Media Tone Goes Viral:
Global Evidence from the Currency Market

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Abstract

Using several million news and social media articles related to currencies, we examine the role of media tone in predicting the exchange rate returns of 12 developed and 24 emerging markets from 1998 to 2016. The text-based currency *Media tone* is a strong positive predictor of currency excess returns beyond fundamentals of one to three months ahead and six months cumulatively, with the average in-sample and out-of-sample R^2s of 4.45% and 9.03% in the US. The one-month predictability is observed in four other developed markets and 18 emerging market currencies, with the latter showing a stronger pattern. This predictability encompasses previous month currency returns, currency factors, macro fundamentals, and market sentiment and is stronger for currencies that are freely floating, less liquid, difficult to value, costly to arbitrage, and which have high interest rates. The effect is channeled through expectation errors and driven by the forecasting component rather than risk. The predictability of *Media tone* is driven by non-mainstream financial media.

Keywords: Media tone, Text analysis, Exchange rates, Forecasting

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"*The 1920-21 Depression, the Great Depression of the 1930s, the so-called "Great Recession" of 2007-9 and the contentious political- economic situation of today, are considered as the results of the popular narratives of their respective times.*"

Robert Shiller
Keynote Address at American Economic Association, 2017

"*Panicked Shoppers Empty Shelves as Coronavirus Anxiety Rises*"
New York Times, March 13, 2020

Shiller (2017) claims that the human brain is highly tuned towards narratives and whether or not they are factual. When these narratives go viral, they can affect human behavior and have economic impacts. Shiller (2107)'s animal spirit can be clearly seen from the recent COVID-19 outbreak in March 2020 where media inundated public with a series of the news related to the outbreak. Related stock market downfall further induced general public's fear and anxiety leading to excessive demand of necessities. Recent studies in finance provide concerted evidence supporting Shiller's premise (e.g., Veldkamp, 2006; Bhattacharya, Galpin, Ray and Yu, 2009; Engelberg and Parsons, 2011; Peress, 2014). Our study augments this literature by examining media content's role in foreign exchange.

We propose the tone of currency-related news and social media content, *Media tone*, as a predictor of currency returns. As *Media tone* includes all the news related to exchange rate fundamentals and any other possible factors related to currency movements, it enables us to incorporate the effects from all the possible predictor variables. Currency market is an appropriate market for studying the impact of media content. Trading in the currency market can be done for 24 hours, and the market is populated by sophisticated professional investors and characterized by high trading volume, high liquidity, low transaction costs, and few short-selling constraints. Thus, the currency market is expected to have high efficiency. Many papers also show that few arbitrage opportunities in the currency market are apparent, and when they are discovered, they tend to disappear very fast (Pukthuanthong et al., 2007). Thus, the currency market provides a high threshold for a study of any trading strategies to be profitable in a long term. Considering the pronounced impact of *Media tone* in this market, it is not surprising to see its impact on other markets. However, while it is regarded as one of the most efficient markets, some anomalies still persist in the currency market, such as momentum, value, term spread, output gap, and carry trade. Bartram et al. (2019) show that the profitability of currency anomalies declines after their publication but does not go away. They argue that currency anomalies are attributable to behavioral explanations, not mispricing or data snooping.

Although currency markets have a long history, the literature is inconclusive about the predictors of exchange rates. There is a consensus that macroeconomic variables have little predictive power for exchange rates in the short to medium term and that a random walk forecasts exchange rates better than macroeconomic models (see the seminal work of Meese and Rogoff (1983) and subsequent literature and Rossi (2013) for a survey). However, market analysts often point to particular macroeconomic variables to determine exchange rates. Cheung and Chinn (2001) survey US foreign exchange traders and find that practitioners regularly change the weight they attach to different macro indicators, which might explain why empirical models have only found a minor role for macro variables in determining exchange rates. This unstable relation between exchange rates and macro variables is an underlying idea of the scapegoat theory, according to which some variable is given excess weight during a certain period. For example, although the exchange rate might change due to non-macro fundamental effects, such as unobserved liquidity trading, the market participants might relate the movement to some observed macroeconomic variables. This macro indicator thus becomes a scapegoat and influences trading strategies. Over time, the role of scapegoat varies between different observed macro variables, and hence their role as the determinants of exchange rate movements becomes unstable (Bacchetta and van Wincoop, 2004 and 2013). Applying survey data, Fratzscher et al. (2015) find that the weights of macro fundamentals vary over time, supporting the scapegoat theory. This does not imply that macroeconomic variables are useless in explaining exchange rate movements. As an efficient market with low transaction costs, the foreign exchange market has proven to be very sensitive to any relevant new information. The effects of macroeconomic news on exchange rate returns are reported, for example, in Almeida et al. (1998), and those on exchange rate volatility is reported in Andersen et al. (2003). Cheung and Chinn (2001) provide survey evidence that macroeconomic news is rapidly incorporated into exchange rates, and for long horizons, exchange rates have been found to be closely related to the observed fundamentals (Mark (1995) and Bachetta and van Wincoop (2006)). Order flow in foreign exchange market conveys rapidly all kind of information about the exchange rate. It includes also the private information, which now becomes public also for the non-informed traders (Evans and Lyons, 2002). Hence, any predictive variable of exchange rates should be able to capture the time varying effects of macro fundamentals and possible non-observable factors.

Our study presents *Media tone* as one of the currency predictors. We propose that *Media tone* is a superior source of information for exchange rates. It includes all the relevant exchange rate fundamentals and possible non-fundamentals (e.g., sentiment) information from traditional news

and social media. It should also be able to avoid problems related to time variations in scapegoats. If some changes in the scapegoats, rumors or reasons for speculation occur (regardless of whether they are true or not), *Media tone* should capture those changes, assuming that the public news or social media reports about them. Thus *Media tone* should reflect the current narratives in the news and social media (see Shiller, 2017).

The tone of the news and social media related to currency is captured utilizing rich, text analysis based-data from the Thomson Reuters MarketPsych Indices (TRMI). The measure is developed based on a proprietary dictionary and textual analysis algorithm applied to several thousand news sources around the world. The score that we use is specific for the currency market and aims to capture *Media tone* related to an individual currency. Our tone data is also available for specific media and social media source. Appendix 2 presents the data formation and three examples showing how *Media tone* is scored.

It is evident that *Media tone* measure includes information related to exchange rate fundamentals. We concentrate mostly on the *Media tone* that is not explained by these variables. Hence, we orthogonalize the measure with known currency factors proposed by the extant literature and business cycle variables and use the residual, *Media tone*$^{\perp}$, as the filtered tone measure throughout the paper. We perform estimations for both currency indices (time series dimension) and characteristics portfolios (cross-sectional dimension).

Following Calomiris and Mamaysky (2019), instead of concentrating on high-frequency data, we examine *Media tone*$^{\perp}$ at the monthly level and thus treat media content similarly to the effects of propaganda. If a similar message is repeated often and widely, people will start to believe in it and might disregard their fundamental knowledge in their decision-making process. However, it is unclear whether currency news induces, amplifies, or simply reflects investors' interpretation of currency market performance. *Media tone*$^{\perp}$ might partially reflect the information on current fundamental variables, could cause sentiment-related shocks (under- or overreactions), and/or might capture fundamental information whose relevance is only revealed over time.

We find the filtered *Media tone* predicts USD returns up to three months ahead. Its predictive power is not limited to the USD, but to other four developed and 18 emerging market currencies. The impact of *Media tone*$^{\perp}$ is economically significant. A standard deviation increase in *Media tone* predicts an increase of 0.29% for the next month to three-month-ahead returns of the trade-

weighted Broad USD index and 0.34% for the equal-weighted index. This impact is six to seven times the average of the Broad index monthly returns of -0.05%. When compared to the predictions by another misperception measure used in the currency literature by Yu (2013), the Baker and Wurgler (2006) market sentiment measure (henceforth BW), *Media tone*$^{\perp}$ is superior. The in-sample results between the measures are comparable, but *Media tone*$^{\perp}$ has substantially better out-of-sample (OOS) predictive capability. Next, we apply forecast-encompassing tests (Chong and Hendry, 1986). The results show that the *Media tone* contains information about future movements of the USD that is not already contained in typical currency predictor variables.

We further study *Media tone*$^{\perp}$ by forming portfolios sorted by hard-to-value characteristics of currencies. The cross-sectional results highlight that the currencies are not unanimously exposed to *Media tone*$^{\perp}$, as there are large variations in the size of sensitivities across the portfolios. In particular, the currencies that are associated with high interest rates, high inflation, high volatility, high political risk, low turnover, low credit ratings, flexible exchange rate regimes, and emerging market currencies are most exposed to the impacts of the USD *Media tone*$^{\perp}$. Though the transaction cost in the currency market is marginal, we test and confirm that transaction costs do not change our results. Puzzled by its predictive power, we further investigate how the predictability of *Media tone*$^{\perp}$ is channeled by examining four possible mechanisms: market sentiment, analysts' forecasts errors, investor attention, and uncertainty. The results show that *Media tone*$^{\perp}$ predicts currency returns through analysts' forecast errors while providing distinct information from market sentiment, investor attention, and uncertainty.

To gain further knowledge about the channel of predictability, we investigate which text-based determinant of *Media tone*$^{\perp}$ induces predictability. Consistent with the mechanism results, we find that the predictability mainly comes from the forecast component rather than risk. Our data allows us to examine *Media tone*$^{\perp}$ for each source. Interestingly, we find the predictability is mainly driven by non-mainstream media rather than mainstream media sources. Finally, we show that readers can apply a simple trading strategy, investing in USD for one or three months when *Media tone*$^{\perp}$ is positive and T-bills when it is negative. We find that this strategy yields a 35% and 9% higher return for one-month and three-month holding, respectively, than the opposite strategy of investing in T-bills when *Media tone*$^{\perp}$ is positive and USD when it is negative. For one-month investment, this strategy yields a 20.78% higher return than investing in the USD or 17% higher

returns than investing in T-bills. Using three-month USD investment, the strategy yields a 42% higher return than just investing in USD and a 38% higher return than T-bills.

