Investor Attention and FX Market Volatility

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Abstract

We study the relationship between investors' active information acquisition, measured by a Google search volume index (SVI), and the dynamics of currency prices. Changes in SVI are correlated with the trading activities of large FX market participants. Changes in SVI affect FX market volatility, after controlling for macroeconomic fundamentals. Causality is found to run mainly from changes in SVI to volatility. In addition, SVI is related to the currency risk premium, and carry trade returns. Our results suggest that investor attention is a priced source of risk in FX markets.

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

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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 (2011)), 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 empirically 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. (2012). 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, macroeconomic fundamentals have been shown to be marginally important in explaining the dynamics of the exchange rates (e.g. Meese and Rogoff (1983)) hence, allowing for the possibility of other factors that might possibly help explain its dynamics. Third, 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. Fourth, 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. [2]

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 (see Sager and Taylor (2006) and Bacchetta and Van Wincoop (2010)). The infrequency of portfolio allocation

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

[2]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. We also extend our list of search keywords to capture more investors information acquisition activity. Our empirical results are not sensitive to the choice of proxy.

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 and carry trade returns. This is partly explained by the difficulty in finding 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. (2012)). 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.[3] 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, as can be verified from visual inspection of Figure 1, search volume for currency pairs is large, consistent over time and, as indicated by Figure 1, not subject to any regular seasonal variation.[4] Fourth, 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 500 to 600 trillion Yen in the trading volume of JPY/USD at weekly frequency.

Preliminary results suggest that an increase in information acquisition intensity is associated with increased volatility in major currency markets in the time-series. Volatility of currency returns during periods when information acquisition is higher than the median is between two and five times larger than during periods when information acquisition is below the median. Information acquisition has predictive power for future volatility over various time horizons, 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.

[3]It is important to mention that even though professional investors are more likely to use professional trading platforms as source 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.

[4]Even though we do not detect any seasonality effects in the raw SVI data, in our empirical analysis we report the results with seasonally adjusted SVI.

The association between information acquisition and currency price volatility demands further investigation of the causal pattern. Based on a vector autoregression (VAR) model, which includes a control for macroeconomic uncertainty, we report empirical evidence of a causal effect running from information acquisition to volatility. This result is substantiated by including currency option price data. Information acquisition correlates with both time-varying risk aversion, and the demand for protection against extreme downturns. 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).[5] We also examine the association between information acquisition and the pricing of deep-out-of-the-money (DOTM) put options, option-implied volatility smile, and option-implied volatility skewness. DOTM puts are commonly used as protection against extreme downside movements in the underlying values.[6] The option-implied volatility smile is the difference between out-of-money (OTM) put and OTM call prices of the same maturity. A positive smile reflects risk aversion on the part of the representative investor. Option-implied volatility skewness is the difference between the OTM put option and the at-the-money (ATM) put option of the same maturity, divided by the strike-to-spot ratio.[7] This reflects investors' concerns over downside risk. Each of these variables is associated with information acquisition, corroborating our findings on the variance risk premium. Overall our results support the notion that investor attention is a priced source of risk in FX markets.

Finally, we examine the relationship between information acquisition and carry trade returns. The carry trade derives from the widely employed investment strategy of borrowing low-interest rate currencies and lending high-interest rate currencies. We find that an increased intensity of information acquisition is associated with reduced carry trade returns. This holds even after controlling for global foreign exchange (FX) volatility risk, a key factor in explaining the cross-sectional variations in carry trade returns (Menkhoff et al. (2011)).

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. Moreover the "overconfidence" hypothesis is not supported by our findings. We find that the prices of options against

[5]The difference between option implied volatility and realized volatility has been advocated as a measure of the risk aversion in the market by Aıt-Sahalia and Lo (2000), among others.

[6]Carr and Wu (2011) show that a DOTM American-style equity put option replicates a pure credit contract that pays off only when the default occurs prior to the option expiry.

[7]This is a commonly used skewness measure by practitioners and academics, (e.g. Cao et al. (2010)).

the extreme downside risk, DOTM puts, are higher when the intensity of information acquisition is increased.

The empirical results presented in this paper challenge several standard theoretical models concerning the association between investor attention and the dynamics of asset prices. Our results are best explained by a recent theory of investor attention and market volatility developed by Andrei and Hasler (2011). 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.[8]

Our findings corroborate those of Vlastakis and Markellos (2012), who also find that investor attention increases with an increase in the expected variance risk premium for the S&P 500 index. Although Andrei and Hasler (2011) do not consider the implications of information acquisition for carry trade returns, the "liquidity spirals" theory of Brunnermeier and Pedersen (2009) suggests a link. Rising attention to information in bad times may encourage investors to unwind their carry trade positions when they face funding constraints, leading to trading losses and further funding shortfalls. Therefore we expect a negative association between the intensity of information acquisition and carry trade returns, consistent with our findings.

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 reminder 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.

[8] They show further that the 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 drift component returns drifts.

In a seminal paper, Da et al. (2012) 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. (2010a)), 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 this study are "crisis", "financial crisis" and "recession", which are best interpreted as sentiment measures. We examine instead the demand for information currency pairs, which is not driven solely by investor sentiment. Our results are shown to be robust to the inclusion of Smith's SVI, which loses predictive power when ours 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) and Flood and Taylor (1996)). Attempts to resolve this puzzle include 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. (2011) 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 (Huang and Liu (2007)) and overconfidence ((Baber and Odean (2001) and Odean (1998)) theories.

3. Data

3.1. Search Volume Index

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 to make them comparable across regions. We download weekly data from January 2004 to September 2011, providing 403 weekly observations on each of seven currency pairs: USD/JPY, GBP/USD, USD/AUD, EUR/USD, EUR/GBP, EUR/JPY and GBP/JPY. 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.[9]

The keywords we use in Google Insights are pairs of three-letter abbreviations for currencies from ISO 4217 (Codes for the Representation of Currencies and Funds). For each currency pair, we aggregate the

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

Google SVI from the search in either order, for example, EUR/USD and USD/EUR. These abbreviations 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.

We consider three measures of investor attention based on the Google SVI. The first is the level of attention index (hereafter "*SVI_level*"), which corresponds to the original Google SVI. The second, the residuals from a regression of SVI level on monthly dummy variables (hereafter "SVI"), eliminates any seasonality. The third measure, the residuals from a regression of "*SVI_level*" on monthly dummies and its own lagged values (hereafter SVI innovation), removes any seasonality and first-order autocorrelation.[10] In the empirical analysis we report results for the seasonally-adjusted attention measure, *SVI*. The *SVI* and *SVI_innovation*are also de-meaned.

Table 1 reports summary statistics for the three attention variables. It can be seen that there are heterogeneous attention across currency pairs. The standard deviation of the level of attention for each currency pair is about the same magnitude as its mean for almost all currency pairs, indicating strong time series variation in attention. We will exploit how the variation in attention is related to the variation in volatility across currency pairs in time series in our regression analysis. The means of SVI and SVI_innovation are both zero. Although not reported in the table, there are still strong cross-sectional variations in these two variables across different currency pairs.

[Insert Table 1 about here]

One important question relating to our attention variables is whether they possess unit roots. For this purpose we conduct three unit root tests *without* a trend component: the Augmented Dickey-Fuller test, the Phillips-Perron test, and the DF-GLS test Elliott et al. (1996). All tests reject the existence of a unit root at the 1% level except the Philips-Perron tests for SVI_level and SVI of EUR/GBP, which reject the existence of unit root without a trend component at the 5% significance level.

3.2. Option Prices and FX Returns

We obtain daily 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

[10]If the autocorrelation coefficient after including the first lag is above 0.1, we include further lags until the autocorrelation coefficient falls below 10%.

the results as market implied volatilities. The data are denominated in US dollars.[11] We use options with one month maturity for each currency. The specific trading conventions of the FX options are described by Malz (1997). In particular, the implied volatility quotes are available from three types of option combinations: delta-neutral straddle, risk-reversal ("RR") and the strangle ("STR"), or butterfly, which are readily reported by Bloomberg. A portfolio of call and put options with same strike price and maturity forms a straddle. For the straddle to be delta-neutral, the strike price needs to be sufficiently close to the forward price to make the implied volatility quotes of straddle an at-the-money (ATM) implied volatilities. The difference between OTM call options and OTM put options gives the risk reversal. The strangle measures the difference between the average volatility of the two 25-Delta options and the delta-neutral straddle implied volatility. Moneyness levels are defined in terms of the Black-Scholes delta of the option, and is conventionally set at 25-Delta. Unfortunately, Bloomberg does not report the strike prices. We also have the 10-Delta call and puts which are considered as DOTM options. For our empirical analysis we rely on implied volatilities of the market obtained from quotes provided by Bloomberg, and derive the call and put prices from the following specification: Call = ATM+STR+RR/2 and Put = ATM+STR-RR/2 for the same maturity and moneyness. From put-call parity we derive two other moneyness levels: 75-Delta call and 75-Delta put.

