# Inattentive Search for Currency Fundamentals

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**Abstract**

We show how economic agents' limited attention can account for a time-varying link between exchange rates and fundamentals. We demonstrate that the higher the attention for a certain economic fundamental, the higher is its value in explaining future currency movements. We proxy economic agents' attention for an economic variable by the Google search intensity index. In a sample of macro-economic data from 1995 to 2016, we find that the fundamentals selected by the Google Trends Index 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 1.0. The best forecasts and the highest returns are delivered by strategies that select the fundamental that is paid the highest attention to. This finding suggests that the attention of economic agents is very limited.

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## 1 Introduction

Traditional exchange rate models assume that there is a stable relationship 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 and substantial evidence suggests that, in reality, attention is a scarce cognitive resource (Kahneman 1973).

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 explaining future 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 the 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 the 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 searched fundamental.

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 of macro-economic data from 1995 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 five out of six bilateral exchange rates. Moreover, positive and significant excess returns are exhibited for five out of six currencies and by 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 1.0.

We study the extension and persistence of inattention of economic agents. We find that economic agents shifts their attention quickly from one fundamental to another. The chosen fundamental remains for on average 2.62

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 construction of the forecasts and investment strategies. This finding suggests that the attention of economic agents is very limited.

This paper contributes to the literature that studies well documented time-varying relationship between exchange rates and macroeconomic fundamentals.[2] Recent theoretical studies provide explanations for the time-varying link between currencies and fundamentals. 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 (a subset of fundamentals) at the time. In this paper, we directly test this implication by using a straightforward measure of investor attention: the Google Trends Index.

The theoretical literature on how limited attention can affect asset pricing includes Hirshleifer and Teoh (2003), Peng and Xiong (2006), and Andrei and Hassler (2015), among others. Motivated by psychological evidence that attention is a scarce cognitive resource, these papers assume 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 financial markets and can account for a set of unexplained asset pricing phenomena. Da, Engelberg and Gao (2011) show that an increase in search volume index predicts higher

[2]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), Rossi (2006), and Sarno and Valente (2009) also find that fundamental exchange rate models have predictive power, but the performance depends on the particular currency and forecast horizon considered.

stock prices in the next 2 weeks and a price reversal over the following year. Sicherman, Loewenstein, Seppi, and Utkus (2016) find that investors pay less attention when the VIX is high and that level of attention is strongly related to investor demographics (gender, age) and financial position (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.

While the GTI has been largely used before to measure investors' attention, 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 how we aim to measure attention with 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 and explain the forecasting procedure based on the GTI. In Section 4 we 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 5 and in Section 6 we discuss a number of robustness tests. The final section 7 concludes the paper.

## 2 Google Trends

In this section we describe how we use Google to measure investor attention (2.1), and explain the construction of the Google Trends Index data and its shortcomings (2.2).

### 2.1 Google as a measure of investor attention

Our aim is to capture the macroeconomic variables that attract attention of economic agents by using data from Google Trends. Google Trends is a public web facility of Google that shows how often a particular search-term is entered relative 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, e.g., Barber and Odean 2008). Hence, the Google Trends may be effective in identifying the fundamentals that economic agents focus on and use to predict currencies.

## 2.2 Construction of Google trends data

The data provided by Google Trends comprises 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: region and time. 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 frequency and time period over which we want the GTI to be computed.

Google Trends data should be applied with caution, as search query data come with some shortcomings. First, we cannot distinguish between search queries performed by financial agents and those performed by other economic agents. Ideally, we would like to measure the attention of investors whose trades influence the currency movements. With the GTI, we measure attention of all the economic agents interested in a particular query for any reason. A second shortcoming is that 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 bias against finding significant results too. 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 from 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 query '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.[3] 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.