Our study contributes to a few branches of the literature. First, it is related to the textual analysis literature, which has been applied frequently in financial, accounting, and economic research during the last decade (see for example the references in Loughran and McDonald, 2016). Second, our paper is also related to media and its role of information diffusion in the financial market. These two streams of literatures are related. The application of textual analysis to measure the tone of newspaper articles has increased after Tetlock (2007). His work, later supported by Garcia (2013), shows that negative media content decreases stock market returns on the next day, with a reversal a few days afterwards. Their results support the theories related to noise trader activities (De Long et al., 1990). Meanwhile, Tetlock et al. (2008) argue that news content analysis is able to capture information about firm fundamentals, which helps to predict firm earnings.[1] Calomiris and Mamaysky (2019) and Glasserman and Mamaysky (2019) examine news article content further and find that sentiment, frequency, and entropy predict stock market returns, volatilities, and drawdowns. These effects are time varying and especially visible in emerging markets. It is notable that the results of Calomiris and Mamaysky (2019) occur at annual rather than daily or monthly levels. Hence, the authors argue their news content captures fundamentals-related information rather than behavioral (sentiment)-induced effects.[2]

Textual analysis is not limited only to newspaper articles. For example, Antweiler and Frank (2004) examine internet message boards, Loughran and McDonald (2011) and Jegadeesh and Wu (2013) concentrate on 10-K reports, Chen et al. (2014) examine a social media platform, Da et al. (2015) study Google searches, and Jiang et al. (2019) analyze corporate financial statements and

[1] Tetlock (2007) and Tetlock et al. (2008) use the Harvard Dictionary and Garcia (2013) relies on the word dictionaries by Loughran and McDonald (2011) to capture positive and negative words from the Wall Street Journal and New York Times.

[2] The influence of media is not only related to content and the choice of words. News outlets and journalists can decide which events, topics, firms, and people receive media coverage and which are left outside their scope. Consequently, every news report and written article will always contain subjective component that reflect the author's views, values, and beliefs (Hillert et al., 2018). It has, for example, been reported that the writing styles of reporters and differences in their opinions affect market reactions (Dougal et al. (2012); Hillert et al. (2018)), the effects are larger during more turmoil periods (Dougal et al. (2012), García (2013), and Hillert et al. (2018)), and media coverage and its tone can be related to higher momentum strategy profits and can in general exacerbate investor biases (Hillert et al., 2014). In a similar vein, biased media coverage or media slant also affects both firm and investor behavior. Baloria and Heese (2018) argue that due to slanted media coverage, firms strategically suppress the release of certain negative information, as it can impose excess reputational costs, while Gurun and Butler (2012) argue that local newspapers tend to use more positive terms when describing news related to their local area companies. Engelberg and Parsons (2011) report that local media has a significant impact on the trading behavior of local investors, partly due to the timing of local reporting.

conference calls. Although most of these studies concentrate on stock markets, Soo (2018) and Bork et al. (2019) find that the sentiment extracted from news predicts the housing market.

Third, our paper contributes to the forward premium puzzle in the currency market literature. We propose that *Media tone*$^{\perp}$ is another explanation for the puzzle. Numerous papers have attempted to explain the forward premium puzzle using behavioral explanation. Frankel and Froot (1987, 1990) document early evidence of irrationality in the currency market. Mark and Wu (1998) construct a model based on De Long et al. (1990)'s noise trading behavior. Their model predicts that traders overweigh the forward premium when predicting future changes in exchange rates. Closest to our paper is Yu (2013), who argues that investors' misperception of the real growth rate explains the forward premium puzzle. Directly testing whether investor misperception explains carry trade returns is difficult, as it is not only unobservable but also cannot be quantified straightforwardly. Typical proxies for stock market misperceptions, such as mutual fund flows, dividend premiums, and closed-end fund discounts, are not naturally available for the currency market. Yu (2013) applies the investor sentiment measured by Baker and Wurgler (2006), which is mostly used to explain stock market returns, together with surveys on expected business conditions and finds support for the sentiment-based explanation. Menkhoff and Rebitzky (2008) use survey data on professional investors' euro/dollar exchange rate expectations and find it explains the exchange rate returns for longer (more than two years) horizons.

Although we filter all possible fundamental variables proposed by the literature that we can think of, the fact that we do not observe any sentiment shock-related return reversals questions whether the effects of *Media tone*$^{\perp}$ are related to exchange rate fundamentals or behavioral biases. The cross-sectional portfolio results lend support to sentiment theory, according to which the effects are assumed to be larger for assets that are harder to value and more difficult to arbitrage, although the lack of reversal prevents us from making final conclusions. The reversal might be time or state dependent, and/or *Media Tone* might capture some hard-to-value feature related to fundamentals (Tetlock et al., 2008). We leave this for future research.

The paper proceeds in the following order. Sections 1 and 2 present related literature and the theory underlying risk and currency excess returns, respectively. Section 3 describes the data and methodologies. Section 4 presents descriptive statistics, determinants of *Media tone*, and basis results for the USD as well as for 11 other developed and 24 emerging market currencies. We also present the validation test of *Media tone*$^{\perp}$ and robustness tests. Section 5 examines the channel

through which *Media tone*$^{\perp}$ predicts currency returns, while Section 6 discusses the predictive power of *Media tone*$^{\perp}$ from different news sources. Section 7 shows the application of our findings using Exchange Traded Funds (ETFs). Section 8 argues the results are robust with and without transaction costs, and Section 9 concludes the paper.

1. Literature Review

Our study pertains to the intersection of exchange rate determination, investor sentiment, and the media content analysis literature. The following provides a short review of these literature and their relationships.

The forecasting ability of the forward foreign exchange has been an active topic of research for decades (see e.g., Bilson (1981), Fama (1984) Frankel and Froot (1987), and Levich (1989)). Two reasons for the failure of uncovered interest rate parity have been proposed: non-rationality and a non-constant risk premium. Fama (1984) states that the forward premium is the sum of two unobserved components, the expected rate of depreciation and a normalized risk premium. He demonstrates that the rejection of the unbiasedness hypothesis typically implies that the risk premium is more variable than the expected rate of depreciation and that the two are correlated negatively. The magnitude of the variability of risk premium has remained an open question. Among others, the latent variable applications (see e.g., Hansen and Hodrick (1983), Korajczyk, (1985)) relate the variability in the risk premium to the variation in the expected real interest rate, while Wolf (1987) studies variance of the exchange rate and expected real interest rate.

The failure of the uncovered interest rate parity is evident from the viability of carry trade returns. Lustig and Verdelhan (2007) posit that excess returns compensate US investors for taking more US consumption risk. They are among the first who use currency portfolios in their analysis and indicate that low interest rate currencies offer a consumption hedge to US investors when US interest rates are high and foreign interest rates are low. Low (high) interest rate currencies do not appreciate (depreciate) as much as interest rate differential suggests. High interest rate currencies depreciate when US consumption growth is low and US investors want to be compensated for the risk. In general, previous studies follow the same line and regard carry trade returns as compensation for higher risks. Menkhoff et al. (2012a) posit that large carry trade returns compensate for exposure to global foreign exchange volatility risk and that volatility is the main driver of the risk premia in the cross section of carry trade returns. Christiansen et al. (2011) report that the level of foreign exchange volatility affects the risk exposure of carry trade returns in stock

and bond markets. Burnside et al. (2011) propose that high carry trade payoffs reflect a peso problem, which implies a low probability of large negative payoffs, and Farhi and Gabaix (2016) introduce disaster risk as a determinant for carry trade excess returns. Brunnermeier et al. (2009) stress the role of liquidity in foreign exchange risk premiums, while Burnside et al. (2009) suggest that the forward premium exists due to adverse selection risk. Verdelhan (2010) explains the risk premium as a result of consumption habit performance.

Empirical studies explaining the puzzle have increasingly examined the cross-sectional pricing of carry trade returns. Typically, the empirical tests are executed using currency portfolios and regard carry trade returns as compensation for risk related to foreign exchange (see e.g., Lustig and Verdelhan, 2007; Lustig et al., 2011; Cenedese et al., 2014; Menkhoff et al., 2012a). For example, Lustig and Verdelhan (2007) and Lustig et al. (2011) posit that carry trade can be understood cross-sectionally in relation to two risk factors: the dollar risk factor and the return from the carry trade portfolio itself. The volatility risk premium seems to be a key factor in explaining the time variation in currency returns. During time of high volatility innovations carry trade performs poorly. The low interest rate currencies perform well compared to high interest rate currencies when the market is volatile. In effect, low interest rate currencies, which are funding currencies in carry trade, provide a hedge in times of market turmoil. Cenedese et al. (2014) use market variance and decompose it into the average variance and average correlation. They focus on predicting carry trade returns and indicate that currency market variance has a significant negative effect on the left tail of future carry trade returns. High market variance is related to large future currency losses, and thus the returns from carry trade do not emerge without costs. Market variance predicts currency returns when it matters the most (returns have large negative values), whereas the relationship is weaker in normal times. They also show that when carry trade displays a large loss, market variance provides useful information about whether subsequent losses will occur.

Londono and Zhou (2017) examine the impacts of world currency and US stock variance risk premiums on expected currency premiums for individual currencies. Their theory is based on the consumption-based asset pricing model with local consumption uncertainty and global inflation uncertainty. The slope of the world currency risk premium is negative, implying higher dollar safety value for investors. The impact of the stock variance risk premium in turn is positive, which implies greater US uncertainty and higher return premium compensation for currency investors.

