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Goddard, J.A.; Kita, A.; Wang, Q.

Journal of International Financial Markets, Institutions and Money

DOI:
10.1016/j.intfin.2015.05.001

Published: 19/05/2015

Peer reviewed version

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Abstract

We study the relationship between investors' active attention, measured by a Google search volume index (SVI), and the dynamics of currency prices. Investor attention is correlated with the trading activities of large FX market participants. Investor attention comoves with comtemporaneous FX market volatility and predicts subsequent FX market volatility, after controlling for macroeconomic fundamentals. In addition, investor attention is related to the currency risk premium. Our results suggest that investor attention is a priced source of risk in FX markets.

Keywords: Investor Attention, FX Volatility, Option Pricing, GARCH

JEL: G12, G14

☆We thank Daniel Andrei (discussant), Owain ap Gwilym, Peter Reinhard Hansen (discussant), Stephan Jank (discussant), Philip Molyneux, Alexandra Niessen-Ruenzi, Evgenia Passari (discussant), Stefan Ruenzi, Andreas Schrimpf, Elvira Sojli, and the seminar participants at Bangor Business School, ZEW Conference "The Role of Expectations in Financial Markets", the "3rd Emerging Scholars in Banking and Finance" Conference at Cass Business School in London, 2013 Swiss Finance Association (SGF) annual conference and 2014 European Central Bank workshop "Using big data for forecasting and statistics" for helpful comments. Errors and omissions remain the responsibility of the authors.

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1. Introduction

Standard asset pricing models have difficulty in explaining some stylized empirical facts on price dynamics that are unrelated to fundamentals. These findings have motivated a growing literature, concerned with behavioral biases in trading. A literature on the implications of investor attention for the dynamics of asset prices has emerged in the last two decades. A commonly maintained assumption in traditional finance is that information acquisition is costless. In reality, the collection and processing of information requires scarce resources, such as attention, time and effort. Allocation of attention precedes portfolio allocation, and can lead to infrequent portfolio decisions, affecting aspects of the dynamics of asset prices such as stock market volatility (Andrei and Hasler, 2014), return comovement, and return predictability (Peng and Xiong, 2006).

The objective of this paper is to examine empirically the link between investor attention and the dynamics of currency prices. We test the predictions of the limited attention theory. We use a measure of search intensity through Google as an indicator of investors' information acquisition, and we examine its impact on currency prices.[1] This paper contributes to a growing literature on the role of investor attention measured by online search intensity through Google, following the seminal paper by Da et al. (2011). In contrast to the previous literature that focuses on stock markets, we examine major foreign exchange (FX) markets. FX markets offer several advantages for this type of investigation. First, the marginal investor is not subject to any short-selling constraints in FX markets. Second, exchange rates are unlikely to be driven by private information. This creates an ideal environment for the investigation of information-driven trades in the absence of private information. Third, investors' acquisition of information on FX markets using Google is unlikely to be subject to accidental increment in search volume, a well-known problem for the use of search volume data based on firm ticker or firm name, both of which have multiple meanings. A search for a keyword such as "EUR/USD" is a clear indication of intent to locate a foreign exchange rate.

Even in highly liquid markets such as the FX market, information acquisition may be important for asset price dynamics. Only a small fraction of international financial holdings are actively managed (Sager and Taylor, 2006; Bacchetta and Van Wincoop, 2010). The infrequency of portfolio allocation decisions may be explained by optimal attention allocation, when information acquisition costs are added to transaction costs (Bacchetta and Van Wincoop, 2005). Rational inattention slows down the process whereby new information becomes impounded into the exchange rate, leading to predictable excess returns. Bacchetta and Van Wincoop (2005) show that rational inattention provides a solution to the forward discount puzzle. There is limited empirical evidence, however, concerning the impact of investors' information acquisition on the dynamics of currency prices, including volatility. This is partly explained by the difficulty in finding

[1] Since online query reflects investors' active attention to information, we refer to investor attention and information acquisition interchangeably in this paper.

a suitable empirical proxy for information acquisition, a question that we address below.

Our empirical analysis begins by examining whether the search volume index (SVI) captures the demand for information in FX markets. The previous literature suggests individual investors frequently use Google to acquire information (Da et al., 2011). Conventional wisdom suggests, however, that individual investors play little role in dealer-dominated FX markets. We argue that Google search intensity is a good measure of information demand for FX investors in general, for the following reasons. First, exchange rates are unlikely to be driven by private information. Google search intensity provides a reasonable measure of acquisition of publicly-available information. In addition to professional trading platforms, Google collates information from a wide range of other sources, providing the investor with a highly diversified information set.[2] Second, individual investors have become increasingly significant as FX market participants in recent years, accounting for between 8% and 10% of global spot FX turnover according to King and Rime (2010). Third, and most importantly, we provide direct evidence that the trading activity of even the biggest market participants is related to SVI. For example, a unit increase in SVI is associated with an increment of about 600 trillion Yen in the trading volume of JPY/USD at weekly frequency.

By employing the SVI we are able to investigate the impact of information acquisition on FX price dynamics at the currency-specific and general market levels.[3] Information acquisition has predictive power for future volatility, after controlling for the current level of volatility. We also include in our analysis an indicator of the degree of macroeconomic uncertainty, interpreted as a determinant of the need for information acquisition.

The relationship between information acquisition and currency price volatility demands further investigation. Based on a vector autoregression (VAR) model, we report a lead-lag relationship between information acquisition and volatility whilst controlling for news supply and macroeconomic variables. This result is substantiated by including currency option price data. We find a positive association between SVI and risk aversion measured by the variance risk premium (the difference between option implied volatility and realized volatility).[4] For robustness we also examine the association between the level of information acquisition and option pricing.[5] We find option pricing to be associated with information acquisition, corroborating our findings on the variance risk premium. Overall our results support the notion that investor

[2] Although professional investors are more likely to use professional trading platforms as sources of information such as Bloomberg or Reuters, these platforms still disseminate publicly available information only, which will be captured by Google almost instantaneously at the moment of their release.

[3] We thank an anonymous referee for the suggestion of studying the effects of currency-specific and general market attention jointly.

[4] The difference between option implied volatility and realized volatility is proposed as a measure of market risk aversion by Aıt-Sahalia and Lo (2000), among others.

[5] In estimations that are not reported in this paper we investigate the relationship between attention and traditional proxies for investors' concern over downside risk such as deep-out-of-the-money (DOTM) put options, option-implied volatility smile, and option-implied volatility skewness.

attention is a priced source of risk in FX markets.

Although a positive association between investor attention and uncertainty measured by volatility is intuitive, several theories suggest the opposite. For example, Freixas and Kihlstrom (1984) argue that when there is uncertainty concerning the value of information, risk averse investors are less willing to acquire information if it is costly. Huang and Liu (2007) argue that investors invest less in risky assets when they are more risk averse, reducing the benefit of more frequent information updates. Therefore information acquisition is less frequent when risk aversion is greater. Our finding of a positive association between the intensity of information acquisition and the variance risk premium is contrary to this prediction. The findings reported in this paper corroborate and extend those of Vlastakis and Markellos (2012), who find that investor attention increases with an increase in the expected variance risk premium for the S&P 500 index.

Our results are best explained by a recent theory of investor attention and market volatility developed by Andrei and Hasler (2014). In their model, the economy has a single output process with an unobservable drift (fundamental). Investors learn about the fundamental by observing the actual output and a signal. The signal reveals more accurate information when the attention level is higher. Attention is state dependent, and related to time-varying risk aversion to extreme downturns. In bad times, investors become increasingly worried about their investments, and seek to acquire more information about fundamentals. In good times, investors have less incentive to acquire information, since they know the probability of a large downturn is low. Increased attention reveals information about the unobserved volatility of fundamentals. Market volatility is linear in filtered fundamental volatility. Under Bayesian learning, filtered volatility is higher when the signal reveals more about fundamentals. Accordingly, investor attention drives market volatility.[6]

To disentangle the effects of investor attention on volatility from those of macroeconomic uncertainty, news impact, liquidity risk, crash risk, investor sentiment, and differences of opinion, we include measures of these variables in our robustness checks. In addition, we examine the potential bias due to nonlinearity, outliers, and unobserved currency-specific effects. We also consider alternative lists of keywords when constructing our investor attention measures. Our main results are shown to be robust to these variations.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes and summarizes our data. Section 4 reports empirical results. Finally, Section 5 concludes.

[6] Andrei and Hasler (2014) show that market volatility increases quadratically due to a decline in posterior variance through learning. We do not find strong empirical support for this hypothesis.

2. Related Literature

Given an abundance of information, investors with limited attention need to allocate their attention efficiently across different assets and over time. Recent theoretical studies examine the implications of limited attention for asset pricing. Peng (2005) shows that attention constraints lead to delayed investor reactions to fundamental shocks and predictable consumption changes. Huang and Liu (2007) develop a model of portfolio selection in the presence of rational inattention. Investors with higher risk aversion or longer investment horizons update news less frequently, but choose more accurate news updates. Peng and Xiong (2006) show that investor inattention is reflected in a tendency to focus on market- and industry-level information, rather than firm-specific information. This "category-learning" behavior, together with investor overconfidence, makes cross-sectional returns predictable. Peng et al. (2007) report empirical evidence.

Testing the empirical implications of limited attention theory requires a measure of attention. Traditional approaches rely on media coverage, extreme price movements, or advertising expenditure. These are indirect proxies that capture mainly investors' passive attention. Barber and Odean (2008) find individual investors are net buyers of attention-grabbing stocks, such as those in the news, with abnormal trading volumes, or with extreme one-day returns. According to Yuan (2011), attention-grabbing events tend to produce high selling volumes when the stock market is high, or moderate purchasing when the stock market is low. DellaVigna and Pollet (2009) report evidence that responses are less immediate, and that there is more drift for announcements on Fridays than for other weekdays. They attribute their findings to lower attention on Fridays owing to the distraction of the coming weekend. Fang and Peress (2009) show that variations in media coverage help explain cross-sectional variation in stock returns. Tetlock (2010) find patterns in post-news returns and trading volumes consistent with asymmetric information models. Engelberg and Parsons (2011) find that local media coverage predicts local trading. Fang et al. (2009) show that stocks with high media coverage are more heavily traded by mutual funds. According to Cohen and Frazzini (2008), stock prices do not incorporate news of economically linked firms, which generates a predictable subsequent price moves.

