Dispersed information in FX trading: a martingale representation

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Abstract

Informational heterogeneity is an important feature of real world foreign exchange markets. The abstraction from this feature is therefore likely a major reason for the poor empirical performance of many exchange rate models. Explicitly modeling this heterogeneity reveals a close correspondence between standard macroeconomic exchange rate models and the jump-diffusion type martingale representation of asset prices. This explains the better empirical performance of statistical jump diffusion models.

Introducing dispersed information and news releases on macroeconomic conditions into a monetary model of exchange rates results in price dynamics that appear similar to the classical jump diffusion commonly assumed for many asset prices. The presence of dispersed information in conjunction with news releases on macroeconomic conditions leads to time-coordinated expectation revisions that produce jumps in the exchange rate path. This paper appears to be the first attempt to bridge the gap between the two modeling approaches.

Employing newly developed statistical methods for disentangling jumps from integrated variance of jump diffusions using bi-power variation at an hourly frequency, I illustrate that jump activity is closely linked to news releases. This supports the notion that exchange rate jump activity arises as a consequence of expectation revisions from the arrival of new price relevant information.

Introduction

Exchange Rates are notoriously difficult to model. Currencies are major objects of speculation, with purely financial transactions accounting for nearly 90% of market turnover (BIS, 2010a). Exchange rates appear to be highly influenced by market sentiments and are excessively erratic and volatile. Yet, they are not chaotic in a mathematical sense (Federici and Gandolfo, 2011).

The seminal paper of Meese and Rogoff (1983) demonstrated that the existing macroeconomic models for exchange rates were largely unable to explain dynamics out of sample. A random walk outperformed all combinations of the flexible price monetary model (Frenkel-Bilson), sticky-price monetary model (Dornbusch-Frankel) and the sticky-price asset model, (Hooper-Morton)[1] in terms of out-of-sample forecasting. Despite some empirical evidence of a connection between exchange rates and macroeconomic fundamentals at least in the long-run (Mark, 1995), even the exchange rate models developed during the nineties fail the random walk test (Cheung et al., 2005). This "exchange rate disconnect puzzle", as coined by Obstfeld and Rogoff (2001), suggest that the traditional macroeconomic assumptions of homogenous completely informed rational agents in a time invariant world are too simple to capture essential features of exchange rate dynamics. Relaxing these assumptions is therefore likely to bring new understanding of exchange rate dynamics.

Allowing for parameter instability has some success in reconnecting exchange rates with fundamentals for the long horizon (Rossi, 2005; Sarantis, 2006; Beckmann et al., 2009). Chen et al. (2010) found connections between commodity prices and exchange rates for commodity exporting economies, by combining the approach of Engel and West (2005) and Rossi (2005).

Arguing that as an asset price the exchange rate is more influenced by expectations about the future than by current conditions, Engel and West (2005) developed an asset price formulation for exchange rate determination. They show that most modern macro exchange rate models conform to this formulation, where the exchange rate can be written as a sum of current conditions plus the expectation of the sum of future

[1]Flexible price see Bilson (1979) and Frenkel (1976), sticky-price see Dornbusch (1976) and Frankel (1979), Frankel (1981) and sticky-price asset see Hooper and Morton (1980)

conditions.

Most studies of foreign exchange, asset and derivative market price dynamics stand in stark contrast to the models with a more macroeconomic origin. Following the tradition of the seminal models of Merton (1973) and Black and Scholes (1973), most models of options and other financial derivatives assume a continuous time diffusion or jump diffusion for the price process rather than attempting to explain the process as such (see for instance Eraker et al., 2003).

Economic intuition would dictate that there should be a close connection between exchange rates and fundamentals. The fact that statistical models for financial derivatives have such significant advantage in explaining exchange rates would suggest that these models are capturing something vital to exchange rate dynamics.

To my knowledge, this paper is the first attempt to link models of exchange rates developed from macroeconomic fundamentals with the price processes commonly assumed in derivative models. The paper will demonstrate that under certain assumptions on the informational structure of the economy, several of the most seminal macroeconomic models of exchange rates will in fact produce the price dynamics commonly assumed for option models. I will demonstrate that the key to this dynamic is the presence uncertainty about the current state of the economy, and agents forming expectations based on private information.

Departures from the assumption of homogenous information has attracted much research attention and proved to be fruitful for understanding the dynamics of exchange rates, and several sources of heterogenous information have recently been explored.

In the presence of heterogenous beliefs short selling restraints will lead to (rational) bubbles as only the beliefs of optimists has impact on price. This is true both in the presence of irrational noise traders (De Long et al., 1990), and pessimistic and optimistic buyers as in e.g. Favar and Song (2011); Hellwig et al. (2006).

Another source of heterogeneity is how much knowledge a trader in the exchange market has on current aggregate trade, as trade does not take place in one centralized clearing house, but rather in multiple locations simultaneously. This heterogeneity is the essential feature of the Evans and Lyons (2002) Portfolio Shifts model, using order flows to summarize the trade information. Contrary to the public information in most macroeconomic models, trade information in this model is treated as dispersed and private. The passing of information through the trading process produces order flow that carries information. Empirically this information is found to be more important than traditional measures of current macroeconomic conditions (see for instance Evans and Lyons, 2005).

The impact of dispersed information outside the setting of order flows has received far less attention. Heterogenous expectations resulting either from heterogenous model beliefs or heterogenous information will in general lead to complex dynamics, where the forecasting of the forecasts of others is an important part of the formation of expectations. One important contribution is the model of Bacchetta and Wincoop (2006) demonstrating the importance of higher order expectations in the presence of noise traders and heterogenous signals on fundamentals. [2]

In this paper I will examine the impact of dispersed information in conjunction with the arrival of new public information trough news releases. I will demonstrate that under some additional assumptions on the informational structure of the economy, the asset price formulation of Engel and West (2005), converges to the standard time varying parameters jump diffusion commonly assumed for asset price dynamics (as in Andersen et al., 2003, 2007).

New information about the economy should have impact on exchange rates if they behave as asset prices and are linked to fundamentals even though this link is unobservable to the econometrician due to excess volatility. Numerous empirical studies have assessed the impact of news releases on exchange rate returns (Andersen and Bollerslev, 1998; Almeida et al., 1998; Dominguez and Panthaki, 2006; Faust et al., 2007, among others) and volatility (DeGennaro and Shrieves, 1997; Melvin and Yin, 2000; Chang and Taylor, 2003) and in general find a significant link between news releases and exchange rate activity. However, they generally do not attempt to explain the mechanism leading to such a link. Evans (2011) and Lahaye et al. (2011) document a significant impact of news releases on the jump activity of several asset classes including exchange rates.

The remainder of the paper is organized as follows: The next section demonstrate the converging asset price dynamics under dispersed information and public news announcements on macroeconomic conditions,

[2] Implications of dispersed information has additionally been analyzed in the setting of businesses and price setting: Albagli et al. (2011); Hellwig and Venkateswaran (2011).

and concludes with the convergence to a jump diffusion. The next section explains the theory for the empirical exercise, in particular the strategy for disentangling the jumps from the overall price dynamics. The next section briefly describes the data used, followed by the empirical connection between news releases and jump activity. The final section concludes.

Exchange rate dynamics under dispersed information and public news releases

I consider the impact of two important characteristics of financial markets often left out of macroeconomic analysis. Namely, the combined presence of dispersed information, modeled as a continuous heterogeneous flow of information to agents about the fundamentals of the economy, and release of public news that may contain information unexpected by the agent.

Engel and West (2005) demonstrate how a wide set of commonly used macroeconomic models of exchange rates all produce a pricing equation that can be written on the following condensed form:

$$s_t = (1-\lambda)[h(f_t) + \sum_j \lambda^j E_t(h(f_{t+j}))] - \lambda[\phi_t + \sum_j \lambda^j E_t \phi_{t+j}], \quad (1)$$

where $h(f)$ is the link between macroeconomic fundamentals and the exchange rate and ϕ_t is the risk premium[3].

One of the most parsimonious and straight forward models of exchange rate determination that conforms with the above reduced form equation, is the basic monetary model. In order to fix ideas interest rates can therefore be though of as determined by central banks following a standard Taylor rule. However, the general results derived herein apply to any macroeconomic model of exchange rates conformable to the above reduced form equation, with varying implications for the interpretation of model coefficients.

In addition to the standard framework, introduce a continuum of agents trading in the foreign exchange market who all receive partial

[3]The same result applies to order flow based models of exchange rates, i.e. the general order flow based model of Evans (2010) can be written as a similar linear combination of current and future fundamentals and risk premia (Evans and Rime, 2010).

information about fundamentals.[4]

Assumption 1 (Dispersed information)**.** Agents receive a continuous flow of signals about the fundamentals, f_t, of the economy, $\omega_t^i = f_t + \xi_t + \varepsilon_t^i$. The errors ξ_t are persistent with symmetrically distributed innovations, and ε_t^i is an idiosyncratic noise component, independent across agents. Further, assume that ξ_t^i evolves according to $\xi_t^i = \xi_{t-1}^i + \varepsilon_t^\xi$, where ε_t^ξ is an aggregate uncertainty innovation with mean zero and variance σ_t^ξ.