Ismailov and Rossi (2018) indicate that the uncovered interest rate parity holds better during low foreign exchange uncertainty periods, while Berg and Mark (2018) find significant impacts of uncertainty on carry trade returns using several measures of uncertainty. The authors utilize uncertainty indices based on econometric analysis of macroeconomic data and analysis of professional forecasts as well as measures based on text analysis. They argue that US-centered measures of uncertainty are not sufficient for pricing currency excess returns. Rather, a global uncertainty factor from a cross-sectional newspaper analysis of Baker et al. (2016) is significantly priced into the monthly carry-trade excess returns. Overall, the evidence supports the notion that currency excess returns tend to fall in times of high uncertainty. In sum, the prior literature proposes that the required rate of returns from carry trade strategy is high to compensate for the high uncertainty of this strategy.

Another potentially important but previously omitted explanation for currency and carry trade returns is currency sentiment. Although the impact of sentiment on asset prices is receiving increasing interest, its effects on exchange rates have received little attention. Sentiment-induced shocks are based on the assumption that asset price movements and investor decisions cannot be justified by the facts at hand (Baker and Wurgler, 2007). Rather, sentiment shocks reflect investors' actions based on their moods and emotions. Sentiment is typically related to the behavior of noise traders, whose sentiment-induced actions drive the asset value away from its fundamental value (De Long et al., 1990).[3] Based on this, Baker and Wurgler (2006) argue that sentiment-related mispricings are the result of uninformed demand shocks in the presence of arbitrage constraints. Hence, assets that are the most subject to speculative demand (assets with highly subjective valuations) or arbitrage constraints (assets which are the riskiest and costliest to arbitrage) should also be more sensitive to sentiment shocks. In the literature, these are often simply referred to as hard-to-value and hard-to-arbitrage assets, and in empirical settings, sentiment-related shocks should show this cross-sectional variation. Another requirement for a sentiment-induced shock is a reversal of prices. As the shock is not related to actual changes in asset fundamentals, at some point in the future, the arbitrageurs are assumed to offset the effects, and the prices should return to their correct level. Some of the studies examining the role of sentiment in stock pricing include Baker and Wurgler (2006), Kumar and Lee (2006), Baker et al. (2012), Ben-Rephael et al. (2012), Da et al. (2015), and Jiang et al. (2019), although some justify their measures more carefully than others.

[3] Occasionally, rational investors may base their decisions on irrational sentiment-type trading if they believe that the trend of sentiment may last and thus it is rational and profitable to ride the trend. Accordingly, the impact of sentiment on asset returns could be strongly time dependent.

The relationship between media content analysis and sentiment is somewhat complicated. On one hand, several studies claim that their text-based measures capture sentiment. For example, Tetlock (2007) and García (2013) indicate that news-driven sentiment is able to predict stock price movements, and Soo (2018) states the same for the housing market. On the other hand, others argue that their measures capture information related to asset fundamentals instead of sentiment (Tetlock et al. (2008) and Calomiris and Mamaysky (2019)).

Our approach to this question is conservative, and instead of making preliminary statements regarding the role of our measure, we study whether *Media tone* can be considered a sentiment measure. In the currency literature, sentiment has attracted much less attention than it has in the equity and bond literature, but this does not mean that exchange rates are unaffected by it. Menkhoff and Rebitzky (2008) indicate that professional investors' currency expectations explain euro/dollar exchange rates for a horizon over two years. Their professional investors' currency expectation is based on a survey of financial professionals, which is related to the change in the euro/dollar exchange rate only. However, due to the nature of their measure, they cannot detangle whether the expectation is from EUR or USD. Yu (2013) constructs a model to analyze the impact of an investor's misperception on foreign exchange and proposes that due to sentiment, investors over- or underestimate endowment growth, which explains the forward premium puzzle. He applies Baker and Wugler's (2006) monthly data on US sentiment, Baker et al. (2012)'s annual sentiment data for the largest industrialized countries, and survey-based sentiment measures for the other seven countries. He shows the forecasting power of sentiment on real exchange rate changes and proposes that an increase in sentiment positively affects changes in the real exchange rate. These few previous studies still leave many questions unanswered about the relationship between misperception and currency exchange rates. The current study is the first that examines the predictive power of *Media tone* in the currency market and attempts to fill this knowledge gap in the literature.

2. Risk and return in currency excess returns

As the interest rate difference between currencies predicts exchange rate change, exchange rate movements in excess of this prediction are considered currency excess returns. Our research strategy involves the estimation of the *Media tone* data over the currency excess returns.

We follow a standard setup (see e.g., Jordá and Taylor 2012, Lustig et al., 2011) and calculate one-month bilateral ex-post nominal log currency excess returns FX_{t+1} as the sum of the rate of exchange rate appreciation of the USD with respect to the other currencies and interest rate differentia. We use s to denote the log of the spot exchange rate, in units of USD per foreign currency, and f for the log of the forward exchange rate, also in units of USD per foreign currency. An increase in s means an appreciation of the USD or depreciation of the foreign currency. The log excess return FX on buying a foreign currency in the forward market and then selling it in the spot market after one month is simply:

$$FX_{t+1} = s_{t+1} - f_t \tag{1}$$

This excess return can be stated as the change in the spot rate minus the log forward discount:

$$FX_{t+1} = \Delta s_{t+1} - (f_t - s_t)$$

During the normal economic condition, the forward discount is equal to the interest rate differential:

$$f_t - s_t \approx i_t^* - i_t$$

where $i^*$and i are the foreign and US interest rates over the maturity of the contract. Akram et al. (2008) and Lustig and Verdelhan (2007) show the rate of depreciation less the log currency excess returns approximately equals the interest rate differential:

$$FX_{t+1} \approx \Delta s_{t+1} - (i_t^* - i_t)$$

In the absence of arbitrage, the expected return to a risk-neutral investor is zero, that is, $E_t FX_{t+1} = E_t \Delta s_{t+1} - (i_t^* - i_t) = 0$. Non-zero ex-post returns imply rejection of uncovered interest rate parity and that investors are not risk-neutral and require returns as a compensation of risk. Throughout the paper, we compute currency excess returns (FX_{t+1}) as the difference between the end-of-month one-month future spot rate and the one-month forward rate, known at time t.

3. Data and Methodologies

3.1 Currency data

Our sample period is dictated by the TRMI currency *Media tone* data, which are available for the period from 1/1998 to 12/2016. All the analyses are done utilizing monthly data. To compute USD returns, our sample includes 74 currencies against the USD with varying time periods (see

Appendix 1 for details). For the portfolio formation, the dataset ranges between 26 and 58 currencies. The data are divided into three groups: the whole sample, developed country currencies, and emerging country currencies. Our definition of developed countries is similar to that of Lettau et al. (2014), and a currency is considered to be developed if the country is included in the MSCI World Market Equity Index. As the euro was introduced in 1999, the currency amount for developed markets is the same for almost the whole sample period. The rest of the currencies are defined to be emerging country currencies. It is notable that we include currencies regardless of their currency regime. In the further analysis, we also study the sample separately for freely floating, managed floating, and pegged currencies. All the exchange rates are measured against the USD (i.e., an increase in the rates means USD appreciation). All spot and forward rates are from Thomson-Reuters Eikon Datastream.

To take into account the largest and most obvious failures of interest rate parity, we winsorize the excess returns at the 5% level from below and above.[4] Moreover, to mitigate the concerns that our *Media tone*-related results might be driven by unusual circumstances, we also exclude high inflation periods, where high inflation is defined following Lettau et al. (2014) (i.e., annualized inflation is at least 10% higher than the US inflation in the same month). Bansal and Dahlquist (2000) note that the uncovered interest parity condition cannot be rejected for the currencies in high inflation economies, while Lettau et al. (2014) raise a general concern about the effective tradability of these currencies during periods of economic turmoil.

As for USD indices, we use the broad USD index with both trade- and equal weighting. The broad index includes 25 economies that are major trading partners with the US. The index constituents are defined similarly as in the broad currency index available in the Federal Reserve Bank of St. Louis' Federal Reserve Economic Data (FRED) database.[5] See Appendix 1 for currencies. We choose to present only the USD returns based on the broad index because it is more generalized.[6]

[4] The results without winsorizing remain the same.

[5] The exception is that we exclude Venezuela, as its currency values do not change at all for the shorter periods.

[6] We focus on the broad USD index rather than the other currency index by FRED, the major index, due to the increasing amount of trade with the countries in the broad index. From 1998 to 2005, the trade weights of the countries in the major index decline from 58.75% to 51.67% and after 2005 they account for less than 50% of US trading.

Both indices are calculated utilizing end-of-month currency excess returns from bilateral exchange rates.[7] The trade weights used for the calculations are from the FRED database.[8]

3.2 Currency Media tone

As our main currency *Media tone*, we use the text-based measure developed by TRMI for the USD. TRMI evaluates the text content from several thousand global news and social media sources and identifies references relevant to USD exchange rates (both bilateral and general).[9] The tone of the phrases and words and their intensities are evaluated and subsequently converted into measurable variables and scaled with the amount of references. *Media tone* is measured as the difference between the overall number of positive and negative references and scaled with the amount of references. TRMI analyses more than two million articles a day. The TRMI database uses news from several of the mainstream news sources for the entire historical sample period. After 2005, Internet news content is also used for the analysis. Internet news sources are restricted to top international, regional, and business news sources and leading industry sources.[10]

The value of the TRMI variable can be a non-integer when any of the words/phrases used to form it are described with a "minimizer" ("maximizer"), which reduces (increases) the intensity of the primary word or phrase. For example, in the phrase "less concerned" the score of the word "concerned" is minimized by that of "less." As a result, the scores of common words/phrases with minor contributions can be minimized while more intense emotions are weighted more heavily. TRMI data formation is presented in more depth in Appendix 2.