A search term related to monetary policy in recent years is 'quantitative easing'. Figure 1 shows the development of the GTI for this search query during the period of January 2014 until September 2016 for Germany, France, Italy and Spain. During this 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 investors for these decisions fairly well. The first event indicated in the figure was September 4th 2014, when the ECB decided to start with quantitative easing in the form of asset purchases of asset backed securities and covered bonds. The GTI more strongly captures the second event, on 22nd January 2015, when the ECB announced a purchase program of sovereign bonds. The third event is the actual start of the purchase program, where the GTI again captures an increase in attention. These examples suggest that the GTI succeeds to capture swings in attention to a large extent.

[3] The search term monetary policy also includes queries like monetary policy ECB, monetary policy Governing Council or monetary policy Europe. By consequence, the above mentioned results also contain search queries containing the words in the mentioned search terms. See Appendix for more detailed information about the technical specificities of Google Trends.

# 3 Model selection and forecasting with Google trends

We assume that economic agents pay attention to fundamentals defined by a set of traditional exchange rate models. Each model corresponds to one fundamental. In what follows we explain in detail the fundamentals and how the GTI is used to make a selection among them. Next, we describe how we create the predictions based on the GTI 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 are expected to be leading variables and therefore predict exchange rate movements, as well as financial models such as commodity prices. This pool of models matches partly that of Kouwenberg et al. (2017).[4] Note that all variables are in natural logarithms, such that $\Delta s_t$ 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 that exchange rate movements are explained by differences in the nominal interest rate:

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

where $i$ is the interest rate and an asterisk ($*$) denotes a foreign variable. The sign of $\beta_1$ determines whether this model represents uncovered interest parity ($\beta_1 < 0$) or a carry-trade model ($\beta_1 > 0$).

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

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

where $p_t$ and $p_t^*$ are the home and foreign price level, respectively. Next

[4] We left out some common exchange rate models because of their limited applicability in combination with Google Search Index data.

to the absolute PPP, we also consider its relative variant, which relates exchange rate movements to the inflation differential rather than absolute price differences:

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

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

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

where $m$ 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:

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

where $CG$ is the (yearly) consumption growth. This rule states 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:

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

where $TB$ 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:

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

where $NFA_t$ 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:

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

where $\Delta COM_t$ stands for 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:[5]

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

where $\Delta OIL_t$ stands for 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 the search queries. Table 2 shows the selected search queries for each model. For each of them, we have selected several search queries to measure investor attention as well as possible. For this purpose, we made use of Google Correlate. This tool offers search queries, which 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 monetary model.

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

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-YEN, 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.[6] 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 data is retrieved), we use both the English search query as well as its native counterpart. In the ultimate case that this does not result in enough Google coverage as well, we omit the search query involved from the analysis. In Appendix A we present further details on how we used the Google Trends tool.

As a validation of the selected search queries, we calculated the correlations between the GTI series of the different search queries. For the United States, these correlations are presented in Table 3. Table 3 shows that in most cases, correlations are positive and strong, showing that individual search queries for the same fundamental are interrelated. Still, applying multiple search queries may have important benefits: it 'diversifies' away the idiosyncratic risk that adheres to each single search query.

### 3.3 Forecasting procedure

To investigate the ability of Google Trends data to measure investor attention and, subsequently, use this information to forecast currencies, we set out a forecasting procedure to predict monthly exchange rate movements for the January 2004 – December 2016. We perform the analysis for the CAD-GBP, CAD-YEN, GBP-YEN, USD-CAD, USD-GBP and USD-YEN currency pair. The sample period could not be extended, due to Google Trends data only dating back to January 2004. We have not extended the analysis to other currencies due to limitations in the availability of Google Trends. Google coverage decreases considerably outside the countries we incorporated in our analysis. Also, including the Euro is impossible as it involves a lot of countries and languages.

Our forecasting procedure consists of the following steps:

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

1. Collect the GTI data for all time series of search queries for every point in the sample period and for each country separately.

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 monthly frequency to match the one available for fundamentals. This means that we collect 140 GTI data series, as we selected 35 search queries (see Table 2) for 4 countries.