Note that ω_t^i does not partition f_t. Further, the signal noise persistence implies that the agents receives similar types of signals each period. This dissumes discontinuous changes in the information content of the signal flow received by the agent.

According to standard definitions the risk premium on holding currency is given by, $\rho_t := E_t s_{t+1} - s_t - (i_t - i_t*)$, where s_t denotes the log exchange rate, i_t and i_t^* denote the nominal interest rate home and abroad, respectively, and E_t denotes expectation conditional on information available at time t. Given that agents no longer hold the same information, exchange rate expectation conditional on information available at time t will be individual specific, $E_t^i s_{t+1} = s_t + (i_t - i_t^*) + \rho_t^i$. The appropriate definition of market wide risk premium is then implicitly equal to the *average* expected exchange rate appreciation, minus the interest rate differential:

$$\bar{\rho}_t := \bar{E}_t s_{t+1} - s_t - (i_t - i_t*), \tag{2}$$

where $\bar{E}_t$ denotes the average expectation, i.e. across agent conditional expectations. The expected excess return on FX then implicitly determines the current exchange rate: $s_t = \bar{E}_t s_{t+1} - (i_t - i_t^*) - \rho_t$, and likewise next period $s_{t+1} = \bar{E}_{t+1} s_{t+2} - (i_{t+1} - i_{t+1}^*) - \rho_t$.

For any set of information available to agent i at time t, $\mathfrak{I}^i(t)$, the expectation conditional on this information will be given by the sum of the agents conditional expectation of next periods fundamentals and the second order expectation of the exchange rate,

$$E\left[s_{t+1}|\mathfrak{I}^i(t)\right] = E\left[\bar{E}_{t+1} s_{t+2}|\mathfrak{I}^i(t)\right] - E\left[i_{t+1} - i_{t+1}^* + \rho_{t+1}|\mathfrak{I}^i(t)\right] \tag{3}$$

[4]Note that as a continuum of agents is assumed, no strategic interaction is allowed for between agents, as each agents trade will not have price impact. Due to the vast liquidity in most FX markets, this is a standard assumption.

To fix ideas, assume that each agent has a currency demand based on his expected excess return and individual exchange/hedging demand on the form:

$$FX_t^{d,i} = \alpha_s \left(E_t^i \Delta S_{t+1} - (i_t - i_t^*) \right) + h_t^i, \tag{4}$$

where $FX_t^{d,i}$ denotes the currency demand of agent i at time t, α_s measures the degree of speculation and h_t^i is the agents exchange/hedging demand, which without loss of generality can be taken to be on the form $h_t^i = \beta_i X_t + \epsilon_t^{h,i}$. This currency demand follows Evans (2010) and takes a very general form that can be derived either from a mean-variance portfolio or an OLG asset allocation model (Bacchetta and Wincoop, 2006).

Market clearing then requires that the aggregate currency demand is zero,

$$\int_I FX_t^{d,i} di = \int_I \alpha_s \left(E_t^i \Delta S_{t+1} - (i_t - i_t^*) \right) di + h_t^i = 0 \tag{5}$$

$$\Rightarrow s_t = \int_I E_t^i S_{t+1} + \frac{1}{\alpha_s} h_t^i \, di - (i_t - i_t^*), \tag{6}$$

where the latter expression follows from simple manipulation of the terms in the market clearing condition. This then implies that the risk premium is equal to the average hedging demand, $\rho_t = \frac{1}{\alpha_s} \int_I h_t^i di$.

However, as the law of iterated expectations does not apply to average expectations, $\bar{E}_t \left[\bar{E}_{t+1} s_{t+2} \right] \neq \bar{E}_t \left[s_{t+2} \right]$. When iterating forward, the equation for exchange rate determination will contain an infinite iterative average expectation of future exchange rates, as well as the sum of iteratively average expectations on future fundamentals. For ease of notation, denote the higher order expectation $\bar{E}_t \bar{E}_{t+1} \cdots \bar{E}_{t+k}$ as $\underbrace{\overbrace{\bar{E}_{t+k}}}_{t,t+k}$.

$$s_t = i_t^* - i_t - \frac{1}{\alpha_s} \bar{h}_t + \sum_{k=0}^{\infty} \underbrace{\overbrace{\bar{E}_{t+k}}}_{t,t+k} \left[i_t^* - i_t - \frac{1}{\alpha_s} \bar{h}_t \right] + \lim_{k \nearrow \infty} E_t \underbrace{\overbrace{\bar{E}_{t+k}}}_{t,t+k} s_{t+k} \tag{7}$$

where $\bar{h}_t = \int_I h_t^i di$ is the average hedging demand. Alert readers will notice that this expression is the current setting parallel to (1). Due to the presence of higher order expectations, the risk premium will in part be determined by how agents (consistently) form their exchange rate expectations.

Agents are assumed rational and ex ante identical, that is, they hold the same beliefs about the structure of the economy. Then, given the same information, they will form the same expectations. Therefore, assume that expected future interest rates and average hedging demand can be described by a general mapping from expected future fundamentals.

Assumption 2 (Homogeneous conditional expectations)**.** Agents interest rate expectations can be described by a mapping $d^f(i^* - i)(\cdot)$ from the expected fundamentals of the economy. Likewise, let $d^h(\cdot)$ denote the mapping between expected fundamentals and average hedging demand. Together,

$$E_t^i \left[i_{t+1}^* - i_{t+1} - \frac{1}{\alpha_s} \int_I h_{t+1}^i di \right] = E_t^i[d(f_{t+1})]. \tag{8}$$

This assumption implies that unlike models of learning in financial markets (see e.g. Pastor and Veronesi (2009)), individual heterogeneity is not on subjective beliefs about the parameters of the model, but rather on the current and expected future values of the fundamentals due to differences in available information.

In order to shed light on the resulting exchange rate dynamics it is necessary to be more precise about the information structure of the economy. To this end, let $\mathfrak{S}$ be the natural filtration generated by the process $s(t)$. Further, let $\Omega(t)$ denote the adopted filtration $\Omega(t) = \left\{ \mathfrak{S}(t), \mathfrak{F}^P(t), \mathfrak{H}(t) \right\}$, where $\mathfrak{F}^p(t)$ is the cumulative publicly observable partition of fundamental information (such as nominal interest rates, federal funds rate, stock prices), and $\mathfrak{H}(t)$ is the natural filtration of the news arrival process.

Assumption 3 (Efficient Markets)**.** There is no arbitrage opportunities from publicly available information; with respect to the filtration $\Omega(t)$, s_t is a Martingale difference. $E\left[E(s_{t+\tau} - s_t) | \Omega(t)\right] = 0$, for all t.

In addition to the publicly available filtration $\Omega(t)$, each agent has access to an individual filtration $\mathfrak{F}^i(t) = \{\Omega(t), \omega^i(t)\}$, where $\omega^i(t)$ is the history of the flow of signals to the agents on the fundamentals of the economy, $\omega_t^i = f_t + \xi_t + \varepsilon_t^i$, where ξ_t is a common error component measuring the overall signal dispersion and ε_t^i is idiosyncratic noise. The agents expectation of τ-period return, conditional on his available information is therefore given by:

$$E_t^i[r(\tau)] = E\left[s_{t+\tau} - s_t | \mathfrak{F}^i(t)\right] = E\left[s_{t+\tau} - s_t | \mathfrak{S}(t), \mathfrak{F}^P(t), \mathfrak{H}(t), \omega^i(t)\right]$$
$$= 0 + E\left[s_{t+\tau} - s_t | \omega^i(t), \mathfrak{S}(t)\right] \tag{9}$$

Assumption 4 (Evolution of fundamentals)**.** Price relevant fundamentals, $f_t = \beta X_t$, evolve according to $X_t = X_{t-1} + \varepsilon_t^f$ and ε_t^f, conditional on the public filtration $\Omega(t)$, is symmetrically distributed with mean zero and variance σ_t^f.

Given the distributional assumption on ε_t^f, fundamentals will be a martingale difference sequence with respect to the public filtration $\Omega(t)$. Based on public information alone, the best guess on future fundamentals will be that they are equal to the current (unobserved) fundamentals. Therefore, in any equilibrium, rational agents will form their expectations according to their nowcast of current fundamentals, forecast of fundamental innovation ε_{t+1}^f and his expectation of average expectations.

Proposition 1 (Exchange rate expectations.)**.** *Define an equilibrium expectation formation rule as a rule which, if followed by all agents of the exchange market, will be mutually consistent. That is, given that all other agents follow the same rule of expectation formation, the agent will not be consistently wrong. One such equilibrium expectation rule will then be given by* [5][6]

$$E_t^i(s_{t+1}) = E[d(f_{t+1})|\mathfrak{F}^i(t)] + E[\lambda^i d(f_{t+2})|\mathfrak{F}^i(t)] \tag{10}$$

where λ^i *is the agents estimated correlation between his signal flow and the average signal flow.*

Proof. se appendix, 0.0.1 □

[5]see Bacchetta and Wincoop (2006) for a motivation for such a rule in a simple infinite horizon standard monetary model with two economies and four asset markets.