Media tone variable is originally available for daily frequency, but in order to avoid problems related to nonsynchronous trading and the publishing of news and to limit the role of transaction costs,

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[7] We have also estimated the results using the monthly average value of the trade-weighted index (TWEXBMTH index available in the FRED database), and the results are stronger. Results have also been estimated with larger currency baskets consisting of 36 and 41 currencies. Again, the results generated from them are stronger than those from our original indices.

[8] https://www.federalreserve.gov/releases/h10/weights/default.htm

[9] Although both traditional news and social media sources are included, the sample is heavily tilted towards traditional news, as about 88% of the references are from these sources, and that number is even higher during the early part of our sample.

[10] According to the TRMI manual, "The social media collection process is more diverse. It starts in 1998 with Internet forum and message board content. Starting in late 2008, LexisNexis social media content was added. Starting in late 2009, tweets were included. Using popularity ranks measured by incoming links, this includes generally the top 20% of blogs, microblogs, and other financial social media content. MarketPsych Data also included content from hundreds of less-popular asset-specific blogs and forums."

the data are aggregated to the monthly level by taking a mean of daily values for each month. Only English-language texts are used for the analysis.

The TRMI currency *Media tone* data consist of all the currency-related news. Since our main focus is on the USD, we primarily include only the *Media tone* that is extracted from USD-related news except for those in Table 5 that are news related to non-US countries. In theory, the constructed *Media tone* might include both the exchange rate fundamental-related information component as well as the possible non-fundamental-related component; however, the raw *Media tone* data do not differentiate between these two components. In our empirical estimations, we use filtered tone, which is a residual from regressing tone on the variables related to the fundamentals of US macroeconomics, including currency factors and business cycle components (all independent variables in Table 2 Panel B).

3.3 Methodologies

Our main regression is the following:

$$FX_{t+1,t+k} = \beta_0 + \beta_1 Media\_Tone_t + \varepsilon_{t+1} \quad (2)$$

where $k = 1,3,6,12$, $FX_{t+1,t+k}$ denotes the change in foreign exchange rate returns (either for currency index or currency portfolios) from $t+1$ to $t+k$, and $Media\_Tone_t$ is the standardized currency *Media tone* at time t. Hence, the coefficient β_1 measures the effect from a change of one standard deviation in the *Media tone* variable. For return periods, we use all monthly, geometric average, and cumulative returns. We use Newey–West standard errors with 12 lags to account for the heteroscedasticity and autocorrelation in error terms and alleviate the bias caused by overlapping returns for return periods longer than 1 month.

Out-of-sample estimations: All of the predictors and regression slopes of Equation (2) are estimated recursively, using information available at the forecast formation time. For all the estimations, we use the period 1/1998–8/2010 as an in-sample period (this corresponds to 2/3 of the sample period) and the period from 9/2010 till the end (the remaining 1/3 ending at 12/2016 for the $t+1$ estimations) as the out-of-sample evaluation period. We report the out-of-sample adjusted R^2 (R^2_{OOS} %) and compare the predictability of the *Media tone* variables to the predictability performance of the historical average. The predictability is measured by Mean Square Forecast Error (MSFE). The null hypothesis is that the historical average MSFE is less than or equal to the predictive regression forecast, against the one-sided alternative hypothesis that the historical

average MSFE is greater than the predictive regression forecast MSFE (see Clark and West (2007) regarding the MSFE test). The test has an asymptotically standard normal distribution when we compare different forecasts from the nested model. The test can also reject the null even when the R^2_{OOS} statistic is negative.

Forecast encompassing: To compare *Media tone* to other predictor variables, we apply forecast encompassing tests following Chong and Hendry (1986). We regress the currency excess returns at time $t+k$, FX_{t+k}, on a constant (δ), the forecast from currency predictor i, $\widehat{FX}^i_{t+k}$, and the *Media tone* forecast, $\widehat{FX}^{MediaTone}_{t+k}$:

$$FX_{t+k} = \delta + \lambda_i \widehat{FX}^i_{t+k} + \lambda_{MediaTone} \widehat{FX}^{MediaTone}_{t+k} + \varepsilon_{t+k} \tag{3}$$

If $\lambda_{MediaTone}$ differs from zero, *Media tone* contains relevant information relative to other currency predictors. If $\lambda_i = 0$, *Media tone* forecast encompasses the forecast of other currency predictors i.

4. Results – Predictability of *Media tone* on foreign exchange returns

4.1 Descriptive statistics

Table 1 presents the descriptive statistics of our sample. In Panel A, the raw currency *Media tone* consists of mostly negative observations, indicating that the news tone of the USD-related news has been mostly negative. However, once the fundamentals-related information (currency factors and business cycle variables) is removed from the *Media tone*, Filtered *Media tone* or *Media tone*$^{\perp}$ are symmetrically distributed, having both mean and median of zero.

The broad indices in Panel B are formed as traded- and equal-weighted indices of the 25 largest US trading partners, respectively. Portfolios 1–5 in Panel C refer to the excess returns of currency portfolios formed on previous month currency characteristics. The portfolio formation is rebalanced every month. For instance, Panel C.1 presents portfolios formed based on interest rate differentials from the previous month. In each month, each currency is sorted based on its one-month interest rate differential with the US from the previous month into quintiles. Portfolio 1 (Portfolio 5) refers to currencies with the lowest (highest) values for the characteristic in question. We then compute equal weighted exchange rate excess returns in month t of each quintile portfolio. We perform the same routine every month and then take an average of returns across

months throughout our sample period. We do the same for other characteristics. Portfolio P5–P1 refers to a high minus low portfolio (i.e., the difference between the returns of portfolio 5 and portfolio 1). Portfolios are formed using all the available currencies and excluding the periods of high inflation (see Section 3.1 for our explanation). We expect the high-risk (i.e., harder to value) currency portfolios to have higher returns in absolute terms than the low-risk portfolios. This can be seen from most of our results. Panels C.1 and C.2 sort currencies by interest rate differential relative to the US interest rate and inflation. P5 in both panels shows the smallest returns, and P5–P1 in both panels is negative and significant at least at the 5% level. Panels C.3 and C.9 sort portfolios by currency turnover and credit rating. The highest turnover and credit rating portfolios have significant higher returns than the lowest turnover and credit rating portfolio. Panel C.10 shows that the lowest political risk portfolios have 41 basis point returns higher than those with the highest political risk. Panels C4–C6 present portfolios sorted by momentum following Menkhoff et al. (2012b) and Asness et al. (2013). We find that portfolios with higher momentum provide higher returns and P5–P1 is positive and highly significant at the 1% level. The evidence is consistent for one-month, six-month, and 12-month momentum portfolios. Surprisingly, the portfolios sorted based on exchange rate volatility in Panels C7 and C8 exhibit a counterintuitive pattern, as the 12-month highly volatile portfolios have lower returns, and the same pattern is noted for portfolios sorted by past month volatility, although the return difference is not statistically significant. This analysis is too crude to allow us to offer any explanation for this finding. It is possible that exchange rate volatility is mostly attributed to idiosyncratic risk volatility, which many studies find to be negatively related to returns (Ang et al., 2006). See Appendix 3 for definitions and sources of all the variables we describe in this and the following sections.

Insert Table 1 here

4.2 Determinants of USD Media tone

What characterizes *Media tone*? In this section, we attempt to answer this question. We collect data on several determinant alternatives related to financial markets, macroeconomic environments, uncertainty, and USD expectations.[11] It is obvious that *Media tone* captures information related to exchange rate fundamentals, but several previous studies have also used variables constructed in a similar fashion to measure sentiment of the news articles (see e.g., Antweiler and Frank (2004), Tetlock (2007), Tetlock et al. (2008), García (2013), Loughran and McDonald (2011), and

[11] We test other variables proposed by the extant literature, but they are not consistently significant. We do not report here or use them to filter our *Media tone*.

Calomiris and Mamaysky (2019)). Hence, our determinants dataset includes both fundamentals- and sentiment-related variables.

Our financial market-related determinants include contemporaneous monthly returns from the broad trade-weighted USD index (*FX*) and the stock market (*S&P500Return).* Naturally, it is expected that appreciation of the USD will also lead to more positive media coverage, and hence their correlation is positive. The stock returns reflect expectations of overall firm performances. If the firms are doing well, the whole economy is in good shape, and hence the currency should also be strong. Thus, we expect the stock returns to have a positive correlation with the USD *Media tone*.

Previous studies have indicated that volatility and uncertainty are significant determinants for systematic risk factors in foreign exchange market (i.e., large carry trade returns compensate for exposure to global foreign exchange volatility risk) (see e.g., Menkhoff et al. (2012a)). Burnside et al. (2011) propose that high carry trade payoffs reflect a peso problem, which implies a low probability of large negative payoffs, while Farhi and Gabaix (2016) introduce disaster risk as a determinant for carry trade excess returns. Based on this evidence, we expect that the relationship between *Media tone* and uncertainty measured by *US Equity Market Uncertainty* and *VIX* is negative, with higher uncertainty leading to lower *Media tone* and vice versa. As the final variable, we include USD expectations. More positive expectations (*USD Expectations*) should be related to more positive *Media tone*. We also include the past value of *Media tone* as a control variable.

Table 2 reports the results in two panels. Panel A shows the results for the contemporaneous determinants of USD *Media tone*, where the examined determinants are related to *Media tone* and currency market in general. Panel B focuses on the determinants of USD *Media tone* that are related to currency factors proposed by the extant literature and business cycle variables.