2. Calculate the average GTI over the different search queries per fundamental model for every point in the sample period and for each country separately.

As explained before, we selected multiple search queries for each fundamental model to mitigate dependency on a single search query and reduce noise. In this step we calculate the average GTI over the different search queries.

3. At each point in time, 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 of which the economic variables have the highest attention of Google users in the country involved. Our hypothesis is that this model will have the best predictive performance as this one is identified as the model that uses macroeconomic information that has been paid the most attention to. We select the model with the highest average GTI for its search queries, whereby we take the average over both countries involved.[7]

4. Take the one-step-ahead forecast of the model selected in step 3.

Based on the model selection in steps 1-3, we take the one-step-ahead forecast generated by the selected model. The procedure is recursive and is repeated for each point in time.

[7] In fact, this means that the selected model might not be the model with the highest average GTI for both countries.

### 3.4 Data on fundamentals

We use monthly data for 1995M1-2016M12 for Canada, Japan, 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 3 month 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 section. 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 Google Trends. The sample period of January 2004 – December 2016 contains 156 monthly forecasts for each currency.

## 4 Statistical and economic performance measures

Once we have the predicted currency 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

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

in which $l$ is the total number of forecasts. We employ the CW statistic to test the null hypothesis that backward elimination based model has the same predictive ability as a random walk without drift ( "no-predictability") benchmark model.

In addition, we calculate the non-parametric sign test of Pesaran and Timmermann (1992), which tests the ability of the fundamental 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 the model selection rules. For this purpose we calculate the returns of an investment strategy that buys (sells) one unit of the foreign currency vis-a-vis the US dollar when the model predicts an appreciation (depreciation) of the foreign currency. In case of subsequent buy-signals, the long position is rolled over. We calculate two types of returns to this strategy, namely with and without the interest rate differentials. The former does not take deposit interest rates into account when calculating investment strategy returns, such that it only captures the foreign exchange rate returns. The raw foreign-exchange return of the strategy $i$ is given by

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

The second measure does include the interest rate differential and thus implies borrowing in the currency on the short end and lending in the currency on the long end of the investment. This is equivalent to buying (selling) a foreign currency forward when the backward elimination model predicts an appreciation (depreciation) of the foreign currency vis-a-vis the US dollar. The return is given by

$$r_t^i = \frac{E_{t-1}^i(\Delta s_t)}{\left|E_{t-1}^i(\Delta s_t)\right|} (s_t - f_{t-1}) \tag{13}$$

where $f_{t-1}$ is the log three-month forward exchange rate in period $t - 1$.

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.[8]

In addition to assessing model performance for each country individually, we form equally-weighted and volatility-weighted portfolios of all currencies. Volatility is measured and forecasted using the exponentially weighted moving average (EWMA) method, given by

$$\sigma_{t+1}^2 = \lambda \sigma_t^2 + (1-\lambda)\Delta s_t^2 \tag{14}$$

in which we follow the RiskMetrics approach and set $\lambda = 0.94$.[9] The return of the volatility weighted portfolio is given by

$$r_t^{vw} = \left( \sum_p \frac{1}{\sigma_{p,t+1}^2} \right)^{-1} \sum_p \frac{1}{\sigma_{p,t+1}^2} r_t^p. \tag{15}$$

where $p$ 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 five 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).

# 5 Results

First, we present the evaluation, both statistically and economically, of the forecasting exercise with model selection based on investor attention measured by the GTI. Second, we investigate how inattentive economic agents are and how persistent the selected models are.

[8] 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, this will not affect the results much.

[9] The RiskMetrics model is the specification developed to measuring financial risk by J.P. Morgan.