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. The drawback is that option prices are estimated in a risk-neutral fashion, while the representative investor may not be risk-neutral. This drives a wedge between the investor's actual forecast of the future distribution of underlying asset values, and risk-neutral prices. In section 4.4.1we explore this difference in the context of the representative investor's risk aversion and the investor's attention. Table 2 reports summary statistics for the option-implied volatility smile, option-implied volatility skew and the DOTM put options. We describe in detail the computation of the smile and the skew in section 4.4.2. Table 2 shows that on average the smile and skewness are forward (positive) for the entire sample period, suggesting high implied volatility.

Panel E of Table 2 reports summary statistics for the weekly logarithmic FX returns $r_t^i = (log(s_t^i) - log(s_{t-1}^i)) \times 100$ where s_t^i is the spot price for currency pair i in week t. Most FX returns display high volatility and leptokurtosis during our sample periods.

[Insert Table 2 about here]

[11] For example GBP/JPY is calculated using GBP/USD and USD/JPY, as FX rates are by convention quoted against the US dollar.

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 likely to use Google to acquire information (Da et al. (2012)), 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,[12] traditional 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, accounting for 8-10%.[13] The rapid growth of trading by retail investors might be attributed to the spread of electronic execution methods.

Furthermore, 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 foreign exchange 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 foreign exchange spot contracts, foreign exchange forward contracts, foreign exchange futures contracts and one half of foreign exchange options. All these positions are reported as bought and sold. Since trading records for options contain many missing observations, we consider buying and selling volumes for spot, forward and future contracts only. Data on trading volumes are available for three pairs of currencies: JPY/USD, GBP/USD and EUR/USD. Note that 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, and the demand for information in the FX market overall is expected to be more strongly related to SVI than the correlations for large traders suggest.

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

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

4.1. Trading Volume and Investor Attention

The level of the trading volume is highly correlated with SVI, but this may be due to non-stationarity in both series. Therefore we examine the relationship between weekly changes in trading volume and changes in SVI. Table 3 reports the quartile breakdown of average changes in the currency holdings of large FX market participants by changes in attention. "Δ_Volume" " refers to the change in trading volume. "$\Delta\_Volume_{usd\_jpy}$" is in billions of Japanese Yen. $\Delta\_Volume_{gbp\_usd}$ is in millions of pounds. "$\Delta\_Volume_{eur\_usd}$" is in millions of euros. There are large differences in the average changes in trading volume across the change in SVI quartiles. For the first change in SVI quartile, the average trading volume for JPY/USD declines by 1.3 trillion Yen. For the fourth change in SVI quartile, the average trading volume for the same currency pair increases by 4.7 trillion Yen. The pattern for the other two currency pairs is similar.

[Insert Table 3 about here]

Table 4 reports regressions in which the weekly change in trading volume is the dependent variable, and the weekly change in SVI is the principal explanatory variable. In the first specification the lagged change in trading volume is also included, to control for persistence in the dependent variable. In the second specification, additional lags of the change in trading volume and the change in SVI are also included. These regressions indicate that the change in trading volume is positively associated with the change in SVI at the 0.05 level or below, for all three currency pairs. The coefficients are economically significant. For example, one unit increase in the change of SVI is associated with an increase of 500 to 600 trillion Yen in the trading volume of JPY/USD.

[Insert Table 4 about here]

4.2. Volatility and Investor Attention

Figure 1(a) illustrates the relationship between investor attention and FX market volatility for USD/JPY. There is a positive correlation of 0.31 between attention and the conditional volatility estimated from GARCH (1,1). We also estimate global volatility as an equally-weighted average of the conditional volatilities for the seven currency pairs estimated from GARCH (1,1). Figure 1(b) illustrates the relationship between investor attention to the foreign exchange market (Google search on keywords: "FOREX" or "Foreign Exchange") and global volatility. The association is even stronger, with a correlation of 0.75.

[Insert Figure 1 about here]

We also investigate the variation in volatility across different levels of attention. For each currency pair, we separate the sample into periods of high (above the sample median) attention and low (below the sample median) attention, and calculate the average conditional volatility of log returns in both periods. The conditional volatilities are obtained by fitting a GARCH(1,1) model to the weekly log returns for the spot rates (obtained from Bloomberg). Table 5 indicates that the volatility is between two and three times higher during periods of high attention than it is during periods of low attention. As an alternative measure of average volatility, we calculate the average daily volatility of log returns on spot rates over 30 days. This is compared to the contemporaneous monthly attention obtained by aggregating the weekly attention index to a monthly frequency. Panel B of Table 5 indicates that the average daily volatility during periods of high attention is between three and five times higher than it is during periods of low attention.

[Insert Table 5 about here]

In order to investigate how attention affects the conditional volatility of FX returns, we augment the GARCH(1,1) model by including an investor attention measure in both the conditional mean and conditional variance equations. Below this augmented model is referenced SVI-GARCH(1,1).

$$r_t = \alpha + \beta SVI_t + \epsilon_t \tag{1}$$

$$\sigma_t^2 = \exp(\lambda_0 + \lambda_1 SVI_t) + \gamma\sigma_{t-1}^2 + \delta\epsilon_{t-1}^2 \tag{2}$$

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

Panel A of Table 6 reports the estimation results for the SVI-GARCH(1,1) model. For six of the seven currency pairs, attention is strongly and positively related to contemporaneous conditional volatility. The relationship is significant at 0.01 level for for five currency pairs, and at the 0.05 level for USD/AUD. GBP/USD is the only currency pair for which attention is not significant, though it is still positively related to the contemporaneous conditional volatility. In the conditional mean equation, we do not find any association between attention and the log return of the FX spot rate for most of the currency pairs, with the exception of USD/JPY and EUR/GBP. Even for these two currency pairs, the coefficients on attention in the mean equation are opposite in sign.

[Insert Table 6 about here]

As an alternative to the SVI-GARCH model, we first estimate conditional volatility without taking attention into account, and then run OLS regressions of estimated volatility on contemporaneous attention and lagged volatility.

$$\mathtt{Volatility}_t = \lambda_0 + \lambda_1 SVI_t + \lambda_2 \mathtt{Volatility}_{t-1} + \eta_t \tag{3}$$

We estimate $\mathtt{Volatility}_t$ over a month/quorter. At the weekly frequency, we use GARCH (1,1) to estimate $\mathtt{Volatility}_t$.[14] This procedure accounts for ARCH/GARCH effects in weekly FX spot rates, while avoiding imprecisely estimating the second moments with a limited number of observations over a week. We include one lag of estimated volatility to account for persistence in volatility, and we use Newey-West standard errors to correct for serial correlation in the residuals. Panel B of Table 6 reports the results. Consistent with the findings for the SVI-GARCH model, in most cases attention is positively related to contemporaneous volatility at all frequencies. The coefficient on the attention measure tends to be less significant at the quarterly frequency, owing to the limited number of observations. The results are robust to the inclusion of additional lags of Volatilityt, and a median regression with the same specifications produces similar results.

One possible concern is that volatility in the fundamentals may drive both volatility of exchange rates, and investor attention. To control for this possibility 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, R_t. We then regress R_t on its own first 12 lags and monthly dummies D_j. Denoting the absolute values of the residuals from these regressions as $|\hat{\varepsilon}_t|$, we estimate a regression of the following specification:

$$|\hat{\varepsilon}_t| = \sum_{j=1}^{12} \gamma_j D_{jt} + \sum_{i=1}^{12} \rho_i |\hat{\varepsilon}_{t-i}| + u_t \tag{4}$$

The fitted values from the estimation of (4), $\tilde{\varepsilon}_t$, are a proxy for the standard deviation of R_t. We include the absolute value of $\tilde{\varepsilon}_t$ of both countries in our OLS regressions. We find the role of investor attention unchanged after controlling for macroeconomic uncertainty.