Insert Table 2 here

Panel A shows that most of our expectations hold. As the USD appreciates, this is also mentioned in news, and hence the current USD returns are positively related to *Media tone*. The link between USD *Media tone* and the stock market seems to be strong, as stock returns have a positive value while *US Equity Uncertainty* and *VIX* have negative and significant values. The most important contributors to USD *Media tone* are USD *Media tone* from the previous month, followed by the

current currency and stock market movements and analyst expectations regarding the exchange rate. Surprisingly, *Media tone* is negatively related to analyst forecasts. In unreported results, we find that the average correlation between the expectation of the major three currencies pairs (EUR/USD, GBP/USD, and Yen/USD) and the next month USD return at month t (next month) is -0.93 and significant (-0.05 and insignificant), thus suggesting that analysts seem to have a contrarian view of the future spot rate. For the kitchen sink regression in column (6), all of the variables are significant with the same signs, but the ones related to stock markets (*US Equity Expectations* and *VIX*) have smaller coefficients, indicating that much of their impact on *Media tone* is encompassed by other variables.

To gain a deeper insight on whether USD *Media tone* predicts the exchange rate or simply captures the effects of the currency factors, we examine its relation to commonly used exchange rate factors. We utilize the currency factors and variables related to business cycle fluctuations. We use the currency factors applied by Aloosh and Bekaert (2019), including the Global Dollar factor (*Dollar*), Currency Carry Factor (*Carry*), one-month Currency Momentum (*MOM*), Currency volatility (*Volatility*), Currency Value (*Value*), Commodity factor (*Commodity*), and World equity factor (*World Equity*). To capture business cycle fluctuations, we include the yearly change in industrial production index (*IndProd*), the change in real values of consumer durables (*Durable*), non-durables (*NonDurable*), and services (*Services*), the change in employment (*Employment*), an NBER recession dummy variable (*Recession*), and the three-month Treasury bill interest rate (*Interest rate*). The first six are the same business cycle variables Baker and Wurgler (2006) use to filter their sentiment variable. The correlation between the raw and filtered currency tone measures is about 0.76. Figure 1 compares the raw and filtered *Media tone* with the broad USD index and suggests that they have a rather similar trend, which is not surprising for raw media tone, as it can be assumed that media reports the appreciation and depreciations of the USD, but it is surprising for filtered tone, as the fundamental information is filtered out.

Insert Figure 1 here

Table 2 Panel B presents the regressions including currency factors and business cycle as independent variables. We find Dollar factor and World Equity to increase while Momentum and Volatility decrease with the *Media tone* of the USD. For business cycle, it is noteworthy that industrial production and interest rate have a negative correlation with *Media tone* whereas employment has a positive correlation. Interestingly, currency factors and business cycle seem to

provide different information, as, in the pool regression (Specification (3)), the variables that are significant in specifications (1) and (2) remain significant with a similar magnitude, while adjusted R^2 increases by 16%. For the rest of the paper, we use $MediaTone^{\perp}$ or the residual from regressing *Media tone* by all the variables in Table 2 Panel B.

4.3 Media tone$^{\perp}$ and currency indexes

Table 3 summarizes some of our main results for the USD broad indices. The left side of the table uses excess returns of the trade-weighted broad currency index as the dependent variable, while the right side uses equally weighted excess returns of the same index. The latter corresponds to the USD currency basket used in Aloosh and Bekaert (2019). Panel A reports the results for the non-overlapped period using geometric average returns for the periods t, $(t+1)$, $(t+1, t+3)$, $(t+4, t+6)$, and $(t+7, t+12)$, while Panel B shows cumulative returns for return horizons from $t+1$ to $t+3$, $t+6$, $t+9$, and $t+12$.

The table reports the coefficient β_1 from Equation 2, its t-value, adjusted R^2, and the recursively estimated R^2_{OOS} (%), comparing the predictability of the $MediaTone^{\perp}$ variable to the predictability of the historical average using Clark and West's (2007) MSFE test.

Insert Table 3 here

Table 3 shows that *Media tone$^{\perp}$* contemporaneously increases returns and predicts returns for the next three months (t+1, t+3). The results are strongly significant and robust across trade- (TW) and equal-weighted (EW) broad indices. R^2_{OOS} is also significant at about the 5% level. The result for EW is marginally stronger, as *Media tone$^{\perp}$* also predicts the next month return (t+1). The returns are highly significant with rather large coefficients of determinations in both in-sample and out-of-sample periods. The effect of *Media tone$^{\perp}$* in Panel A begins to dissolve after three months in terms of coefficient size, its significance, and R^2, but in Panel B, the coefficient shows slightly longer persistence. In Panel B, *Media tone$^{\perp}$* has predictive power up to six months. The results are consistent for TW and EW in both in- and out-of sample periods. R^2_{OOS} is significant up to nine months ahead. To give a comparative picture, we show R^2_{OOS} of the BW measure in Table 9 and their R^2_{OOS} are not significant in any period. This indicates the predictability of *Media tone$^{\perp}$* is significant both in- and out-sample, and it is more powerful than the BW measure, which has been shown by Yu (2013) to have predictive power in the currency market. *Media tone$^{\perp}$* is not only

statistically but also economically significant. Compared to the average excess USD returns of -0.05% and -0.17% from TW and EW, respectively, a standard deviation increase in tone is related to a 0.29% excess return increase in the USD trade-weighted index contemporaneously and increases the excess returns by 0.20% from t+1 until t+3. With the same increasing magnitude, the excess trade-weighted return of the USD increases by 0.63% for three months (t+1 to t+3) and by 0.87% for six months (t+1 to t+6). The economic significance of equal-weighted returns for the time period mentioned is even stronger. In Appendix 4, we perform similar analyses as those in Panels A and B using unfiltered *Media tone*, and the results are qualitatively similar but quantitatively stronger.

In Panel C, we show the results of a forecast encompassing test, which is a horserace among predictors of USD returns. In detail, we predict next month USD returns for both trade- and equal-weighted broad indices using each of the currency factors separately and the USD *Media tone* in month t. Then, we include those predicted USD returns one by one together with the *Media tone*-predicted USD returns. Similar to Bork et al. (2019), we force the coefficients to sum to one. Since we compare *Media tone* to other currency factors, we use the raw *Media tone* in this analysis, which is economically similar to what we test in Panels A and B. Interestingly, of all other currency predictors, $\widehat{FX}_{t+k}^{i}$ is insignificant. In contrast, $\widehat{FX}_{t+k}^{MediaTone}$ is significant at least at the 5% level, except when *Media tone* competes with carry and commodity factors for trade-weighted broad index returns. In those cases, *Media tone* is significant only at the 10% level and insignificant, respectively. *Media tone* encompasses other predictors for equal-weighted broad index returns. Notably, *Media tone* has superior predictive power compared to USD returns, which is known to have strong power in the AR(1) process.

Next, we study whether the effects of *Media tone*$^{\perp}$ are time and state dependent. Garcia (2013) shows that the impact of *Media tone* is greatest for stock markets during recession periods. We study the USD market to examine whether the impact of *Media tone*$^{\perp}$ changes during recession and Global Financial Crisis periods. Table 4 presents the results for USD *Media tone*$^{\perp}$ when we use the trade-weighted index in Panel A and the equal-weighted index in Panel B. We define the Global Financial Crisis to start from the collapse of Lehmann Brothers, and thus the *PostCrisis* -dummy variable gets a value of 1 for the period during and after 9/2008 and 0 otherwise. As the period cuts the sample set into two almost equally sized samples, we are able to study the time period dependency of the USD *Media tone*$^{\perp}$. Excess returns of the broad, trade-weighted USD index are

used as the dependent variable. We find that the predictability of *Media tone*$^{\perp}$ is lower after the crisis period.

Insert Table 4 here

To see how the beta varies with the business cycle, Figure 2 plots betas from rolling 60-month windows using returns in t+1 and returns during t+1 to t+3. The last two NBER recessions occurred during our sample period. Focusing on the regression of returns in t+1, we find that betas decrease initially and then increase. Interestingly, the betas of returns using broad trade-weighted index are negative during the two recession periods (3/2001–11/2001 and 12/2007–6/2009). This pattern is especially striking for the last recession, when the beta dives to -0.28. The beta of returns from the equal-weighted index is positive during the recession in 2001 but decreases to -0.21 during the last recession period. This implies that the two recession periods are different in nature. The most recent one impacted all countries around the globe, while the crisis in 2001 mostly affected the major traders with the US. For returns in t+1 to t+3, we observe a similar but smoother pattern. Both figures show a negative beta during the last financial crisis in June 2009.

