Inattentive Search for Currency Fundamentals*

Agnieszka Markiewicz[†], Ralph Verhoeks[‡], Willem F.C. Verschoor[§]
and Remco C.J. Zwinkels[¶]

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Abstract

We show how economic agents' limited attention can account for the time-varying link between exchange rates and economic fundamentals. We demonstrate that the higher is the attention for a certain fundamental, the higher is its predictive power in forecasting currency movements. We proxy attention for a fundamental by its search intensity on Google. In a sample of fifteen bilateral exchange rates from 2004 to 2016, we find that the fundamentals selected by the Google Trends Index significantly outperform the random walk, both statistically and economically. An equally-weighted portfolio earns 4.9% per annum with a Sharpe ratio of 1.3. The highest performance is delivered by strategies that select the single fundamental that receives the highest attention, confirming the limited attention hypothesis.

Keywords: *exchange rate forecasting, investment strategies, attention*

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[†]Erasmus School of Economics and Tinbergen Institute; markiewicz@ese.eur.nl.

[‡]De Nederlandsche Bank and Vrije Universiteit Amsterdam; r.c.verhoeks@dnb.nl.

[§]Vrije Universiteit Amsterdam and Tinbergen Institute; w.f.c.verschoor@vu.nl.

[¶]Vrije Universiteit Amsterdam and Tinbergen Institute; r.zwinkels@vu.nl.

1 Introduction

Traditional exchange rate models assume that there is a stable relation between exchange rates and economic fundamentals and that all relevant information is incorporated in currency prices. This implies that investors pay attention to all the existing information. We know, however, that empirically there is a time-varying link between exchange rates and fundamentals (Schinasi and Swami, 1989; Cheung et al., 2005; Rossi, 2013; Sarno and Valente, 2009). Furthermore, empirical evidence suggests that attention is a scarce cognitive resource.[2] In this paper, we show that the time varying link between exchange rates and fundamentals can be attributed to economic agents' limited attention. Specifically, we demonstrate that the higher the attention for a certain economic fundamental, the higher its value in forecasting exchange rate movements. By measuring the relative attention for different fundamentals, we detect the variables that investors use to form expectations about the future exchange rate. Due to the self-referential structure of exchange rates, the fundamental that investors pay attention to feeds back into the exchange rate itself. We exploit this feature and identify fundamentals that investors focus on to construct predictions. We proxy investor attention for an economic variable by its search intensity on the Google search engine. The interpretation of the Google Trends Index (GTI) in this context is rather intuitive: the higher the GTI, the higher the relative search intensity for the fundamental in question, and the higher the attention paid to the fundamental.

By using the Google search volume as indicator of attention, we are not necessarily implying that all market participants are using Google to search for information. In fact, it is rather unlikely that institutional market participants use Google as a source of information. Da et al. (2011) confirm that in the case of individual stocks, search volume captures the attention of retail investors. Instead, we assume that search volume represents a proxy of a more general measure of attention which can affect investment decisions of various market participants. These currency market participants include central banks, goods and services importers and exporters, individuals, and to some

[2]Examples include Kahneman (1973), Da, Engelberg and Gao (2011) and Yuan (2015).

extent institutional investors. As long as we manage to capture the attention of a non-negligible share of currency markets participants whose decisions can impact prices, we are able to identify the economic factors that can predict the future value of the currency. In fact, we show that the fundamental selected by the GTI is an excellent predictor of the future exchange rate and therefore it is likely that it captures the market-wide attention to fundamentals.

If investors' attention is to some degree persistent, we should be able to make use of the GTI to predict the exchange rates out-of-sample and implement profitable investment strategies. In a sample ranging from 2004 to 2016 we find that the GTI-based forecasting procedure significantly outperforms the random walk, both statistically and economically. It reduces the mean squared prediction error significantly for nine out of 15 bilateral exchange rates. Moreover, it generates positive and significant excess returns for eight out of fifteen individual currencies and all portfolio investment strategies. The size of economic profits is considerable: an equally-weighted currency portfolio, for instance, earns an annualized return of 4.9% with a Sharpe ratio of 1.3.

We find that economic agents shift their attention quickly from one fundamental to another. The chosen fundamental remains a predictor for on average 2.26 months, before it is replaced by another one. The best forecasts and the highest returns are delivered by strategies that select the fundamental that is paid the highest attention to. Other fundamentals with high GTI should be discarded when constructing the forecasts and investment strategies. This finding suggests that the attention of economic agents is limited to a single fundamental, making information embedded in other fundamentals redundant.

This paper contributes to the literature that studies the well documented time-varying relationship between exchange rates and macroeconomic fundamentals.[3] Recent theoretical studies provide explanations for the time-varying link between currencies and funda-

[3]Schinasi and Swamy (1989) show that exchange rate models with time-varying parameters outperform a random walk in an out-of-sample forecasting test. Cheung et al. (2005), Sarno and Valente (2009), and Rossi (2013) find that fundamental exchange rate models have predictive power, but the performance depends on the particular currency and forecast horizon considered.

mentals. These papers exploit the asset pricing representation of the exchange rate where its dynamics are mainly determined by investors' expectations. The reasons why the expectations may change are multiple. For example, in the scapegoat theory of Bacchetta and van Wincoop (2004, 2006, 2013), investors wrongly attribute currency movements to an economic variable that happens to change at the same time as the true movement-generating factor. In the model of Markiewicz (2012), investors are continuously testing the set of fundamentals and keep only the ones that significantly influence the currency movements. These theoretical models imply that, for some reason, investors pay attention to a certain fundamental (or a subset of fundamentals) at the time. In this paper, we directly test this implication by using a straightforward measure of investor attention: the search intensity on Google.

Research from the psychology literature has provided sufficient evidence to conclude that it is hard to process multiple information sources.[4] Pashler (1998) and Pashler and Johnston (1998) show, for instance, that people have severe limitations on their ability to simultaneously carry out certain cognitive processes that actually seem fairly trivial from a computational perspective. Motivated by this evidence, Hirshleifer and Teoh (2003), Peng and Xiong (2006), and Andrei and Hassler (2015) assume, in a theoretical framework, that investors discard part of the available information. Limited attention can then generate important features observed in asset returns that are otherwise difficult to explain with standard rational expectations models.

Abundant empirical literature confirms predictions of the theoretical studies. Limited attention is a common feature of agents in financial markets and can account for a set of unexplained asset pricing phenomena. Da, Engelberg and Gao (2011) show that an increase in the search volume index predicts higher stock prices in the next two weeks and a price reversal over the following year. Sicherman, Loewenstein, Seppi, and Utkus (2016) find that investors pay less attention to news when the VIX is high, and that the level of attention is strongly related to investor demographics (gender, age) and financial position

[4] Studies on the topic include Stroop (1935), Rensink, O'Regan and Clark (1997), Simons and Chabris (1999).