[6]Note that as long as expectations are formed according to the *same* mapping for all agents from public information on fundamentals, their private signal on fundamentals and the correlation between this signal and the average market signal, the following results hold. The specific expectation formations rule is used for expositional clarity.

Hence, the agent will amplify[7] his own prediction based on the extent to which he believes his signal is correlated with the average market signal and therefore important for the higher order expectations in the infinite regress.[8]

Proposition 2 (Private information is diffusive)**.** *The stream of private information received by agents, ω_t^i evolve according to a noisy Brownian motion with variance $\sigma^\omega(t)$*

$$\omega^i(t) \xrightarrow[\Delta t \to 0]{D} \sum_{j \in J} \sigma_j B(\tau_j) + \varepsilon^i(t) \xrightarrow[\dim(J) \to \infty]{D} \sigma^\omega(t) B^\omega(t) + \varepsilon^i(t), \tag{11}$$

where $\sigma^\omega = \sqrt{{\sigma_t^f}^2 + {\sigma_t^\xi}^2}$

Proof. See appendix 0.0.2 □

The resulting exchange rate dynamics are given by the sum of the change in fundamentals and the change in expectations:

$$\Delta s_{t+1} = s_{t+1} - s_t = \left(i_{t+1}^* - i_{t+1} - \frac{1}{\alpha_s}\bar{h}_{t+1}\right) - \left(i_t^* - i_t - \frac{1}{\alpha_s}\bar{h}_t\right) \tag{12}$$
$$+ \left(\bar{E}_{t+1}\left[d(f_{t+2})\right] + \bar{E}_{t+1}\left[\lambda_i d(f_{t+3})\right]\right) - \left(\bar{E}_t\left[d(f_{t+1})\right] + \bar{E}_t\left[\lambda_i d(f_{t+2})\right]\right)$$

In the setting of Ostrovsky (2009), if a finite number of agents each receive a partition of total price relevant information, the information will be aggregated into price in at most two rounds and therefore revealed to all agents. In this setting on the other hand, due to the measurement errors in the signals observed by agents, the flow of signals does not represent a perfect partition of the fundamentals. Therefore, current fundamentals will not be perfectly aggregated into current price.

The exchange rate will be a function of the agents private information signal. As demonstrated by Chen et al. (2004) the market will converge in at most two rounds and can therefore be assumed to converge instantaneously as τ converges to zero. The individual forecasting rules are then consistent with the market outcome provided agents estimates of

[7] Note that λ^i may be negative for some i.

[8] This is the same amplification effect as described for heterogenous beliefs in Bacchetta and Wincoop (2006) and for dispersed information in the form of order flows in Evans and Lyons (2002).

the correlation between their signal and the market average signal, λ^i, are unbiased (see proof of proposition 1 for details).

The aggregate price dynamic of the exchange rate will converge to a jump diffusion with time varying parameters and non-predictable jump direction and amplitude, though potentially predictable jump intensity. In the presence of both dispersed flows of information to agents as well as public news releases, signalling the state of current fundamentals, the asset formulation for standard macro models of exchange rates (as well as the order flow based model), converge as the sampling length diminishes, to the standard time varying parameters jump diffusion assumed for the exchange rate in much of the modern finance literature.[9]

Theorem 1 (Convergence to a Jump-Diffusion)**.** *In the presence of continuous dispersed information and news releases, the standard macroeconomic models of exchange rates converge to a standard time varying parameter jump diffusion.*

$$\Delta s_{t+1} \underset{\Delta t \to 0}{\longrightarrow} ds(t) = \sigma^s(t) B^s(t) + \kappa(t) dq(t). \tag{13}$$

where $\sigma^s(t)$ is a measure of current informational dispersion in the economy directly related to the variance of the error on agents private signals on fundamentals, and $\kappa(t)$ measures the aggregate expectation revision at time t. The jump intensity parameter of the process $q(t)$, $\lambda^s(t)$, is the arrival rate of public news.

Proof. The proof is comprised of two steps each deriving the origins of the two terms in the jump diffusion. The first demonstrates how the private signals received by agents will be impounded into the price according to a diffusion, whereas the second part demonstrates how public releases of news (prescheduled and otherwise) about fundamentals, will lead to jumps at any such time points.

Step one: For ease of notation define the two terms in (12) as $\Delta s_{t+1} \equiv D(f_{t+1}) + E_{t+1} g(f_{t+2})$. Where the interest rate premium minus the average hedging demand, is defined as $D(f_{t+1})$, a function of fundamentals. The aggregate expectation revision between t and $t+1$, the expression in the second line of (12), is defined as $E(g(\cdot))$, reflecting the fact that it is a function of *expected* fundamentals, and therefore of the information held by agents.

By the arguments of proof 0.0.2 in the appendix, f_t converges to a Brownian motion, so

$$D(f_{t+1}) \underset{\Delta t \to 0}{\longrightarrow} D(\sigma^f(t) B^f(t)).$$

[9] See for instance Andersen et al. (2003, 2007); Eraker et al. (2003), and, considering the results of Lee (2004), the analysis in Vlaar and Palm (1993)

Consider the second term,

$$E(g(\cdot)) : \int_I E[g(f_{t+2})|\mathfrak{F}^i(t)]di = \int_I E[g(f_{t+2})|\Omega(t), \omega^i(t)]di.$$

As the fundamental innovation, ε_t^f, is a martingale with respect to public information $\Omega(t)$,
$E[g(f_{t+2})|\Omega(t)] = 0$. Therefore, the only component which may shift the expectation, is the private signals $\omega^i(t)$. Consider the convergence of this expectation as the sample length diminishes, using the result of proposition 2.

$$\begin{aligned}\int_I E[g(f_{t+2})|\Omega(t), \omega^i(t)]di \underset{\Delta t \to 0}{\longrightarrow} & \int_I E[g(\sigma^f(t)B^f(t))|\Omega(t), \sigma^f(t)B^f(t) + \sigma^\xi(t)B^\xi(t) + \varepsilon_t^i]di \\ & \equiv G_t^\xi \sigma^f(t)B^g(t) \qquad (14)\end{aligned}$$

where a linear approximation G_t^ξ is used for the function $E(g(\cdot))$. Note that as the idiosyncratic noise component ε_t^i is distributed independently across agents, it will influence individual expectations, but not the cross agent average. At the limit of diminishing sample length the approximation G_t^ξ can be made arbitrarily fine. As the fundamental Brownian motion will be inseparable to the noise Brownian motion for the agents, the expectations will not be formed as a multiple of the fundamental Brownian motion, but as a multiple of a linear combination of the two. Hence,

$$\Delta s_{t+1} \underset{\Delta t \to 0}{\longrightarrow} \qquad (15)$$

$$D_t \sigma^f(t)B^f(t) + G_t^\xi \sigma^f(t)B^g(t) \equiv \sigma^s(t)B^s(t), \qquad (16)$$

for all t such that $\Omega(t^+) = \Omega(t^-)$, that is, for all t at which there are no news arrivals.

Step two: Consider s_t at any news arrival time τ. Then,

$$\Delta s_{\tau^+} = D(f_{\tau^+}) + E_\tau g(f_{\tau^+}) = D(f_{\tau^+}) + \int_I E[g(f_{\tau^+})|G(\tau), \mathfrak{F}^P(\tau), \mathfrak{h}(\tau), \omega^i(\tau)]di. \qquad (17)$$

At the marginal time τ there is no other information arriving than the news release, ie

$$\{G(\tau^-), \mathfrak{F}^P(\tau^-), \omega^i(\tau^-)\} = \{G(\tau^+), \mathfrak{F}^P(\tau^+), \omega^i(\tau^+)\}, \text{ and,} \qquad (18)$$

$$E[s(\tau^+)|G(\tau), \mathfrak{F}^P(\tau), \omega^i(\tau)] = s(\tau^-). \qquad (19)$$

Any market announcement can be represented by a σ subset of $\mathfrak{F}$, where $\mathfrak{F}$ is the natural σ-algebra for the fundamentals process, i.e. f_t is $\mathfrak{F}_t$ measurable, so all market announcements m^j can be given the representation $m_t^j = E(f_t|\mathfrak{H}_t^j)$ where $\mathfrak{H}^j$ is the σ-algebra corresponding to m^j.

By the tower property of conditional expectations, and the Radon-Nikodym theorem, the average instantaneous conditional expectation at the news arrival time will be given by

$$\int_I E\left[g\left(f(\tau^+)\right)|\Omega^i(\tau^-), m_\tau^j\right] di. \qquad (20)$$

Letting the market expectation of m_t^j be given by ${m_t^j}^e = \bar{E}\left[m_\tau^j|\Omega(\tau^-), \omega^i(\tau^-)\right]$, the standardized news, n_t^j can be defined as $n_t^j = \frac{m_t^j - {m_t^j}^e}{\sigma(m^j)}$. Then the average future exchange rate expectation revision at arrival time for news about fundamental j, can be written

$$\bar{E}\left[g\left(f(\tau^+)\right)|\Omega_(\tau^-), \omega^i(\tau^-), m_\tau^j\right] = G_\tau(n_t^j) \equiv \kappa(\tau). \tag{21}$$

Hence, the exchange rate dynamic at τ will be given by $ds(\tau) = s(\tau^+) - s(\tau^-) = \kappa(\tau)$.