## 5.1 Limited attention and currency forecasts

We first assume the strictest form of investor's inattention as we pick only the fundamental that receives the highest GTI.[10] Table 4 presents the results of the currency forecasting exercise when the fundamental is selected at each point in time. The GTI-based forecasts are significantly better than a random walk. The MSPE ratios are all below one, meaning that the mean squared prediction error have been reduced on average for each currency. The p-values of the CW-statistic indicate that the MSPE reduction is significant for five out of six currencies at the 10% confidence level. The p-value of the PT-statistic reports significance for three currencies.

Table 5 presents the economic evaluation of the forecasting exercise. The table shows the annualized return, the annualized standard deviation of returns, the corresponding Sharpe ratio and p-value of the t-test to test the significance of the average return. The long-short investment strategy for individual currencies results in a positive investment return for all six currencies, with all but one being significant at the 10% level. 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 5.0% with an annualized volatility of 4.9% and a Sharpe ratio of 1.01. All three portfolios have a Sharpe ratio of at least 1.0.

The long-short portfolio earns a very high return of 16.9%, although this is achieved at the cost of a much higher volatility (16.2%) as well. The magnitude of the investment returns earned by our investment portfolios becomes apparent by comparing it to, for instance, the performance of the MSCI World Index in the period 2004-2016, yielding a Sharpe ratio of 0.35, which is significantly lower than the Sharpe ratios achieved by our currency portfolios.

## 5.2 How often does the fundamental change?

Table 6 shows how often the GTI selected fundamental changes and the resulting duration in months. On average, in 42% of cases (months), the selected model changes. Accordingly, the chosen fundamental remains for

[10]Later on, we also include more than one fundamental and study how this affects the results.

on average 2.62 months, before it is replaced by another fundamental model, which means 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 CAD-YEN, the time-variation of the chosen fundamental model is even higher, with switches in 59% of the cases and the selected model being selected for 1.67 months on average.

### 5.3 How inattentive are economic agents?

So far, we have used only one fundamental with the highest GTI to make currency predictions. We now compare these benchmark results to a setting where more than one fundamental are considered. Specifically, we implement forecasting and investment strategies based on a set of fundamentals identified and weighted by the GTI outcomes. The weights are computed as follows:

$$E_t \Delta s_{t+1} = \sum_{i=1}^{N} w_{i,t} \left[ \widehat{\alpha}_{i,t} + \widehat{\beta}_{i,t} f_{i,t} \right] \tag{16}$$

with i being the subscript for the different fundamentals and $w_{i,t}$ being defined as follows:

$$w_{i,t} = \frac{GTI_{i,t}^{av}}{\sum_{i=1}^{N} GTI_{i,t}^{av}} \tag{17}$$

where $GTI_{i,t}^{av}$ is the average GTI computed for the fundamental i for two countries of a given currency.

Table 7 presents the results of the statistical evaluation of the forecasts combinations. The MSPE relative to RW reduce only by 0.73% on average and are never significant, whereas the PT-statistic reports significant outperformance for two currencies. The economic evaluation presented in Table 8 delivers comparable outcomes. The annualized returns are positive for all individual currencies and all three portfolios, but only significant for the USD-CAD and for the equally-weighted and volatility-weighted portfolio. These results are at odds with the existing empirical literature that shows that model combinations can perform better than individual fundamental-based models.[11]

Table 9 presents the average weights attached to each of the fundamental models. It also shows the difference between the average maximum and average minimum weights averaged over six currencies. The maximum weight is about four times higher than the minimum weight so undoubtedly the relative GTI generates large differences in weights attached to fundamentals. Still, the least relevant fundamental receives the average minimum weight of 4% which is not negligible. The fact that only one fundamental at the time is the best predictor of the currency movements suggests that the attention of economic agents is very limited.