(wealth, holdings). Yuan (2015) shows that attention-grabbing events predict the trading behavior of investors and hence market returns. Ben-Rephael, Da, and Israelsen (2017) study institutional investor attention. They find that price drifts following both earnings announcements and analyst recommendation changes are driven by announcements to which institutional investors fail to pay sufficient attention. Search intensity on Google has been used before to measure investors' attention; see e.g. Da, Engelberg, and Gao (2011). This paper exploits its potential in a novel way. Specifically, instead of measuring the aggregate investors' attention to the asset (currency), we use the GTI to capture the attention paid to different fundamentals at different points in time and map them into an exchange rate specification.

The remainder of this paper is organized as follows. Section 2 outlines our measure of attention based on the Google Trends data and describes the construction of our data on attention. In Section 3, we present the fundamental models and describe how we map them into the search queries. In Section 3, we also describe the data on fundamentals, explain the forecasting procedure based on the GTI, and present a set of statistical and economic measures that are used to assess the performance of the GTI-based predictions. The results are presented in Section 4. Section 5 concludes the paper.

2 Google Trends

In this section we describe how we use Google to measure investor attention, and explain the construction of the Google Trends Index data.

2.1 Google Trends as a measure of investor attention

Our aim is to capture the macroeconomic fundamental that attracts the attention of currency market participants by using data from Google Trends.[5] Google Trends is a public web facility of Google that shows how often a particular search-term is entered relative

[5]Da, Engelberg, and Gao (2011) use Google search volume to proxy for attention of individual stocks and find that it is a more timely measure than other measures of attention. Search engine data has recently been applied in several forms of so-called nowcasting of macro-economic variables (Choi and Varian, 2011). Goel et al. (2005) show that search behavior has predictive content further in the future.

to the total search volume across various regions and in various languages. Internet users in general commonly use a search engine to search information, where Google has by far the majority of market share (91%). More critically, search is a measure of revealed attention: if someone searches for a certain variable, this person is undoubtedly paying attention to this variable. This is a critical advantage compared to indirect proxies of attention, like trading volume or extreme returns (as employed by Barber and Odean 2008, for instance). Hence, Google Trends may be effective in identifying the fundamentals that economic agents focus on and use to predict currencies.

We are not claiming that (all) market participants are using Google to search for information. Indeed, it is unlikely that sophisticated market participants use Google as a source of information. Instead, we argue that search volume represents a proxy of a more general measure of attention. If a particular economic fundamental attracts more search volume, it implies that it has attracted the attention of Google users. It is therefore also likely to have attracted the attention of market participants. In addition, we do not need that it captures the attention of *all* market participants but of a non-negligible portion just large enough to affect prices.

2.2 Construction of the Google Trends Index

The data provided by Google Trends comprises of time series indices of search queries that users enter in the Google search engine. This data can be refined to regional locations and/or time. The index is not a nominal search volume in absolute terms, but a relative index number between 0 and 100. The index is relative in two dimensions: time and space. First, it is calculated as the total search volume for each item divided by the total number of all search queries in the same region in a given time period. Second, the index is calculated for a given point in time relative to the number of searches in a certain time period. In other words, Google needs to be provided with a period, a frequency, and a time period over which we want the GTI to be computed.

Google calculates the index from a random subset of the actual historical search data to increase the response speed. As a result, the GTI time series on the same search term are often slightly different when they are downloaded at different points in time. On average, the impact of this sampling error is small and would work against our results. To evaluate the possible noise introduced by this sampling error, we compute the correlation between the GTI data series when we download this twice for five different search queries (monetary policy, money supply, interest rate, inflation and GDP). This is done for both monthly data (January 2004 - December 2015) and weekly data (January 2015 - December 2015) to capture any differences between time frequencies. Correlations resulting from this preliminary exercise vary between 0.985 and 0.996. This confirms the minor impact of Google drawing only a random subset of the historical search data.

To illustrate to what extent the GTI captures the attention of investors, we show the behavior of the GTI around meetings of the Governing Council of the European Central Bank (ECB). The Governing Council of ECB has met 20 times during the years 2014 and 2015 to discuss the monetary policy. Table 1 shows the average increase of the weekly GTI for the search topic 'monetary policy' during the weeks in which the Governing Council decided about the monetary policy instruments, compared to the week prior to it, for both 2014 and 2015 and for six euro countries.[6] The statistics suggest that the GTI captures the attention that economic agents pay to monetary policy around critical Frankfurt meetings. In the vast majority of cases, the GTI rises considerably (averaged over the year) during weeks in which the Governing Council meets. Since the Financial Crisis, several central banks in developed economies implemented non-conventional monetary policies. One of them was quantitative easing and Figure 1 shows the development of the GTI for this particular search during the period of January 2014 until September 2016 for Germany, France, Italy and Spain. During this same time period, the Governing Council decided on a set of fundamental changes in its monetary policy. The figure shows that the GTI captures the attention of market participants for these decisions fairly well. The first event indicated in the figure was September 4th 2014, when the ECB decided to implement quantitative easing in the form of asset purchases of asset backed securities

[6]The search topic monetary policy includes the following queries: 'monetary policy', 'ECB', 'monetary policy Governing Council' or 'monetary policy Europe'.

and covered bonds. On January 22nd 2015, the ECB announced a purchase program of sovereign bonds and this event is captured by the GTI more strongly as the second spike in Figure 1 is the highest. The third event is the actual start of the purchase program, where the GTI again captures an increase in attention but to a lesser extent. These examples suggest that the GTI succeeds to capture swings in attention.

3 Model selection and forecasting with Google trends

The GTI captures swings in attention to different economic fundamentals and we expect that these fundamentals affect economic decisions of the currency market participants.[7] We translate each of these economic fundamentals into an exchange rate model and we estimate it. We then use the GTI to select the model that the economic agents pay the most attention to and use it for predictions. In what follows, we explain in detail the fundamentals and how the Google search intensity is used to make a selection among them. Next, we describe how we create the predictions based on the fundamental model selection.

3.1 Pool of fundamental models

We compile a pool of macroeconomic and financial fundamental models that are commonly used in the literature to forecast exchange rates. This set includes macroeconomic models that contain variables which are expected to predict exchange rate movements, as well as financial models taking into account commodity prices. This pool of models matches partly that of Kouwenberg et al. (2017).[8] Note that all variables are in natural logarithms, such that Δs_t is the period t currency return. Each of our eight models includes a constant term.

The first fundamental model is the uncovered interest rate parity (UIRP), which states

[7] By economic decisions we mean here investment and hedging decisions, central banks interventions, goods and services trading decisions, etc.

[8] We left out some common exchange rate models because of their limited applicability in combination with the Google Trends Index. One of them is the Taylor rule model which is difficult to translate into the GTI query due to its complexity. We focus on the simple models that can be easily translated into the Google search queries.

that exchange rate movements are explained by differences in the nominal interest rate:

$$\Delta s_{t+1} = \alpha_1 + \beta_1[i_t - i_t^*] + \varepsilon_{t+1}, \tag{1}$$

in which i is the interest rate and an asterisk ($*$) denotes a foreign variable. The sign of β_1 determines whether this model represents uncovered interest rate parity ($\beta_1 < 0$) or a carry-trade model ($\beta_1 > 0$). We take a combination of the 3 months and 1-year interest rates.