Therefore, a market announcement deviating from the average expectation will produce a jump in the price-process. Note that the jump occurrences do not change the fact that the price process is a martingale, as for any infinitesimal τ, $E[n_{t+\tau}] = 0$, so $E(s_{t+\tau}) - s_t = \bar{E}[g(f_{t+\tau})] - s_t|\mathfrak{S}_t, \mathfrak{F}_t^p, \omega_t^i, \mathfrak{H}_t) = 0$. Thus $\kappa(t) = G_t(n_t^j)$, while the jump intensity (i.e. the frequency with which jumps occur) is the arrival rate of news n_t. □

Empirical analysis

Traditional macroeconomic models have typically had a hard time relating exchange rates to macroeconomic fundamentals (Cheung et al., 2005). However, if future innovation to some fundamentals is anticipated whereas other fundamentals are only discovered by agents ex-post, the typical empirical testing of these models is invalid. The implicit assumption in most, if not all, existing empirical application of macroeconomic exchange rate models implicitly assume that all agents observe the same thing as the econometrician, i.e. "current observables" such as e.g. GDP, consumption and stock prices. From the agents point of view there is, however, an important informational timing and accuracy distinction between the three series. Whereas stock prices can be contemporaneously observed by the agent with very little error, current realization of output is unlikely to be revealed to the agent before some time later.[10]

The innovations relevant to the agent are then unanticipated news about on the fundamentals, not the ex-post measurable innovations in observables. To the extent that survey data on release expectations can give a representative measure of agents conditional expectations, the impulses to which agents respond will be the arrival of such surprises. Therefore,

[10]Indeed the considerable difficulties related to contemporaneous measurement of output has sparked a huge literature on Nowcasting GDP(see e.g. Giannone et al., 2008). On the other hand, for instance consumption innovations might to a large extent be anticipated by agents.

the failure of traditional empirical procedures to confirm the relevance of macroeconomic fundamentals for exchange rates does not necessarily imply that they give an inaccurate reflection of reality. If the exchange rate fundamentals disconnect is indeed not in fact a disconnect but rather a reflection of the failure to observe the relevant fundamentals one would expect exchange rates to respond to the relevant innovation in fundamentals, i.e. to news surprises, according to the direction that theory would predict. While a closer investigation of the sign response of exchange rates to news surprises is beyond the scope of this paper, it poses an interesting path for future empirical investigation.

The empirical strategy taken herein is to employ recently suggested econometric procedures of singling out exchange rate jumps (instantaneous large price adjustments) and test whether these can be explained by the arrival of new information about macroeconomic fundamentals. Whereas this procedure is of course unable to discriminate between various models leading to the same prediction: namely that new information about macro conditions causes jumps, given the above theoretical framework a strong effect of such news surprises about fundamentals would lend support to the notion that exchange rates are in fact determined by fundamentals, and that uncertainty about current conditions matter.

Following the notation of the model above, and of Andersen et al. (2003), take a standard continuous time time varying parameter jump-diffusion for an asset price, $dp(t) = \sigma(t)dB(t) + \kappa(t)q(t)$, where B is a standard Brownian motion, and q is a Poisson counting process. [11]

The quadratic variation (QV) of the cumulative return process $r(t) = p(t)-p(0)$ of this jump-diffusion is given by $[r,r]_t = \int_0^t \sigma^2(\tau)d\tau + \sum_{0<\tau\leq t} \kappa^2(\tau)$. That is, the quadratic variation is the sum of the integrated volatility and the cumulative squared jump activity.

Disentangling the jumps

Denoting the discretely sampled Δ period returns $r_{t,\Delta} \equiv p(t) - p(t-\Delta)$ and normalizing the lower frequency interval of analysis to unity, the per period realized volatility is the sum of the inter period squared returns: $RV_{t+1}(\Delta) \equiv \sum_{j=1}^{1/\Delta} r^2_{t+j\times\Delta,\Delta}$. By the theory of quadratic variation the realized volatility converges uniformly in probability to the quadratic

[11] Additionally, $\mu(t)$ is required to be a continuous locally bounded process, the stochastic volatility $\sigma(t)$ is a strictly positive cadlag, and $\kappa(t)$ is the jump hight process.

variation of the process as the length of the underlying sampling intervals tends to zero. That is $RV_{t+1}(\Delta) \rightarrow_{\Delta \to 0} \int_t^{t+1} \sigma^2(\tau)d\tau + \sum_{0<\tau\leq t} \kappa^2(\tau)$. As demonstrated by Barndorff-Nielsen et al. (2006, 2005) the standardized realized bipower variation,

$$BV_{t+1}(\Delta)(\sqrt{2/\pi})^2 \sum_{j=2}^{1/\Delta} |r_{t+j\Delta,\Delta}||r_{t+j\Delta-1,\Delta}| \tag{22}$$

converges to the integrated volatility as the sampling interval tends to zero.

Thus, as first noted by Barndorff-Nielsen and Shephard (2004) and further demonstrated by Barndorff-Nielsen and Shephard (2006) the jump activity of a time-varying parameter jump-diffusion can be consistently estimated as the (significant) differences between the realized volatility (RV) and the bi-power variation BV of the observed squared price path. That is, the difference consistently estimates the contribution of jumps to the quadratic variation, $RV_{t+1}(\Delta) - BV_{t+1}(\Delta) \rightarrow \sum_{0<\tau\leq t} \kappa^2(\tau)$. As the squared jumps cannot possibly be strictly negative, a natural minimum restriction for the estimated squared jump series is a non-negativity truncation of the estimated difference. Such a non-negativity restriction corresponds to accepting all estimates for which a jump occurred with probability greater than 1/2, as the difference has a symmetric distribution.

A transparent measure of the significance of the estimated differences is provided by Andersen et al. (2003), allowing both for the extraction of significant jumps as well as testing for the presence of jumps. From the distributional results in Barndorff-Nielsen et al. (2006, 2005) it follows that in the absence of jumps, for diminishing sampling length,

$$\frac{RV_{t+1}(\Delta) - BV_{t+1}(\Delta)}{\sqrt{((\pi/2)^2 + \pi - 5)\Delta \int_t^{t+1} \sigma^4(\tau)d\tau}} \xrightarrow{D} N(0,1) \tag{23}$$

Further, the integrated quadricity, $\int_t^{t+1} \sigma^4(\tau)d\tau$, in the denominator may be consistently estimated by the standardized realized tri-power quadraticity,

$$TQ_{t+1}(\Delta) \equiv \frac{1}{4\Delta}\frac{\Gamma(7/6)}{\Gamma(1/2)}^{-3} \sum_{j=3}^{\frac{1}{\Delta}} |r_{t+j\Delta,\Delta}|^{4/3}|r_{t+(j-1)\Delta,\Delta}|^{4/3}|r_{t+(j-2)\Delta,\Delta}|^{4/3}. \tag{24}$$

As a log scaled version of the test statistic has been shown to display better finite sample behaviour (Huang and Tauchen, 2005), following the avocations by Barndorff-Nielsen and Shephard (2004) and Andersen et al. (2003), this rescaled statistic is used in the estimated time series of jumps significant at the five, one and 0.1 percent level.

In addition to this approach another approach that has been advocated in latter years is the threshold jump detection method proposed in MANCINI (2009). This approach is more straight forward than the Bipower variation approach. The intuition behind the method is that jumps should be expected to be large. There is a limit to how much volatility one would expect from the diffusional component in a jump diffusion, hence if a large pricemovement occurs, larger in this setting meaning greater than what one would expect if the process was driven by a diffusion alone, then it must be that this movement was caused by a jump in the process. Formally,

$$\hat{J} = \sum_{i:\, t_i < t} \hat{\gamma}_i \tag{25}$$

$$\hat{\gamma}_i = \Delta R \, I_{(\Delta_i R)^2 > \vartheta(\delta)} \tag{26}$$

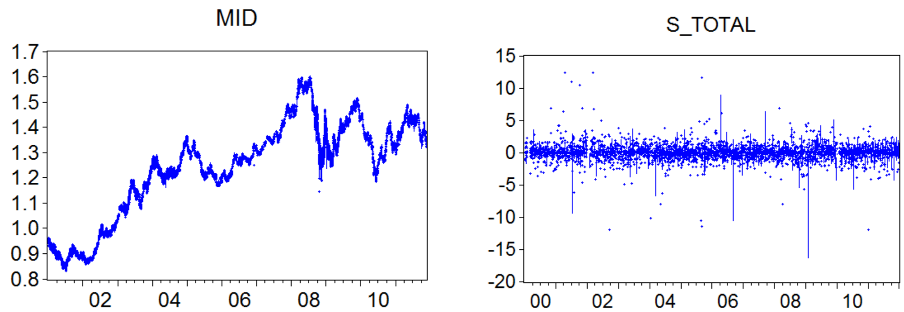
where $\hat{J}$ is the estimated jump component of the process, $\hat{\gamma}_i$ are the path-wise estimated jumps, R is the return of process and $\vartheta(\delta)$ is the estimated realized volatility over the interval δ. I is the indicator function for whether or not the squared innovation is bigger than what one would expect given the threshold estimate.