In a seminal paper, Da et al. (2011) propose a new measure of investor attention constructed from Google search intensity data. Unlike a number of previous proxies, search intensity reflects investors' active information acquisition, and hence provides a direct measure of active investor attention. The Google SVI helps predict short-term momentum and long term reversals. Subsequently, the Google SVI has been used to examine stock price adjustments to earnings announcements (Drake et al., 2011), liquidity and returns (Bank et al., 2011), prediction of firms' future cash flows (Da et al., 2010), biased attention towards local stocks (Mondria and Wu, 2012), and stock market volatility (Vlastakis and Markellos, 2012). While this literature focuses on stock markets, we examine major currency markets.

Smith (2012) reports that SVI has incremental predictive ability beyond GARCH(1,1). The keywords used in his study are "crisis", "financial crisis" and "recession", which are best interpreted as sentiment measures. We examine instead the demand for information on specific currency pairs, which is not driven solely by investor sentiment. Our results are robust to the inclusion of Smith's SVI measure, which loses predictive power when our measure is also included in a GARCH regression.

This study is also related to the literature on excess volatility in foreign exchange rates. The excess volatility puzzle refers to observed volatility that is too high to be explained by movements in fundamentals according to traditional asset pricing models (Meese, 1990; Flood and Taylor, 1996). Attempts to resolve this puzzle draw on explanations such as Bayesian learning (Brennan and Xia, 2001) or adaptive learning (Adam et al., 2009) on the part of homogeneous investors, differences of opinions (Scheinkman and Xiong, 2003; Buraschi and Jiltsov, 2006), and Knightian uncertainty (Cagetti et al., 2002). Beber et al. (2010) show differences of opinions have a strong effect on implied FX volatility beyond the volatility of fundamentals. Menkhoff et al. (2012) report that global FX volatility risk explains the cross-sectional variation in carry trade returns. Unlike these papers, this study focuses on the role of investor attention in explaining variations of currency returns over time. Our results suggest that investor attention is a priced source of risk in FX markets.

We contribute to this literature by analyzing causal links between investor attention and currency price volatility, in contrast to previous studies that examine the contemporaneous relationship between attention and volatility. We fail to find empirical support for the rational inattention theory of Huang and Liu (2007).

3. Data

3.1. Search Volume Index and information supply

Google Trends provides a search volume index (SVI) computed as the ratio of worldwide Google web search on specific keywords to the total number of Google searches over a given period. These data are normalized and scaled from 0 to 100. We download weekly data from January 2004 to September 2011, providing 403 weekly observations on aggregate search volume for each of six currency pairs: USD/JPY, GBP/USD, USD/AUD, EUR/USD, EUR/GBP, EUR/JPY and GBP/JPY; and 245 weekly observations for a seventh pair GBP/JPY, for which there were missing observations n the SVI series. The choice of currency pairs is based on their importance and the availability of SVI data. Trading volumes for these seven pairs represents more than 69% of the total FX trading volume in 2004.[7]

The SVI for each currency pair is defined using a standard set of keywords. Take USD/JPY as an example, we use the following keywords "USD/JPY" + "JPY/USD" + "USD JPY" + "JPY USD" + "Dollar

[7]See Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity in 2007 at http://www.bis.org/publ/rpfxf07t.htm

Yen" + "Yen Dollar" + "Dollar to Yen" + "Yen to Dollar" + "Dollar/Yen" + "Yen/Dollar".[8] These keywords are unlikely to be subject to the problem of accidental increment in search volume, as in the case of SVI based on a firm's ticker or name, both of which may have multiple meanings.[9] In addition to investor attention to individual currency pairs, we also consider a global investor attention measure for the FX market as a whole. For the latter we obtain the SVI on the following keywords: "FOREX" + "Foreign Exchange".

In order to account for the effect of news information supply in FX markets, we collect data from the LexisNexis database for the same observation period as the SVI data. As a measure of the intensity of foreign exchange market news coverage for each currency pair, we count the number of articles per week containing any of the same keywords used to define the Google SVI published in three major financial newspapers, *Financial Times*, *Wall Street Journal* and *New York Times*. We also consider a global foreign exchange market news information supply measure, based on a count of the number of articles per week containing the same keywords used to define the global SVI measure. Table 1 reports summary statistics for the raw SVI and news information supply measures for the seven currency pairs, and for the global SVI and global news information supply measure.

[Insert Table 1 about here]

We let svi_t and and $news_t$ denote the natural logarithms of the SVI and the news information supply measures for the seven currency pairs, respectively; and we let svi_m_t and and $news\_m_t$ denote the natural logarithms of the global FX SVI and the global FX news information supply measure, respectively. We test for the stationarity or non-stationarity of svi_t, svi_m_t, $news_t$ and $news\_m_t$, using the Augmented Dickey-Fuller test (ADF) test (Dickey and Fuller (1979)), the Phillips-Perron (PP) test (Perron and Phillips (1988)), and the Kwiatkowski, Phillips, Schmidt and Shin tests (KPSS) tests (Kwiatkowski et al. (1992)). The null hypothesis for the ADF and PP tests is that the series contains a unit root, while the null hypothesis for the KPSS test is that the series contains no unit root. The unit root test results for svi_t and svi_m_t are varied and sometimes contradictory: predominantly the ADF and KPSS tests indicate that these series are non-stationary, but the PP tests indicate stationarity. The unit root tests for $news_t$ and $news\_m_t$ indicate that these series are stationary. Unit root tests on the first difference of the log SVI series, denoted Δsvi_t and Δsvi_m_t, indicate that these series are stationary.[10]

[8] Google trend treats "+" as "or".

[9] We also consider alternative keywords based on pairs of three-letter abbreviations for currencies from ISO 4217 (Codes for the Representation of Currencies and Funds). The empirical results are similar to those reported in this paper.

[10] For the tests on svi_t and svi_m_t an intercept and linear trend are included in the ADF autoregressions; for the tests on $news_t$, $news\_m_t$, Δsvi_t and Δsvi_m_t an intercept only is included. The maximum lag-lengths are calculated using the method of Schwert (1989a). The unit root test results are available from the corresponding author on request.

We also test for evidence of deterministic seasonality in the Δsvi_t, Δsvi_m_t, $news_t$ and $news\_m_t$ series. Table 2 reports the results of F-tests of a null hypothesis of equality of means across months of the year. Panel A indicates that in respect of Δsvi_t the null hypothesis of equal means can be rejected at the 0.05 level for five of the seven currency pairs. The same null hypothesis is rejected in respect of Δsvi_m_t. Panel C indicates that in respect of $news_t$ the null hypothesis of equal means can be rejected at the 0.05 level for two of the seven currency pairs. The same null hypothesis is rejected in respect of $news\_m_t$. Despite the variation in the results of the equality of means test, for consistency of treatment and following Vlastakis and Markellos (2012), we create a deseasonalized transformation of each of the series as follows. We calculate the mean value of each series for each week of the year, and obtain the deseasonalized series by subtracting the relevant weekly mean value from each observation. We let ΔSVI_t, $\Delta SVIm_t$, $NEWS_t$ and $NEWSm_t$ denote the deseasonalized transformations of Δsvi_t, Δsvi_m_t, $news_t$ and $news\_m_t$ series. Table 2 Panels B and D report the results of the equality of means tests for the deseasonalized series.

[Insert Table 2 about here]

3.2. Option Prices and FX Returns

In the empirical analysis we use option data to explore the relationship between investors' risk aversion and investor attention. We obtain daily/weekly currency option implied volatility data from Bloomberg. The sample period is January 2004 to September 2011. The data are over-the-counter (OTC) European-style option prices provided by Bloomberg contributors. Bloomberg interpolates between the different implied volatility quotes and reports the results as market implied volatilities. The data are all denominated in US dollars. For example GBP/JPY is calculated using GBP/USD and USD/JPY, as FX rates are by convention quoted against the US dollar. We use options with one month maturity for each currency. The specific trading conventions of the FX options are described by Malz (1997).

Options data offer several informational advantages over futures or stocks. Options exist for different investment horizons, allowing the study of preferences over both specific and multiple horizons. Options provide multiple prices for different payoffs on the same underlying asset. The cross-section of options allows for forward-looking estimation of the implied volatility. Option derived distributions from a single point in time, rather than from historical time series, are more sensitive to changing market expectations.

According to the theory, if investors are rational their subjective density forecasts (risk-neutral) should on average correspond to the objective (physical) distribution from which realizations are de facto drawn. It follows that if the risk-neutral probability density function reflects market expectations, it should be an accurate predictor of the realized density function. Prediction failure due to risk aversion on the part of the representative agent drives a wedge between the subjective and objective density forecasts. We use this wedge as a candidate to explain the intensity of investors' information acquisition.

Aıt-Sahalia and Lo (2000) argue that the time-varying risk aversion and subjective variance estimates, known as variance risk premium (VRP), are appropriate market-level measures of risk aversion. Bollerslev et al. (2009) show that during recessions and financial crises, their time-varying risk aversion measure increases significantly. Using a particular portfolio of call options of different maturities and moneyness, Britten-Jones and Neuberger (2000) show that it is possible to derive the risk-neutral expected value of the quadratic variation of returns. Unfortunately Bloomberg does not report the data (strike prices) that would permit estimation of the quadratic variation of returns.[11] Despite the advantages of "model-free" estimation documented by Jiang and Tian (2005), we are data-constrained in approximating the risk-neutral expected value of return quadratic variation from at-the-money (ATM) implied volatilities of currency options. Under physical measures the quadratic variation in returns is usually estimated using squared returns. We use the exponential moving average (EMA) as an empirical proxy for the physical expected value of quadratic variation in returns. EMA is widely used by practitioners (e.g. JP Morgan's RiskMetrics, 1996).