The second model is based on the purchasing power parity (PPP). Its absolute version implies that the expected exchange rate is a function of the deviation of the spot rate from its PPP-based fundamental value:

$$\Delta s_{t+1} = \alpha_2 + \beta_2[(p_t - p_t^*) - s_t] + \varepsilon_{t+1}, \tag{2}$$

in which p_t and p_t^* are the home and foreign price levels, respectively. Next to the absolute PPP, we also consider its relative variant, which relates exchange rate movements to the inflation differential rather than absolute price differences:

$$\Delta s_{t+1} = \alpha_3 + \beta_3[(\pi_t - \pi_t^*) - s_t] + \varepsilon_{t+1}. \tag{3}$$

We combine the forecasts from the absolute and relative PPP models into one forecast because they are based on the same underlying variable. As a result, we use the same search queries for both models.

The third model is the canonical monetary model which presents exchange rates in terms of relative demand for and supply of money in the two countries involved:

$$\Delta s_{t+1} = \alpha_4 + \beta_4[(m_t^* - m_t) - k(y_t^* - y_t) - s_t] + \varepsilon_{t+1}, \tag{4}$$

in which m is the log money supply and y is log output (GDP). Following Molodtsova and Papell (2010), we set k equal to 0.5.

The fourth model, the international risk sharing model, relates the exchange rate to differences in consumption growth between the two countries involved:

$$\Delta s_{t+1} = \alpha_5 + \beta_5[CG_t - CG_t^*] + \varepsilon_{t+1}, \tag{5}$$

in which CG is the (annual) consumption growth. The intuition behind this model is that a relatively high consumption growth leads to a higher income, a higher money demand and, consequently, to a stronger currency.

As suggested by macroeconomic international trade models, for instance the elasticity model of the balance of trade, the trade balance is an important determinant to explain exchange rate movements. Therefore, our fifth model relates exchange rate movements to the balance of trade:

$$\Delta s_{t+1} = \alpha_6 + \beta_{6,1}(TB_t/GDP_t) + \beta_{6,2}(TB_t^*/GDP_t^*) + \varepsilon_{t+1}, \tag{6}$$

in which TB is the trade balance. We scale the trade balance by GDP to control for the size of the economy. The trade balance model derives from the assumption that exchange rates move in response to imbalances in the market for goods.

The capital flows model incorporates the net foreign asset position, which is defined as the difference between purchases and sales of securities. This model states that exchange rates move in response to imbalances in the market for capital and is defined as follows:

$$\Delta s_{t+1} = \alpha_7 + \beta_7 NFA_t + \varepsilon_{t+1}, \tag{7}$$

in which NFA_t stands for the position in net foreign assets.

In addition to the fundamentals discussed above, which are all derived from macroeconomic reduced-form models, we also incorporate two financial factors. The first one relates exchange rate movements to changes in commodity prices:

$$\Delta s_{t+1} = \alpha_8 + \beta_8 \Delta COM_t + \varepsilon_{t+1}, \tag{8}$$

in which ΔCOM_t represents the commodity price index change.

The second financial factor is oil. Oil seems to be the most important commodity related to changes in the exchange rates and therefore we look at changes of its prices separately[9]:

$$\Delta s_{t+1} = \alpha_9 + \beta_9 \Delta OIL_t + \varepsilon_{t+1}, \tag{9}$$

in which ΔOIL_t represents the movement in the oil price index.

3.2 Mapping models into search queries

In order to implement the GTI we need to map the models into relevant search queries. Table 2 shows the selected search queries for each model. For each of them, we select several search queries to measure investor attention as close as possible. For this purpose, we use of Google Correlate. This tool suggests search queries that are highly correlated in terms of search intensity with the one entered by the user. For example, in the case of monetary policy, Google Correlate informs us that monetary supply and monetary demand display an average correlation of 0.903 between 2004 and 2015. They are thus natural candidates for search queries for the monetary model.

The search queries shown in Table 2 are always restricted to the countries of the currency involved. For instance, when we search for fundamentals for the USD-JPY, we restrict the regional area of the GTI to the United States and Japan. It is important to bear in mind that Table 2 presents the Google search queries in English. English search queries have the most significant coverage, also for Japan where English is not the main language.[10] However, when the English search query does not have enough data to calculate the GTI for the country involved (which is automatically indicated by Google when the series is collected), we use the search query both in English as well as the home language. If this procedure does not deliver enough Google coverage either, we omit the particular search query from the analysis.

For each of the economic fundamentals, we calculate the correlation coefficients be-

[9] See for instance Chen, Rogoff and Rossi (2010).

[10] The reason could be that even in Japan most investors read international news in English and hence search for queries in English.

tween the GTI series of the different search queries. We present these correlations for the U.S. in Table 3. Table 3 shows that in most cases, correlations are positive and strong, confirming that individual search queries for the same fundamental are related. Still, applying multiple search queries may have important benefits: it 'diversifies' away the idiosyncratic risk that adheres to each individual search query.

3.3 Forecasting procedure

Based on the GTI, we build the forecasting procedure to predict monthly exchange rate movements between January 2004 and December 2016. We perform the analysis for fifteen currency pairs combinations between the CAD, GBP, JPY, CHF, AUD, and USD. The sample period could not be extended because Google Trends data only dates back to January 2004. We have not extended the analysis to other currencies due to limitations of Google Trends. More precisely, Google coverage decreases considerably outside the countries we incorporated in our analysis. Also, including the euro is hard as it involves multiple countries and languages.

Our forecasting procedure goes as follows. First, we collect GTI data for all search queries that are listed in Table 2, for each point in time and for each country. We choose the monthly frequency to match the availability of the fundamentals. This means that we collect 210 GTI data series, as we selected 35 search queries (see Table 2) for six countries. Second, we calculate the average GTI over the different search queries per fundamental model for every point in the sample period and for each country separately.

Third, at each point in time, we select the fundamental model with the highest average GTI for its search queries, averaged over both countries involved. The model with the highest average GTI for its search queries is the model for which Google users have the highest attention in the country involved. Our hypothesis is that this model will have the best predictive performance because it incorporates economic information that receives the most attention. Finally, we make one-step-ahead out-of-sample forecast of the model selected by the GTI. This procedure is recursive and is repeated for each point in time.

3.4 Data on fundamentals

We use monthly data for 1995M1-2016M12 for Australia, Canada, Japan, Switzerland, the United Kingdom and the United States from different data sources. We use seasonally adjusted data for the GDP from the National Accounts database of the OECD. Private consumption data is taken from the Key Short Term Economic Indicators of the OECD. Data for the seasonally adjusted trade balance, net foreign assets, monetary base (M3) and CPI are from the Main Economic Indicators dataset of the OECD, where we define net foreign assets as the sum of foreign direct investments and portfolio investments. If applicable, these data are in national currency. We use two commodity data series. The composite commodity price index comes from Goldman Sachs. The oil price is measured by the price per barrel of West Texas Intermediate (WTI). Interest rates are LIBOR rates for both the three months and one-year maturity.