Insert Figure 2 here

4.4 The predictive power of Media tone across currencies

The previous results show the predictability of USD *Media tone*$^{\perp}$ on USD returns. In this section, we examine whether the predictability of *Media tone*$^{\perp}$ applies to any currency. That is, we utilize the *Media tone*$^{\perp}$ of developed and emerging market currencies and test the predictability of their currency returns. According to sentiment-related theories, the impact of *Media tone*$^{\perp}$ should be more pronounced on emerging market currencies. As a dependent variable, we use the changes in the broad nominal effective exchange rate from Bank for International Settlement (BIS) without subtracting interest rate differentials.[12] Our goal in this analysis is to study whether the impact of *Media tone*$^{\perp}$ is stronger for hard-to-value currencies, such as emerging currencies, and thus we want the left-hand side to be pristine and capture only exchange rate returns without any influences of inflation and interest rate. In theory, the effect on the interest rate differences should be very small,

[12] We also apply *real* effective exchange rate indices and the results remain qualitatively similar. We apply the trade-weighted broad index. See the BIS's website for the construction of the indices. https://www.bis.org/statistics/eer.htm

as the interest rate differences related to the following month's currency excess returns are already known at the time that the investment decision is made. We demonstrate in Appendix 5 that the results and pattern are similar for raw and currency excess returns. In Panel A of Appendix 5, we replicate Table 3 Panels A and B without taking interest rate differentials into account. The results are similar to those of Panels A and B in Table 3. In Panel B of Appendix 5, we decompose excess returns into change in spot rate (Δs_{t+1}) and interest rate differentials ($f_t - s_t$). We sort excess returns into five portfolios according to interest rate differentials. The results show that the significance of excess returns is explained by change in exchange rate more than by interest rate differential. This is not surprising since the interest rate differential is already known at time t. The only portfolio for which *Media tone* and *Media tone*$^{\perp}$ predict interest rate differentials is portfolio 5, the portfolio with the highest interest rate differentials. The difference in the impact of *Media tone* between P5 and P1 is weakly significant regardless of whether or not we winsorize the returns and whether or not we filter *Media tone*. It is noteworthy the test in Appendix 5 is based on media tone and returns of USD only. We assume the global market is integrated and assume US is the world market in the same vein as and Atanasov et al. (2019), and Rapach et al. (2013). Under this assumption and the weak (almost insignificant) impact of the *Media tone* on interest rate differential in Appendix 5, not including interest rate differentials in the currency excess returns estimation seems to be less of a concern and does not change our qualitative conclusion. However, a word of caution is in order for the results. As the interest rate differences in Appendix 5 are mostly positive (i.e. the foreign interest rates is larger than the US interest rate), excluding interest rate might lead the impact of the *Media tone* to be overestimated, i.e. the magnitude of the estimated coefficients is larger than they should be.

Table 5 uses the trade-weighted average returns of each currency against their most important trading partners. The trade weights are three-year average trade weights, updated every three years. The indices, information about the trading amount, and each country's trading partners are available from BIS. Broad indices comprise 48–60 economies (conditional on the existence of the Eurozone) and are available at monthly frequency. We use the data from BIS because it is the only reliable source that provides the trade-weighted index of each country. We present the results only for the contemporaneous (left side of Table 5) and following periods (right side of Table 5). To simplify the comparison, countries are divided into developed and emerging markets, where the Eurozone is considered to be developed.

The *Media tone* is the tone of news related to each of the currencies. For instance, for Japan, the *Media tone* is a tone from Japanese-Yen related news. The use of only English media might well be subject to criticism. However, the results could be generalized since the currency market is mainly traded by sophisticated investors who should access to news that are in English. We leave it for future research to develop tone for non-English language.[13] All of the *Media tones* are orthogonalized using currency factors.[14]

Insert Table 5 here

As expected, most of the contemporaneous exchange rates are predicted by *Media tone*$^{\perp}$. All of the developed country currencies are significantly impacted by their own currency's *Media tone*$^{\perp}$. Interestingly, the coefficient of *Media tone*$^{\perp}$ for the USD in this specification (0.80) is more than twice the size of that in Table 3 (0.29 for TW and 0.34 for EW). R^2 also increases from 3% to 40.03%.[15] Of the emerging markets, the Argentine peso, Chinese renminbi, Peruvian sol, Saudi riyal, and UAE dirham are not impacted by USD *Media tone*$^{\perp}$. The currencies of these economies are all pegged or controlled and are allowed to move within a 4% band (see the regime classification data by Ilzetzki et al., 2017). For the rest of the currencies, *Media tone*$^{\perp}$ and the changes in value seem to be related, but there are no clear differences in the sizes of the relation between developed and emerging country currencies. On average, the coefficient of *Media tone*$^{\perp}$ in developed country currencies is about 0.56, whereas that in emerging country currencies is 0.81.

For the next periods' returns, four out of 12 developed and 17 out of 24 emerging country currencies are significantly predicted by the currency's *Media tone*$^{\perp}$ at least at the 5% level. Hence, it seems that emerging countries are more subject to *Media tone*$^{\perp}$. It is noteworthy that the currencies that are most impacted include the Australian dollar, Japanese Yen, New Zealand dollar, and USD, and these currencies are the largest instruments for carry trade. In sum, the results in

[13] Calomiris and Mamaysky (2019) also use only the English language news when forming sentiment measures for international markets.

[14] As the US business cycle variables might not be appropriate measures of business cycles for all non-US countries, for national currency *Media tones*, we use only the currency factors as the filtering variables. The results, however, remain similar when US business cycle variables are used.

[15] The difference might be attributed to the followings: (1) The trade-weight currency index used to compute returns in this table is from BIS and is based on 48–60 trading partners, whereas the currency index used in Table 3 is based on 25 trading partners. (2) BIS updates the trade weights every three years, whereas the trade weights in Table 3 are updated annually. (3) We do not take interest rate differentials into account when we compute currency excess returns whereas Table 3 does. (4) This table computes returns using the monthly average of the daily currency values, whereas Table 3 uses the end-of-month value to compute monthly returns.

Table 5 show that the effect of *Media tone*$^{\perp}$ is apparent in both emerging and some of largest currencies.

4.5 Validation test of Media tone

Sections 4.3 and 4.4 establish that *Media tone*$^{\perp}$ predicts monthly currency index returns. Next, we analyze which currency characteristics are associated with *Media tone*$^{\perp}$ predictability by forming currency portfolios based on different currency and country characteristics. More specifically, we divide a set of currencies into portfolios according to their characteristics and examine how the *Media tone*$^{\perp}$ of the USD affects them. This analysis is also a validation test of *Media tone*$^{\perp}$ as a measure for sentiment. If the measure captures sentiment, it should have stronger predictability for currencies that are difficult to value or arbitrage (Baker and Wurgler, 2006).

Unlike stocks, currency markets do not have standardized characteristics that are commonly used to form portfolios. We rely on some variables that have been used in the literature and also introduce some new ones as follows.

Interest rate difference: We follow Lettau et al. (2014) and rank currencies into portfolios based on their previous month's interest rate differences with the US interest rate. In theory, large interest rate differences should lead to large changes in exchange rates in absolute, but according to the carry trade literature, instead of converging towards the predictions of uncovered interest rate parity, exchange rates are diverging and thus lead to high carry trade returns. Sudden changes in the exchange rates can cause major losses to carry trade investors, and thus the strategy is often likened to "picking up pennies in front of a steamroller." We assume that the currencies with higher interest rate differentials are also more difficult to value and thus are more sensitive to *Media tone*$^{\perp}$.

Inflation: Inflation is also closely related to exchange rates, and it is one of the factors affecting investors' willingness to hold a country's currency. High inflation is typically related to a weaker macroeconomic environment and thus related to weaker currencies. The effect of inflation is apparent through interest rates, as low interest rates encourage consumer spending and lead to economic growth. With more spending, inflation increases, but as long as it remains at manageable levels, it supports economic activity and typically has a positive impact on currency values. If the inflation grows out of control, the economic growth and exchange rate are weakened based on purchasing power parity. Moreover, investors avoid cash balances in high inflation currencies,

which may weaken the value of these currencies. Hence, the higher the inflation, the more uncertain the value of the currency. We form portfolios with respect to inflation values and assume that the currencies from high inflation countries are also more difficult to value.

Turnover: We use currency size or liquidity, measured by the currency turnover in the OTC market, to form portfolios. Size is one of the most commonly used variables to form portfolios for stocks. It can be assumed that the more the currency is traded, the closer the currency is followed by currency traders, and thus the closer its value should be to its fundamental value.

Momentum: We use currency momentum as a measure of hard-to-arbitrage currency. The extant literature does not explicitly show a connection between momentum and the difficulty of valuation or arbitrage. However, Baker and Wurgler (2006) argue that stocks that are likely to be most sensitive to speculative demand tend to be costliest to arbitrage. Moskowitz et al. (2012) show that time-series momentum appears in all assets, and thus we speculate that a currency that exhibits a high degree of (time-series) momentum will be the costliest to arbitrage and thus sensitive to *Media tone*$^{\perp}$. As the results of momentum portfolios tend to vary depending on the formation period, we form momentum portfolios based on the cumulative excess returns from the past month, past six months, and past 12 months.

Volatility, credit ratings, and political risks: We also include previous month and 12-month exchange rate volatility, credit ratings, and political risk and form portfolios of month t based on their previous month value. The higher the volatility and political risk and the lower the credit ratings, the more difficult it is to value. The definitions and data sources of all the variables are presented in Appendix 3.

For all portfolios, the constituents are updated monthly, except for credit ratings, political risk, and turnover portfolios, which are updated every three months, 12 months, and three years, respectively due to data availability.[16] For each of the aforementioned portfolios, we calculate monthly excess returns according to Equation (1) and regress the returns of period $t+1$ on the *Media tone*$^{\perp}$ from month t to study whether *Media tone*$^{\perp}$can predict the returns and whether there are differences in the impact of *Media tone*$^{\perp}$ across different characteristics-sorted portfolios.

[16] BIS provides turnover, and it is updated every three years. See the description here: https://www.bis.org/statistics/derstats3y.htm or https://www.bis.org/list/triennial/index.htm

Insert Table 6 here

Table 6 Panel A presents the portfolio results for portfolios that are formed based on the previous month's interest rate difference with the US one-month interest rate. Portfolio 1 (P1) has the excess returns for the smallest interest rate differences, while Portfolio 5 (P5) has the returns of the largest ones. The currency portfolio with the highest interest rate difference also has the largest *Media tone*$^{\perp}$ coefficient (in absolute terms), and the *Media tone*$^{\perp}$ is able to explain the return difference between portfolios P5 and P1, or carry trade return. Its impact is both statistically and economically significant at the 1% level. A standard deviation increase in *Media tone*$^{\perp}$ increases the excess returns of currency in the fifth portfolio by 0.48%, which is about a half of the mean excess return of 0.90% of this portfolio (see Table 1).