Following Beber et al. (2010), we estimate the expected realized volatility as follows:

$$E_t[RV_{t,T}] = \sqrt{(1-\alpha_{T-t})(r_{t-1}^2 + \alpha_{T-t} r_{t-2}^2 + \alpha_{T-t}^2 r_{t-3}^2 + \cdots)}, \tag{1}$$

where r_t is the log return of the underlying asset on day t, and α_{T-t} is a smoothing parameter that depends on the horizon.[12]

Variance Risk Premium (VRP) is obtained as the difference between the risk-neutral ATM implied volatilities (IV) and the expected realized volatility in (1):

$$VRP_t = IV_{t,T} - E_t[RV_{t,T}]. \tag{2}$$

Panel C of Table 1 reports summary statistics for the variance risk premium, our proxy for the representative investor's risk aversion. Panel D of Table 1 reports summary statistics for the weekly logarithmic FX returns $r_t^i = 100 \times [log(s_t^i) - log(s_{t-1}^i)]$ where s_t^i is the spot price for currency pair i in week t. Most FX returns

[11] We also estimate the currency-specific "model-free" variance risk premia from currency option prices provided by Datastream and the intra-day spot prices obtained from Bloomberg. First, we estimate the expected value of the quadratic variation of returns as in Britten-Jones and Neuberger (2000). We then estimate the excepted realized volatility (RV) based on high-frequency data as in Barndorff-Nielsen (2002) and Andersen et al. (2001). Our principal results remain unchanged when we estimate the VRP using the "model-free" method. Bollerslev et al. (2009) discuss the advantages of using "model-free" estimates of the risk-neutral and subjective variance.

[12] The smoothing parameter decreases with the horizon and is set at 0.1 and 0.03 for one-week and one-month horizons, respectively.

display high volatility and leptokurtosis during the sample period.

4. SVI and FX Investor Attention: Empirical Results

What type of information search is captured by SVI data for FX markets? Our conjecture is that individual investors are more likely to use Google to acquire information (Da et al., 2011), while dealers acquire information through trading platforms such as Bloomberg and Reuters. Therefore SVI should reflect individual investors' demand for information. While there is evidence that the trading activities of small investors are correlated and capable of moving equity prices,[13] conventional wisdom suggests that individual investors play only a limited role in dealer-dominated FX markets. However, King and Rime (2010) report that small retail investors have contributed significantly to the growth in spot currency markets, and may account for 8-10% of the total trading volume.[14] The rapid growth of trading by retail investors might be attributed to the spread of electronic execution methods.

4.1. Trading Volume and Investor Attention

We argue that Google search intensity provides a reasonable measure of the demand for information on the part of FX investors in general, if it is correlated with the trading activities of institutional investors. For example, when a dealer receives information from the trading platform, she faces a tradeoff between rapid trading, and reducing uncertainty through the acquisition of additional information from multiple sources which may include Google. Below, we report evidence that the trading activity of large institutional investors is related to SVI. Although the correlation is relatively low, it is both statistically and economically significant. We obtain weekly amounts of foreign currency holdings of large FX market participants (with more than 50 billion US Dollar foreign exchange contracts on the last business day of any calendar quarter during the previous year) from U.S. Department of the Treasury "Treasury Bulletin" reports. The "Treasury Bulletin" provides information on the amounts of FX spot contracts, FX forward contracts, FX futures contracts and one half of FX options. All these positions are reported as bought and sold. Since trading records for options contain many missing observations, we consider trading volume as the sum of buying and selling volumes for spot, forward and future contracts only. Data on trading volumes are available for three currency pairs: JPY/USD, GBP/USD and EUR/USD. Our use of trading volume data for large FX market participants is conservative. These traders are less likely than retail investors to obtain information through Google.

[13] See, for example, Kumar (2007), Barber et al. (2009a), and Barber et al. (2009b).

[14] The authors rely on data from the eighth Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity ("The Triennial") of BIS. Japanese retail investors are the most active, with an estimated turnover accounting for 30% or more of spot Japanese yen trading (more than $20 billion per day).

We examine the relationship between the weekly change in the natural logarithm of trading volume, $\Delta Volume_t$ and the change in the natural logarithm of the SVI series without the deseasonalizing transformation, Δsvi_t. We estimate the following OLS regressions with Newey-West standard errors for each of the three currency pairs:

$$\Delta Volume_t = \gamma_0 + \gamma_1 \Delta svi_t + \gamma_2 \Delta svi_{t-1} + \gamma_3 \Delta Volume_{t-1} + \gamma_4 \Delta Volume_{t-2} + \eta_t \tag{3}$$

Table 3 indicates that the change in trading volume is positively associated with the change in SVI for all three currency pairs. The coefficients are economically significant. For example, a one percent increase in the attention measure Δsvi_t is associated with increases in trading volume measure $\Delta Volume_t$ of 2.9%, 12.6% and 14.5% for the USD/JPY, GBP/USD and EUR/USD currency pairs, respectively.

[Insert Table 3 about here]

4.2. Volatility and Investor Attention

We now turn to examine the relationship between FX volatility and investor attention. Figure 1(a) plots the time series of the raw SVI series downloaded from Google and FX market conditional volatility estimated from GARCH (1,1), for one currency pair, USD/JPY. There is a positive correlation of 0.31 between these two series. We also estimate global volatility as an equally-weighted mean of the conditional volatilities for the seven currency pairs estimated from GARCH (1,1). Figure 1(b) illustrates the relationship between the raw FX market-level SVI series and the global volatility measure. The association is stronger, with a correlation of 0.75.

[Insert Figure 1 about here]

In order to investigate the relationship between investor attention, news supply and the conditional volatility of FX returns, we augment the GARCH(1,1) model by including the investor attention and news supply variables in the conditional variance equation. We refer to this augmented model as SVI-GARCH(1,1):[15]

$$r_t = \alpha + \epsilon_t \tag{4}$$

$$\sigma_t^2 = \lambda_0 + \lambda_1 \Delta SVI_t + \lambda_2 \Delta SVIm_t + \lambda_3 NEWS_t + \lambda_4 NEWSm_t + \gamma \sigma_{t-1}^2 + \delta \epsilon_{t-1}^2 \tag{5}$$

[15]We also employ an alternative specification of the GARCH model in which attention variables are non-linearly related to conditional volatility. The results confirm the positive relationship between attention and volatility.

where $\epsilon_t = \sigma_t z_t$ and $z_t \overset{\text{iid}}{\sim} N(0, 1)$.

Table 4 reports the estimation results for the SVI-GARCH(1,1) model. In the conditional variance equation the coefficients on ΔSVI_t are positive for all seven currency pairs, and significant at the 0.1 level or below for six pairs. EUR/GBP is the only currency pair for which coefficient on ΔSVI_t is not significant. The coefficients on the general FX market attention measure $\Delta SVIm_t$ are positive for all seven currency pairs and significant at the 0.1 level or below for five pairs. Currency-specific news supply, by contrast, does not appear to exert any consistent effect on the conditional variance. The coefficients on the FX market-level news supply variable $NEWSm_t$ are positive for six of the seven currency pairs, but significant at the 0.1 level for EUR/GBP only.

[Insert Table 4 about here]

In addition to conditional volatility estimated from GARCH(1,1), as a robustness check, we consider two alternative volatility measures: realized volatility (RV), and option-implied volatility (IV).[16] Since we do not have intra-daily data for most of our sample period, we use daily returns to calculate the weekly RV:

$$RV_t = \sum_{j=1}^{N} r_{t,j}^2, \qquad (6)$$

where $r_{t,j}$ is the daily return for day j in week t, and N is the number of trading days in week t.

We examine the relationship between attention and each of these volatility measures by estimating the following OLS regression in which we control for the information supply and returns:

$$Vola_t = \lambda_0 + \lambda_1 \Delta SVI_t + \lambda_2 \Delta SVIm_t + \lambda_3 NEWS_t + \lambda_4 NEWSm_t + \lambda_5 Vola_{t-1} + \lambda_6 Return_t + \eta_t, \qquad (7)$$

where *Vola* denotes either RV, or IV as defined above, and *Return* denotes the weekly return for the relevant currency pair. In (7), the lagged dependent variable accounts for persistence in volatility, and the contemporaneous return controls for any relationship between returns and volatility.

Table 5 Panel A reports positive coefficients on the currency-specific or general FX market attention measures in the regressions for RV for all seven pairs. The coefficients on the general FX market attention measure are positive for all seven currency pairs and statistically significant at the 0.05 level for USD/JPY and USD/AUD. The coefficients on the currency-specific attention measure are borderline significant for USD/AUD and EUR/USD, while the coefficents are significant at the 0.05 level for EUR/JPY. The coefficients

[16] We thank an anonymous referee for this suggestion. IV is estimated using the Black-Scholes formula. We download IV directly from Bloomberg, and interpolate where necessary to construct a weekly series.

on the news supply measure are predominantly positive and significant at the 0.01 level for EUR/USD and at the 0.05 level for GBP/JPY. The coefficients on the general FX market news supply measure are also predominantly positive, and statistically significant at the 0.1 level or below for four currency pairs.

Table 5 Panel B reports the estimations with *IV* as dependent variable. The coefficients on the currency-specific attention measure are positive for five currency pairs and significant at the 0.01 level for three pairs, GBP/USD, EUR/USD and EUR/GBP. The coefficient on the general FX market attention measure are positive for all six pairs, significant at the 0.05 level for three pairs, and significant at the 0.1 level for one further pair. The coefficients on the currency-specific news supply measure are predominantly positive, and significant at the 0.1 level or below for three currency pairs. Similarly the coefficients on the market-level FX news supply measure are positive for all currency pairs, and significant at the 0.1 level or below for four pairs.

[Insert Table 5 about here]

These results are consistent with the findings for the SVI-GARCH model. In most cases attention is positively related to contemporaneous volatility. Overall, the positive relationship between investor attention and volatility seems to be stronger than the relationship between news supply and volatility. The results are robust to the inclusion of additional lags for any of the volatility measures. Median regressions with the same specifications produce similar results. If news rumors circulate firstly on the internet, and subsequently are reported by official news channels, this should result in a higher predicitve power for the investor attention measures than for the news supply measures. In the following section we investigate further where the information discovery takes place, while controlling for macroeconomic uncertainity as defined below.