This estimator is implemented by taking a linearly interpolated estimate both of daily realized variation and bipower variation. This then gives two alternative estimated jump-paths. Although considerable noise is likely to hamper the estimated path, at least significant jumps should be captured by this procedure, and importantly it enables the estimation of the actual jumps, that is, of their precise timing and direction. The bipower variation approach, on the other hand, is only able to capture the cumulative squared jumps over an aggregated interval.

Data

One minute round the clock bid and ask quotes for the dollar pr euro (EURUSD) exchange rate stem from the Thompson Reuters high fre-

Raw data



(a) Exchange rate (b) Standardized news

quency quotes database, and span from January 2001 to December 2004, composing a total of nearly 400000 midquote observations. EURUSD is the most liquid of all the foreign exchange markets, with an estimated daily turnover of 1101 billion US dollars (BIS, 2010a). The quote data, cleaned according to the recommendations of Barndorff-Nielsen et al. (2009)[12], are displayed in figure 1a.

The data on economic market releases were kindly provided by Briefing.com and contains three measures of market expectations in addition to the actual release value, for 83 regularly released US market statistics. The market expectation measure used in this study is the market average expectation from survey inquiries prior to the release. The series of market news used in the study (shown in figure 1b), is constructed as the standardized sum of market news following Andersen et al. (2007),

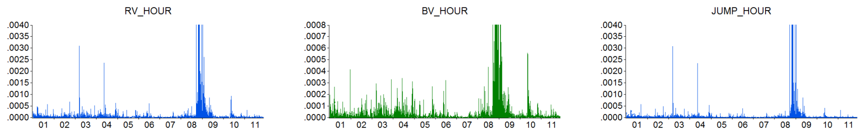
$$\text{news}_t = \sum_{j=1}^{J} \frac{\text{released}_j - \text{market expectation}_j}{\text{std. err. } (\text{released}_j)}, \tag{27}$$

where the standard error is computed over the entire sample and $J = 83$ are the released statistics. The measures of US macroeconomic activity used in this study (the j's) are all released by Thompson Reuters, and consist of nearly 3 500 news release incidents. A full listing with descriptive statistics of the release series can be found in table 10 in the appendix.

[12]Note that only P2 and Q1 to Q4 are applicable.

Figure 1: Decomposition of the realized variance

(a) Realized Variance (b) Bi-power Variation (c) Significant Jumps



Results

The unit length for the jump detection testing is taken to be one hour. That is, for each hour of each 24 hour trading day with a sufficient number of trades the hourly bi- and tri-power variation and realized variance are estimated. For hours with significant jump activity, the estimated cumulative square jump is separated from the estimated integrated volatility to form the jump and bipower variation series, respectively.

The microstructure of the financial market under study has been demonstrated to potentially have major impact on market behaviour by numerous studies (e.g. Osler, 2006; Goodhart and Payne, 1996). As institutional particularities of the EURUSD market not shared by other foreign exchange (FX) markets or general microstructural noise could therefore potentially play a major role for the results. Although most basic data noise such as direct misrecordings (such as zero prices) should be filtered out by the applied data cleaning procedure of Barndorff-Nielsen et al. (2009), microstructural noise might still be important. In order to accommodate the presence of such noise and obtain results that do not depend on its particular structure, developing estimators that are robust to microstructure noise is prominent in current high-frequency econometrics research (see for instance Aït-Sahalia et al., 2012). Simulations have demonstrated that robustified realized bipower variation and realized tripower quadraticity are robust to a large class of microstructural noise, (see Andersen et al., 2011, and references therein). The generalizations are essentially smoothers of the original estimators using a larger number of neighboring observations in order to aggregate out the microstructural noise. The robust variants of the realized bipower variation (BV) and realized tri-power quadraticity (TQ) estimators used herein uses observations one further away than the original estimators, for instance, observations at t and $t-2$ are used for the BV.

Table 1: Summary statistics for hourly EURUSD Realized Volatilities, Bi-power variations and Jumps

	price	RV	BV	Jumps^2	news	$\sqrt{RV}$	$\sqrt{BV}$	$\sqrt{\text{Jump}^2}$	$\lvert\text{news}\rvert$
Mean	1.06	7.05E-05	10.3-05	1.77E-05	0.29	0.006	0.007	0.003	0.66
Median	1.08	1.9E-05	2.44E-05	4.93E-06	0	0.004	0.005	0.002	0.56
Max	1.36	0.006	0.01	1.6E-03	3.79	0.08	0.10	0.04	3.79
Min	0.84	0	0	1.16E-09	-1025	0	0	3.4E-05	0
Std.Dev.	0.15	0.0002	0.0003	5.8E-05	0.89	0.006	0.007	0.003	0.60
Skewness	0.07	11.6	10.9	16.7	0.11	2.7	3.4	1.37	
Kurtosis	1.6	253	241	395	4.07	16.3	15.7	27.6	5.37
Obs	11156	10651	9103	2642	822	10651	9103	2642	822

The difference in observation between the various components of the squared price are due to the need of several consequitive price obervations for estimation of the integrated volatility (BV), and the jump activity. Any hour for which less than 5 prices are reported is omitted, hence the reduction from price to RV. The BV requires a sufficient number of recorded price triplets, whereas the jump series requires sequences of four prices recorded (robustified estimators).

The descriptive statistics for the raw mid-quote series and the estimated realized volatility, realized bipower variation and jump series (table 1), show that jumps only account for a limited fraction of exchange rate volatility. At least one significant jump is estimated for 519 of the 1458 days in the sample. However, at least one quote is only registered for 569 of the days in the sample, as for most weekends and bank holidays no trades were recorded, leaving only 50 days with trade for which no jumps appear to have occurred at an hourly frequency. When aggregated up to the more commonly employed daily frequency however, significant jumps are only observed for 37 of the days.

The drastically lower frequency of significant jump activity when testing at a daily frequency seem to indicate that testing for jump-activity at a higher frequency can reveal a greater fraction of occurred jumps. At a daily frequency some jumps are likely to be concealed by time variation in the diffusive component of the price process.

Do exchange rates respond to new information about macroeconomic fundamentals?

As market expectations arguably can only be measured with some, perhaps considerable, measurement error, it would seem natural to impose the same significance assumption on the estimated news, defined as market surprises as on the series for significant jumps. Significant news is therefore defined as news greater in absolute value than two times the standard deviation of news in the corresponding month.

Table 2: Simple Regressions

Dependent	$\sqrt{\text{Jump}}$			$\sqrt{\text{BV}}$
$\lvert\text{news}_{\text{significant}}\rvert$	0.58			
t-stat.	[4.3]			
$\lvert\text{news}\rvert$		0.57		5.17
t-stat.		[4.2]		[6.0]
AR(1)	0.81	0.86	0.75	0.36
t-stat.	[3.4]	[3.4]	[18.2]	[11.5]
adj.R^2	0.20	0.20	−0.50	−0.22
obs.	267	378	2642	406

The table shows the results from the regression of the square root of significant jumps regressed the absolute value of the significant standardized news and itself lagged (first column), using instead all standardized news (column two), contrasted with an autoregressive model of order one (column 3), and regressing standardized news on the square root of bipower variation. In all regressions, the standardized news are scaled up with 1000.

The estimates from the regression of significant jumps (square roots) on significant news (absolute values) are reported in table 2. Both coefficients, for the significant news and the auto regressive (AR) term, are highly significant. Considering that this is a regression of two highly volatile stationary series, the resulting R^2 of 0.20 is uplifting.

The results are not particularly sensitive to the omission of small news. Regressing instead on the full set of news still results in highly significant coefficients, and the fit is essentially the same. Similar results are found for the series of positive differences, i.e. jumps significant at the 50% level.[13] Furthermore, the importance of news does not seem to hinge on the inclusion of the AR term, as a simple AR(1) model for the jump series has a very poor fit (see table 2). The inability of past jumps to explain future ones is entirely as one would expect if the jump sequence

[13]Results available upon request.

has been consistently extracted, as the sequence of jumps will not be forecastable from public information, which includes past exchange rate dynamics.

In stark contrast to these results, an AR(1) explains the estimated integrated volatility very well, whereas news have essentially no explanatory power for the bi-power variation (see table 2).

Figure 2: Significant jumps explained by news releases

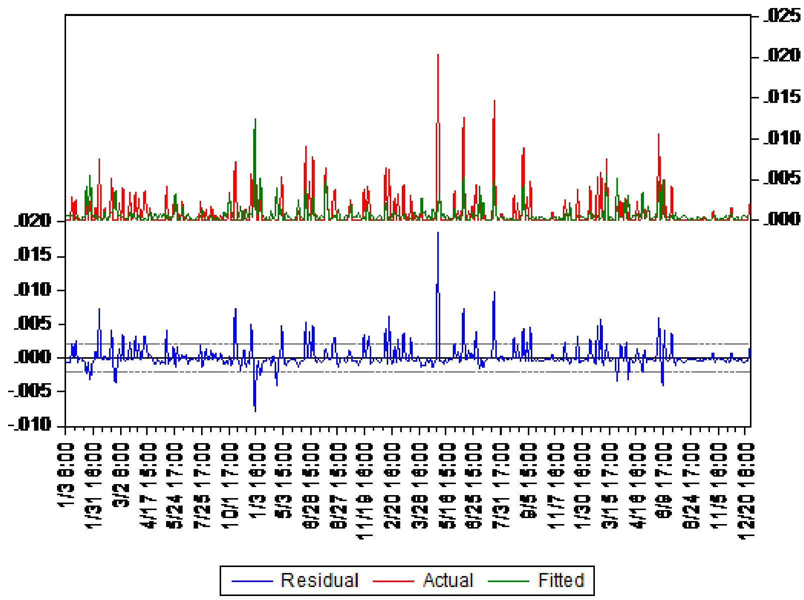


Figure 2 shows the estimated model of jumps using all standardized news. Given the small number of macroeconomic news releases considered, arrival of news appear to track a significant amount of the overall jump activity.