In Panel B, the currency excess trade portfolios are formed based on the previous period's inflation values. Again, the currencies from countries with higher past inflation rates and hence weaker macroeconomic conditions are more susceptible to the influence of *Media tone*$^{\perp}$. Similar to Panel A, P5–P1 also has a significant coefficient but a weaker impact of *Media tone*$^{\perp}$.

Panel C reports the results for currency portfolios that are formed based on past turnover values. Our assumption is that the lower the currency turnover, the costlier it is to arbitrage. Although the data used for turnover calculations are rather rough (triennial data for every April), the general picture is clear. The larger currencies with higher turnovers in P5 have smaller coefficient (in absolute terms) than the currencies with lower turnover. *Media tone*$^{\perp}$ can explain return differences between these portfolios at a 5% significance level.

In Panels D–F, the results between different momentum portfolios are ambiguous, and the effects for high minus low portfolios are not significant.[17] As Baker and Wurgler (2006) suggest, in theory, there is no direct connection between stocks that have high momentum and sentiment. Burnside, Eichenbaum and Rebelo (2011) argue currency momentum is associated with speculation. Baker and Wurgler (2006) argue stocks that are subject to speculation are also costly to arbitrage and thus are subject to sentiment. Combining these two arguments, we conjecture currencies that have high degree of momentum should be sensitive to Media tone. We find weak evidence of this conjecture for one-month momentum portfolios but no evidence for six-month and 12-month momentum.

[17] This cannot be attributed to the fact that we use the momentum factor to filter our raw *Media tone*. The results remain qualitatively the same even though we do not filter $MediaTone$ by momentum.

In fact, we find the opposite pattern (i.e., currencies that have a lower degree of momentum are more sensitive to *Media tone*$^{\perp}$ for six- and twelve-month momentum portfolios). *Media tone*$^{\perp}$ can predict the lowest six-month and 12-month momentum portfolios at the 1% and 5% significance levels, respectively, and the difference in the impact of the 12-month momentum portfolio between P5 and P1 is significant at the 10 level%.

Panels G and H utilize past volatilities as a hard-to-value measure. Panel G concentrates on the past 12-month exchange rate standard deviation, and Panel H focuses on the daily return volatility of the previous month when forming the portfolios. The results for both of these are rather similar, clearly supporting the previous findings regarding the impact of *Media tone*$^{\perp}$ (i.e., the higher the uncertainty related to the currency, the larger its sensitivity to *Media tone*$^{\perp}$). Similar to momentum, we filter raw *Media tone* by currency volatility, thereby moderating its impact.

Panels I and J show the coefficient values for portfolios formed by past credit ratings and political risks. The results suggest that portfolios with low credit ratings (P1) and high political risks (P5) are more significantly impacted by *Media tone*$^{\perp}$. Notably, the return difference between P5 and P1 is only significant for portfolios formed based on credit ratings, not on political risks.

In aggregate, *Media tone*$^{\perp}$ is impactful for currencies that are difficult to value (high interest rate differential, high inflation, low turnover, high volatility, low credit rating, and high political risk).

Table 5 shows that emerging markets are more impacted by *Media tone*$^{\perp}$ than developed markets, and Table 6 confirms that *Media tone*$^{\perp}$ has predictive power for currencies possessing hard-to-value qualities, supporting the sentiment-related explanation. Next, we examine whether the impact of hard-to-value characteristics is more pronounced for emerging or developed markets. Of our full sample, which varies between 26 and 58 currencies (pre-2/2004: 26–35, post-2/2004: 51–58), the number of currencies is between 14 and 46 (pre-2/2004: 14-18 currencies, post-2/2004: 39-46)[18] for emerging markets and between 12 and 22 for developed markets. Following the adoption of the euro in 1999, the number of developed country currencies decreases to 12 (pre-1999: 21–22 currencies, post-1999: 12 currencies).

[18] The increase in the number of currencies is surprising. *Datastream,* our main data source of currency index, reports an increase of the number of currencies of emerging economies over two times after 2004.

Due to the small number of developed country currencies, we form three portfolios, while we keep five portfolios for emerging country currencies. Table 7 reports the results in Panels A–J for developed country currencies on the left side and for emerging country currencies on the right side. Interestingly, across all characteristics, except for one-month momentum and currency turnover, the predictability of *Media tone*$^{\perp}$ is apparent only in emerging markets. *Media tone*$^{\perp}$ does not have any impact on the returns of developed market currencies except when portfolios are formed by one-month momentum. It is noteworthy that the results based on six-month and 12-month momentum portfolios are similar to those in Table 6 in that portfolios formed by small momentum in the previous month are more impacted by *Media tone*$^{\perp}$, and the results are significant only in emerging markets. As the results are mixed among momentum portfolios, we hesitate to draw any conclusions regarding the relation between momentum and *Media tone*$^{\perp}$.

Insert Table 7 here

Taken together, the results in this table support the results in Table 5 and indicate that the predictability of *Media tone*$^{\perp}$ is more accentuated for emerging market currencies, thus supporting the view that its effects are sentiment related.[19]

As a final validation, we examine the predictability of the USD *Media tone*$^{\perp}$ on USD returns computed against currencies of economies with different regimes. We utilize the time varying classification of different currency arrangements of Ilzetzki et al. (2017) (IRR hereafter) and classify the currencies into three regimes: freely floating, managed floating, and fixed. Freely floating currencies are classified in the IRR database as freely floating (classification code 13); managed floating currencies are those that are partly managed, have a de facto or pre-announced crawling band that is narrower than or equal to $\pm 2\%$, or have a de facto crawling peg (codes from 6 to 12); and fixed currencies have a pre-announced peg, currency board arrangement, de facto peg, or de facto moving band narrower than or equal to $\pm 1\%$ (codes 2 to 5). Currencies that do not have a separate legal tender belonging to the currency union (e.g., individual Eurozone countries) (classification code 1), are freely falling (code 14), or have a dual market in which parallel market data are missing (code 15) are excluded from the analysis. We form portfolios based on the past

[19] Avid readers might be surprised why the impact of Media Tone is much weaker in this table. Mathematically interest rate differentials should strengthen the results. $\Delta FX = \Delta S - \Delta interest$. The coefficient of $\Delta interest$ is negative and thus the coefficient of ΔFX should be higher and that is supported by the results in Appendix 5. One highly possible reason is In Table 5, exchange rate index is calculated against 48-60 currencies, including both developed and emerging country currencies, whereas, in this table, the portfolios include only about 3-4 developed market currencies against the USD so the effects might/should be weaker.

month's interest rate differences and expect the fixed currencies to be less affected by *Media tone*$^{\perp}$ than freely floating and managed floating currencies. In terms of freely floating currencies, there are only 3 to 4 currencies during the sample period after the adoption of the euro, and thus we include them as a single portfolio. For managed floating and fixed regime currencies, the number of currencies varies substantially before and after 2/2004. For managed floating currencies, the pre-2004 sample includes 16 to 21 currencies and the post-2004 sample includes 32 to 38 currencies. As a compromise, we divide them into three portfolios. Regarding fixed currencies, the pre-2004 period has four to 11 currencies, while post-2004 includes 12 to 16 currencies. Thus, we divide those into three portfolios. Table 8 shows the sensitivities of those portfolios to *Media tone*$^{\perp}$.

Insert Table 8 here

As expected, the portfolio formed using only freely floating currencies has a significant coefficient. Similarly, the results for managed floating currencies are also in line with the expectations, as they are mostly significant and similar to Table 6, with sensitivity increasing along with the level of interest rate difference. For fixed currencies, we find no significant effects.

4.6 Robustness check of causal relation

Cautious readers might raise a possibility of reverse causality or omitted bias. That is, it is possible that editors might present positive news about the USD after it appreciates. In fact, Table 2 Panel A shows that USD returns contemporaneously increase with *Media tone*$^{\perp}$. We alleviate this concern by orthogonalizing our measure with all variables presented in that table. However, this might not entirely eliminate this concern; thus, we perform a few robustness checks. First, if a causal relation between *Media tone*$^{\perp}$ and currency returns is mechanical, the relation should not persist once we expand the window of *Media tone*$^{\perp}$ and currency returns measured. Table 3 shows that *Media tone*$^{\perp}$ can predict currency returns up to one to three months ahead and one to six months ahead. In unreported results, we examine the predictability of *Media tone*$^{\perp}$ for non-overlapping month $t + i$ returns and find it can predict returns in month t (contemporaneous) and the next one-, two-, and three-month returns at the 1% level and in the fifth month at the 10% significance level. We do not observe predictability in the fourth month. This result is consistent for value- and equal-weighted returns and for filtered and unfiltered *Media tone*. Thus, these results show that the causal relation between *Media tone*$^{\perp}$ and currency returns does not seem to be mechanical.

5. What are the channels through which *Media tone* predicts returns?

So far, we have shown that *Media tone*$^{\perp}$ predicts future exchange rate movements in both time series and cross-sectional dimensions. In this section, we examine the mechanisms behind the results. We examine four possible channels through which *Media tone*$^{\perp}$ could impact currency excess returns. As several previous studies have used text-based measures as sentiment variables (more or less validating them), our first channel is sentiment. It is also partly related to our second channel, forecasts and especially forecast error, as a sentiment-related shock should drive the expectations of the future away from their fundamental level. The third possible mechanism is investor attention, which relies on the assumption that positive or negative news leads investors to seek more information. The last possible channel is related to financial market uncertainty, which has been found to be a significant determinant of currency excess returns (see Section 1).