A possible concern is that volatility in fundamentals may drive both volatility in exchange rates and investor attention. We investigate this possibility using a procedure adapted from Schwert (1989b). We obtain monthly series for industrial production (IP), 3-month interest rate (SR), consumer price index (CPI), unemployment rate (UE), broad money (BM) and calculate their first differences in logarithms, denoted ΔX_t. We regress ΔX_t on its own first 12 lags and a set of monthly dummy variables, denoted D_{jt}. Denoting the absolute values of the residuals from these regressions as $|\hat{\varepsilon}_t|$, we estimate the following specification:

$$|\hat{\varepsilon}_t| \quad = \quad \sum_{j=1}^{12} \gamma_j D_{jt} + \sum_{i=1}^{12} \rho_i |\hat{\varepsilon}_{t-i}| + u_t. \tag{8}$$

The fitted values from (8), $\hat{\varepsilon}_t$, are used as a proxy for the standard deviation of ΔX_t. We include the absolute value of $\tilde{\varepsilon}_t$ for both countries (for each currency pair) and for each of the five series listed above as additional covariates in (7). We find that the magnitudes and significance of the coefficients on the investor attention variables are qualitatively similar to those reported in Table 5.[17]

4.3. Vector Autoregressions

In this section we examine the lead-lag relation among investor attention, news supply and volatility, using a Vector Autoregression (VAR) framework. We estimate the following VAR(2) model with exogenous variables:

$$\mathbf{Y_t} \quad = \quad \beta_0 + \beta_1 \mathbf{Y_{t-1}} + \beta_2 \mathbf{Y_{t-2}} + \Phi_1 \mathbf{X_{t-1}} + \Phi_2 \mathbf{X_{t-2}} + \eta_t \tag{9}$$

where $\mathbf{Y_t} = (vola_t\ \Delta SVI_t\ NEWS_t)'$, $\mathbf{X_t} = (\ \Delta SVIm_t\ NEWSm_t)$ and $vola_t$ denotes conditional volatility estimated from a GARCH(1,1) model.

In (9) the FX market-level investor attention and news supply measures $\Delta SVIm_t$ and $NEWSm_t$ are treated as exogenous, and the volatility, attention and news measures for each currency pair are treated as endogenous. Table 6 reports the estimation results.[18] We find that the investors' attention measure leads the news supply variables in the equations for volatility. Four of the seven coefficients on the currency-specific attention variables ΔSVI_t are statistically significant at 0.01 level, and one more is significant at the 0.05 level. Five of the seven coefficients on the FX market-level attention measure $\Delta SVIm_{t-1}$ are significant at the 0.01 level, and one more coefficient is significant at the 0.05 level. Three of the seven coefficients on the FX market-level news supply variable $NEWSm_t$ are significant in the equations for volatility; but in general the news supply variables have weaker statistical significance and therefore less predictive capability than the attention measures in the volatility equations.

In the equations for investor attention, neither the lagged volatility measures nor the lagged news supply variables demonstrate evidenceof predictive capability, with many coefficients insignificant and inconsistently signed. Likewise in the equations for news supply, neither the lagged volatility nor the lagged attention measures demonstrate evidence of predictive capability. Accordingly, the principal conclusions drawn from Table 6 are that an increase in the investor attention measure leads an increase in volatility in the following week; an increase in the FX-market level news supply measure may also lead an increase in volatility in the following week; but there is no evidence that either investor attention or news supply are led by the other variables included in the VAR.

[Insert Table 6 about here]

[17] The results are not reported, but are available from the corresponding author on request.

[18] The Bayesian information criterion (BIC) selects lag-lengths of one or two in most of the regressions. For ease of presentation, we report results based on a VAR(2) specification for all currency pairs. Our principal findings are not affected by changes in the lag length.

4.4. Attention and Variance Risk Premium

In this section, we examine the association between risk aversion measured by variance risk premium (*VRP*) and investor attention. Asset pricing theory suggests that the pricing kernel, the Arrow-Debreu state price per unit probability, forms the link between the subjective density functions used by risk averse and rational investors in forming their expectations, and the risk-neutral density function used in option pricing.[19] The possibility of the pricing kernel becoming disconnected from marginal rates of substitution in the real economy, even in the absence of arbitrage opportunities, is considered in the asset pricing theory of Cochrane (2001).[20] It follows that if investor attention affects asset prices, this will be reflected in the slope of the volatility spread (i.e., *VRP*), the difference between the implied and realized volatility.

Empirically we consider the following regression, which includes lagged *VRP* and current and lagged attention.

$$VRP_t = \alpha + \beta_1 \Delta SVI_t + \beta_2 \Delta SVI_{t-1} + \beta_3 VRP_{t-1} + \varepsilon_t. \tag{10}$$

Table 7 reports the estimation results. The coefficients on ΔSVI_t are positive for all six currency pairs and significant at the 0.1 level or below for four pairs. The coefficients on ΔSVI_{t-1} are positive for five pairs and significant at the 0.05 level or below for three pairs. These results are consistent with the notion that risk aversion is positively related to information demand. When risk aversion increases, investors are motivated to reduce uncertainty by increasing their intensity of information acquisition. This increased effort translates into higher volatility in returns, providing the link between risk aversion and volatility in returns during times of financial distress. This channel might provide an explanation for the effects of market conditions on the relationship between the demand for information and volatility documented in Table 6.

[Insert Table 7 about here]

Our results for the relationship between SVI and *VRP* are relevant for testing the Huang and Liu (2007) rational inattention hypothesis, that information acquisition becomes less frequent when risk aversion is greater. This is because investors invest less in risky assets as the benefit of frequent information updates declines due to higher risk aversion. However, our findings on the positive relationship between information

[19]Under the classic assumptions of complete and frictionless markets and a single asset, Aıt-Sahalia and Lo (2000) formulate the theoretical link between the risk-neutral $q(S_T)$ and physical $p(S_T)$ functions via the representative's investor utility function $U(S_T)$ as:

$$\frac{p(S_T)}{q(S_T)} = \lambda \frac{U'(S_T)}{U'(S_t)} \equiv \zeta(S_T)$$

where λ is constant, and $\zeta(S_T)$ is the pricing kernel.

[20]Figlewski (1989) and Green and Figlewski (1999), among others, permit sentiment to affect option prices. Stein (1989) and Poteshman (2001) show that behavioral biases affect options prices.

acquisition and variance risk premium are contrary to the rational inattention hypothesis.

4.5. Robustness Check

4.5.1. Sub-sample analysis

In this section we check for the stability of our results. For this purpose we divide the sample period into two roughly equally sized sub-periods, 2004-2007 and 2008-2011, and repeat the estimations of (7). The second sub-period includes the recent global financial crisis, allowing for the possibility that the structure of the relationship between information acquisition and the dynamics of currency pricing varies with market conditions.

[Insert Table 8 about here]

Table 8 reports the estimation results for the *RV* and the *IV* volatility measures. Panel A and B suggest that the positive relationships between the currency-specific attention measure and *RV* are mostly insignificant in both sub-samples. The general FX market attention measures are positively and significantly associated with *RV* in the second sub-period for USD/JPY and USD/AUD, but not in the first sub-period, suggesting only weak evidence of any link between investor attention and *RV*. Similar patterns are observed for the news supply measures. The positive relationship between the attention measures and *IV* is more pronounced. In Table 8 Panel C for the first subperiod the coefficients on the currency-specific attention measure are positive for all currency pairs and significant for two pairs. The coefficients on the FX market-level attention measure are positive and significant at the 0.1 level or below for three out of six pairs. In Panel D for the second sub period the coefficients on the currency-specific attention measures are significant at the 0.05 level or below for three pairs, and the coefficients on the FX market-level attention measure are positive and significant at the 0.1 level or below for four pairs. The results for *IV* suggest that the structure of the relationship between investor attention and volatility is sensitive to changes in market conditions, and became stronger during the financial crisis. The weaker results for *RV* might be due to measurement error arising from the use of daily data, rather than high-frequency (intra-daily) data, to estimate *RV*.[21]

4.5.2. Other Search Keywords

So far we have considered general search keywords for each currency pair. Alternatively, we consder pairs of three-letter abbreviations as the only search keyword for each currency pair. Take USD/JPY as an

[21] The recent literature on stochastic volatility modeling (Andersen et al. (2001); Barndorff-Nielsen (2002)) suggests, realized variance measures from high-frequency data reflect more accurately the true variance of the underlying continuous-time process than those from low-frequency data.

example, we consider the keywords "USD/JPY" + "JPY/USD". These abbreviations are from ISO 4217 (Codes for the Representation of Currencies and Funds) and have been long used by investors and the international banking community. A search for the keyword "USD/JPY" is a clear indication of investors' interest in foreign exchange rates. The estimation results based on SVI defined using three-letter abbreviations (not reported) are qualitatively similar to those reported above.

4.5.3. Global FX market attention and volatility

We also examine the relationship between the global FX market attention measure and global FX market volatility, measured as the equally-weighted mean of the GARCH(1,1) conditional volatilities for the seven currency pairs. The estimation results (not reported) are similar to those for the individual currency pairs.

4.5.4. Liquidity Risk, Crash Risk, Investor Sentiment and Differences of Opinion

We consider alternative competing explanations of volatility dynamics and investors' behavior, using the following regression:

$$\begin{aligned} \mathtt{Vola}_t &= \lambda_0 + \lambda_1 \Delta SVI_t + \lambda_2 \Delta SVIm_t + \lambda_3 \mathtt{Vola}_{t-1} + \lambda_4 \mathtt{NEWS}_t + \lambda_5 \mathtt{NEWSm}_t + \lambda_6 \mathtt{Liquidity}_t \\ &\quad + \lambda_7 \mathtt{Skewness}_t + \lambda_8 \mathtt{Fear}_t + \eta_t, \end{aligned} \tag{11}$$

where $Vola_t$ denotes either RV, or IV as defined above.

It is widely recognized that conditional volatility may vary due to temporary changes in liquidity: high volatility is likely to correspond to low liquidity. $Liquidity_t$ is the difference between the ask price and bid price for each currency pair.[22]

Brunnermeier et al. (2008) report that periods of high risk of a crash in the carry trade market coincide with high market volatility measured by VIX. Investors may become more anxious when there is high risk of a crash, and hence demand more information. Our proxy for the risk of a crash is $Skewness_t$, the skewness coefficient for the daily log returns series over the past month.

Black (1986), De Long et al. (1990), and Foucault et al. (2011), among others, suggest that variation in investor sentiment affects volatility. Da et al. (2013) argue that internet search behavior reflects the sentiment of investors. By aggregating the volume of internet queries that are related to household concerns such as "recession" or "bankruptcy", Da et al. (2013) construct a FEAR index to measure investor sentiment, and show that increases in the FEAR index predict excess volatility. If our measure of investor attention in the FX market reflects sentiment, inclusion of the FEAR index in a regression for volatility should reduce the significance of the attention variable. We follow the same approach in Da et al. (2013) and construct a fear

[22]The results are unaffected if we use the bid ask spread defined as $2 \times (ask - bid)/(bid + ask)$.

index for household-level concerns, denoted $\Delta Micro\_Fears_t$ and a fear index for concerns about business conditions, denoted $\Delta Macro\_Fears_t$.