[14] We also use implied volatility from option data to estimate Equation 3. The estimation results are robust to the use of this alternative measure.

We also examine the predictive capability of attention for future volatility. We re-estimate (3) with the attention variable lagged by one period. The results, not reported, are consistent for one-week, one-month and one-quarter forecasting horizons, and indicate that attention has predictive power for almost every currency pair. Neither the inclusion of additional volatility lags, nor the inclusion of controls for macroeconomic uncertainty affects the predictive capability of the attention measure.

4.3. Granger Causality Tests for the Relationship between Volatility and Investor Attention

In this section we address the important question of the causal relationship between investor attention and asset prices, using a Vector Autoregression (VAR) framework. The causal relationship between attention and the volatility of currency prices is examined, while controlling for macroeconomic uncertainty.

We estimate the following VAR(2) model:[15]

$$\begin{aligned} \mathtt{SVI}_t &= \beta_0 + \beta_1 \mathtt{Volatility}_{t-1} + \beta_2 \mathtt{Volatility}_{t-2} + +\beta_3 \mathtt{SVI}_{t-1} + \beta_4 \mathtt{SVI}_{t-2} + \eta_{1,t} \\ \mathtt{Volatility}_t &= \lambda_0 + \lambda_1 \mathtt{SVI}_{t-1} + \lambda_2 \mathtt{SVI}_{t-2} + +\lambda_3 \mathtt{Volatility}_{t-1} + \lambda_4 \mathtt{Volatility}_{t-2} + \eta_{2,t} \end{aligned}$$

Table 7 reports the estimation results at weekly, monthly and quarterly frequencies. Across all frequencies, the first lag of attention is significantly related to current volatility for at least four of the seven currency pairs, at the 0.01 significance level. At the monthly frequency these coefficients are significant for six of the seven currency pairs. The coefficients on the second lagged value of the attention measure in the volatility equation are negative and significant in around half of the estimations, but these coefficients are generally smaller in absolute value than those for the first lagged values. Past volatilities, however, seldom affect current attention. Where the coefficients are significant, they are usually weaker, and their signs vary across currency pairs and frequencies. These results suggest that the direction of causality is mainly from attention to volatility. Formal Granger Causality Wald tests (not reported) supports this interpretation, which is robust to the inclusion of controls for macroeconomic uncertainty.

As a robustness check we divide the sample period into two roughly equal sized sub periods, 2004-2007 and 2008-2011, and repeat the estimations that are reported in Table 7. The results, not reported, are similar for both sub-periods.

[Insert Table 7 about here]

[15]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 VAR(2) specification for all currency pairs. Our principal findings are not affected by changes in the lag length.

4.4. Attention and Option Prices

As before, initially we examine the relationship between attention and currency option prices by dividing the sample into periods of high and low attention (above and below the median for the entire sample period). Table 8 suggests attention is related to option implied volatility. The implied volatility estimates are higher during high attention periods (up to three times for the option implied smile, and between two and three times for the variance risk premium and DOTM).

[Insert Table 8 about here]

4.4.1. Variance Risk Premium

According to 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. 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.[16] 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).[17] It follows that if investors' attention affects asset prices, this will be reflected in the slope of the volatility spread, the difference between the implied and realized volatility. We test this hypothesis in this section.

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.

[16]Under classic conditions such as complete and frictionless markets and a single asset, Aıt-Sahalia and Lo (2000) formulate the theoretical link between risk-neutral $q(S_T)$ and physical $p(S_T)$ function 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.

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

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.[18] 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 the 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), the expected realized volatility model is:

$$E_t[RV_{t,T}] = \sqrt{(1-\alpha_{T-t})(r_{t-1}^2 + \alpha_{T-t} r_{t-2}^2 + \alpha_{T-t}^2 r_{t-3}^2 + \cdots)} \tag{5}$$

where r_t is the log return of the underlying asset on day t, while α_{T-t} is the smoothing parameter.

Variance Risk Premium (VRP) is the difference between the ex-ante risk-neutral expectation constructed from the ATM implied volatilities and the objective or statistical expectation estimated from EMA:

$$VRP_t \equiv E_t^Q(IV_{t,T}) - E_t^P(E_t[RV_{t,T}])$$

We examine the association between risk aversion on investor attention using the following regression, which includes a lagged dependent variable to control for persistence in risk aversion.

$$VRP_{t,i} = \alpha + \beta SVI_{t,i} + \eta VRP_{t-1,i} + \varepsilon_{t,i} \tag{6}$$

Table 9 reports the estimation results.Panel A reports the estimations with the term in VRP_{t-1} omitted. Attention has a positive effect on the variance risk premium for all currency pairs. For four of the six currency pairs the coefficient on attention is significant at the 0.01 level, and for the other two currency pairs the coefficient is significant at the 0.05 level. To account for the positive correlation between volatility and variance risk premium, we also consider VRPt defined as the ratio of implied to realized volatility, instead

[18] 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) andAndersen 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.

of the difference. The coefficients on attention are significant at the 0.1 level for all six currency pairs, at the 0.05 level for five pairs and at the 0.01 level for four pairs.

Panel B reports the estimation results with the term in VRP_{t-1} included. For VRP defined as the difference between implied and realized volatility, the coefficients on SVI_t are significant at the 0.05 level for three out of six currency pairs, and the 0.1 level for five pairs. For VRP defined as the ratio of implied to realized volatility, the coefficients on SVI_t are significant at the 0.05 level for two currency pairs, but are significant the 0.1 level for all six pairs.

[Insert Table 9 about here]

Our results for the relationship between SVI and variance risk premium are relevant for testing Huang and Liu (2007) rational inattention hypothesis concerning the frequency of information updating and risk aversion. They predict 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 acquisition and variance risk premium are contrary to the rational inattention hypothesis.

4.4.2. Volatility Smile, Deep Out-of-the-money Put and Option Implied Volatility Skewness

In this section we examine the relationship between attention and derivative contract prices. With reference to currency option implied volatility for different moneyness levels, we examine the implied volatility smile. In volatile markets, put option premia increase significantly as fund managers purchase put options in order to protect their portfolios from a significant drop in stock prices. This demand-supply imbalance is reflected in the option smile, defined as the difference between an OTM put and an OTM call of the same maturity. Bates (2001) and Bakshi et al. (2003) show that the option-implied smile is indistinguishable from negative skewness of the risk-neutral density of the S&P500 index return, with the latter being symmetrical (Aıt-Sahalia and Lo (1998), Rosenberg and Engle (2002)). It follows that the slope of the option-implied volatility *smile* is determined by the slope of the pricing kernel. The determinants of the slope of the volatility smile are affected by attention, as well as fundamentals, only if attention influences option prices. A positive difference in the option implied volatility smile is associated with an increase in the risk-aversion of the representative investor. We estimate the following regression:

$$smile_{t,i} = \alpha + \beta SVI_{t,i} + \varepsilon_{t,i} \tag{7}$$

Table 10 Panel A reports the estimation results. The association between the attention variable and the option-implied volatility smile is positive and significant at the 0.01 level for all currency pairs except GBP/EUR, for which the association is negative and significant at the 0.01 level.

[Insert Table 10 about here]

We also examine the association between investor attention and the option-implied volatility skewness. The skewness reflects the market assessment of future risk by taking into account the asset's current price, pricing trends, and the likelihood of sudden price jumps. We estimate the option-implied skewness as the difference between OTM and ATM put option prices, divided by their strike-to-spot ratio.[19] This measure reflects investors' concerns over the risk related to the left-tail of the distribution. We estimate the following regression:

$$skew_{t,i} = \alpha + \beta SVI_{t,i} + \varepsilon_{t,i} \tag{8}$$

Table 10 Panel B reports the estimation results. The association between the attention variable and the option-implied skewness is positive and significant at the 0.01 level for all currency pairs except GBP/EUR, for which the association is negative and significant at the 0.05 level. These and above reported results are puzzling.