We estimate all eight models described above in-sample and make an out-of-sample forecast for the first observation thereafter. The first in-sample estimation runs from 1995M1 to 2003M12 and returns an out-of-sample forecast for 2004M1. This is the first month for which Google Trends data is available and we can perform the procedure set out in the previous subsection. The second estimation period runs 1995M1 to 2004M1 and delivers an out-of-sample forecast for 2004M2, and so forth. We create these rolling forecasts with expanding window for each model separately, after which we apply our selection mechanism based on the Google Trends Index. The sample period of January 2004 - December 2016 contains 156 monthly forecasts for each of the 15 currency pairs.

3.5 Statistical and economic performance measures

Once we have the predicted exchange rate series, we implement a set of measures to judge the ability of the GTI to trace the fundamentals that investors focus on. First, we measure forecast accuracy of model i by the mean squared prediction error (MSPE) relative to the MSPE of the random walk model. In comparing the forecast errors, we use the Clark and West (2007) adjustment and statistic, given by

$$CW_i = \frac{1}{l}\sum_{t=1}^{l}\frac{(E_{t-1}^i(\Delta s_t) - \Delta s_t)^2 - E_{t-1}^i(\Delta s_t)^2}{(\Delta s_t)^2}, \tag{10}$$

in which l is the total number of forecasts. We employ the CW statistic to test the null hypothesis that the GTI-based forecast has the same predictive ability as a random walk without drift benchmark model.

In addition, we calculate the non-parametric sign test of Pesaran and Timmermann (1992), which tests the ability of our model to forecast the direction of change correctly, again relative to the random walk forecast. The Pesaran and Timmermann (1992) statistic is given by

$$PT_i = \left(\frac{p^*(1-p^*)}{l}\right)^{-1/2}(\widehat{p} - p^*), \tag{11}$$

in which p^* is the benchmark proportion of correct sign predictions and $\widehat{p}$ the observed proportion of correct sign predictions. We set $p^* = 0.5$ to represent the random walk without drift model. The PT statistic is asymptotically distributed as $N(0,1)$.

In addition to statistical forecast evaluation measures, we also examine the economic value added of our forecasting procedure. For this purpose, we calculate the returns of an investment strategy that buys (sells) one unit of the foreign currency when the model predicts an appreciation (depreciation) of the foreign currency. In case of subsequent buy-signals, the long position is rolled over. The foreign-exchange return of the strategy i is given by

$$r_t^i = \frac{E_{t-1}^i(\Delta s_t)}{|E_{t-1}^i(\Delta s_t)|}\Delta s_t. \tag{12}$$

The investment strategy's Sharpe ratio is calculated as $\frac{1}{l}\sum r_t^i / \frac{1}{l}\sum(r_t^i - \overline{r}^i)^2$. By definition, this measure also evaluates the performance of the strategy relative to the random walk without drift benchmark, because the benchmark random walk strategy always yields the risk-free return.[11]

[11] For simplicity, we ignore transaction costs when calculating strategy returns. Given the liquidity of foreign exchange markets and the relatively low frequency of our analyses, however, we do not expect the transaction costs to affect the results much.

In addition to assessing model performance for each currency individually, we form equally-weighted and volatility-weighted portfolios of all currencies. We measure and forecast volatility using the exponentially weighted moving average (EWMA) method, given by

$$\sigma_{t+1}^2 = \lambda \sigma_t^2 + (1 - \lambda) \Delta s_t^2, \tag{13}$$

in which we follow the RiskMetrics approach and set $\lambda = 0.94$. The return of the volatility weighted portfolio is given by:

$$r_t^{vw} = \left(\sum_p \frac{1}{\sigma_{p,t+1}^2} \right)^{-1} \sum_p \frac{1}{\sigma_{p,t+1}^2} r_t^p, \tag{14}$$

in which p denotes the currency.

Note that the equally-weighted and volatility-weighted portfolios of currencies can contain both long and short positions, depending on the signs of the return forecasts for the currencies. As an additional performance measure, we also form pure long-short portfolios based on the forecasts. Specifically, we construct a portfolio that goes long in the currency with the highest forecasted appreciation and short in the currency with the lowest forecasted appreciation (i.e., the largest deprecation).

4 Results

First, we assess to what extent the GTI selected fundamental carries predictive power and delivers statistically and economically significant returns. Second, to understand how inattentive economic agents are, we include additional fundamentals into the forecasts and evaluate their predictive performance relative to the one, GTI selected fundamental. Finally, we investigate the properties of the GTI-based fundamentals to assess the persistence of the selected models.

4.1 Limited attention and currency forecasts

Table 4 presents the results of the currency forecasting exercise where the fundamental is selected by the GTI at each point in time.

The MSPE ratios are below unity for 12 out of 15 currencies, and significantly so for 9 out of 15 currencies. The average improvement is 3.3% based on the MSPE, ranging from 8.9% for the USD-AUD to -1.1% for the CHF-JPY. The p-value of the PT-statistic reports significance for six out of fifteen currencies.

Table 5 presents the economic evaluation of our forecasting exercise. The table shows the annualized return, the annualized standard deviation of returns, the corresponding Sharpe ratio and the p-value of the t-test to test the significance of the average return. The investment strategy for individual currencies results in a positive investment return for all currencies except one (CHF-JPY). For eight currencies, the positive return is significant. Moreover, the three currency portfolios (equally-weighted, volatility weighted, and long-short) all have a significantly positive mean return. Given the implemented strategies, the magnitude of the portfolio returns is considerable. The equally-weighted portfolio for instance has an annualized investment return of 4.9% with an annualized volatility of 3.7% and a Sharpe ratio of 1.297. The long-short portfolio earns a very high return of 10.8%, although this is achieved at the cost of a much higher volatility (17.7%) as well.

4.2 How inattentive are economic agents?

So far, we have used only one fundamental with the highest GTI to make foreign exchange rate predictions. We now compare these benchmark results to a setting in which more than one fundamental is considered. Specifically, we implement forecasting and investment strategies based on a set of fundamentals weighted by their Google search intensities.[12]. The weights are computed as follows:

$$E_t \Delta s_{t+1} = \sum_{i=1}^{N} w_{i,t} \left[\widehat{\alpha}_{i,t} + \widehat{\beta}_{i,t} f_{i,t} \right], \tag{15}$$

[12]Other studies implementing model averaging to improve on forecasting performance include, for instance, Timmerman (2006), Della Corte, Sarno and Tsiakas (2009) and Wright (2008)

in which i being the subscript for the different fundamental models and $w_{i,t}$ being defined as follows:

$$w_{i,t} = \frac{GTI^{av}_{i,t}}{\sum_{i=1}^{N} GTI^{av}_{i,t}}, \tag{16}$$

in which $GTI^{av}_{i,t}$ is the average GTI computed over the different search queries for fundamental i for the two countries involved in a given currency.

Table 9 presents the average GTI-based weights attached to each of the fundamental models. It also shows the difference between the mean maximum and the mean minimum weights averaged over the currencies involved. The maximum weight is about five times higher than the minimum weight so undoubtedly the relative GTI generates substantial differences in weights attached to fundamentals. The least relevant fundamental receives the average minimum weight of 4.3% which is not negligible.