The results indicate that macroeconomic fundamentals matter. This seemingly close connection between the arrival of new information about macroeconomic fundamentals and exchange rate jump activity is in fact a somewhat surprising find when contrasted to the customary nonrecoverable connection between macroeconomic fundamentals and exchange rates in previous empirical macroeconomic studies. The evidence cannot easily be aligned with the exchange rate disconnect, i.e. with the notion that macroeconomic fundamentals are entirely irrelevant for the pricing of foreign currency.

In fact, the model of dispersed information presented herein would give a very nice and intuitive interpretation of the perhaps somewhat surprising results of Evans (2010), namely that order flow can forecast macroeconomic fundamentals, and that this forecast capable information is in fact price relevant for the exchange rate. If order flow contains information about macroeconomic fundamentals (e.g. large currency order flows from export businesses signaling that they are experiencing good times), this is precisely the result one would expect in the present context. Namely, in general observed macroeconomic innovations are irrelevant because they are anticipated by the agents, whereas unexpected innovations, in this case measured as macro innovations orthogonal to order flow, do move exchange rates.

In the current framework fundamentals matter, yet the link between exchange rates and fundamentals would remain indiscoverable in a standard empirical framework if the (higher order) expectations accounted for much of the exchange rate movement. If the average information of agents has a very poor connection to the information the econometrician is conditioning on, macroeconomic fundamentals will *appear* to be irrelevant even though they are not.

A closer investigation of the relation between new market information and exchange rate jump activity

Estimating the impact on jump intensity

Although the simple correlation results presented in the previous section do seem to indicate some nontrivial link between the release of new aggregate information and the EURUSD exchange rate jump activity, it cannot offer any causal indications.

In order to assess the relative importance of news releases for jump-rate activity, the impact of releases and the amount of new information contained in releases on the conditional hazard rate of the exchange rate is estimated using a standard time inhomogenous poisson hazard model. Specifically, assume that the jump intensity $\lambda(t)$ in hour τ can be formulated as,

$$\lambda_\tau = \lambda_0 e^{Z(\tau)\beta}.$$

Then the log likelihood of a jump occurring within hour τ is given by,

$$L = y \ln(m_\tau) - m_\tau - \ln(y!),$$

where y is an indicator function for one jump having occurred, and $m(\tau)$ is the jump intensity function $m(\tau) = \lambda_0 e^{Z(\tau)\beta}$. However, the employed method of jump detection only allows for the approximate detection of whether at least one jump has occurred within the interval. Hence the more appropriate likelihood to employ would therefore be the likelihood of no jumps occurring in a given aggregation interval. The likelihood of k jumps over the interval is given by the poisson distribution, $P(y_s = k) = \frac{e^{-m}m^k}{k!}$. Thus the log likelihood of no jumps occurring in an interval is then, as $P(y_s = 0) = \frac{e^{-m}m^0}{0!} = e^{-m}$, given by,

$$L(X_s = 0) = -m(1 - X_s) = \lambda_0 \exp\{Z\beta\}(1 - X_s).$$

Both likelihood specifications are employed in the empirical analysis. As the probability of more that one jump occurring in the same interval is minute by standard properties of the poisson distribution, the two likelihood specifications ought to bring similar results, although the results from the binomial specification are likely to be more unstable due to the numerical instability inevitably present due to the $e^{(\cdot)}$ term.

The results confirm that there is little discrepancy between the Poisson and the Binomial likelihood specification, although the Binomial specification generally is much more slowly converging. For both likelihood specifications the estimation is done by the iteration over two steps, first estimating the base hazard (λ_0) and then the impact on the hazard through releases (β), iteratively updating coefficients over the two likelihoods until the implied likelihood for the two specifications is the same. The "iteration" column in the results table 11 refer to the number of such iterations. It appears that the most important influence over the jump intensity is the presence of surprises, measured by the release-indicator taking the value 1 whenever there is a release and zero otherwise, rather than the cumulative amount of such surprises, measures by the cumulative absolute value of standardized news released within the hour.

The table 6 show the estimated impact of the various aggregated news release groups on jump intensities. The estimates span the entire 2001-2011 sample. As is clear from the table there is huge discrepancy between how great impact various news release categories have. Whereas a highly significant relation is found for some categories, other seem far less im-

Table 3: Simulation evidence on validity of poisson approximation

Method	Likelihood	Iterations	a	beta			
		Lik. Improvement					
TRUE			**0.05**	**0.368**	**0.224**	**1.164**	**-1.169**
Iteratively							
	Poisson	75	**0.049**	**0.344**	**0.081**	**1.172**	**-1.276**
			157	5.42	1.27	18.51	-20.27
	Altered-Binomial	2	**0.049**	**0.000**	**0.000**	**0.000**	**0.000**
			161	0.00	0.00	0.00	0.00
	Binomial	40	**0.050**	**0.354**	**0.083**	**1.203**	**-1.310**
			162	5.72	1.34	19.52	-21.39
Directly							
	Poisson		**0.049**	**0.344**	**0.081**	**1.172**	**-1.276**
		-108290.8	155	5.4	1.3	18.4	-20.1
	Altered-Binomial		**0.048**	**0.362**	**0.085**	**1.233**	**-1.342**
		176.8	155	5.8	1.4	19.9	-21.7
	Binomial		**0.050**	**0.362**	**0.085**	**1.233**	**-1.343**
		-112632.6	155	5.9	1.4	19.9	-21.8

portant. Detailed results for the estimated impact of each single news release, together with the definition of the categories can be found in the appendix.

Table 4: Estimated jump intensity impacts

Measure	Iterations	Lik.imp	a	beta	tstat on beta	#series	#obs
Consumer	36	2.38	0.1628	0.196	1.99		
Housing market	3048	0.65	0.1629	0.09	0.98		
Industrial	7429	0.38	0.1629	0.06	0.71		
Labour Market	8009	10.1	0.1626	0.18	4.79		
Macro	126	2.41	0.1629	0.21	1.7		
Sales	7695	6.53	0.1628	0.18	4.11		
Sentiment	1295	7.33	0.1627	0.21	3.84		
Trade	18	1.97	0.1629	0.33	1.81		
Total	18	1.97	0.1629	0.33	1.81		

Estimating the impact on jump directions and heights

Actual jump heights will according to the theoretical model presented above be equal to the mapping $\kappa(n_t^j)$, where n_t^j denotes the arrival at t of news of type j. As an approximation, this mapping is assumed to be linear, and news are assumed to be roughly normally distributed. The relation can then be written

$$J_t = \beta n_t.$$

However, as the econometric technique used to recover the jumps imply that only jumps of some size will be recovered. Therefore, the data will in effect be censored according to the employed threshold. Therefore the model to be estimated is rather

$$\hat{J}_t = \beta n_t | \beta n_t > \vartheta_t,$$

where ϑ_t denotes the threshold used for the jump detection.

Using the estimated jump part of the process as detailed above, using both the realized variation and the realized bipower variation as threshold estimators, the impact of the individual news releases on actual exchange rate jump innovations can be estimated.

Table 5: Correlation structure for the news release groups

Series	jumps bv H	Cor	jumps rv H	Cor	Obs
core	137	**-0.126**	81	**-0.121**	2164
total	273	**-0.095**	186	**-0.108**	3425
CONSUMER	33	0.104	41	-0.321	244
CORE	137	**-0.126**	81	**-0.121**	2164
HOUSING MARKET	20	**-0.049**	15	**-0.334**	465
INDUSTRIAL	25	**-0.082**	12	**-0.237**	495
LABOUR MARKET	52	**-0.181**	31	**-0.279**	773
MACRO	48	-0.175	33	0.016	373
SALES	47	0.023	29	-0.024	586
SENTIMENT	58	-0.213	37	0.100	817
TRADE	6	**-0.670**	2	1.000	140

Table 6: Estimated jump direction and height impacts

Measure tstat on beta	Iterations	Lik.imp	a	beta
Auto Sales	42	28021	-0.46	-1.98
Avg workweek	61	28027	-1.79	-4.92
Hourly Earnings	51	28022	-452.55	-2.75
Nonfarm Payroll	52	28026	1.30	5.99
Treasury Budget	59	28022	5.55	2.10

Estimating coefficients for the diffusional component for forecasting purposes

For the estimation of the diffusional process a measure of the amount of the exchange market open is constructed to correct for varying trading opportunities within each day. This measure is constructed by taking weighting the opening hours of each major EURUSD trading house by their share of overall market turnover as estimated in the latest triennial foreign exchange survey by the Bank of International Settlement from 2011 BIS (2010b).