Table 9 Panel A reports most of the coefficients on $Liquidity_t$ are positive in the RV_t regressions. This indicates that attention is higher during periods of low liquidity (high bid-ask spread). During periods of high volatility, investors may require a substantial discount in order to trade, and the effort devoted to information acquisition may tend to increase. The coefficient on $Skewness_t$ are all positive, but significant for one currency pair only. None of the coefficients on $\Delta Micro\_Fears_t$ and $\Delta Macro\_Fears_t$ are significant. Table 9 Panel B reports that the liquidity, skewness and fear index measures display somewhat weaker association with IV_t. Median regressions (not reported) produce qualitatively similar results. Overall, the coefficients on the currency specific and the general FX market-level investor attention measures in specifications that control additionally for liquidity risk, crash risk and sentiment are consistent with our previous findings.

[Insert Table 9 about here]

Finally, Beber et al. (2010) show that differences of investor opinion have a strong effect on implied FX volatility, in addition to volatility measures for fundamentals. They also examine the association between differences of opinion and volatility smile, variance risk premium and carry trade returns. We use monthly analysts forecast data on FX rates from the Centre for European Economic Research (ZEW) to build an empirical proxy for sentiment and differences of opinion. The ZEW data consists of monthly forecasts on the following currency pairs: EUR/USD, EUR/GBP and EUR/JPY. We compute a sentiment measure, denoted $Sentiment_t$ as the cross-sectional average of forecasts made by a panel of about 250 analysts each month. A measure of differences of opinion, denoted $Disagreement_t$, is the cross-sectional standard deviation of the forecasts made by the analysts each month. To control for the effect of sentiment and differences of opinion, we estimate the following regressions:

$$\begin{aligned} \mathtt{Vola}_t &= \lambda_0 + \lambda_1 \Delta SVI_t + \lambda_2 \Delta SVIm_t + \lambda_3 \mathtt{Vola}_{t-1} + \lambda_4 \mathtt{NEWS}_t + \lambda_5 \mathtt{NEWSm}_t + \lambda_6 \mathtt{Sentiment}_{t-1} \\ &\quad + \lambda_7 \mathtt{Disagreement}_{t-1} + \eta_t, \end{aligned} \tag{12}$$

[Insert Table 10 about here]

Table 10 reports the results for the RV_t and IV_t volatility measures for the EUR/USD, EUR/GBP and EUR/JPY currency pairs. The currency-specific attention measures are positively associated with both volatility measures. The coefficients are significant at the 0.05 level for one currency pair in the RV regression, and significant at the 0.01 level for all three pairs in the IV regression. The coefficients on the general FX market-level investor attention measure are predominantly positive. The coefficients on the currency-specific and general FX market-level news supply measures are all positive, but predominantly insignificant. The coefficients on the sentiment and disagreement measures suggest that these have some predictive power for FX returns volatility.

5. Conclusion

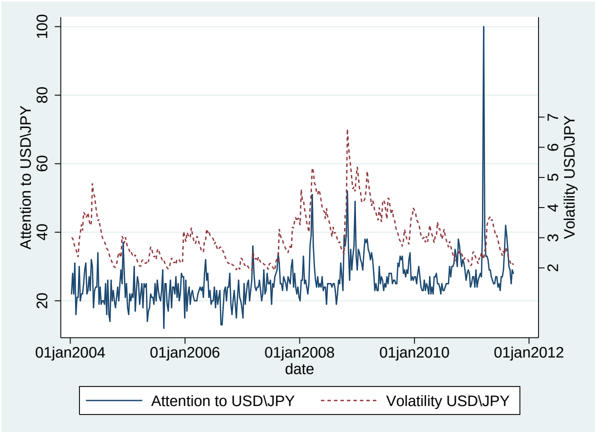
This paper reports an empirical investigation of the association between investor attention and volatility for the foreign exchange (FX) rates of seven major currency pairs, which accounted for more than 69% of the total turnover in FX markets in 2004. We examine the relationship between attention and volatility in returns, both contemporaneously and using a VAR framework, while controlling for macroeconomic uncertainty.

We report that changes in investor attention are strongly associated with changes in trading volume of the largest traders in FX markets. There is a positive and significant association between attention and volatility. Investors' attention appears to be able to forecast the future volatility of the currency returns even after controlling for news supply and macroeconomic uncertainty. Investor attention is also associated with time-varying risk aversion measured by the variance risk premium.

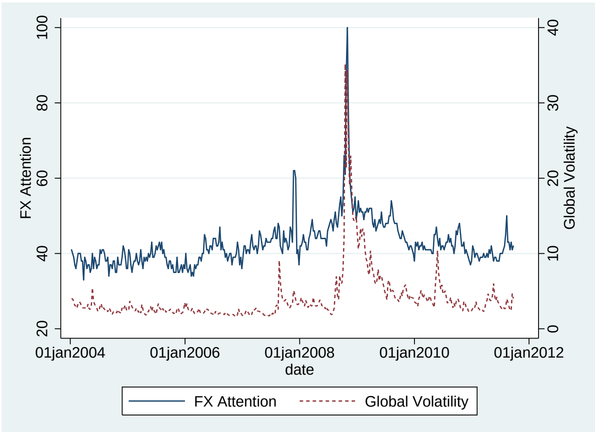
Our results are consistent with the notion that time-varying investor attention is a priced risk factor in FX markets. Given the (still) limited theoretical evidence, these findings suggest a need for the development of more rigorous models on the role of investor attention, in order to explain the impact on currency returns and related derivative prices.

6. Tables and Figures

Figure 1. Attention and volatility



(a) USD\JPY Attention and Volatility



(b) FX Attention and Volatility

Panel (a) plots the weekly conditional volatility of the USD/JPY exchange rate returns, and the raw SVI series downloaded from Google, which forms the basis for the investor attention measure for USD/JPY. The raw SVI series is obtained using the following keywords: “USD/JPY” + “JPY/USD” + “USD JPY” + “JPY USD” + “Dollar Yen” + “Yen Dollar” + “Dollar to Yen” + “Yen to Dollar” + “Dollar/Yen” + “Yen/Dollar”. Panel (b) plots the weekly global conditional volatility series for the FX market and the raw SVI series downloaded from Google which forms the basis for the global FX market-level investor attention measure. The raw SVI series is obtained using the following keywords: “FOREX” + “Foreign Exchange”. Conditional volatility is estimated using a GARCH (1,1) specification. Global conditional volatility is an equally-weighted mean of the GARCH(1,1) conditional volatilities for the seven currency pairs. The sample period is January 2004 to September 2011.

Table 1. Summary statistics for SVI, news, variance risk premium and weekly FX returns

This table reports summary statistics. Panel A reports summary statistics for the raw (untransformed) SVI series, downloaded from Google following the procedure described in section 3.1. Panel B reports summary statistics for the raw (untransformed) news supply series, obtained from LexisNexis following the procedure described in section 3.1. Panel C reports summary statistics for the variance risk premium, the difference between option-implied volatility and expected realized volatility. Panel D reports summary statistics for the weekly returns series calculated from spot FX rates, defined as $Return_t = 100 \times [log(s_t) - log(s_{t-1})]$, where s_t is the spot rate in week t. Owing to missing observations in the option implied volatility data for USD/AUD, only six currency pairs are reported in Panels C and D. The sample period is January 2004 to September 2011, and the data are weekly.

	USD/JPY	GBP/USD	USD/AUD	EUR/USD	EUR/GBP	EUR/JPY	GBP/JPY	FX Market
	Panel A: Raw (untransformed) SVI series							
Mean	25.84	45.81	26.65	45.03	35.84	28.07	23.91	42.64
Std. Dev.	6.66	11.79	14.79	13.63	12.85	8.89	21.62	6.46
Min.	12.00	27.00	8.00	24.00	15.00	12.00	0.00	33.00
Max.	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
No. Observation	403	403	403	403	403	403	243	403
	Panel B: Raw (untransformed) news supply series							
Mean	3.40	1.03	0.12	5.76	1.09	3.37	0.41	30.59
Std. Dev.	2.91	1.11	0.38	3.50	1.30	2.10	0.71	13.27
Min.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.00
Max.	18.00	6.00	2.00	21.00	10.00	12.00	4.00	104.00
No. Observation	403	403	403	403	403	403	403	403
	Panel C: Variance risk premia							
Mean	0.014	0.013	–	0.013	0.011	0.015	0.018	
Std. Dev.	0.006	0.007	–	0.006	0.007	0.010	0.013	
Min.	0.004	0.004	–	0.003	0.003	0.002	0.004	
Max.	0.051	0.057	–	0.044	0.052	0.093	0.112	
	Panel D: FX return							
Mean	-0.10	-0.02	-0.11	0.03	0.07	-0.09	-0.16	
Std. Dev.	1.73	1.77	2.39	1.74	1.39	2.07	2.39	
Min.	-7.32	-8.86	-5.92	-6.96	-7.50	-13.86	-16.51	
Max.	5.05	5.68	19.53	6.70	5.87	4.83	7.77	
Skewness	-0.32	-0.66	1.81	-0.24	-0.24	-1.33	-1.29	
Kurtosis	3.55	5.71	14.36	4.40	7.29	9.16	9.82	

Table 2. Mean comparison tests

This table reports the results of the F-tests for the null hypothesis of equality of means across months of the year for the investor attention and news supply measures. Δsvi_t is the first difference of the natural logarithm of the weekly SVI series. ΔSVI_t is the deseasonalized transformation of Δsvi_t defined using the procedure described in section 3.1. $news_t$ is the natural logarithm of the weekly news supply series. $NEWS t_t$ is the deseasonalized transformation of $news_t$, defined using the procedure described in section 3.1.