5.1 Sentiment

When considering the mechanism behind the effect of *Media tone*$^{\perp}$ on exchange rate returns, one obvious candidate is market sentiment (i.e., behavior-related mistakes investors make regarding the value of the asset). These effects should stem from two sources: the speculative demand by uninformed investors or the general pessimism or optimism about the specific asset.

There are two main characteristics related to sentiment-induced mispricings. First, sentiment theory assumes that harder to value and harder to arbitrage assets should be more subject to sentiment. Second, the effects of sentiment should be mean reverting (i.e., the impact is temporary). The general idea behind this is that a sentiment shock drives the prices away from their fundamental value for a short period of time, but eventually the effects should disappear and the prices should return to their correct level. Baker and Wurgler (2006) suggest ten stock characteristics that are hard to value, but there is no study specifying those characteristics for currencies. In addition, there is no study stating whether the reversion should be immediate or occur during the subsequent days. It might take several months or longer. For example, Calomiris and Mamaysky (2019) concentrate on a 12-month horizon, and, in general, most studies on sentiment utilize monthly data (e.g., Brown and Cliff (2004), Baker and Wurgler (2006), Schmeling (2009) and Huang et al. (2015)).

Our results from the previous sections support *Media tone*$^{\perp}$ as a measure of sentiment. First, the portfolio results in Tables 5, 6, 7, and 8 show that currencies that could be understood as harder to value (more volatile, lower credit ratings, higher political risk, higher inflation, past interest rates and floating exchange rate) or harder to arbitrage (smaller turnover, emerging country currencies)

assets seem to be more sensitive to *Media tone*$^{\perp}$. Second, sentiment should be related to expectations and especially to general optimism and expectations, which we test in Table 10. However, we do not observe a reversal of returns, which should occur if the effects of *Media tone*$^{\perp}$ are related to sentiment. In Table 3, we test for several return periods, but we do not observe any reversal. Thus, the effect of *Media tone*$^{\perp}$ seems to be more persistent than what is assumed by sentiment theory.

There are four potential reasons for the absence of reversal. First, the news-based *Media tone*$^{\perp}$ measure might be dominated by fundamental information that diffuses slowly to the currency value. The measure might capture aspects of news that are not understood when the articles are published but whose relevance increases over time (Calomiris and Mamaysky, 2019). Second, the reversal might be conditional and time varying (i.e., it could be observed for some interval for some time period but not during others). Third, as Soo (2018) argues for the housing market, the lack of reversal could be due to the transaction process and frictions (e.g., the lack of short-term liquidity). However, this explanation is unlikely because the currency market has higher liquidity and thus smaller frictions than the housing market. Fourth, it has been found that sentiment has momentum and tends to last for a while (Hillert et al., 2014). Thus, the reversal might not occur for the return periods we are studying.

To examine the issue further, we also study whether the traditionally used sentiment measure of Baker and Wurgler (2006) (BW) is able to explain and predict the currency results in our framework. The BW sentiment measure is probably the most commonly applied sentiment index and is constructed by extracting sentiment from five sentiment proxies with principal component analysis.[20] The BW measure and its derivatives are widely used and have been found to be related to stock returns (e.g., Baker and Wurgler (2006, 2007); Yu and Yuan (2011); Baker et al. (2012); Stambaugh et al. (2012); and Huang et al. (2015)), commodity returns (Gao and Süss, 2015), and carry trade returns (Yu, 2013). However, the BW measure has not been developed for currency market; rather, it aims to capture more general financial market investor sentiment. Hence, it provides a natural comparison to *Media tone*$^{\perp}$.

[20] The five sentiment proxies are: value-weighted dividend premium; first-day returns of IPOs; IPO volume; closed-end fund discount; and equity share in new issues. Earlier versions also included NYSE turnover, but this has been dropped due to changes in the trading environment (increase in high-frequency trading and migration of trading to various venues).

We perform the channel testing in three steps. First, we show a contemporaneous relation of *Media tone*$^{\perp}$ and a possible channel. A channel candidate should have a contemporaneous relation with *Media tone*. Second, a potential channel candidate should predict currency excess returns. Finally, a channel should subsume the predictability of *Media tone*$^{\perp}$ when it is included in the same regression as *Media tone*$^{\perp}$. Our testing procedure is in line with that described by Jiang et al. (2018). To illustrate, Table 9 Panel A tests the contemporaneous relation between *Media tone*$^{\perp}$ and BW by performing the following regressions:

$$BW_t = \alpha + \beta * MediaTone_t^{\perp},$$

where BW_t is the orthogonalized Baker–Wurgler sentiment measure, and $MediaTone_t^{\perp}$ is the filtered USD-related *Media tone*. Panel B shows the predictability of BW on currency excess returns by regressing the broad USD index returns with BW using a model:

$$FXRet_{t+i} = \alpha + \beta * BW_t.$$

Consistent with the findings of Yu (2013), BW can predict carry trade returns during t+1, t+3, and the cumulative returns up to the next three months. Our results also show that BW sentiment is able to predict currency returns, but the R^2s are substantially smaller than that of *Media tone*$^{\perp}$ in Table 3 for the next three months and R^2_{OOS}s of BW are insignificant. In unreported results, we also perform Table 6 using BW. Although the results are rather similar to *Media tone*$^{\perp}$ for volatility-based currency portfolios, BW does not show significant results for high interest rate differential currencies. On the contrary, for BW, low interest rate portfolios have significant coefficients. This finding is surprising because it contradicts the results of Yu (2013).[21]

To compare the impact of *Media tone*$^{\perp}$ and the BW measure on currency excess returns, we include them in the same model and estimate the results in Panel C.

$$FXRet_{t+i} = \alpha + \beta MediaTone_t^{\perp} + \gamma BW_t.$$

[21] Yu (2013) also uses surveys on expected business conditions as proxies of sentiment. Hence, we also use the US consumer confidence index in our estimations, but, since it does not show any significant results, we do not report them.

The results show that *Media tone*$^{\perp}$ and BW sentiment capture distinct information, as both are significant, and their coefficients remain almost the same as those in Table 3. Only the significance levels and R^2s change. Overall, the results suggest that *Media tone*$^{\perp}$ does not measure a general market sentiment. The sentiments of the stock market and the USD market are segmented, and thus BW sentiment does not seem to be a mechanism behind our results.

Insert Table 9 here

5.2 Forecast error

Investor expectations regarding an asset's future value are a key determinant of the prices. Optimistic investors drive prices up while general pessimism lowers them. Every month, banks receive a questionnaire from Refinitiv asking them to submit their forecasts on currency values.[22] No FX retail brokers or money transfer companies are asked to provide forecasts. We examine the forecast error of these analyst forecasts, which is defined as ln $E_t[S_{t+1}]$ - ln S_{t+1}, where $i = 1, 3, 6,$ and 12.

Table 10, Panel A reports the estimation results related to the relationship between the USD-related forecast errors and the USD *Media tone*$^{\perp}$. USD *Forecast Error* is formed as a cross-sectional average expectation error of forecasts of the USD against the euro, Japanese Yen, and British pound.[23] For the predictive regression of USD returns for t and t+1, we use one-month forecasts. We use the three-month forecasts for return periods (t+3) and (t+1 to t+3), the six-month forecast for periods (t+6) and (t+4 to t+6), and the 12-month forecast for periods (t+12) and (t+7 to t+12). The data are taken from 1/1999 to 12/2016. Positive values of *Forecast Errors* indicate more optimistic views on the development of the USD exchange rate.

To study the relationship between the variables, we perform three regressions as we do for BW. Panel A Table 10 suggests that analyst *Forecast Errors* and *Media tone*$^{\perp}$ are significantly and negatively related for $t = 1, 3$ and 6, suggesting that analysts hold contrarian views regarding the media. Although the relationship is clear, the direction of effect cannot be seen. That is, either analysts are affected by the articles in the media or the media follows the recommendations of the analysts. However, the sign of the relationship is unintuitive. According to the result, analysts are contrarians and assume a lower expectation of USD when *Media tone*$^{\perp}$ is higher and vice versa.

[22] Our sample uses about 50 forecasts per currency per month.
[23] These are the only currencies for which Refinitiv provides longer samples.

In Panel B, we regress the broad USD index returns with analysts' *Forecast Errors*. Interestingly, *Forecast Errors* are highly significant in all periods for both cumulative and sub periods with large adjusted R^2 values. Panels A and B show that *Media tone*$^{\perp}$ is related to *Forecast Errors,* which by themselves predict returns. Hence, *Media tone*$^{\perp}$ might affect future returns through excess optimism. We test this idea in Panel C, which includes both *Forecast Errors* and *Media tone*$^{\perp}$ in the same regression. The results indicate that when USD *Forecast Errors* is added as an explanatory variable, *Media tone*$^{\perp}$ is no longer significant. *Forecast Errors*, on the other hand, are negative and significant at the 1% level in all periods. The results are consistent for both TW and EW returns; thus, we can conclude that *Forecast Errors* is a channel through which *Media tone*$^{\perp}$ predicts currency returns.

Insert Table 10 here

5.3 Attention

The tone of news and social media about the USD might inspire investors to pay more attention to the USD value and search more for news regarding the USD. Da et al. (2011) quantify investor attention using search frequency in Google. They argue that their measure captures retail investors' attention and predicts stock prices for the next two weeks. In a perfect setting, we would like to have a measure of institutional investors' attention. For stocks, Ben-Raphael et al. (2017) measure abnormal institutional investors' attention from using news searching and news reading activity for specific stocks on Bloomberg terminals, but to the best of our knowledge, there is not one for currency.

To be consistent with *Media tone*$^{\perp}$, we utilize the number of media mentions (Buzz) generated by the TRMI. Similarly to previous sub-sections, we examine whether the predictability of *Media tone*$^{\perp}$ is through attention in the three steps. First, