwijmeren, P. (2017). Divergence of sentiment and stock market trading. *Journal of Banking and Finance*, *78*, 130–141.

Smales, L.A. (2013). Impact of macroeconomic announcements on interest rate futures: high-frequency evidence from Australia. *Journal of Financial Research*, *36*(3), 371–388.

Sul, H. K., & Dennis, A. R. (2017). Trading on Twitter: Using social media sentiment to predict stock returns. *Decision Sciences*, *48*(3), 454–488.

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

Timm O., Sprenger, T., Sandner, P., Tumasjan, A., & Welpe, I. M. (2014). News or noise? Using Twitter to identify and understand company-specific news flow. *Journal of Business Finance and Accounting*, *41*(7), 791–830.

Zivney, T.L., Bertin, W.J., & Torabzadeh, K.M. (1996). Overreaction to takeover speculation. *The Quarterly Review of Economics and Finance*, *36*(1), 89–115.

Appendix

List of 'ECB sources' stories quoted by more than 50 Twitter accounts.

Timestamp	ECB Rumour Quote
01/10/2013 1320	ECB Sources: New LTRO may not yield benefit if launched now
22/10/2013 1433	ECB Sources: ECB to impose 8% capital buffer on Eurozone banks
25/10/2013 1115	ECB Sources: Governing council hesitant over negative rates
29/10/2013 1423	ECB Sources: No realistic prospect of refinancing or deposit rate cut
06/11/2013 1449	ECB Sources: Rate change unlikely. LTRO not on top of the communication agenda
07/11/2013 1605	ECB Sources: Weidmann opposed to today's rate cut
11/11/2013 1047	ECB Sources: Considering package of stimulus for December meeting
20/11/2013 1514	ECB Sources: Governing council considering negative deposited rate of 0.1%
26/11/2013 1449	ECB Sources: 25 basis point rate cut and negative repo rate discussed
06/01/2014 1530	ECB Sources: No major policy change expected in January
28/01/2014 1139	ECB Sources: Governing council content with current monetary policy stance
04/02/2014 0649	ECB Sources: Draghi looking closer at ending SMP sterilization
05/02/2014 0953	ECB Sources: No consensus among governing council members on action tomorrow
26/02/2014 0910	ECB Sources: No consensus among governing council members for March policy move
13/03/2014 1423	ECB Sources: ECB and Treasury building emptied under security concern
19/03/2014 1039	ECB Sources: Spanish banks face property reviews for ECB check-up
02/04/2014 0909	ECB Sources: Markets over-interpreting possibility of QE. No consensus but intense debate
24/04/2014 1141	ECB Sources: No consensus among governing council members for May policy action
13/05/2014 1104	ECB Sources: Bundesbank sources say Bubba willing to accept significant stimulus
14/05/2014 0827	ECB Sources: Preparing package of measures, including cuts to all 3 rates for June meeting
20/05/2014 1102	ECB Sources: Considering 6-week meeting schedule to help write minutes, take policy decisions
02/06/2014 1651	ECB Sources: ECB to lead revamp of global FX code of conduct
04/06/2014 0641	ECB Sources: Draghi is likely to signal rate cut this week, won't necessarily be the last
16/06/2014 1341	ECB Sources: Governing council likely to refrain from new measures for next few months
26/06/2014 1434	ECB Sources: Governing council may not have reached lower bound on key rate
22/07/2014 1251	ECB Sources: June rate cut affecting markets exactly the way Governing council want
27/08/2014 1510	ECB Sources: New ECB action next week is unlikely
28/08/2014 0010	ECB Sources: ECB policy action unlikely without inflation slump
29/08/2014 1127	ECB Sources: No consensus among governing council members on QE next week
04/09/2014 1137	ECB Sources: G.C. discussing ABS purchases worth up to €500 billion which could start this year
08/09/2014 0757	ECB Sources: Policy measures could amount to €500 billion
21/10/2014 1025	ECB Sources: ECB buying Spanish short-dated covered bonds
27/10/2014 1231	ECB Sources: ECB cites barriers to QE. Need to let old measures work
27/10/2014 1451	ECB Sources: Current stimulus may lack desired scale. QE an option
31/10/2014 1512	ECB Sources: Existential threat to Euro if fiscal policy reform is not tackled
03/11/2014 1023	ECB Sources: ECB considering improvement to LTRO if economy deteriorates, too early to say
04/11/2014 1513	ECB Sources: Central bankers to challenge Draghi on leadership style
06/11/2014 1055	ECB Sources: Governing council members did NOT confront Draghi at council dinner
14/11/2014 1534	ECB Sources: Said to allow 24 hours to make smaller ABS purchases

26/11/2014 1249	ECB Sources: Governing council prefer additional time to assess current measures
04/12/2014 1633	ECB Sources: German ECB members opposed to new balance sheet language
19/12/2014 1012	ECB Sources: Considering making weaker Eurozone countries bear greater risk burden in QE plan
06/01/2015 0639	ECB Sources: ECB is working on a discussion paper to execute government bond buying.
09/01/2015 0951	ECB Sources: €500 billion plan showed to Governing Council members but no decision made
09/01/2015 1114	ECB Sources: ECB considering risk sharing mix for QE plan
16/01/2015 1640	ECB Sources: QE timing, size and scope yet to be decided
19/01/2015 1445	ECB Sources: Bundesbank still striving to put limits on ECB QE
21/01/2015 1430	ECB Sources: QE proposal calls for roughly €50 billion in bond buying per month
03/02/2015 0957	ECB Sources: 3 Greek banks have tapped ECB ELA window
03/02/2015 1420	ECB Sources: ECB won't accept Greek bond swap and wants full repayment
04/02/2015 1927	ECB Sources: ECB believes Greece may run out of cash as early as March
05/02/2015 1347	ECB Sources: ECB to allow Greek banks ELA up to €60 billion
10/02/2015 1202	ECB Sources: ECB to accept Greek bonds as collateral if deal is reached
17/02/2015 1645	ECB Sources: ECB member resisting support from ECB for Greek banks
18/02/2015 1642	ECB Sources: ECB divided over extra funds for Greek banks
18/02/2015 2011	ECB Sources: Greek banks asked for €5 billion extra in ELA funding
19/02/2015 0709	ECB Sources: ECB has extended ELA to Greek banks from €65 billion to €68.3 billion
02/03/2015 1442	ECB Sources: Staff projections may show 2017 inflation target return, signal end to QE Sep 2016
09/03/2015 0827	ECB Sources: ECB has started QE programme
19/03/2015 0925	ECB Sources: ECB has approved additional €400 billion for Greek banks as emergency liquidity
25/03/2015 1400	ECB Sources: ECB raising ELA for Greek banks to €71 billion
01/04/2015 1921	ECB Sources: ECB raised emergency funding cap by €700 million for Greek banks
17/04/2015 1914	ECB Sources: ECB examines possibility of I.O.U. currency in case of default