Tests	USD/JPY	GBP/USD	USD/AUD	EUR/USD	EUR/GBP	EUR/JPY	GBP/JPY	FX Market
	Panel A: Δsvi_t							
F-test	2.75	3.98	5.30	5.42	6.05	1.29	9.49	6.62
P-value	0.03	0.00	0.00	0.00	0.00	0.31	0.25	0.00
	Panel B: ΔSVI_t							
F-test	0.12	0.21	0.10	0.23	0.24	0.14	58.42	0.21
P-value	1.00	0.99	1.00	0.99	0.99	1.00	0.10	0.99
	Panel C: $news_t$							
F-test	0.76	0.74	2.32	4.46	0.88	1.39	0.74	2.91
P-value	0.67	0.69	0.05	0.00	0.57	0.26	0.69	0.02
	Panel D: $NEWS_t$							
F-test	0.68	0.32	0.29	0.40	0.25	0.12	0.20	0.40
P-value	0.74	0.97	0.98	0.94	0.99	1.00	0.99	0.94

Table 3. Regressions of currency trading volume on attention

This table reports estimations of (3). The dependent variable is $\Delta Volume_t$ the first difference of the natural logarithm of the weekly currency trading volume of large FX market participants. "Treasury Bulletin" reports of the US Department of the Treasury. Currency holdings include FX spot, forward and futures contracts. Major market participants are defined as those market players that have more than 50 billion US Dollar FX contracts on the last business day of any calendar quarter during the previous year. Trading volume is calculated as the sum of buying and selling volumes for spot, forward and future contracts. Δsvi_t is the first difference of the weekly log SVI series for each currency pair, as defined in section 3.1. Newey-West standard errors are in parentheses. The sample period is January 2004 to September 2011. $***$ denotes coefficient significantly different from zero, 0.01 level; $**$ 0.05 level; $*$ 0.10 level.

	USD/JPY	GBP/USD	EUR/USD
Δsvi_{t-1}	0.029	0.126*	0.145
	(0.076)	(0.072)	(0.107)
Δsvi_{t-2}	0.098	0.130*	0.235**
	(0.077)	(0.072)	(0.108)
$\Delta Volume_{t-1}$	-0.989***	-0.991***	-0.999***
	(0.077)	(0.074)	(0.074)
$\Delta Volume_{t-2}$	-0.697***	-0.715***	-0.709***
	(0.078)	(0.074)	(0.075)
Constant	0.021*	0.026**	0.033***
	(0.012)	(0.011)	(0.011)
Adj. R-squared	0.65	0.67	0.67
N	90	90	90

Table 4. Contemporaneous volatility and attention

This table reports estimations of the SVI-GARCH(1,1) model, (4) and (5). ΔSVI_t is the investor attention measure for each currency pair. $\Delta SVIm_t$ is the global FX market-level investor attention measure. $NEWS_t$ and $NEWSm_t$ are the currency-specific and global FX market-level news supply measures respectively. The transformations of the raw SVI and news series used to obtain the attention and news measures are described in section 3.1. ϵ^2 and σ^2 are the ARCH and GARCH terms, respectively. The sample period is January 2004 to September 2011, and the data are weekly. $***$ denotes coefficient significantly different from zero, 0.01 level; $**$ 0.05 level; $*$ 0.10 level.

	USD/JPY	GBP/USD	USD/AUD	EUR/USD	EUR/GBP	EUR/JPY	GBP/JPY
Mean Equation							
Constant	-0.041	0.050	-0.150	0.060	0.076	0.032	-0.259*
	(0.077)	(0.078)	(0.098)	(0.076)	(0.047)	(0.080)	(0.133)
Variance Equation							
ΔSVI_{t-1}	4.024***	3.105*	5.481***	4.928*	0.916	5.491*	5.525**
	(0.643)	(1.256)	(1.213)	(2.970)	(0.695)	(2.824)	(1.988)
$\Delta SVIm_t$	5.033**	5.893*	7.784*	5.879**	3.177**	8.943	11.405
	(2.379)	(2.436)	(4.536)	(2.752)	(1.270)	(7.202)	(6.413)
$NEWS_t$	0.328	-0.100	-0.188	0.429*	-0.021	0.025	0.911
	(0.192)	(0.090)	(0.918)	(0.251)	(0.046)	(0.697)	(0.648)
$NEWSm_t$	0.783	0.043	-0.043	0.334	0.220*	1.653	0.146
	(0.413)	(0.086)	(0.380)	(0.367)	(0.088)	(1.037)	(0.0382)
ϵ^2_{t-1}	0.121	0.053**	0.161***	0.195***	0.096***	0.123*	0.128**
	(0.074)	(0.020)	(0.040)	(0.073)	(0.035)	(0.067)	(0.050)
σ^2_{t-1}	0.442**	0.910***	0.682***	0.455***	0.848***	0.430**	0.825***
	(0.201)	(0.032)	(0.083)	(0.155)	(0.053)	(0.162)	(0.069)
N	402	402	402	402	402	402	242

Table 5. Investor attention, realized and option-implied volatility

This table reports estimations of (7). The dependent variable is volatility, measured using realized volatility (Panel A) and implied volatility (Panel B). *RV* denotes realized volatility, defined in (6). *IV* denotes implied volatility, obtained from Bloomberg. ΔSVI_t is the investor attention measure for each currency pair. $\Delta SVIm_t$ is the global FX market-level investor attention measure. $NEWS_t$ and $NEWSm_t$ are the currency-specific and global FX market-level news supply measures, respectively. The transformations of the raw SVI and news series used to obtain the attention and news measures are described in section 3.1. $Return_t$ denotes the weekly percentage logarithmic return for each currency pair. Newey-West standard errors are in parentheses. The sample period is January 2004 to September 2011, and the data are weekly. $***$ denotes coefficient significantly different from zero, 0.01 level; $**$ 0.05 level; $*$ 0.10 level.

	USD/JPY	GBP/USD	USD/AUD	EUR/USD	EUR/GBP	EUR/JPY	GBP/JPY
	Panel A: Realized volatility (*RV*)						
ΔSVI_t	0.489	0.085	4.537*	3.734*	0.014	3.072**	-0.117
	(0.565)	(1.258)	(2.380)	(2.183)	(1.100)	(1.534)	(1.860)
$\Delta SVIm_t$	6.921**	6.472	19.038**	1.346	0.540	4.497	22.607
	(3.247)	(5.801)	(8.742)	(1.956)	(1.908)	(5.698)	(15.838)
RV_{t-1}	0.151***	0.420***	0.531***	0.386***	0.429***	0.393***	0.425***
	(0.055)	(0.104)	(0.086)	(0.101)	(0.083)	(0.100)	(0.054)
$NEWS_t$	0.332	-0.098	2.537	0.572***	0.303	0.098	2.651**
	(0.212)	(0.204)	(2.809)	(0.180)	(0.283)	(0.390)	(1.143)
$NEWSm_t$	0.760*	1.133**	0.737	0.631*	0.761**	1.253	0.215
	(0.417)	(0.507)	(1.513)	(0.352)	(0.380)	(0.774)	(1.562)
$Return_t$	-0.219**	-0.044	1.436**	0.055	0.124	-0.732***	-0.678**
	(0.105)	(0.147)	(0.668)	(0.154)	(0.227)	(0.226)	(0.339)
Constant	1.923***	1.242***	2.289***	1.280***	0.766***	1.888***	2.781***
	(0.194)	(0.212)	(0.434)	(0.191)	(0.137)	(0.361)	(0.446)
Adj. R-squared	0.10	0.21	0.52	0.22	0.21	0.34	0.35
N	402	402	402	402	402	402	242
	Panel B: Implied volatility (*IV*)						
ΔSVI_t	0.430	2.055***	–	2.922***	1.036***	1.142**	-0.321
	(0.460)	(0.506)	–	(0.975)	(0.333)	(0.443)	(0.730)
$\Delta SVIm_t$	8.015*	4.807**	–	4.731**	1.910	6.694**	0.347
	(4.703)	(1.958)	–	(2.095)	(1.298)	(3.148)	(1.900)
IV_{t-1}	0.855***	0.955***	–	0.964***	0.969***	0.932***	0.929***
	(0.040)	(0.017)	–	(0.018)	(0.017)	(0.016)	(0.026)
$NEWS_t$	0.229*	0.191**	–	0.013	0.131	0.292*	-0.481
	(0.118)	(0.079)	–	(0.084)	(0.080)	(0.173)	(0.470)
$NEWSm_t$	0.501*	0.234*	–	0.311**	0.180	0.441*	0.499
	(0.273)	(0.124)	–	(0.158)	(0.115)	(0.232)	(0.469)
$Return_t$	-0.403***	-0.175***	–	-0.061	0.156***	-0.498***	-0.089
	(0.121)	(0.056)	–	(0.057)	(0.048)	(0.098)	(0.065)
Constant	1.560***	0.450***	–	0.393**	0.245*	0.806***	1.180***
	(0.433)	(0.154)	–	(0.171)	(0.125)	(0.177)	(0.371)
Adj. R-squared	0.83	0.95	–	0.93	0.95	0.94	0.87
N	402	402	–	402	402	402	177

Table 6. VAR regressions of volatility and the search volume index

This table reports estimations of (9). The dependent variables in the three-equation VAR(2) model are: conditional volatility, measured by fitting a GARCH(1,1) model to the FX returns series for each currency pair, and denoted $Vola_t$; and the attention and news measures. ΔSVI_t is the investor attention measure for each currency pair. $NEWS_t$ is the news supply measure for each currency pair. The exogenous variables in the VAR(2) model are $\Delta SVIm_t$, the global FX market-level investor attention measure, and $NEWSm_t$ the global FX market-level news supply measure. The transformations of the raw SVI and news series used to obtain the attention and news measures are described in section 3.1. To conserve space standard errors are not reported. The sample period is January 2004 to September 2011, and the data are weekly. $***$ denotes coefficient significantly different from zero, 0.01 level; $**$ 0.05 level; $*$ 0.10 level.