### 5.4 Robustness tests

To measure the investor attention to a certain fundamental variable, we incorporated 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 show that deleting these search queries does not qualitatively impact our results. On the level of individual currencies, some differences occur. For instance, the statistical significance disappears for the GBP-YEN, but on the other hand, the MSPE difference turns significant for the CAD-YEN and the PT-statistic for the USD-CAD. The economic evaluation in Table 11 shows a similar picture. Moreover, all portfolio returns are similar in size and significance when compared to the situation before deletion of search queries. Unreported analysis shows that omitting other queries, instead of the last one in Table 2 for each model, does not impact the qualitative outcomes either. This is as expected since the GTIs of the queries involved are mutually highly correlated for each model.

To assess the robustness of our findings to the sample period over which the forecasting exercise is carried out, graph 2 presents 3-year rolling returns

[11] See for instance Timmerman (2006), Della Corte, Sarno and Tsiakas (2009) and Wright (2008).

and Sharpe ratios for the all three investment portfolios that we evaluate. The graphs show that the rolling returns and Sharpe ratios swing around the total sample mean (represented by the dashed line), but never get insignificant or negative for a longer period of time. This implies that the performance of our forecasting method is time-varying but even in the worst-performing periods it delivers positive returns and high Sharpe ratios. We 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 includes the financial crisis period, the results do not differ a lot across samples.

# 6 Conclusion

The weight that economic agents attach to different fundamentals as drivers of currencies fluctuates considerably over time. In this paper, we demonstrate how economic agents' limited attention can account for this empirical feature of the exchange rates. The attention of economic agents is proxied by the Google search intensity index. In a sample of macro-economic data from 1995 to 2016, we find that the fundamentals selected by the Google Trends Index 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 1.0. By comparaison, between 2004 and 2016 the MSCI World Index generated a Sharpe ratio of 0.35, which is significantly lower than the Sharpe ratios achieved by our currency portfolios.

We study the extension and persistence of inattention of economic agents. We find that economic agents shifts their attention quickly from one fundamental to another. The chosen fundamental remains for on average 2.62 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 construction of the forecasts and investment strategies. This finding suggests that the attention of economic agents is very limited.

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# A Appendix

Figure 1: GTI behavior around important quantitative easing decisions

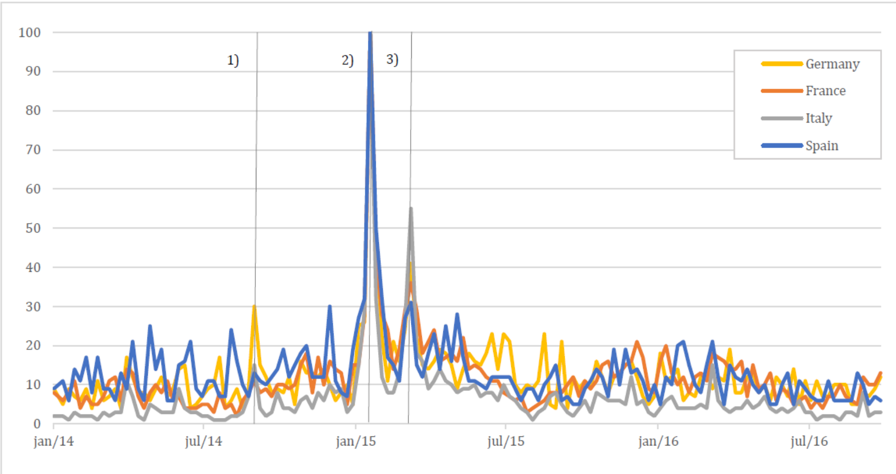

Table 1: **Investment Returns for Individual Models**

| Search query: 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% |

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, money stock, 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 |

The 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 will be translated if the exchange rate under consideration requires this. For more details on the use of Google Trends, we refer to Appendix A.