Table 7 presents the results of the statistical evaluation of the forecast combinations. The MSPE relative to the RW reduces by 0.89% on average, and the reduction is only significant for three exchange rates. The PT-statistic reports significant out-performance for three exchange rates. The economic evaluation presented in Table 8 is somewhat more positive. The annualized returns are positive and significant for three exchange rates and all three portfolios. However, the absolute size of returns is substantially lower compared to our forecasting procedure which selects one model with the highest attention measure. These results are consistent with the findings of Kouwenberg et al. (2017) who find that selecting a single model works best in forecasting exchange rates. These results also suggest that the attention of economic agents is very limited.

4.3 How often does the fundamental change?

Table 6 shows how often the selected fundamental changes and the resulting duration in months. The selected model changes in 46% of cases (months) on average. Accordingly, the chosen fundamental remains for on average 2.26 months, before it is replaced by another fundamental model. This implies that the fundamental gaining the highest average attention is rather quickly substituted by another. The extent of time variation differs slightly across currencies. For instance, for the AUD-CHF, the time-variation of the chosen fundamental model is the highest, with switches in 62% of the months and the selected model being selected for a duration of 1.61 months on average. For the USD-JPY, the model only changes in 23% of the time leading to an average duration of 4.11 months.

Table 6 also shows how often each model is chosen for each of the currencies. The consumption growth, trade balance, and commodity fundamentals are selected most often. The net-foreign assets and interest rate parity models are hardly ever chosen. There is, however, ample variation across currencies. For example, the trade balance model is chosen in 79% of the months for the USD-JPY. This might be explained by the export-oriented economy of Japan.

4.4 Robustness tests

4.4.1 Importance of different queries

To measure the attention to a certain fundamental variable, we incorporate a number of search queries to create the Google Trends Index for each fundamental model, as listed in Table 2. An important robustness check is to assess whether our results are sensitive to which queries are taken into account for each fundamental. Tables 10 and 11 show the statistical and economic evaluations of forecasts if we delete the last query for each model in our pool from the list in Table 2, provided that at least three search queries per model remain available.

The statistical evaluation of the resulting forecasts shows that the elimination of these queries does not qualitatively impact results. On the level of individual currencies, some changes do occur. For instance, the statistical outperformance based on the PT-statistic disappears for the CAD-CHF and the AUD-GBP. The economic evaluation of portfolios returns in Table 11 shows a similar picture. After the elimination of the queries, the estimated mean returns slightly decrease, but they remain economically and statistically significant. We also remove other search queries and find (unreported) qualitatively unaffected results. The limited impact of elimination of queries is in line with expectations since the GTIs of the queries for each fundamental are strongly correlated.

4.4.2 Sample period

To assess the robustness of our findings to the sample period selection, Figure 2 presents 3-year rolling returns and Sharpe ratios for all the three investment portfolios that we evaluate. The graphs show that the rolling returns and Sharpe ratios oscillate around the total sample mean (represented by the dashed line), but never become insignificant or negative for a longer period of time. It is worth noting that all the three portfolios perform particularly well during the Great Recession.

We also formally test for differences in performance during the first and second half of the sample period: 2004M1-2010M6 and 2010M7-2016M12, respectively. Table 10 and 11 also include the results for these two periods separately. Even if the first half of the sample covers the financial crisis period, the results do not differ a lot across both samples.

4.4.3 Financial crisis

It is well known that the profitability of certain currency investment strategies is procyclical (carry trade) while the profitability of the others is countercyclical (PPP). We investigate the extent to which our GTI-based forecast can detect an adequate strategy (fundamental) during financial distress. Table 11 includes the results for recessions separately (rows entitled Recessions), where recessions are all periods during which one of the countries involved was in a recession (according the OECD definition). It also includes the results for periods of financial stress (rows entitled VIX 10-percentile). We define the latter as the periods during which the value of the VIX was in its upper 10th percentile. The results show that our attention-based strategies perform, in fact, better during stress and recessions. The difference in returns is statistically significant when compared to calm and expansion periods. These results are consistent with Sicherman et al. (2016), who show that investors pay less attention to news when the VIX is high and hence limited-attention based measures score particularly well.

4.4.4 GTI-based strategies versus carry trade

Carry trades are a relevant benchmark for our foreign exchange investment strategy based on forecasts selected by Google Trends. Carry trading is a popular currency strategy, that invests in high interest rate currencies and borrows in low interest rate currencies. It aims to exploit deviations from the uncovered interest rate parity, a strategy which generated significant investment profits in the past, particularly in the pre-crisis period (Burnside et al., 2011). To compare our results with carry trades, we take the perspectives of an American, Australian, British, Canadian, Japanese and Swiss investor, respectively, and compute the returns of a long-short currency portfolio for all of them. We form a portfolio by sorting the six currencies each month from high to low interest rate and we exclude the home currency of the investor. Secondly, we go long in the two currencies with the highest interest rate and go short in the two currencies with the lowest. We also calculate the returns of an investment in one leg only (long and short), again with two currencies per leg. The portfolio weights of the currencies are always equal and we rebalance each month.

Table 12 shows that the results of the carry trade strategies are characterized by lower (and sometimes even negative) Sharpe ratios. Also, in the case of positive carry trade returns, they are statistically insignificant. The one exception is the long leg for the U.K. investor, which yields a significant return. These results show that our forecasting procedure based on the relative search intensity for different fundamentals outperforms simple carry strategies. The results for the carry trade strategies reported in the literature are usually higher than reported here. This is most likely explained by the sample period, which is relatively short and includes the drawdown of carry during the Global Financial Crisis of 2007-2008.

5 Conclusion

The weight that economic agents attach to different fundamentals as drivers of currency movements fluctuates considerably over time. In this paper, we demonstrate how economic agents' limited attention can account for this empirical feature of the exchange rate. We proxy the attention of economic agents by the Google Trends Index. In a sample of macro-economic data from 1995 to 2016, we find that the forecasts based on fundamental selection by Google Trends significantly outperform the random walk, both statistically and economically. The size of economic profits is considerable: an equally-weighted currency portfolio, for instance, earns an annualized return of 4.9% with a Sharpe ratio of 1.3. By comparison, between 2004 and 2016 a carry trade strategy based on the same currencies yielded a Sharpe ratio of 0.31.

We study the existence and persistence of inattention of economic agents. We find that economic agents shift their attention quickly from one fundamental to another. The chosen fundamental remains for on average 2.26 months, before it is replaced by another one. The best forecasts and the highest returns are delivered by strategies that select the fundamental that is paid the highest attention to. Other fundamentals with high GTI should be discarded in the construction of the forecasts and corresponding investment strategies. This finding suggests that the attention of economic agents is limited.

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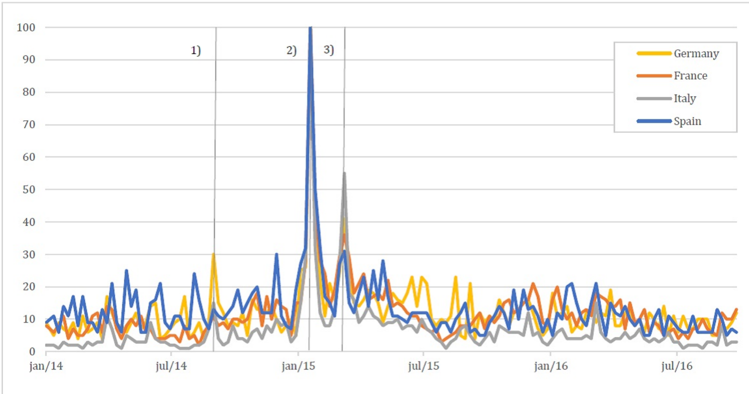
Appendix

Figure 1: GTI behavior around important quantitative easing decisions



This figure presents the Google Trends Index for a number of countries on the term 'quantitative easing'.

Tables and Figures

Table 1: **Google Trends Index illustration**

Monetary policy	Germany	France	Netherlands	Spain	Italy	Austria
2014	23.30%	40.70%	36.60%	6.50%	26.80%	19.00%
2015	-0.80%	13.20%	24.50%	-14.60%	15.40%	32.70%

Notes: This table presents the average change in the Google Trends Index for the monetary policy topic per country per year in the week of ECB Governing Council meetings. The search topic monetary policy includes the following queries: ‘monetary policy’, ‘ECB’, ‘monetary policy Governing Council’ or ‘monetary policy Europe’.

Table 2: **Search queries for Google Trends data**

Model	Google search queries
UIRP	Interest rate, libor rate, interest rate parity, carry trade, central bank rate
PPP	Inflation, rate of inflation, CPI, purchasing power parity, consumer price index, price index
Monetary model	Money supply, money demand, M1, monetary base
Consumption growth	Consumption growth, GDP growth, economic growth, consumption
Trade balance	Trade balance, balance of trade, export, import, international trade
Net foreign assets	Foreign assets, foreign reserves, foreign exchange reserves, net foreign assets, capital flows, net international investment position
Commodities	Commodities, commodity price, commodity index
Oil price	Oil price, West Texas Intermediate, WTI oil, crude oil

Notes: This table lists the search queries that are employed for each fundamental exchange rate model. Google Trends data is collected for each search query and for each geographical area separately. The search queries are listed in English, but are translated if the exchange rate under consideration requires this.

Table 3: **Correlations between search queries for the United States**

	Interest rate	Libor rate	Int. rate parity	Fed. Reserve rate
Libor rate	0.60			
Int. rate parity	0.38	0.25		
Fed. Reserve rate	0.81	0.56	0.30	
Carry trade	0.23	0.38	0.12	0.27

	Money supply	Money demand	M1 money
Money demand	0.79		
M1 money	0.71	0.48	
Monetary base	0.70	0.44	0.69

	Consump-tion	Cons. growth	GDP growth
Cons. growth	0.14		
GDP growth	0.29	0.50	
Economic growth	0.61	0.65	0.69

	Trade balance	Balance of trade	Internatio-nal trade	Export
Balance of trade	0.34			
International trade	0.81	0.19		
Export	0.65	0.06	0.89	
Import	0.68	0.00	0.93	0.95

	Inflation	Rate of inflation	Price index	CPI	Cons. Price Index
Rate of inflation	0.63				
Price index	0.60	0.76			
CPI	0.61	0.72	0.93		
Cons. Price Index	0.54	0.76	0.98	0.90	
PPP	0.67	0.63	0.73	0.68	0.72

	Foreign assets	Foreign reserves	Foreign exch. res.	Net foreign assets	Net. int. inv. position
	0.46				
Foreign exch. res.	0.48	0.47			
Net foreign assets	0.35	0.31	0.24		
Net. int. inv. position	0.50	0.43	0.44	0.37	
	0.71	0.48	0.55	0.17	0.43

	Commo-dities	Commodity price
Commodity price	0.69	
Commodity index	0.66	0.58

	Oil price	Crude oil	West Texas Int.
Crude oil	0.97		
West Texas Int.	0.34	0.35	
Wti oil	0.30	0.31	0.99

Notes: This table shows the pairwise correlation coefficients between the different search queries per fundamental model included in our pool of models. Correlations presented are those for the Google Trends Index data of the United States.

Table 4: **Statistical evaluation of forecasting performance with model selection based on the average Google Trends Index**

Currency	**MSPE ratio**	**CW p-value**	**PT p-value**
CAD-GBP	0.953	0.025	0.626
CAD-JPY	0.955	0.009	0.168
CAD-CHF	0.967	0.020	0.039
CAD-AUD	1.001	0.511	0.168
GBP-JPY	0.967	0.042	0.002
GBP-CHF	0.985	0.211	0.375
USD-CAD	0.927	0.012	0.075
USD-GBP	0.945	0.027	0.100
USD-JPY	0.987	0.330	0.500
USD-CHF	1.005	0.567	0.212
USD-AUD	0.911	0.009	0.075
CHF-JPY	1.011	0.772	0.500
AUD-CHF	0.984	0.275	0.500
AUD-GBP	0.975	0.056	0.039
AUD-JPY	0.931	0.009	0.027
Average	0.967		

Notes: This table presents the statistical evaluation of the out-of-sample forecasting performance with model selection based on Google Trends. The column labeled "MSPE ratio" represents the Clark-West adjusted ratio of mean squared forecast errors. The columns labeled "CW p-value" and "PT p-value" show p-values for the Clark-West and Pesaran-Timmermann statistics, respectively. The p-values test the null hypotheses of equal forecast accuracy of our forecasts and the random walk.

Table 5: **Economic evaluation of forecasting performance with model selection based on the average Google Trends Index**

Currency	**Average**	**Stdev**	**Sharpe**	p-value
CAD-GBP	2.42%	9.11%	0.266	0.169
CAD-JPY	8.70%	13.10%	0.663	0.009
CAD-CHF	8.55%	11.42%	0.749	0.004
CAD-AUD	2.35%	9.61%	0.244	0.190
GBP-JPY	9.38%	13.31%	0.705	0.006
GBP-CHF	2.65%	10.34%	0.256	0.179
USD-CAD	5.63%	9.82%	0.573	0.020
USD-GBP	6.09%	9.31%	0.654	0.010
USD-JPY	0.59%	9.91%	0.059	0.415
USD-CHF	0.36%	10.90%	0.033	0.453
USD-AUD	9.11%	13.45%	0.678	0.008
CHF-JPY	-1.49%	12,13%	-0.123	0.329
AUD-CHF	1.12%	10.71%	0.104	0.354
AUD-GBP	7.02%	10.59%	0.663	0.009
AUD-JPY	10.41%	15.21%	0.685	0.007
EW-P	4.86%	3.75%	1.297	0.000
VW-P	4.53%	3.65%	1.242	0.000
LS-P	10.80%	17.67%	0.611	0.014

Notes: This table presents the economic evaluation of the out-of-sample forecasting performance with model selection based on Google Trends. It shows the returns of an investment strategy that goes long (short) in the currency which is forecasted to appreciate (depreciate). The rows "EW-P", "VW-P" and "LS-P" show the statistics for the equally weighted, value weighted and long-short portfolios, respectively. The table shows the average annualized return, the annualized standard deviation, the Sharpe ratio and the p-value of testing the significance of the average return.