Finally, we examine the association between investor attention and DOTM put options. Carr and Wu (2011) show that DOTM American-style equity put options replicate a pure credit contract that pays out only when default occurs prior to the option expiry. DOTM put options reflect the market's bearish outlook, in contrast to ATM options that are equally sensitive to a bearish and a bullish outlook. A striking effect of the 2008 financial crisis was that many previously worthless DOTM put options quickly became in-the-money (ITM). We estimate the following regression:

$$DOTMput_{t,i} = \alpha + \beta SVI_{t,i} + \varepsilon_{t,i} \tag{9}$$

Table 10 Panel C reports the estimation results. The association between the attention variable and the price of DOTM put options is positive and significant at the 0.01 level for five of the seven currency pairs. The coefficients for the other two currency pairs are positive but not significant. These results are

[19] As Bloomberg does not report strike prices we infer midpoint strike prices, X, from the following specification:

$$X = Se^{\sigma^2 T/2}$$

where S is the underlying, σ is it's volatility and T is the time to maturity.

consistent with the over-confidence hypothesis of Odean (1998), which suggests a negative association between attention and the desire for insurance against downside risk. Overall, our results are consistent with the notion that investor attention is a priced source of risk in FX markets.

4.5. Attention and Carry Trade Returns

In this section we examine whether there is any association between investor attention and carry trade returns to investors buying high interest rate and selling low interest rate currencies. According to Menkhoff et al. (2011), global foreign exchange (FX) volatility risk is an important determinant of carry trade returns. "Volatility innovation" is shown to be a systematic risk factor for the cross-sectional returns on carry-trade portfolios. We estimate "global" FX volatility using the sum the volatilities of the six currency pairs in our sample. Following Menkhoff et al. (2011), we apply an AR(1) filter to global FX volatility, and interpret the residual as "volatility innovation". Table 11 reports the estimation results for a regression of the carry trade return for each currency pair on SVI, volatility innovation, and the lagged carry trade return to account for serial correction in the dependent variable. The results are reported with Newey-West standard errors.

[Insert Table 11 about here]

For four of the six currency pairs, the association between SVI and carry-trade returns is negative and significant at the 0.1 level or below. The coefficient for USD/JPY, the most widely traded carry trade currency pair, is significant at the 0.01 level. These results suggest that investor attention is a priced risk factor. Consistent with Menkhoff et al. (2011) , the coefficients on volatility innovation are negative and significant at the 0.01 level for all six currency pairs.

Although Andrei and Hasler (2011) do not suggest any link between information acquisition and carry trade returns, the "liquidity spirals" theory of Brunnermeier and Pedersen (2009) may be relevant in this context. Rising investor attention to information in bad times may encourage investors to unwind their carry trade positions owing to funding constraints, leading to trading losses and further pressure on funding. This suggests a negative association between information acquisition and carry trade returns, consistent with our findings.

4.6. Robustness Check

4.6.1. Other Search Keywords

We have considered three-letter abbreviations for world currencies in Google Insights. These abbreviations have been long used by investors and the international banking community. A possible concern is that investors may use other phrases in their online query, in which case our attention proxy may not represent investors' attention adequately.

We adopt two approaches to address this concern. First we consider investor attention to the FX market, instead of individual currency pairs, measured using the SVI for a Google search on either "FOREX" or "Foreign Exchange". We examine the relationship between this attention measure and global FX market volatility, proxied by the equally-weighted mean of the conditional volatilities for the seven currency pairs, estimated using GARCH (1,1). The results (not reported) are similar to those for the cases where attention is measured using the SVI for individual currency pairs. Following a similar procedure for the variance risk premium, volatility smile, DOTM Put, and option implied volatility skew, we also obtain results similar to those reported previously.

Our second approach expands the list of keywords to 10 phrases. Using USD/JPY as an example, we use the Google SVI for any of the following keywords "USDJPY", "JPYUSD", "USD$*JPY*”,”*JPY*$USD", "Dollar Yen", "Yen Dollar", "Dollar to Yen", "Yen to Dollar", "DollarYen" and "YenDollar".[20] The results are similar to those reported previously. None of our principal findings is affected by either of these changes to the SVI definition.

4.6.2. Liquidity Risk

It is widely recognized that conditional volatility may vary due to temporary changes in liquidity: high volatility is likely to correspond to low liquidity. Therefore it is important to disentangle the effects of liquidity and investor attention.

We use the difference between the ask price and bid price as a liquidity measure,[21] and examine the association between liquidity and SVI. All estimated coefficients on the bid-ask spread are positive, and six of the seven coefficients are significant at the 0.01 level. This indicates that attention is higher during periods of low liquidity (high bid-ask spread), suggesting that during periods of high volatility investors require a substantial discount in order to trade, and the effort devoted to information acquisition increases. The untabulated estimations report smaller coefficients As a robustness check, median regressions produce similar results. These results are available upon request.

4.6.3. Crash Risk

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

[20] Google trend treats “USD\JPY” as equivalent to "USDJPY".
[21] The results are unaffected if we use the bid ask spread defined as $2 \times (ask - bid)/(bid + ask)$.

of a crash, and hence demand more information. We examine the relationship between the risk of a crash risk, investor attention, and the volatility of FX returns by running VAR regressions. The risk of a crash is measured using the skewness of the daily log return over a month or a quarter. The coefficient on the lagged SVI in the volatility equation is positive and significant, suggesting that SVI has predictive ability for volatility after controlling for past crash risk. There is little evidence that past crash risk drives investor attention.

4.6.4. Impact of News

We collect news data from the Lexis-Nexis database for the same sample period as the attention data. We restrict our attention to three major newspapers: Financial Times, Wall Street Journal and New York Times. We search for all news related to "currency/exchange rates", and use the number of articles in these newspapers in each month to obtain a proxy for the intensity of currency market news coverage. We include this variable as an additional regressor in (3). In the regression based on monthly data the coefficients on the news coverage measure are insignificant for all currency pairs, and the results for the investor attention measure are unaffected. The principal results from (5) are also robust to the inclusion of the news coverage measure.

4.6.5. Investor Sentiment and Differences of Opinion

A long strand of literature (Black (1986), De Long et al. (1990), and Foucault et al. (2011)) shows that investor sentiment has a positive effect on volatility. Da et al. (2010b) argue that the internet search behaviors 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. (2010b) construct a FEAR index to measure investor sentiment, and show that increases in the FEAR index predict excess volatility. If our measure of information acquisition in FX markets captures investor sentiment, inclusion of the FEAR index in the volatility regression should reduce the significance of the information acquisition variable. However, we find that the coefficients in on the FEAR index are insignificant, and our results for the role of investor attention measured by the SVI index are not affected when the FEAR index is considered. In a closely related paper, Smith (2012) provides evidence that SVI for keywords "crisis", "financial crisis" and "recession" has incremental predictive ability beyond the model GARCH(1,1). However, we find that the coefficients on an SVI measure defined in this manner are insignificant when included in a conditional volatility equation alongside our attention measure.

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 differences of opinion. The SVI investor attention measure is highly correlated with the differences of opinion measure, and our results remain robust after controlling for differences in opinion.

5. Conclusion

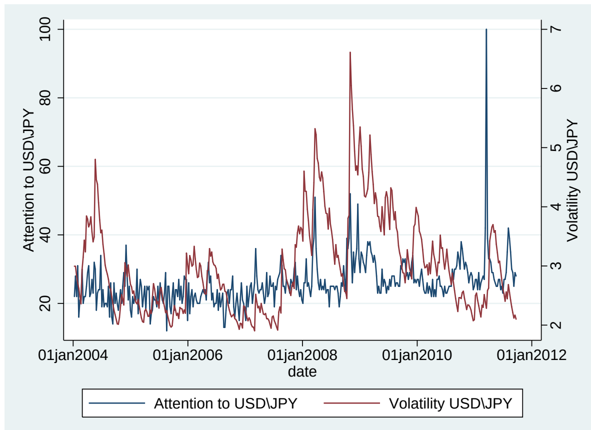
This paper reports an empirical investigation of the association between investor attention and volatility for several foreign exchange (FX) rates for major international currencies, which accounted for more than 69% of the total turnover in FX markets in 2004. We examine the causal relationship between attention and volatility, while controlling for macroeconomic uncertainty. We discuss the implications of our findings for the limited attention and overconfidence hypotheses, neither of which is supported by our results.