	USD/JPY	GBP/USD	USD/AUD	EUR/USD	EUR/GBP	EUR/JPY	GBP/JPY
$vola_t$							
$vola_{t-1}$	0.883***	0.841***	0.546***	0.504***	0.865***	0.806***	0.692***
$vola_{t-2}$	0.064	0.121**	0.116**	0.051	0.074	0.152***	0.240***
ΔSVI_{t-1}	0.107	0.913***	6.481***	3.207***	0.743**	1.600***	0.083
ΔSVI_{t-2}	0.073	0.076	2.949*	1.515	0.494*	0.959	-0.422
$NEWS_{t-1}$	0.038*	0.146**	0.490	0.193	0.097	0.107	1.159**
$NEWS_{t-2}$	-0.018	0.053	3.514***	0.011	0.099	-0.209	0.557
$\Delta SVIm_{t-1}$	1.298***	1.390**	16.366***	7.053***	-0.631	10.482***	21.972***
$\Delta SVIm_{t-2}$	0.244	-0.892	-1.989	-1.709	-0.834	1.078	-2.582
$NEWSm_{t-1}$	0.155***	0.050	2.051*	0.504	0.082	0.631**	2.110**
$NEWSm_{t-2}$	-0.060	0.127	-2.431**	-0.047	-0.001	-0.341	-0.856
Constant	0.157***	0.117**	1.923***	1.390***	0.116**	0.194*	0.313
ΔSVI_t							
$vola_{t-1}$	-0.012	-0.005	0.001	-0.008***	-0.005	-0.002	-0.003
$vola_{t-2}$	-0.002	0.002	-0.003**	0.001	-0.001	-0.000	0.002
ΔSVI_{t-1}	-0.553***	-0.343***	-0.478***	-0.301***	-0.601***	-0.535***	-0.524***
ΔSVI_{t-2}	-0.225***	-0.194***	-0.273***	-0.048	-0.325***	-0.221***	-0.307***
$NEWS_{t-1}$	0.021	-0.002	0.034	-0.007	0.021*	0.019	0.114***
$NEWS_{t-2}$	-0.035**	-0.004	-0.056	-0.005	-0.016	-0.025*	-0.011
$\Delta SVIm_{t-1}$	0.442***	-0.041	0.432**	0.162**	-0.057	0.221*	0.144
$\Delta SVIm_{t-2}$	-0.428***	-0.019	-0.304	-0.099	-0.014	0.003	-0.345
$NEWSm_{t-1}$	0.007	0.005	-0.012	0.013	0.021	-0.010	0.061
$NEWSm_{t-2}$	-0.019	-0.008	0.014	0.002	-0.006	0.012	-0.064
Constant	0.042	0.009	0.012	0.022***	0.010	0.013	-0.001
$NEWS_t$							
$vola_{t-1}$	0.036	-0.055	-0.000	0.005	0.039	0.003	-0.001
$vola_{t-2}$	-0.006	0.066*	-0.002	0.016	-0.030	-0.001	0.007
ΔSVI_{t-1}	0.422**	-0.007	-0.004	0.352	0.083	-0.445**	0.029
ΔSVI_{t-2}	0.557***	0.129	0.018	-0.058	0.002	-0.271	-0.077
$NEWS_{t-1}$	0.245***	0.048	-0.036	0.219***	0.165***	0.018	-0.011
$NEWS_{t-2}$	0.196***	0.059	-0.018	0.163***	-0.046	0.007	0.101
$\Delta SVIm_{t-1}$	-0.045	0.757	-0.216	-0.376	1.276***	0.505	0.369
$\Delta SVIm_{t-2}$	-0.390	0.457	0.203	-0.065	-0.127	0.995**	-0.048
$NEWSm_{t-1}$	0.026	0.005	0.034	0.206**	0.083	0.073	0.067
$NEWSm_{t-2}$	0.068	0.200**	0.002	0.062	0.176*	-0.022	-0.109
Constant	-0.089	-0.032	0.011	-0.064	-0.015	-0.007	0.019
N	400	400	400	400	400	400	236

Table 7. Investor attention and the variance risk premium

This table reports estimations of (10). The dependent variable is variance risk premium defined as the difference between option implied volatility and the expected realized volatility and denoted VRP. ΔSVI_t is the investor attention measure for each currency pair as defined in section 3.1. Owing to missing observations for option implied volatility for USD/AUD, results are reported for six currency pairs only. Newey-West standard errors are in parentheses. The sample period is January 2004 to September 2011, and the data are weekly. $***$ denotes coefficient significantly different from zero, 0.01 level; $**$ 0.05 level; $*$ 0.10 level.

	USD/JPY	GBP/USD	EUR/USD	EUR/GBP	EUR/JPY	GBP/JPY
ΔSVI_t	0.001	0.008***	0.011***	0.003*	0.007**	0.001
	(0.001)	(0.002)	(0.004)	(0.001)	(0.003)	(0.002)
ΔSVI_{t-1}	0.002	0.007**	0.013***	0.002	0.010***	-0.002
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
VRP_{t-1}	0.723***	0.856***	0.795***	0.896***	0.855***	0.845***
	(0.043)	(0.034)	(0.029)	(0.031)	(0.047)	(0.045)
Constant	0.004***	0.002***	0.003***	0.001***	0.002***	0.003***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Adj. R-squared	0.52	0.73	0.61	0.80	0.72	0.71
N	398	398	398	398	398	235

Table 8. Investor attention and realized volatility for sample sub-periods

This table reports estimations of (7), using the data for two sample sub-periods: January 2004 - December 2007 (Panel A), and January 2008 - September 2011 (Panel B). The dependent variable is volatility, measured using realized volatility, denoted RV and defined in (6) (Panels A and B) and implied volatility, denoted IV (Panels C and D). ΔSVI_t is the investor attention measure for each currency pair. $\Delta SVIm_t$ is the global FX market-level investor attention measure. $NEWS_t$ and $NEWSm_t$ are the currency-specific and global FX market-level news supply measures, respectively. The transformations of the raw SVI and news series used to obtain the attention and news measures are described in section 3.1. $Return_t$ is the weekly percentage logarithmic return for each currency pair. The data are weekly. Newey-West standard errors are in parentheses. $***$ denotes coefficient significantly different from zero, 0.01 level; $**$ 0.05 level; $*$ 0.10 level.

	USD/JPY	GBP/USD	USD/AUD	EUR/USD	EUR/GBP	EUR/JPY	GBP/JPY
Panel A: Realized volatility (RV) in Jan. 2004 - Dec. 2007							
ΔSVI_t	0.542	-1.074*	0.645	1.117	-0.393	1.874*	3.490
	(0.484)	(0.631)	(0.955)	(0.901)	(0.271)	(1.057)	(2.347)
$\Delta SVIm_t$	3.856	0.416	3.595	0.937	-0.354	4.058	-2.468
	(3.289)	(1.425)	(4.103)	(1.395)	(0.548)	(3.871)	(7.960)
RV_{t-1}	0.055	0.177**	0.037	0.150**	0.146*	0.140**	0.080
	(0.058)	(0.080)	(0.073)	(0.069)	(0.080)	(0.062)	(0.053)
$NEWS_t$	0.188	-0.143	-0.505	0.483**	-0.000	-0.116	1.908
	(0.295)	(0.196)	(0.810)	(0.196)	(0.064)	(0.268)	(1.390)
$NEWSm_t$	0.232	0.427	1.865***	-0.215	0.082	0.923***	0.893
	(0.328)	(0.298)	(0.667)	(0.236)	(0.101)	(0.271)	(0.894)
$Return_t$	-0.303	-0.083	0.565**	-0.108	0.028	-0.709	-1.278**
	(0.207)	(0.058)	(0.268)	(0.077)	(0.046)	(0.463)	(0.568)
Constant	1.639***	1.147***	2.498***	1.191***	0.491***	1.511***	1.911***
	(0.239)	(0.135)	(0.360)	(0.138)	(0.050)	(0.227)	(0.426)
Adj. R-squared	0.05	0.05	0.18	0.05	0.02	0.21	0.41
N	207	207	207	207	207	207	47
Panel B: realized volatility (RV) in Jan. 2008 - Sept. 2011							
ΔSVI_t	0.383	1.031	8.630*	8.162	2.033	5.182	-0.732
	(1.669)	(3.135)	(4.760)	(5.205)	(3.520)	(3.764)	(2.005)
$\Delta SVIm_t$	11.712**	13.893	34.584***	-0.919	-1.150	5.146	32.972
	(5.912)	(12.323)	(12.125)	(4.176)	(3.669)	(12.667)	(21.626)
RV_{t-1}	0.147***	0.432***	0.532***	0.352***	0.358***	0.383***	0.444***
	(0.053)	(0.124)	(0.083)	(0.115)	(0.104)	(0.117)	(0.047)
$NEWS_t$	0.278	-0.494	4.261	0.680**	0.632	0.623	2.805**
	(0.331)	(0.427)	(4.596)	(0.312)	(0.546)	(0.661)	(1.365)
$NEWSm_t$	0.894	1.552	-1.537	1.177	1.043	0.699	0.390
	(0.903)	(0.981)	(3.717)	(0.797)	(0.766)	(1.984)	(2.174)
$Return_t$	-0.117	0.006	1.821**	0.140	0.113	-0.687***	-0.583
	(0.133)	(0.208)	(0.809)	(0.209)	(0.261)	(0.253)	(0.357)
Constant	2.342***	1.600***	3.482***	1.704***	1.275***	2.770***	3.038***
	(0.294)	(0.387)	(0.943)	(0.322)	(0.237)	(0.715)	(0.509)
Adj. R-squared	0.08	0.20	0.58	0.22	0.15	0.31	0.35
N	195	195	195	195	195	195	195
Panel C: Implied volatility (IV) in Jan. 2004 - Dec. 2007							
ΔSVI_t	0.349	0.902***	–	0.725*	0.042	0.494	0.421
	(0.245)	(0.227)	–	(0.409)	(0.149)	(0.354)	(2.120)
$\Delta SVIm_t$	0.645	1.165*	–	1.012*	1.132***	0.733	-4.786
	(1.233)	(0.675)	–	(0.578)	(0.325)	(1.076)	(5.065)
IV_{t-1}	0.770***	0.940***	–	0.953***	0.959***	0.819***	0.870***
	(0.072)	(0.026)	–	(0.020)	(0.018)	(0.067)	(0.045)
$NEWS_t$	0.049	-0.053	–	0.034	-0.008	-0.059	-0.878
	(0.138)	(0.070)	–	(0.061)	(0.040)	(0.132)	(1.311)
$NEWSm_t$	0.386*	0.196	–	0.044	0.054	0.593**	1.333
	(0.201)	(0.119)	–	(0.128)	(0.076)	(0.260)	(1.135)
$Return_t$	-0.255***	-0.044	–	0.000	0.144***	-0.372***	-0.679
	(0.079)	(0.028)	–	(0.030)	(0.031)	(0.127)	(0.569)
Constant	2.074***	0.484**	–	0.389**	0.223**	1.632***	2.777**
	(0.648)	(0.208)	–	(0.173)	(0.096)	(0.580)	(1.328)
Adj. R-squared	0.71	0.89	–	0.91	0.93	0.81	0.84
N	207	207	–	207	207	207	47
Panel D: Implied volatility (IV) in Jan. 2008 - Sept. 2011							
ΔSVI_t	0.173	2.894**	–	4.683**	3.858***	1.298	-0.977