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 |

| | Consumption | 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 | International 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 |

| | Commodities | 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 |

The table shows the correlations 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 | 0.948 | 0.015 | 0.374 |
| CAD-YEN | 0.969 | 0.077 | 0.212 |
| GBP-YEN | 0.967 | 0.042 | 0.002 |
| USD-CAD | 0.927 | 0.012 | 0.075 |
| USD-GBP | 0.960 | 0.052 | 0.055 |
| USD-YEN | 0.987 | 0.334 | 0.500 |

The 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 | 3.51% | 9.09% | 0.387 | 0.083 |
| CAD-YEN | 5.62% | 13.25% | 0.424 | 0.064 |
| GBP-YEN | 9.38% | 13.31% | 0.705 | 0.006 |
| USD-CAD | 5.63% | 9.82% | 0.573 | 0.020 |
| USD-GBP | 4.75% | 9.04% | 0.526 | 0.030 |
| USD-YEN | 0.59% | 9.90% | 0.059 | 0.415 |
| EW-Portfolio | 4.91% | 4.75% | 1.035 | 0.000 |
| VW-Portfolio | 4.61% | 4.39% | 1.049 | 0.000 |
| LS-Portfolio | 17.36% | 16.44% | 1.056 | 0.000 |

The 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 | Number of model switches | Average duration of selected model (in months) |
|---|---|---|
| CAD-GBP | 67/155 (43%) | 2.29 |
| CAD-YEN | 92/155 (59%) | 1.67 |
| GBP-YEN | 70/155 (45%) | 2.20 |
| USD-CAD | 71/155 (46%) | 2.17 |
| USD-GBP | 54/155 (35%) | 2.84 |
| USD-YEN | 33/155 (21%) | 4.56 |
| Average | 65/155 (42%) | 2.62 |

The table shows the summary statistics concerning the switching behavior when only the model with the highest attention is taken into account. On average, in 42% of the cases, the selected model in Step 3 of the forecasting procedure switches from one model to another in the next month. The selected fundamental model stays on top for on average 2.62 months, before it is displaced by another fundamental model, which means that the fundamental gaining the highest attention is rather quickly substituted by another.

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 | 0.320 | 0.685 |
| CAD-YEN | 0.995 | 0.338 | 0.212 |
| GBP-YEN | 0.996 | 0.391 | 0.131 |
| USD-CAD | 0.977 | 0.089 | 0.003 |
| USD-GBP | 0.987 | 0.190 | 0.315 |
| USD-YEN | 1.008 | 0.737 | 0.100 |

The 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 | 1.96% | 9.12% | 0.214 | 0.220 |
| CAD-YEN | 1.66% | 13.34% | 0.124 | 0.327 |
| GBP-YEN | 0.42% | 13.58% | 0.031 | 0.455 |
| USD-CAD | 4.17% | 9.88% | 0.422 | 0.065 |
| USD-GBP | 2.46% | 9.11% | 0.270 | 0.166 |
| USD-YEN | 0.63% | 9.91% | 0.064 | 0.409 |
| EW-Portfolio | 1.88% | 5.39% | 0.349 | 0.105 |
| VW-Portfolio | 2.09% | 4.98% | 0.403 | 0.074 |
| LS-Portfolio | 8.10% | 18.76% | 0.435 | 0.059 |

The 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**

| | CAD-GBP | CAD-YEN | GBP-YEN | USD-CAD | USD-GBP | USD-YEN |
|---|---|---|---|---|---|---|
| UIRP | 9% | 10% | 8% | 9% | 8% | 9% |
| PPP | 17% | 16% | 16% | 16% | 15% | 16% |
| MM | 10% | 11% | 9% | 12% | 11% | 11% |
| CG | 18% | 17% | 17% | 18% | 18% | 17% |
| TB | 15% | 17% | 17% | 17% | 16% | 19% |
| NFA | 5% | 6% | 6% | 7% | 7% | 7% |
| COMM | 17% | 17% | 19% | 14% | 16% | 15% |
| OIL | 10% | 6% | 9% | 7% | 9% | 6% |
| Average minimum weight | 5% | 4% | 5% | 5% | 6% | 4% |
| Average maximum weight | 20% | 19% | 19% | 19% | 19% | 19% |
| $max(w_{i,t})/\min(w_{i,t})$ | 4.16 | 4.67 | 3.66 | 4.26 | 3.08 | 4.34 |

The table presents the 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 and the average factor of the maximum weight divided by the minimum weight.