We report that changes in investor attention are strongly associated with changes in holdings of the largest traders in FX markets. There is a strong association between changes in attention and changes in volatility. Causality runs mainly from investor attention to FX market volatility, even after controlling for macroeconomic uncertainty. Investor attention is also associated with time-varying risk aversion measured by the variance risk premium, the implied volatility smile, deep out-of-the-money put, and option implied volatility skewness. These results are consistent with a recent theory of investor attention and market volatility developed by Andrei and Hasler (2011). Finally, an increase in investor attention tends to be associated with a decrease in carry trade returns.

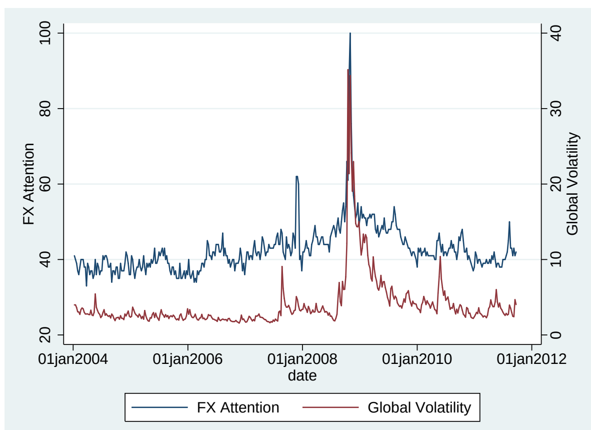
Our results are consistent with the notion that time-varying investor attention is a priced risk factor in FX markets. Given the (still) limited theoretical work, these findings suggest a need for the development of more rigorous models on the role of investor attention, in order to explain the impact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

6. Tables and Figures

Figure 1. Attention and Volatility



(a) EUR_USD Attention and Volatility



(b) FX Attention and Volatility

Note: Sub-figure (a) shows the weekly conditional volatility of USD_JPY exchange rate returns and the investor attention to USD_JPY, and sub-figure (b) shows the weekly global conditional volatility of the FX market and the investor attention to foreign exchange market (Google search on either keywords: "FOREX" or "Foreign Exchange"). Conditional volatility is estimated from GARCH (1,1). Global volatility refers to the equally weighted conditional volatility of the seven currency pairs. The sample spans from January 2004 to September 2011.

Table 1. Summary Statistics of Attention Variables

This table presents the summary statistics of attention variables. The sample spans from January 2004 to September 2011. "*SVI_level*" is the level of attention index corresponding to the original series of google search volume index. "*SVI*" this seasonally adjusted series obtained from regressing level of attention on monthly dummy variables. "*SVI_innovation* " is the residual from regressing "*SVI_level*" on monthly dummies and the first lag of in order to remove both seasonality and the persistency of the original series (If the autocorrelation after including the first lag is still above 10%, we include further lags till the autocorrelation coefficient is below 10%).

	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
	Panel A: *SVI_level*						
Mean	19.09	33.07	17.30	41.64	20.41	16.63	17.32
Std. Dev.	18.01	26.01	20.05	17.90	20.70	21.68	24.40
Min.	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max.	100.00	100.00	100.00	100.00	100.00	100.00	100.00
No. Observation	403	403	403	403	403	403	403
	Panel B: *SVI*						
Mean	0.00	0.00	-0.00	0.00	0.00	0.00	-0.00
Std. Dev.	17.74	25.83	19.33	17.71	20.57	20.93	23.99
Min.	-26.12	-38.34	-31.94	-44.93	-27.24	-28.06	-24.50
Max.	73.88	66.74	77.59	54.21	72.76	76.38	77.65
No. Observation	403	403	403	403	403	403	403
	Panel C: *SVI_innovation*						
Mean	-0.00	-0.00	0.00	0.00	-0.00	0.00	0.00
Std. Dev.	9.75	10.38	8.94	9.89	7.50	10.04	12.12
Min.	-30.55	-59.48	-33.08	-37.41	-28.64	-58.83	-89.06
Max.	68.65	56.09	46.64	40.26	34.56	88.25	78.62
No. Observation	401	401	401	401	401	402	401

Table 2. Summary Statistics of Variance Risk Premia, Option Data and Weekly FX Return

Panels A, B, C and D report the summary statistics of Variance Risk Premia and Option Data. Panel E presents the summary statistics of weekly log return of spot rates, which is given as: $r_t^i = (log(s_t^i) - log(s_{t-1}^i)) \times 100$.The sample spans from January 2004 to September 2011.

	usd_jpy	gbp_usd	aud_usd	eur_usd	eur_gbp	eur_jpy	gbp_jpy
	Panel A: Variance Risk Premia						
Mean	0.85	8.77	–	9.26	7.19	0.52	-0.21
Std. Dev.	4.08	4.03	–	3.75	3.75	6.26	6.58
Min.	-4.49	3.66	–	3.64	2.73	-7.05	-8.66
Max.	21.49	24.71	–	25.85	20.45	31.47	29.19
No. Observation	90	90	–	90	90	90	75
	Panel B: Volatility Smile						
Mean	1.62	0.68	1.26	0.41	-0.42	1.90	2.11
Std. Dev.	1.60	0.82	1.32	0.87	0.54	1.69	1.86
Min.	0.14	-0.45	-0.31	-0.68	-3.08	0.17	0.30
Max.	9.14	3.62	6.69	3.23	0.73	9.28	10.56
No. Observation	91	88	92	91	88	89	71
	Panel C: Deep Out-of-the-money Put						
Mean	13.57	11.44	14.61	11.27	8.19	14.75	17.50
Std. Dev.	5.73	4.83	6.33	3.76	4.13	7.09	8.67
Min.	7.68	6.00	8.73	5.91	2.86	6.15	6.14
Max.	45.74	29.83	42.85	25.85	23.67	45.09	54.69
No. Observation	91	88	92	91	88	89	71
	Panel D: Option Implied Volatility Skew						
Mean	1.13	0.61	0.95	0.47	0.02	1.27	1.39
Std. Dev.	0.88	0.49	0.72	0.47	0.29	0.90	1.06
Min.	0.32	-0.08	0.19	-0.20	-1.32	0.31	0.37
Max.	5.34	2.03	3.67	1.94	0.61	4.98	6.12
No. Observation	91	88	92	91	88	89	71
	Panel E: 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 3. Quartile Breakdown of Changes in Currency Holdings by Changes in Attention

This table presents the quartile breakdown of weekly changes in currency holdings of large foreign exchange market participants (denoted with Δ) by weekly changes in attention. "Treasury Bulletin" reports of the U.S. Department of the Treasury provide weekly amounts of foreign currency holdings of large foreign exchange market participants. Currency holdings include foreign exchange spot, forward and futures contracts. Major market participants are defined those market players that have more than 50 billion US Dollar foreign exchange contracts on the last business day of any calendar quarter during the previous year. "$\Delta_V olume_{usd\_jpy}$" is in billions of Japanese Yen. $\Delta_V olume_{gbp\_usd}$ is in millions of pounds. "$\Delta_V olume_{eur\_usd}$" is in millions of euros. The sample period is January 2004 to September 2011.

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
$\Delta\_Volume_{usd\_jpy}$	-1335.25	-1964.55	3267.88	4655.10
$\Delta\_Volume_{gbp\_usd}$	-4696.26	-1648.25	2758.07	25448.18
$\Delta\_Volume_{eur\_usd}$	-56929.05	30580.17	52631.57	73218.74

Table 4. Regressions of Currency Holdings on Attention

This table presents the regressions of weekly changes in currency holdings of large foreign exchange market participants (denoted with Δ) on weekly changes in attention. The time-subscripts t-1 and t-2 denote the lag one and two of the variables. "Treasury Bulletin" reports of the U.S. Department of the Treasury provide weekly amounts of foreign currency holdings of large foreign exchange market participants. Currency holdings include foreign exchange spot, forward and futures contracts. Major market participants are defined those market players that have more than 50 billion US Dollar foreign exchange contracts on the last business day of any calendar quarter during the previous year. "$\Delta_V olume_{usd\_jpy}$" is in billions of Japanese Yen. $\Delta_V olume_{gbp\_usd}$ is in millions of pounds. "$\Delta_V olume_{eur\_usd}$" is in millions of euros. The sample period is January 2004 to September 2011.