When realized spread, ie the difference between ask and bid prices is included as an explanatory variable of the estimated bipower variation none of the other liquidity measures seem to matter. The measure of market openness is weakly significant if the realized spread is dropped, but the equation has no explanatory power. Even including realized spreads a very small amount of the bipower variation can be explained. The amount of news released is entirely insignificant.

Table 7: Relation between estimated diffusion and liquidity measures

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	4.08E-05	2.90E-05	1.404	0.160
Market openness	9.72E-08	1.45E-07	0.670	0.503
Quotes pr min	-7.73E-06	8.89E-06	-0.869	0.385
Rel. spread	8.50E-05	1.06E-05	7.981	0.000
Buy pressure	-1.28E-06	6.09E-06	-0.210	0.834
(Buy pressure)^2	4.34E-09	3.47E-07	0.013	0.990
Midquote	-2.52E-05	2.27E-05	-1.111	0.266
R-squared	0.002			

Can news releases be used to forecast exchange rates in sample?

In order to assess whether the relation between news releases and exchange rate dynamics is statistically or economically important, the proposed model is challenged by a menu of standard formulations for asset price forecasting and the implied Kullback Leibler divergence measure of each process is used to assess their empirical performance.

The menu of contenders consists of the standard random walk ($s_t = s_{t-1}+\varepsilon_t$), Brownian motion ($ds(t) = \sigma dB(t)$), Brownian motion with drift

$(ds(t) = \mu dt + \sigma dB(t))$, Geometric Brownian Motion, $(ds(t) = \mu s(t)dt + \sigma dB(t))$ and an Ornstein-Uhlenbeck process $(ds(t) = \lambda(\mu - s(t))dt + \sigma dB(t))$. Furthermore, to allow for jumps, a Geometric Brownian Motion with Jumps $(ds(t) = \mu s(t)dt + \sigma dB(t) + \kappa dq(t))$ is estimated. All processes are estimated with time-invariant parameters for 2001-2011. Especially the geometric Brownian motion and the Ornstein-Uhlenbeck processes are commonly used in financial applications.

Note that μ and σ estimates in both tables are multiplied by 100 000.

Table 8: KLIC comparison for level models

model	KLIC*100	R2 of Δ	sigma	mu	lambda
Random walk	0.00		0.1979		
Random walk with drift	40.08		0.1979	0.3510	
Brownian motion	0.00		0.1980		
Brownian motion with drift	40.08		0.1980	0.3510	
Geometric Brownian motion	310.50		0.0500	200	

Table 9: KLIC comparison for log-level models

model	KLIC*100	R2	sigma	mu	lambda
Random walk with drift	0.197	1	114.6	14.33	
Brownian motion	0	0.996	115		
Brownian motion with drift	0.197	0.996	115	14.3	
Geometric Brownian motion	147.7		0.0500	200	
GBM w jumps		1	0.0021	0.34	2.31
Ornstein-Uhlenbeck	64.02	1	1240	-119000	0.0113

Conclusion

In this paper I have argued that the apparent divide between exchange rate models built from macro fundamentals and common assumptions on exchange rate dynamics in models of financial derivatives is less than what it may seem. Allowing for a continuous flow of dispersed information to agents and assuming that fundamentals follow a martingale difference this paper has demonstrated how the interaction of agents trading on their private information in conjunction with public news releases will produce exchange rate dynamics that can be described by a standard time varying parameters jump diffusion.

Extracting the jumping component of the realized exchange rate path for 2001-2011, the correlation of the arrival of news and jump activity is tested. 20% of exchange rate jump activity over the period can be explained by news releases. The results indicate that fundamentals do matter for exchange rates, and lends support to the claim that exchange market jump activity is due revisions in expectations. A large degree of heterogeneity in the impact of various news releases is found and suggest that either some aspects of macroeconomic fundamentals are more important for the euro dollar exchange rate or that certain news releases to a greater extend shed light on the current economic conditions.

The inclusion of news releases for the European end of the market is likely to shed more light on the particular link between exchange rate expectations and macroeconomic conditions.

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Appendix

Proofs

0.0.1 Proof of Proposition 1

Proof. The agents expectation of next periods exchange rate is per definition given by $E_t^i(s_{t+1}) = E[i_{t+1}^* + i_{t+1} - \frac{1}{\alpha_s}\bar{h}_t|\mathfrak{F}^i(t)] + E[\bar{E}_{t+1}s_{t+2}|\mathfrak{F}^i(t)]$. By substituting for s_{t+2},

$$E_t^i(s_{t+1}) = E[i_{t+1}^* - i_{t+1} - \frac{1}{\alpha_s}\bar{h}_{t+1}|\mathfrak{F}^i(t)] + E_t\left[\bar{E}_t[i_{t+2}^* - i_{t+2} - \frac{1}{\alpha_s}\bar{h}_{t+2}|\mathfrak{F}^i(t)]\right] \tag{28}$$

$$+ E_t[\bar{E}_{t+1}\bar{E}_{t+2}S_{t+3}|\mathfrak{F}^i(t)]$$
$$= E\left[d(f_{t+1})|\mathfrak{F}^i(t)\right] + E\left[\bar{E}_{t+1}d(f_{t+2})|\mathfrak{F}^i(t)\right] + E_t[\bar{E}_{t+1}S_{t+3}|\mathfrak{F}^i(t)]$$

Assume all agents form expectations according to (10). The average expectation in the economy will then be given by

$$\begin{aligned}\bar{E}_t s_{t+1} &= \int_I E_t^i(s_{t+1})di = \int_I E\left[d(f_{t+1})|\mathfrak{F}^i(t)\right] + E\left[\lambda^i d(f_{t+2})\right] di \\ &= \int_I E\left[d(f_{t+1})|\mathfrak{F}^i(t)\right] + E_t^i\left[\frac{\sigma_t^{\omega 2}}{\sigma_t^{\omega 2} + \sigma_t^{\omega}\sigma_t^{\varepsilon_i}} d(f_{t+2})\right] di \\ &= \bar{E}_t\left[d(f_{t+1})\right] + \bar{\lambda}_t \bar{E}_t\left[d(f_{t+2})\right]\end{aligned}$$

The exchange rate in $t+1$ will then be given by $s_{t+1} = i_{t+1}^* - i_{t+1} - \frac{1}{\alpha_s}\bar{h}_t + \bar{E}_{t+1}[s_{t+2}] = i_{t+1}^* - i_{t+1} - \frac{1}{\alpha_s}\bar{h}_t + \bar{E}_{t+1}[d(f_{t+2})] + \bar{E}_t[\lambda^i d(f_{t+3})]$. Given that the forecast mapping $d(f)$ is rational, the expected forecast error from $d(f)$ is zero. The expected forecast error of the agent from using the forecasting rule of (10), is therefore given by

$$\begin{aligned}E[E_t^i s_{t+1} - s_{t+1}] &= E\left[E_t^i[d(f_{t+1})] - \left(i_{t+1}^* - i_{t+1} - \frac{1}{\alpha_s}\bar{h}_t\right)\right] \\ &+ E\left[E_t^i[d(f_{t+1})] + E_t^i[\lambda^i d(f_{t+2})] - \bar{E}_t[d(f_{t+1})] + \bar{\lambda}_t\bar{E}_t[d(f_{t+2})]\right] \\ &= 0.\end{aligned} \tag{29}$$

□

0.0.2 Proof of Proposition 2

Proof. $\omega_t^i = f_t + \xi_t + \varepsilon_t^i$. As $f_t = \beta X_t$, and $X_t = X_{t-1} + \varepsilon_t$, it follows that the current value of X is the cumulation of past impulses, $X_t = \sum_{s=0}^t \varepsilon_s$, hence $f_t = \sum_{s=0}^t \beta\varepsilon_s^f \equiv M_t^f$. Likewise, $\xi_t = \xi_{t-1} + \varepsilon_t^\xi$ implies $\xi = \sum_{s=0}^t \varepsilon_s^\xi \equiv M_t^\xi$.

Then, $\omega_t^i = \sum_{s=0}^t \beta\varepsilon_s^f + \sum_{s=0}^t \varepsilon_t^\xi + \varepsilon_t^i \equiv M_t^\omega + \varepsilon_t^i$, a sum of independent terms with mean zero and finite variance. As the ε_ts are distributed with time-varying variance, consider each partition M_j^ω of M_t^ω for which ε_t^ξ has invariant variance σ_j^ω, $M_j^\omega = \sum_{s=t_{j,k}}^{t_{j,k}+\tau_j} \beta\varepsilon_s^f + \sum_{s=t_{j,k}}^{t_{j,k}+\tau_j} \varepsilon_s^\xi = \sum_{s=t_{j,k}}^{t_{j,k}} \varepsilon_s^j$, where ε_s^j is distributed with mean zero and variance σ_j.