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

| Currency | | MSPE ratio | CW p-value | PT p-value |
|---|---|---|---|---|
| CAD-GBP | Full sample | 0.948 | 0.015 | 0.374 |
| | After deletion of queries | 0.956 | 0.041 | 0.261 |
| | 1st half | 0.931 | 0.025 | 0.325 |
| | 2nd half | 0.977 | 0.158 | 0.500 |
| CAD-YEN | Full sample | 0.969 | 0.077 | 0.212 |
| | After deletion of queries | 0.960 | 0.040 | 0.055 |
| | 1st half | 0.979 | 0.237 | 0.248 |
| | 2nd half | 0.950 | 0.064 | 0.325 |
| GBP-YEN | Full sample | 0.967 | 0.042 | 0.002 |
| | After deletion of queries | 0.996 | 0.391 | 0.131 |
| | 1st half | 0.986 | 0.292 | 0.021 |
| | 2nd half | 0.943 | 0.018 | 0.021 |
| USD-CAD | Full sample | 0.927 | 0.012 | 0.075 |
| | After deletion of queries | 0.931 | 0.019 | 0.019 |
| | 1st half | 0.961 | 0.100 | 0.035 |
| | 2nd half | 0.874 | 0.031 | 0.410 |
| USD-GBP | Full sample | 0.960 | 0.052 | 0.055 |
| | After deletion of queries | 0.957 | 0.044 | 0.261 |
| | 1st half | 0.868 | 0.030 | 0.325 |
| | 2nd half | 1.011 | 0.586 | 0.035 |
| USD-YEN | Full sample | 0.987 | 0.330 | 0.500 |
| | After deletion of queries | 0.992 | 0.390 | 0.564 |
| | 1st half | 1.030 | 0.738 | 0.590 |
| | 2nd half | 0.947 | 0.058 | 0.410 |

The 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 11: **Robustness checks: economic evaluation**

| Currency | | Annualized return | St.dev. | Sharpe-ratio | p-value |
|---|---|---|---|---|---|
| CAD-GBP | Full sample | 3.51% | 9.09% | 0.387 | 0.083 |
| | After deletion of queries | 2.21% | 9.12% | 0.242 | 0.192 |
| | 1st half | 5.65% | 10.20% | 0.554 | 0.081 |
| | 2nd half | 1.38% | 7.77% | 0.177 | 0.326 |
| CAD-YEN | Full sample | 5.62% | 13.25% | 0.424 | 0.064 |
| | After deletion of queries | 7.44% | 13.18% | 0.565 | 0.022 |
| | 1st half | 4.42% | 15.05% | 0.293 | 0.228 |
| | 2nd half | 6.83% | 11.16% | 0.612 | 0.061 |
| GBP-YEN | Full sample | 9.38% | 13.31% | 0.705 | 0.006 |
| | After deletion of queries | 7.62% | 13.40% | 0.569 | 0.021 |
| | 1st half | 7.41% | 14.24% | 0.520 | 0.094 |
| | 2nd half | 11.35% | 12.28% | 0.924 | 0.010 |
| USD-CAD | Full sample | 5.63% | 9.82% | 0.573 | 0.020 |
| | After deletion of queries | 6.38% | 9.78% | 0.652 | 0.010 |
| | 1st half | 10.63% | 10.53% | 1.010 | 0.006 |
| | 2nd half | 0.63% | 8.82% | 0.071 | 0.428 |
| USD-GBP | Full sample | 4.75% | 9.04% | 0.526 | 0.030 |
| | After deletion of queries | 2.84% | 9.10% | 0.312 | 0.131 |
| | 1st half | 4.27% | 10.25% | 0.417 | 0.146 |
| | 2nd half | 5.23% | 7.63% | 0.685 | 0.042 |
| USD-YEN | Full sample | 0.59% | 9.91% | 0.059 | 0.415 |
| | After deletion of queries | 0.64% | 9.91% | 0.064 | 0.409 |
| | 1st half | -1.50% | 9.72% | -0.154 | 0.347 |
| | 2nd half | 2.68% | 10.05% | 0.266 | 0.250 |
| EW-P | Full sample | 4.91% | 4.75% | 1.035 | 0.000 |
| | After deletion of queries | 4.52% | 4.97% | 0.910 | 0.001 |
| | 1st half | 5.15% | 5.72% | 0.900 | 0.012 |
| | 2nd half | 4.68% | 3.52% | 1.332 | 0.001 |
| VW-P | Full sample | 4.61% | 4.39% | 1.049 | 0.000 |
| | After deletion of queries | 4.12% | 4.58% | 0.901 | 0.001 |
| | 1st half | 4.88% | 5.23% | 0.934 | 0.010 |
| | 2nd half | 4.33% | 3.35% | 1.291 | 0.001 |
| LS-P | Full sample | 17.36% | 16.44% | 1.056 | 0.000 |
| | After deletion of queries | 17.11% | 16.04% | 1.067 | 0.000 |
| | 1st half | 13.93% | 18.90% | 0.737 | 0.032 |
| | 2nd half | 20.80% | 13.47% | 1.544 | 0.000 |