	$\Delta\_Volume_{usd\_jpy}$		$\Delta\_Volume_{gbp\_usd}$		$\Delta\_Volume_{eur\_usd}$	
Δ_SVI	494.744**	603.876**	2233.259***	2583.250***	13136.276***	14716.909***
	(223.005)	(247.090)	(698.302)	(745.085)	(3463.289)	(3542.231)
$\Delta\_volatility_{t-1}$	-0.308***	-0.335***	-0.293***	-0.316***	-0.354***	-0.384***
	(0.047)	(0.050)	(0.047)	(0.050)	(0.046)	(0.050)
$\Delta\_volatility_{t-2}$		-0.068		-0.028		-0.036
		(0.050)		(0.050)		(0.050)
Δ_SVI_{t-1}		267.295		1544.227*		7427.322**
		(264.428)		(786.056)		(3636.828)
Δ_SVI_{t-2}		48.946		-791.587		3319.664
		(248.398)		(758.642)		(3611.258)
Constant	1194.044	1284.153	6006.429	6134.399	26153.031*	26301.640*
	(1437.586)	(1442.731)	(4497.314)	(4492.948)	(15412.119)	(15476.782)
Adj. R-squared	0.11	0.11	0.11	0.12	0.15	0.16
N	402	401	402	401	402	401

Table 5. Volatility in High and Low Attention Periods

This table presents the summary statistics of monthly variance risk premia, option-implied volatility smile, option-implied volatility skewness and the deep-out-of-the-money put options in high and low attention periods.. The time period is January 2004 to September 2011.

	Panel A: Volatility Estimated from Weekly GARCH(1, 1)						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
Low Attention Period	2.74	2.25	4.38	2.55	1.19	2.49	3.17
High Attention Period	3.25	3.88	7.00	3.68	2.57	6.80	9.18
	Panel B: Daily Volatility in 30 Days						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
Low Attention Period	0.41	0.36	0.59	0.33	0.19	0.47	0.55
High Attention Period	1.14	1.07	2.44	1.00	0.81	1.83	2.72

Table 6. Contemporaneous Volatility and Attention

Note: This table reports regressions of Contemporaneous Volatility and Attention (SVI). Panel A presents SVI-GARCH(1,1) at weekly frequency with contemporaneous search volume index. Newey-West standard errors are in parentheses in Panel B. The sample spans from January 2004 to September 2011. Significance levels : $*$: 10% $**$: 5% $***$: 1%

	Panel A: SVI-GARCH(1,1) at Weekly Frequency						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
Mean Equation							
SVI_t	-0.014***	-0.001	-0.006	-0.006	0.006*	-0.002	0.001
	(0.005)	(0.003)	(0.006)	(0.004)	(0.003)	(0.005)	(0.005)
Constant	-0.120	0.055	-0.249**	0.036	0.059	0.029	0.022
	(0.086)	(0.082)	(0.106)	(0.084)	(0.067)	(0.098)	(0.099)
Variance Equation							
SVI	0.017***	0.001	0.015**	0.016***	0.031***	0.027***	0.022***
	(0.005)	(0.009)	(0.006)	(0.003)	(0.003)	(0.007)	(0.007)
Constant	0.040	-2.065***	0.464	1.091***	0.204	-1.133**	-1.167**
	(0.601)	(0.624)	(0.302)	(0.178)	(0.290)	(0.531)	(0.463)
N	402	402	402	402	402	402	402

	Panel B: Regression of Volatility on SVI at Various Horizons						
	One-week horizon						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
SVI_t	0.003**	0.002*	0.062	0.022***	0.006***	0.007*	0.007*
	(0.001)	(0.001)	(0.043)	(0.006)	(0.002)	(0.004)	(0.004)
$Volatility_{t-1}$	0.923***	0.953***	0.591***	0.506***	0.907***	0.927***	0.912***
	(0.017)	(0.030)	(0.059)	(0.065)	(0.053)	(0.048)	(0.031)
Constant	0.228***	0.142*	2.323***	1.541***	0.175**	0.332**	0.501***
	(0.051)	(0.075)	(0.374)	(0.187)	(0.086)	(0.162)	(0.127)
Adj. R-squared	0.89	0.92	0.41	0.33	0.89	0.89	0.85
N	402	402	402	402	402	402	402
	One-month horizon						
SVI_t	0.004***	0.001*	0.007**	0.003**	0.003**	0.006***	0.005**
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
$Volatility_{t-1}$	0.252***	0.660***	0.333***	0.432***	0.527***	0.249***	0.432***
	(0.083)	(0.097)	(0.052)	(0.077)	(0.142)	(0.062)	(0.084)
Constant	0.579***	0.210***	0.988***	0.359***	0.233***	0.849***	0.845***
	(0.102)	(0.072)	(0.323)	(0.069)	(0.072)	(0.186)	(0.266)
Adj. R-squared	0.24	0.56	0.14	0.43	0.60	0.21	0.28
N	90	90	90	90	90	90	90
	One-quarter horizon						
SVI_t	0.001**	0.001	0.003	0.001**	0.001**	0.002**	0.002*
	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)
$Volatility_{t-1}$	0.403**	0.056	-0.063	0.045	-0.038	-0.219	0.186
	(0.163)	(0.183)	(0.159)	(0.112)	(0.143)	(0.243)	(0.186)
Constant	0.255***	0.382**	0.978**	0.325***	0.272***	0.784***	0.668**
	(0.089)	(0.162)	(0.435)	(0.062)	(0.082)	(0.260)	(0.284)
Adj. R-squared	0.52	0.54	0.11	0.60	0.53	0.44	0.41
N	28	28	28	28	28	28	28

Table 7. VAR regressions of volatility and the search volume index at Various Frequency

Note: This table presents VAR regressions of volatility and the search volume index at Various Frequency. The sample spans from January 2004 to September 2011.

	Panel A: Weekly VAR Regression						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
Volatility							
SVI_{t-1}	0.005***	0.004	0.154***	0.047***	0.017***	0.005	-0.002
	(0.001)	(0.003)	(0.032)	(0.008)	(0.004)	(0.008)	(0.012)
SVI_{t-2}	-0.003**	-0.002	-0.128***	-0.028***	-0.010**	0.003	0.010
	(0.001)	(0.003)	(0.032)	(0.008)	(0.004)	(0.008)	(0.012)
SVI							
$Volatility_{t-1}$	-1.807	1.378*	-0.139*	-0.262	0.198	0.221	0.363*
	(1.804)	(0.757)	(0.073)	(0.296)	(0.553)	(0.300)	(0.209)
$Volatility_{t-2}$	2.094	-1.204	0.084	0.343	0.012	0.109	-0.177
N	401	401	401	401	401	401	401

	Panel B: Monthly VAR Regression						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
Volatility							
SVI_{t-1}	0.007***	0.004***	0.035***	0.003***	0.006***	0.006**	0.005
	(0.002)	(0.001)	(0.008)	(0.001)	(0.001)	(0.003)	(0.004)
SVI_{t-2}	-0.003	-0.002*	-0.025***	-0.001	-0.004***	0.001	0.000
	(0.002)	(0.001)	(0.008)	(0.001)	(0.001)	(0.003)	(0.004)
SVI							
$Volatility_{t-1}$	-8.333	2.774	-1.512	-6.654	18.806**	9.145**	-0.087
	(6.636)	(9.424)	(1.502)	(10.286)	(9.318)	(4.159)	(2.530)
$Volatility_{t-2}$	6.718	5.818	1.112	6.804	-21.602**	7.888*	2.417
	(5.935)	(9.194)	(1.345)	(9.673)	(8.816)	(4.266)	(2.511)
N	89	89	89	89	89	89	89

	Panel C: Quarterly VAR Regression						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
Volatility							
SVI_{t-1}	0.002**	0.000	0.004	0.003***	0.004***	0.004**	-0.001
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)
SVI_{t-2}	-0.000	0.000	-0.000	-0.001	-0.003***	0.000	0.004
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)
SVI							
$Volatility_{t-1}$	-33.167	4.827	-6.578	-41.366	-129.342***	14.536	-11.968
	(53.527)	(47.253)	(9.344)	(48.856)	(41.338)	(24.677)	(15.880)
$Volatility_{t-2}$	-7.444	-60.496	-4.397	2.249	-20.104	7.378	9.575
	(42.715)	(45.588)	(8.728)	(38.371)	(36.809)	(24.424)	(15.423)
N	27	27	27	27	27	27	27

Table 8. Risk Aversion in High and Low Attention Periods

Note: This table presents Volatility in High and Low Attention Periods. Periods with attention above (below) the median attention over the whole sample period are classified as high (low) attention periods. The sample spans from January 2004 to September 2011.