Each such partition will, by Donskers invariance principle converge to a Brownian motion with variance $\sigma_j^i\tau_j$ as the sampling length diminishes, $M_j = \sum_{s=t_{j,k}}^{t_{j,k}+\tau_j} \varepsilon_s^j \xrightarrow{D} \sigma_j B(\tau_j)$, where $B(\tau)$ is a standard Brownian motion. Then, noting that $M_t = M_t^f + M_t^\xi \bigcup_j M_j = \sum_j M_j$, consider the limit of this sum as the number of terms in the sum increases. This corresponds to relaxing the assumption that the variance of ε_t^j is constant over intervals τ_j. Note that for a standard Brownian motion and any t, $B(\tau_j) \overset{\text{dist.}}{=} B(t+\tau_j)-B(t)$. Therefore, it is also true that $M_t \xrightarrow{D} \sum_j \sigma_j^\omega [B(t_j+\tau_j) - B(t_j)]$, where, for time-ordered j, $t_{j,k} + \tau_j = t_{j,k+1}$. Hence,

$$\begin{aligned}
\omega^i(t) = M_t^\omega + \varepsilon_t^i &\xrightarrow[\Delta t \to 0]{D} \sum_{j\in J} \sigma_j B(\tau_j) + \varepsilon^i(t) \\
&= \sum_k \sigma_{j,k}^i [B(t_{j,k+1}) - B(t_{j,k})] + \varepsilon^i(t) \xrightarrow[\dim(J)\to\infty]{D} \sigma^\omega(t)B^\omega(t) + \varepsilon^i(t) \\
&= \sigma^f(t)B^f(t) + \sigma^\xi(t)B^\xi(t) + \varepsilon^i(t),
\end{aligned} \tag{30}$$

where $\sigma^\omega(t) = \sqrt{\sigma^f(t)^2 + \sigma^\xi(t)^2}$ is the limit process of $\{\sigma_j\}$, as the number of elements in J increases. The relation to σ^f and σ^ξ follows from the well known property of a linear combination of two Brownian motions: $cB1 + dB2 = qB$, where $q = \sqrt{a^2+b^2}$. The continuous flow of signals to the agent can thus be written $\omega_t^i = \sigma^\omega(t)B(t) + \varepsilon^i(t)$.

□

Supplementary tables

Table 10: Descriptive statistics for individual news release series

Series	jumps bv	Cor	jumps rv	Cor	Obs	Densest release time
ADP EMPLOYMENT	6	-0.20	4	-0.45	42	13
AUTO SALES	28	0.02	18	0.14	89	5
AVERAGE WORKWEEK	11	0.19	5	0.72	76	13
BUILDING PERMITS	3	0.96	2	1.00	122	13
BUSINESS INVENTORIES	3	0.01	3	-0.15	111	15
CAP UTILIZATION	1		1		121	14
CHICAGO PMI	8	-0.62	5	0.72	128	15
CONST. SPEND	11	-0.54	6	-0.22	123	15
CONS. CONF	5	-0.96	4	-0.45	128	15
CONSUMER CREDIT	31	0.12	39	-0.32	124	20
CORE CPI	8	-0.39	5	-0.04	83	13
CPI	7	-0.04	4	0.54	90	13
CS HOMEPRICES	2	1.00	2	-1.00	32	14
CURRENT ACCOUNT	1		1		38	13
DURABLE ORDERS	7	-0.12	4	-0.52	124	13
DURABLES EXAUTO	3	0.95	2	1.00	34	13
EMP MANUF	6	-0.56	3	0.42	102	13
EMPLOYMENT COST	2		1		32	13
EX HOMESALES	8	-0.20	7	-0.25	124	15
FHFA HOMEPRICES	0		0		5	15
GDP ADV	6	-0.82	3	-0.87	49	13
PGDP	0		0		5	13
PGDP ADV	4	-0.88	2	-1.00	43	13
PGDP FINAL	1		1		30	13
PGDP PRELIM	2	1.00	0		20	13
GDP FINAL	1		1		32	13
GDP PRELIM	2	1.00	0		28	13
HELP WANTED INDEX	0		0		41	15
HOURLY EARNINGS	12	-0.03	7	0.29	94	13
HOUSING STARTS	4	0.54	3	0.55	127	13
IND. PRODUCTION	1		1		116	14
INITIAL CLAIMS	25	-0.31	18	0.47	546	13
ISM INDEX	11	-0.20	6	-0.43	128	15
ISM SERVICES	4	0.44	1		129	15
LEADING INDICATORS	4	-0.75	2	1.00	93	15
LONGTERM TIC	0		0		15	14
MICH. FINAL	1		1		21	14
MICH. PRELIM.	9	-0.19	7	0.09	108	14
MICH. REV.	9	0.15	6	0.38	106	14
MICH. SENT.	0		0		23	14
NEW HOME SALES	4	0.75	5	-0.35	129	15
NFP	3	-0.71	0		18	14
NONFARM PAY PRIV	1		1		16	13
NONFARM PAYROLLS	21	-0.66	9	-0.63	127	13
PCE CORE INFLATION	0		0		6	13
PCE CORE PRICES	1		0		11	13
PCE PRICES	0		0		3	[130, 140)
PERSONAL INCOME	2	1.00	2	-1.00	99	13
PERSONAL SPENDING	2	-1.00	2		97	13
PHILADELPHIA FED	22	0.11	14	0.04	129	17
PPI	6	0.21	2	-1.00	117	13
PRODUCTIVITY PREL.	3	-0.34	3	-0.34	43	13
PRODUCTIVITY REV.	0		0		41	13
RETAIL SALES	2	1.00	0		117	13
TRADE BALANCE	6	-0.67	2	1.00	125	13
TREASURY BUDGET	32	-0.41	25	-0.12	124	19
TRUCK SALES	28	0.03	18	-0.01	91	5
ULC	0		0		13	13
ULC PRELIM	0		0		2	[130, 140)
UNEMPLOYMENT RATE	15	0.23	7	0.07	92	13
WHOLESALE INV.	5	-0.21	3	-0.02	124	15

Cor denotes instantaneous correlation between the news series and the jump series in the column to the left. Jump bv and Jump rv are the jump paths obtained by using threshold jump detection with interpolated daily bipower variation and realized variance respectively as the threshold estimator. Densest release time is the time in GMT when the most releases of the particular series has occurred. Obs. denotes the number of available news release observations for the particular series (not necessarily coinciding with a jump).

Table 11: Maximum Likelihood parameter estimates

	Sample	2001 - 2004
	Poisson	Binomial
Iterations	3	100
λ_0	0.266699	25.21335
releaseindicator	0.631546	-3.27437
surprisemeasure	0.013229	1.409088
Iterations	8	47
λ_0	0.266772	7.151351
releaseindicator	0.640735	-2.82632
Iterations	16	100
λ_0	0.268	9.729244
surprisemeasure	0.4783	7.832802
Iterations	100	100
λ_0	76.39283	79.66033
cm_Labour_market	-1.88218	0.087347
cm_Labour_market_neg	-10.1811	-2.52951
cm_Housing_market	7.662529	-3.17181
cm_Industrial	4.938962	-3.0585
cm_Consumer	10.71656	9.778614
cm_Sales	-9.78055	-5.5052
cm_Sales_neg	9.590415	-10.0718
cm_Prices	-1.53474	-11.266
cm_Macro	-15.1944	-10.8455

Table 12: Jump Intensity from Consumer related news

Measure	Iterations	Lik.imp	beta	tstat on beta
Consumer	36	2.38	0.196	1.99
Consumer Credit	28	3.04	0.45	2.13
Personal Income	36	0.03	0.05	0.2
Personal Spending	66	1.46	0.29	1.37

No convergence: PCE Core

Table 13: Jump Intensity: Labour market

Measure	Iterations	Lik.imp	beta	tstat on beta
Labour market	8009	10.1	0.18	4.79
ADP Employment	10	1.83	0.5	1.28
Average Workweek	17	8.01	0.34	2.13
Employment cost index	12	0.66	0.37	1.05
Help Wanted Index	15	0.7	-0.44	-0.85
Houly Earnings	2343	0.15	-0.37	-0.01
Nonfarm Payroll	12	0.4	0.42	0.85
Nonfarm Payroll private	13	8.09	0.57	3.2
ULC	12	0.17	0.27	0.51
ULC prelim	11	0.64	1.56	0.63
Unemployment rate	2039	1.79	0.19	0.77
Initial Claims	22	5.39	0.27	2.93

Series estimated to have significant effect are listed in bold. No convergence achieved for ULC revision, Challenger jobcuts and Continuing claims.

Table 14: Jump Intensity from Sentiments

Measure	Iterations	Lik.imp	beta	tstat on beta
Sentiment	1295	7.33	0.21	3.84
Consumer confidence	21	1.39	0.31	1.53
Mich. Final	12	0.37	0.35	0.78
Mich. Prelim	911	0.06	0.06	0.23
Mich. Rev.	13	0.9	0.27	1.22
Mich. Sentiment	9	0.65	-0.87	-0.78
Chicago PMI	40	0.14	0.12	0.45
ISM Services	1949	1.35	0.19	0.56
Leading Indicators	16	1.19	0.28	1.43
Philly Fed	17	6.66	0.53	3.44