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Table 8 – Continued from previous page

	USD/JPY	GBP/USD	USD/AUD	EUR/USD	EUR/GBP	EUR/JPY	GBP/JPY
	(1.401)	(1.238)	–	(2.324)	(0.861)	(0.937)	(0.608)
$\Delta SVIm_t$	17.213**	8.326**	–	8.430**	0.730	14.382**	1.932
	(8.174)	(3.495)	–	(4.023)	(2.531)	(5.629)	(1.625)
IV_{t-1}	0.843***	0.952***	–	0.954***	0.940***	0.931***	0.882***
	(0.059)	(0.020)	–	(0.028)	(0.031)	(0.020)	(0.024)
$NEWS_t$	0.142	0.271**	–	0.003	0.290**	0.571**	-0.447
	(0.177)	(0.133)	–	(0.140)	(0.135)	(0.276)	(0.318)
$NEWSm_t$	0.753	0.267	–	0.542*	0.330	0.502	0.144
	(0.534)	(0.241)	–	(0.321)	(0.230)	(0.393)	(0.425)
$Return_t$	-0.452***	-0.212***	–	-0.066	0.121**	-0.488***	-0.032
	(0.164)	(0.071)	–	(0.066)	(0.050)	(0.092)	(0.038)
Constant	1.899**	0.509**	–	0.572*	0.595*	0.952***	1.730***
	(0.730)	(0.223)	–	(0.327)	(0.312)	(0.301)	(0.404)
Adj. R-squared	0.79	0.94	–	0.90	0.91	0.93	0.83
N	195	195	–	195	195	195	130

Table 9. Liquidity, Crash and Fear Index

This table reports estimations of (11). The dependent variable is realized volatility, denoted RV_t (Panel A) and defined in (7) and implied volatility, denoted IV_t (Panel B). ΔSVI_t is the investor attention measure for each currency pair. $\Delta SVIm_t$ is the global FX market-level investor attention measure. $NEWS_t$ and $NEWSm_t$ are the currency-specific and global FX market-level news supply measures, respectively. The transformations of the raw SVI and news series used to obtain the attention and news measures are described in section 3.1. $Liquidity_t$ is the difference between the ask and bid price, a proxy for liquidity risk. $Skeweness_t$ is the skewness coefficient for the daily log returns series over the past month, a proxy for the risk of a crash. $\Delta Macro\_Fears_t$ and $\Delta Micro\_Fears_t$ are fear fear indices for concerns about business conditions, and household concerns, respectively, calculated in accordance with the procedure described by Da et al. (2013). The data are weekly. Newey-West standard errors are in parenthesis. $***$ denotes coefficient significantly different from zero, 0.01 level; $**$ 0.05 level; $*$ 0.10 level.

	USD/JPY	GBP/USD	USD/AUD	EUR/USD	EUR/GBP	EUR/JPY	GBP/JPY
	Panel A: Realized volatility (RV)						
ΔSVI_t	0.781	0.239	5.496	3.552	0.366	4.820***	0.955
	(0.646)	(1.280)	(3.462)	(2.458)	(1.199)	(1.816)	(1.859)
$\Delta SVIm_t$	7.459**	7.032	26.744*	1.290	-0.318	10.070	30.821
	(3.793)	(5.916)	(15.464)	(1.917)	(2.183)	(8.368)	(20.735)
RV_{t-1}	0.131***	0.382***	0.554***	0.326***	0.316***	0.439***	0.421***
	(0.050)	(0.113)	(0.139)	(0.108)	(0.095)	(0.084)	(0.054)
$NEWS_t$	0.326	-0.024	2.934	0.567***	0.355	0.041	3.126**
	(0.226)	(0.225)	(3.077)	(0.165)	(0.260)	(0.357)	(1.244)
$NEWSm_t$	0.915**	1.070*	0.926	0.652*	0.739**	1.188	0.430
	(0.417)	(0.552)	(1.418)	(0.356)	(0.307)	(0.823)	(1.590)
$Liquidity_t$	0.029	7.488*	18.058***	12.781**	12.386**	0.046	-0.022
	(0.041)	(4.217)	(4.536)	(6.396)	(5.118)	(0.042)	(0.054)
$Skewness_{t-1}$	0.414	0.671	1.043	0.612**	0.107	0.768	1.957
	(0.354)	(0.487)	(0.951)	(0.290)	(0.290)	(0.590)	(1.371)
$\Delta Macro\_Fears_t$	5.043	-7.845	14.669	6.392	8.371	14.089	21.005
	(11.793)	(10.049)	(28.259)	(7.660)	(12.810)	(19.108)	(48.125)
$\Delta Micro\_Fears_t$	0.104	-0.026	-0.023	0.013	-0.048	-0.134	-0.324
	(0.082)	(0.061)	(0.258)	(0.069)	(0.063)	(0.182)	(0.296)
Constant	1.952***	1.101***	0.874**	1.154***	0.499***	1.644***	3.610***
	(0.238)	(0.220)	(0.409)	(0.175)	(0.117)	(0.361)	(1.144)
N	398	398	398	398	398	398	242
	Panel B: Implied volatility (IV)						
ΔSVI_t	0.902*	2.281***	–	2.991***	1.216***	2.186***	0.197
	(0.520)	(0.519)	–	(0.986)	(0.421)	(0.648)	(0.826)
$\Delta SVIm_t$	9.529	5.022**	–	5.023**	1.483	10.319*	-1.268
	(5.819)	(2.369)	–	(2.303)	(1.513)	(5.423)	(2.621)
IV_{t-1}	0.851***	0.957***	–	0.976***	0.965***	0.949***	0.872***
	(0.039)	(0.025)	–	(0.028)	(0.029)	(0.027)	(0.030)
$NEWS_t$	0.313**	0.238**	–	0.005	0.112	0.298	-0.130
	(0.158)	(0.094)	–	(0.080)	(0.087)	(0.207)	(0.446)
$NEWSm_t$	0.493*	0.185	–	0.258*	0.236*	0.345	0.827
	(0.267)	(0.131)	–	(0.155)	(0.124)	(0.260)	(0.534)
$Liquidity_t$	0.031	2.299	–	-1.012	0.408	0.012	-0.013
	(0.026)	(1.639)	–	(3.605)	(1.655)	(0.016)	(0.010)
$Skewness_{t-1}$	-0.224	-0.049	–	-0.107	-0.027	-0.145	-1.377
	(0.200)	(0.093)	–	(0.084)	(0.097)	(0.177)	(0.890)
$\Delta Macro\_Fears_t$	-0.787	-0.005	–	-2.586	4.025	5.862	-1.349
	(6.018)	(4.211)	–	(5.328)	(3.810)	(6.885)	(12.487)
$\Delta Micro\_Fears_t$	0.076	0.003	–	-0.016	0.010	-0.016	0.105
	(0.058)	(0.028)	–	(0.033)	(0.020)	(0.049)	(0.150)
Constant	1.533***	0.350*	–	0.278	0.272*	0.568**	2.093***
	(0.392)	(0.190)	–	(0.213)	(0.163)	(0.243)	(0.548)
Adj. R-squared	0.80	0.94	–	0.93	0.95	0.91	0.88
N	398	398	–	398	398	398	177

Table 10. Sentiment and Disagreement

This table reports estimations of (12). The dependent variable is realized volatility, denoted RV_t (Panel A) and defined in (6) and implied volatility, denoted IV (Panel B). ΔSVI_t is the investor attention measure for each currency pair. $\Delta SVIm_t$ is the global FX market-level investor attention measure. $NEWS_t$ and $NEWSm_t$ are the currency-specific and global FX market-level news supply measures, respectively. The transformations of the raw SVI and news series used to obtain the attention and news measures are described in section 3.1. $Sentiment_t$ is the cross-sectional average of the monthly forecasts of approx. 250 analysts of FX rates, obtained from the Centre for European Economic Research (ZEW), on the following currency pairs: EUR/USD, EUR/GBP and EUR/JPY. $Disagreement_t$ is the cross-sectional standard deviation of these forecasts. The data are weekly. Newey-West standard errors are in parentheses. $***$ denotes coefficient significantly different from zero, 0.01 level; $**$ 0.05 level; $*$ 0.10 level.

	EUR/USD	EUR/GBP	EUR/JPY
	Panel A: Realized Volatility (RV)		
ΔSVI_t	3.665	0.208	4.465**
	(2.398)	(1.200)	(1.791)
$\Delta SVIm_t$	1.439	-0.190	10.222
	(1.844)	(1.861)	(8.321)
RV_{t-1}	0.358***	0.289***	0.441***
	(0.099)	(0.092)	(0.091)
$NEWS_t$	0.570***	0.362	0.085
	(0.170)	(0.271)	(0.341)
$NEWSm_t$	0.382	0.565*	0.701
	(0.357)	(0.328)	(0.887)
$Sentiment_{t-1}$	-0.284	8.190***	2.968***
	(0.591)	(2.412)	(0.906)
$Disagreement_{t-1}$	4.339**	0.337	6.896**
	(1.752)	(1.697)	(3.316)
Constant	-2.308	-2.135**	-4.984*
	(1.561)	(1.047)	(2.791)
Adj. R-squared	0.23	0.28	0.27
N	400	400	400
	Panel B: Implied Volatility (IV)		
ΔSVI_t	2.861***	1.181***	2.046***
	(0.967)	(0.409)	(0.618)
$\Delta SVIm_t$	4.906**	1.523	10.409*
	(2.308)	(1.501)	(5.431)
IV_{t-1}	0.960***	0.945***	0.934***
	(0.020)	(0.028)	(0.026)
$NEWS_t$	0.042	0.123	0.279
	(0.084)	(0.086)	(0.204)
$NEWSm_t$	0.244	0.242**	0.348
	(0.164)	(0.118)	(0.281)
$Sentiment_{t-1}$	-0.266	1.348**	1.035**
	(0.287)	(0.559)	(0.483)
$Disagreement_{t-1}$	0.505	0.271	2.230**
	(0.792)	(0.907)	(1.023)
Constant	0.064	-0.240	-1.388
	(0.691)	(0.658)	(0.911)
Adj. R-squared	0.93	0.95	0.91
N	400	400	400

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