Table 6: **Switching behavior**

Currency	Switches	Dur	UIRP	PPP	MM	CG	TB	NFA	COMM	OIL
CAD-GBP	42%	2.36	0%	9%	1%	45%	6%	1%	29%	10%
CAD-JPY	59%	1.73	1%	15%	3%	35%	22%	3%	14%	8%
CAD-CHF	59%	1.73	1%	8%	4%	25%	13%	0%	41%	7%
CAD-AUD	51%	1.95	1%	51%	3%	26%	6%	1%	3%	9%
GBP-JPY	45%	2.20	0%	10%	1%	21%	10%	0%	49%	9%
GBP-CHF	33%	2.98	1%	1%	1%	13%	10%	1%	65%	8%
USD-CAD	46%	2.17	0%	8%	12%	44%	19%	0%	11%	7%
USD-GBP	39%	2.56	0%	7%	6%	50%	10%	0%	21%	6%
USD-JPY	23%	4.11	0%	8%	1%	4%	79%	0%	4%	4%
USD-CHF	55%	1.79	1%	5%	8%	17%	40%	0%	24%	4%
USD-AUD	54%	1.84	1%	33%	6%	24%	30%	0%	1%	6%
CHF-JPY	41%	2.40	1%	4%	0%	5%	28%	1%	54%	7%
AUD-CHF	62%	1.61	1%	15%	1%	24%	29%	0%	21%	8%
AUD-GBP	51%	1.96	0%	21%	1%	34%	8%	0%	26%	10%
AUD-JPY	40%	2.48	1%	37%	3%	15%	32%	0%	4%	8%
Average	46%	2.26	1%	15%	3%	25%	23%	0%	24%	7%

Notes: This table shows the summary statistics concerning the switching behavior when only the model with the highest attention is taken into account. "Dur" represents duration.

Table 7: **Statistical evaluation of forecast combinations with weights based on the relative search attention as measured by the average GTI**

Currency	MSPE ratio	CW p-value	PT p-value
CAD-GBP	0.994	0.327	0.626
CAD-JPY	0.995	0.338	0.212
CAD-CHF	1.007	0.791	0.626
CAD-AUD	0.996	0.335	0.261
GBP-JPY	0.996	0.379	0.131
GBP-CHF	0.986	0.311	0.739
USD-CAD	0.977	0.089	0.003
USD-GBP	0.970	0.007	0.002
USD-JPY	1.008	0.737	0.100
USD-CHF	1.002	0.545	0.374
USD-AUD	0.962	0.024	0.055
CHF-JPY	1.011	0.839	0.374
AUD-CHF	0.988	0.182	0.788
AUD-GBP	0.987	0.202	0.315
AUD-JPY	0.987	0.130	0.100
Average	0.991		

Notes: This table presents the statistical evaluation of the out-of-sample forecasting performance with model selection based on Google Trends. The column labeled "MSPE ratio" represents the Clark-West adjusted ratio of mean squared forecast errors. The columns labeled "CW p-value" and "PT p-value" show p-values for the Clark-West and Pesaran-Timmermann statistics, respectively. The p-values test the null hypotheses of equal forecast accuracy of our forecasts and the random walk.

Table 8: **Economic evaluation of forecast combinations with weights based on the relative search attention as measured by the average GTI**

Currency	**Average**	**Stdev**	**Sharpe**	**p-value**
CAD-GBP	2.17%	9.12%	0.238	0.196
CAD-JPY	1.66%	13.34%	0.124	0.327
CAD-CHF	0.80%	11.68%	0.069	0.402
CAD-AUD	-0.21%	9.63%	-0.021	0.469
GBP-JPY	0.42%	13.58%	0.031	0.455
GBP-CHF	2.66%	10.34%	0.258	0.177
USD-CAD	4.17%	9.88%	0.422	0.065
USD-GBP	8.31%	9.16%	0.906	0.001
USD-JPY	0.63%	9.91%	0.064	0.409
USD-CHF	-1.78%	10.88%	-0.164	0.278
USD-AUD	5.84%	13.60%	0.43	0.062
CHF-JPY	-0.24%	12.14%	-0.02	0.471
AUD-CHF	1.28%	10.71%	0.12	0.333
AUD-GBP	-0.98%	10.78%	-0.091	0.372
AUD-JPY	7.78%	15.34%	0.507	0.035
EW-P	2.17%	4.47%	0.485	0.041
VW-P	2.01%	4.25%	0.472	0.046
LS-P	9.29%	17.30%	0.537	0.059

Notes: This table presents the economic evaluation of the out-of-sample forecasting performance with model selection based on Google Trends. It shows the returns of an investment strategy that goes long (short) in the currency which is forecasted to appreciate (depreciate). The rows "EW-P", "VW-P" and "LS-P" show the statistics for the equally weighted, value weighted and long-short portfolios, respectively. The table shows the average annualized return, the annualized standard deviation, the Sharpe ratio and the p-value of testing the significance of the average return.

Table 9: **Average weight attached to individual fundamental models based on relative attention**

Model	**Avg. Weight**
UIRP	9%
PPP	16%
MM	11%
CG	17%
TB	17%
NFA	5%
COMM	16%
OIL	9%
Average minimum weight	4.30%
Average maximum weight	19.60%

Notes: This table presents the average weights attached each of the fundamental models, averaged over the forecasting period (2004M1-2016M12). Also, it highlights the difference between the average maximum and average minimum weights.

Table 10: **Robustness checks: statistical evaluation**

	Significant CW-stat	**Significant PT-stat**
Full sample	CAD-GBP, CAD-JPY, CAD-CHF, GBP-JPY, USD-CAD, USD-GBP, USD-AUD, AUD-GBP, AUD-JPY	CAD-CHF, GBP-JPY, USD-CAD USD-AUD, AUD-GBP, AUD-JPY
After deleting queries	CAD-GBP, CAD-JPY, CAD-CHF, GBP-JPY, USD-CAD, USD-GBP, USD-AUD, AUD-JPY	CAD-JPY, GBP-JPY, USD-CAD, USD-AUD, AUD-JPY
1st half	CAD-GBP, CAD-JPY, CAD-CHF, USD-GBP, USD-AUD, AUD-JPY	CAD-CHF, GBP-JPY, USD-CAD, USD-AUD, AUD-GBP, AUD-JPY
2nd half	CAD-JPY, CAD-CHF, GBP-JPY, USD-CAD, USD-GBP, USD-JPY, AUD-CHF, AUD-GBP, AUD-JPY	GBP-JPY

Notes: This table presents two different robustness checks to the statistical evaluation of the out-of-sample forecasting performance . The table presents the currencies for which the out-of-sample forecasting performance is significantly better than for the random walk. The table shows the impact of deleting the last query for each fundamental model and shows the results of splitting the sample size.