The 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.

Figure 2: Time-varying performance of investment strategies: equally-weighted portfolio

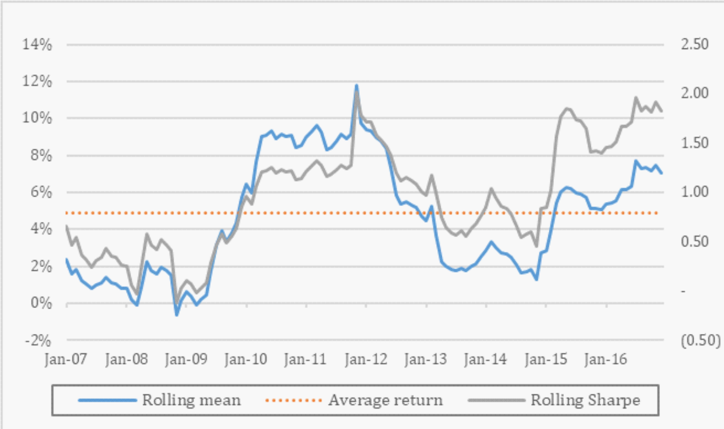


Figure 3: Time-varying performance of investment strategies: Long-short portfolio

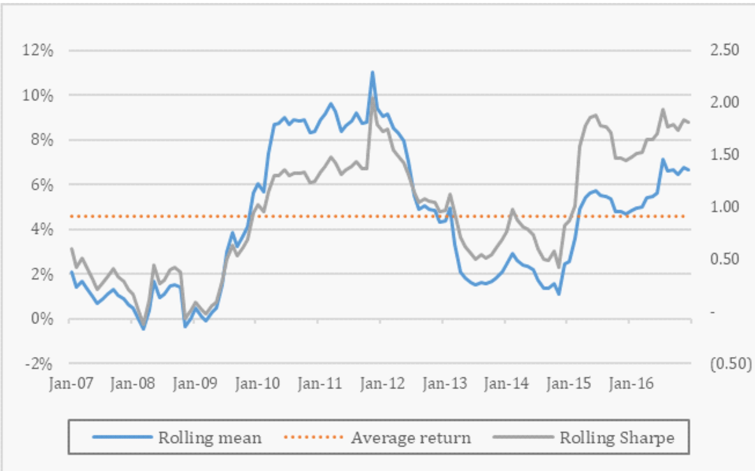

Figure 4: Time-varying performance of investment strategies: equally-weighted portfolio