	Panel A: Variance Risk Premium						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
Low Attention Period	-1.34	7.24	-	7.15	4.97	-3.28	-4.20
High Attention Period	2.94	10.23	-	11.27	9.32	4.32	3.48
	Panel B: Volatility Smile						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
Low Attention Period	0.83	0.34	0.46	-0.07	-0.18	1.01	0.83
High Attention Period	2.38	0.96	2.00	0.81	-0.65	2.70	2.89
	Panel C: Deep Out-of-the-money Put						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
Low Attention Period	10.55	9.88	11.28	10.07	6.58	10.26	11.59
High Attention Period	16.49	12.85	17.79	12.32	9.59	18.95	21.12
	Panel D: Option Implied Volatility Skew						
	usd_jpy	gbp_usd	usd_aud	eur_usd	eur_gbp	eur_jpy	gbp_jpy
Low Attention Period	0.69	0.38	0.46	0.16	0.09	0.75	0.65
High Attention Period	1.55	0.81	1.40	0.73	-0.05	1.73	1.84

Table 9. Regression of Variance Risk Premium on SVI

This table presents Regression of Variance Risk Premium on SVI, formally:

$$VRP_{t,i} = \alpha + \beta SVI_{t-1,i} + \eta VRP_{t-1,i} + \varepsilon_{t,i}$$

where the VRP represents the variance risk premium estimated as i) the difference of at-the-money implied volatilities for options on day t with maturity T and the exponential moving average of realized volatility over the previous month and ii) ratio of at-the-money implied volatilities for options on day t with maturity T and the exponential moving average of realized volatility over the previous month. The results for the VRP estimated as difference and ratio are reported in Panel A and B respectively. Due to missing observations for GBP/JPY we report only six currency pairs in this table only. The SVI_t is the Search Volume Index (SVI) reported by Google, our proxy for investors attention. The VRP_{t-1} is the variance risk premium lagged one. The data are sampled at monthly frequency spanning from January 2004 to September 2011. ***, **, and * denote the statistical significance at 1%, 5% and 10% level respectively. In parenthesis are reported the Newey-West standard errors.

	Panel A: VRP and SVI					
	VRP as the difference between IV and RV					
	usd_jpy	gbp_usd	eur_usd	eur_gbp	eur_jpy	gbp_jpy
SVI_t	0.025***	0.016**	0.020**	0.031***	0.048***	0.045***
	(0.007)	(0.006)	(0.010)	(0.006)	(0.011)	(0.009)
Constant	0.764	8.694***	9.154***	7.073***	0.362	-0.774
	(0.567)	(0.591)	(0.570)	(0.411)	(0.635)	(0.743)
Adj. R-squared	0.18	0.18	0.12	0.52	0.44	0.49
N	93	93	93	93	93	93
	VRP as the ratio of IV to RV					
	usd_jpy	gbp_usd	eur_usd	eur_gbp	eur_jpy	gbp_jpy
SVI_t	0.002***	0.014**	0.015*	0.031***	0.004***	0.003***
	(0.001)	(0.005)	(0.008)	(0.006)	(0.001)	(0.001)
Constant	1.088***	7.661***	8.933***	8.955***	1.046***	0.946***
	(0.056)	(0.500)	(0.505)	(0.418)	(0.056)	(0.052)
Adj. R-squared	0.18	0.18	0.09	0.51	0.44	0.48
N	93	93	93	93	93	93
	Panel B: VRP, Lagged VRP and SVI					
	VRP as the difference between IV and RV					
	usd_jpy	gbp_usd	eur_usd	eur_gbp	eur_jpy	gbp_jpy
SVI_t	0.007*	0.002	0.007**	0.009**	0.017*	0.017**
	(0.004)	(0.001)	(0.003)	(0.004)	(0.009)	(0.008)
VRP_{t-1}	0.749***	0.876***	0.831***	0.793***	0.650***	0.619***
	(0.080)	(0.043)	(0.041)	(0.075)	(0.086)	(0.112)
Constant	0.227	1.061***	1.527***	1.467**	0.158	-0.216
	(0.236)	(0.345)	(0.386)	(0.563)	(0.343)	(0.431)
Adj. R-squared	0.64	0.81	0.76	0.88	0.68	0.68
N	92	92	92	92	92	92
	VRP as the ratio of IV to RV					
	usd_jpy	gbp_usd	eur_usd	eur_gbp	eur_jpy	gbp_jpy
SVI_t	0.001*	0.002*	0.005*	0.009**	0.001*	0.001**
	(0.000)	(0.001)	(0.003)	(0.004)	(0.001)	(0.001)
VRP_{t-1}	0.748***	0.887***	0.833***	0.779***	0.652***	0.618***
	(0.077)	(0.044)	(0.040)	(0.079)	(0.086)	(0.102)
Constant	0.278***	0.856***	1.475***	1.975**	0.367***	0.367***
	(0.089)	(0.309)	(0.368)	(0.755)	(0.110)	(0.105)
Adj. R-squared	0.64	0.83	0.75	0.86	0.68	0.67
N	92	92	92	92	92	92

Table 10. Regression of Volatility Smile, Deep Out-of-the-money Put and Option Implied Volatility Skew on SVI

This table presents regression of option-implied Volatility Smile, option-implied Volatility Skew and Deep Out-of-the-money Put options on SVI. The sample spans from January 2004 to September 2011. Newey-West standard errors are in parentheses. Significance levels : $*$: 10% $**$: 5% $***$: 1%

	usd_jpy	gbp_usd	aud_usd	eur_usd	eur_gbp	eur_jpy	gbp_jpy
	Panel A: Volatility Smile						
SVI_t	0.010***	0.004***	0.009***	0.006***	-0.004***	0.012***	0.010***
	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Constant	1.600***	0.632***	1.224***	0.352***	-0.406***	1.824***	1.895***
	(0.224)	(0.111)	(0.159)	(0.110)	(0.052)	(0.193)	(0.241)
Adj. R-squared	0.20	0.24	0.28	0.20	0.43	0.35	0.30
	Panel B: Option Implied Volatility Skew						
SVI_t	0.006***	0.003***	0.005***	0.004***	-0.001**	0.007***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Constant	1.115***	0.579***	0.927***	0.434***	0.036	1.222***	1.267***
	(0.122)	(0.065)	(0.084)	(0.057)	(0.037)	(0.097)	(0.136)
Adj. R-squared	0.21	0.31	0.35	0.28	0.21	0.41	0.31
	Panel C: Deep Out-of-the-money Put						
SVI_t	0.037***	0.018***	0.035***	0.012	0.004	0.051***	0.060***
	(0.010)	(0.007)	(0.008)	(0.007)	(0.008)	(0.012)	(0.016)
Constant	13.498***	11.275***	14.525***	11.162***	8.046***	14.477***	16.238***
	(0.808)	(0.728)	(0.923)	(0.616)	(0.714)	(0.813)	(0.830)
Adj. R-squared	0.19	0.14	0.19	0.03	-0.01	0.37	0.48
N	93	93	93	93	93	93	93

Table 11. Regression of Carry Trade Return on SVI

This table presents regression of carry trade returns on SVI. ***, **, and * denote the statistical significance at 1%, 5% and 10% level respectively, with Newey-West standard errors.

	usd_jpy	gbp_usd	eur_usd	eur_gbp	eur_jpy	gbp_jpy
SVI_t	-0.001***	0.001	-0.115*	-0.139**	-0.001*	-0.000
	(0.001)	(0.026)	(0.064)	(0.066)	(0.001)	(0.000)
$Volatility\_Innovation_t$	-0.011***	-1.017***	-0.734**	-1.682***	-0.024***	-0.014***
	(0.004)	(0.265)	(0.331)	(0.457)	(0.005)	(0.003)
VRP_t	0.013	0.615	2.350**	2.551*	0.025**	0.002
	(0.014)	(0.799)	(1.091)	(1.456)	(0.011)	(0.007)
$Carry\_trade\_return_{t-1}$	-0.124	-0.073	0.004	-0.341*	-0.190	-0.053
	(0.131)	(0.088)	(0.123)	(0.189)	(0.116)	(0.115)
Constant	-0.045	-7.578	-21.166**	-20.253*	-0.022	-0.017
	(0.033)	(6.776)	(9.805)	(11.743)	(0.036)	(0.031)
Adj. R-squared	0.07	0.06	0.06	0.20	0.12	0.14
N	90	90	90	90	90	76

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References

Adam, K., Marcet, A., Nicolini, J., 2009. Stock Market Volatility and Learning. Working Paper .