Table 11: **Robustness checks: economic evaluation**

		Return	**St.dev.**	**Sharpe**	**PT p-value**
EW-P	Full sample	4.86%	3.75%	1.297	0.000
	After deletion of queries	3.84%	3.66%	1.048	0.000
	1st half	6.14%	3.59%	1.712	0.000
	2nd half	3.58%	3.86%	0.925	0.010
	VIX 10-percentile	11.46%	4.81%	2.383	0.000
	Recessions	7.81%	4.79%	1.630	0.000
VW-P	Full sample	4.53%	3.65%	1.242	0.000
	After deletion of queries	3.54%	3.59%	0.985	0.000
	1st half	5.64%	3.51%	1.609	0.000
	2nd half	3.41%	3.75%	0.910	0.012
	VIX 10-percentile	9.64%	4.71%	2.047	0.000
	Recessions	7.31%	4.75%	1.538	0.000
LS-P	Full sample	10.80%	17.67%	0.611	0.014
	After deletion of queries	8.74%	17.87%	0.489	0.040
	1st half	12.78%	19.11%	0.669	0.046
	2nd half	8.83%	16.08%	0.549	0.083
	VIX 10-percentile	34.10%	30.92%	1.103	0.000
	Recessions	26.36%	20.50%	1.286	0.000

Notes: This table presents the statistical evaluation of the out-of-sample forecasting performance, where we apply two different robustness checks. The table shows the impact of deleting the last query for each fundamental model as presented in table 2. Also, it presents the statistical evaluation criteria for both halves of the sample (2004M1-2010M6 and 2010M7-2016M12). The column labeled "MSPE ratio" represents the Clark-West adjusted ratio of mean squared forecast errors. The columns labeled "CW p-value" and "PT p-value" show p-values for the Clark-West and Pesaran-Timmermann statistics, respectively. The p-values test the null hypotheses of equal forecast accuracy of our forecasts and the random walk.

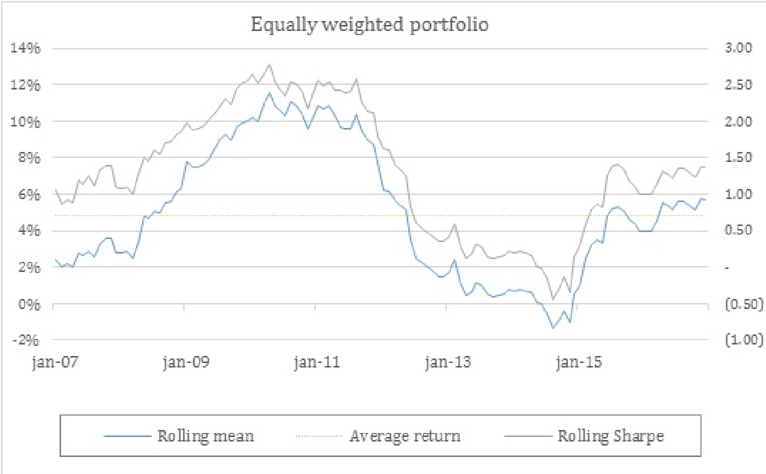
Table 12: **Returns to Carry Trade Strategy**

Perspective	Investment	Average	Stdev	Sharpe	p-value
American	Long-short	0.021	0.162	-0.132	0.319
	Long	-0.012	0.106	-0.116	0.338
	Short	0.009	0.086	0.103	0.357
Australian	Long-short	-0.067	0.193	-0.349	0.106
	Long	-0.034	0.093	-0.369	0.093
	Short	0.033	0.12	0.274	0.163
British	Long-short	0.054	0.171	0.316	0.129
	Long	0.039	0.089	0.433	0.061
	Short	-0.016	0.109	-0.143	0.304
Canadian	Long-short	-0.024	0.161	-0.148	0.298
	Long	-0.008	0.075	-0.102	0.358
	Short	0.016	0.109	0.147	0.299
Japanese	Long-short	0.041	0.22	0.187	0.252
	Long	0.012	0.137	0.085	0.381
	Short	-0.03	0.097	-0.305	0.137
Swiss	Long-short	-0.04	0.175	-0.228	0.207
	Long	0.016	0.098	-0.16	0.283
	Short	0.024	0.113	0.213	0.223

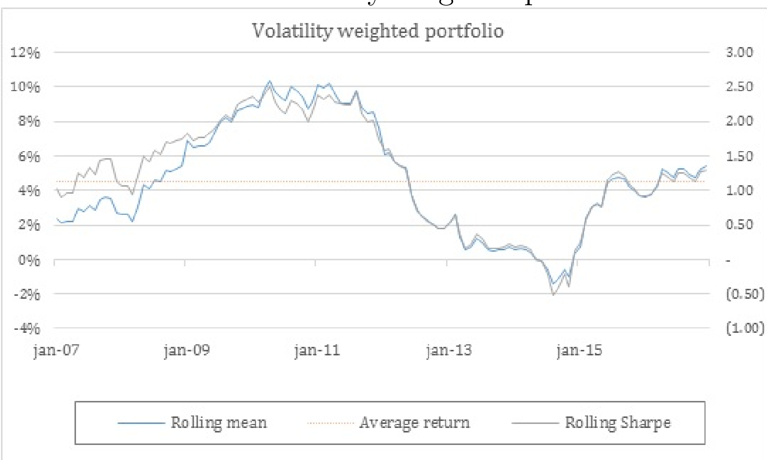
Notes: This table show the returns of carry trade strategies that go long the two currencies with the highest interest rate and go short in the two currencies with the lowest. The annualized average return, the annualized return standard deviation, the Sharpe ratio and the p-value of a t-test on the significance of returns are shown.

Figure 2: Time-varying performance of investment strategies

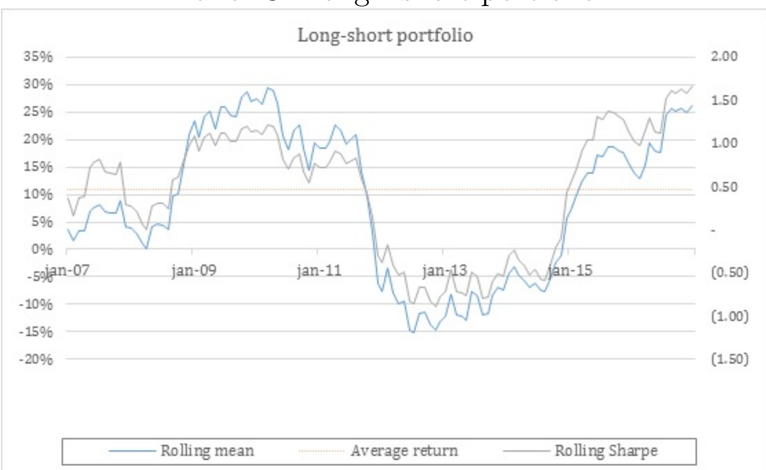
Panel A: Equally weighted portfolio



Panel B: Volatility weighted portfolio



Panel C: Long - short portfolio



Notes: This figure presents the three-year rolling average performance of the equally weighted (Panel A), volatility weighted (Panel B), and long-short (Panel C) portfolios. The construction of portfolios is described in section 3.5.