Aıt-Sahalia, Y., Lo, A., 1998. Nonparametric estimation of state-price densities implicit in financial asset prices. Journal of Finance 53, 499–547.

Aıt-Sahalia, Y., Lo, A., 2000. Nonparametric risk management and implied risk aversion. Journal of Econometrics 94, 9–51.

Andersen, T., Bollerslev, T., Diebold, F., Ebens, H., 2001. The distribution of realized stock return volatility. Journal of Financial Economics 61, 43–76.

Andrei, D., Hasler, M., 2011. Investors' attention and stock market volatility, Working paper, Swiss Finance Institute .

Bacchetta, P., Van Wincoop, E., 2005. Rational inattention: A solution to the forward discount puzzle. Technical Report. National Bureau of Economic Research.

Bacchetta, P., Van Wincoop, E., 2010. Infrequent portfolio decisions: A solution to the forward discount puzzle. The American Economic Review 100, 870–904.

Bakshi, G., Kapadia, N., Madan, D., 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. Review of Financial Studies 16, 101–143.

Bank, M., Larch, M., Peter, G., 2011. Google search volume and its influence on liquidity and returns of german stocks. Financial Markets and Portfolio Management , 1–26.

Barber, B., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21, 785.

Barber, B., Odean, T., Zhu, N., 2009a. Do retail trades move markets? Review of Financial Studies 22, 151–186.

Barber, B., Odean, T., Zhu, N., 2009b. Systematic noise. Journal of Financial Markets 12, 547–569.

Barndorff-Nielsen, O.E.a., 2002. Econometric analysis of realized volatility and its use in estimating stochastic volatility models. Journal of the Royal Statistical Society: Series B (Statistical Methodology) 64, 253–280.

Bates, D.S., 2001. The Market for Crash Risk. Working Paper 8557. National Bureau of Economic Research.

Beber, A., Breedon, F., Buraschi, A., 2010. Differences in beliefs and currency risk premiums. Journal of Financial Economics 98, 415–438.

Black, F., 1986. Noise. Journal of Finance 41, 529–43.

Bollerslev, T., Tauchen, G., Zhou, H., 2009. Expected stock returns and variance risk premia. Review of Financial Studies 22, 4463–4492.

Brennan, M., Xia, Y., 2001. Stock price volatility and equity premium. Journal of monetary Economics 47, 249–283.

Britten-Jones, M., Neuberger, A., 2000. Option prices, implied price processes, and stochastic volatility. The Journal of Finance 55, 839–866.

Brunnermeier, M., Nagel, S., Pedersen, L., 2008. Carry trades and currency crashes. NBER Macroeconomics Annual 23, 313–348.

Brunnermeier, M., Pedersen, L., 2009. Market liquidity and funding liquidity. Review of Financial Studies 22, 2201–2238.

Buraschi, A., Jiltsov, A., 2006. Model uncertainty and option markets with heterogeneous beliefs. The Journal of Finance 61, 2841–2897.

Cagetti, M., Hansen, L., Sargent, T., Williams, N., 2002. Robustness and pricing with uncertain growth. Review of Financial Studies 15, 363–404.

Cao, C., Yu, F., Zhong, Z., 2010. The information content of option-implied volatility for credit default swap valuation. Journal of Financial Markets 13, 321–343.

Carr, P., Wu, L., 2011. A simple robust link between american puts and credit protection. Review of Financial Studies 24, 473–505.

Cochrane, J.H., 2001. Asset Pricing. Princeton University Press.

Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. The Journal of Finance 63, 1977–2011.

Da, Z., Engelberg, J., Gao, P., 2010a. In search of fundamentals, Working paper, University of Notre Dame and University of North Carolina at Chapel Hill .

Da, Z., Engelberg, J., Gao, P., 2010b. The sum of all fears: Investor sentiment and asset prices, Working paper, University of Notre Dame and University of North Carolina at Chapel Hill .

Da, Z., Engelberg, J., Gao, P., 2012. In search of attention. Journal of Finance .

De Long, J., Shleifer, A., Summers, L., Waldmann, R., 1990. Noise trader risk in financial markets. Journal of Political Economy 98, 703–738.

DellaVigna, S., Pollet, J., 2009. Investor inattention and friday earnings announcements. The Journal of Finance 64, 709–749.

Drake, M., Roulstone, D., Thornock, J., 2011. Investor information demand: Evidence from Google searches around earnings announcements. Journal of Accounting Research .

Elliott, G., Rothenberg, T.J., Stock, J.H., 1996. Efficient tests for an autoregressive unit root. Econometrica 64, 813–36.

Engelberg, J., Parsons, C., 2011. The causal impact of media in financial markets. The Journal of Finance 66, 67–97.

Fang, L., Peress, J., 2009. Media coverage and the cross-section of stock returns. Journal of Finance 64, 2023–2052.

Fang, L., Peress, J., Zheng, L., 2009. Does your fund manager trade on the news? media coverage, mutual fund trading and performance. Working Papers .

Figlewski, S., 1989. Options arbitrage in imperfect markets. Journal of Finance 44, 1289–1311.

Flood, R., Taylor, M., 1996. Exchange rate economics: What's wrong with the conventional macro approach? The microstructure of foreign exchange markets , 261.

Foucault, T., Sraer, D., Thesmar, D., 2011. Individual investors and volatility. The Journal of Finance 66, 1369–1406.

Freixas, X., Kihlstrom, R., 1984. Bayesian Models in Economic Theory. North-Holland, Amsterdam. chapter Risk aversion and information demand.

Green, T.C., Figlewski, S., 1999. Market risk and model risk for a financial institution writing options. Journal of Finance 54, 1465–1499.

Huang, L., Liu, H., 2007. Rational inattention and portfolio selection. The Journal of Finance 62, 1999–2040.

Jiang, G.J., Tian, Y.S., 2005. The model-free implied volatility and its information content. The Review of Financial Studies 18, pp. 1305–1342.

King, M., Rime, D., 2010. The $4 trillion question: what explains fx growth since the 2007 survey? BIS Quarterly Review, December .

Kumar, A., 2007. Do the diversification choices of individual investors influence stock returns? Journal of Financial Markets 10, 362–390.

Malz, A.M., 1997. Estimating the probability distribution of the future exchange rate from option prices. The Journal of Derivatives 5, 18–36.

Meese, R., 1990. Currency fluctuations in the post-bretton woods era. The Journal of Economic Perspectives 4, 117–134.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2011. Carry trades and global foreign exchange volatility. Journal of Finance .

Mondria, J., Wu, T., 2012. Asymmetric attention and stock returns, Working paper, University of Toronto .

Odean, T., 1998. Volume, volatility, price, and profit when all traders are above average. Journal of finance , 1887–1934.

Peng, L., 2005. Learning with information capacity constraints. Journal of Financial and Quantitative Analysis 40, 307–329.

Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. Journal of Financial Economics 80, 563–602.

Peng, L., Xiong, W., Bollerslev, T., 2007. Investor attention and time-varying comovements. European Financial Management 13, 394–422.

Poteshman, A.M., 2001. Underreaction, overreaction, and increasing misreaction to information in the options market. Journal of Finance 56, 851–876.

Rosenberg, J.V., Engle, R.F., 2002. Empirical pricing kernels. Journal of Financial Economics 64, 341–372.

Sager, M., Taylor, M., 2006. Under the microscope: the structure of the foreign exchange market. International Journal of Finance & Economics 11, 81–95.

Scheinkman, J., Xiong, W., 2003. Overconfidence and speculative bubbles. Journal of Political Economy 111, 1183–1220.

Smith, G., 2012. Google internet search activity and volatility prediction in the market for foreign currency. Finance Research Letters .

Stein, J., 1989. Overreactions in the options market. Journal of Finance 44, 1011–23.

Tetlock, P., 2010. Does public financial news resolve asymmetric information? Review of Financial Studies 23, 3520.

Vlastakis, N., Markellos, R., 2012. Information demand and stock market volatility. Journal of Banking & Finance .

Yuan, Y., 2011. Attention and trading, Working paper, The Wharton School .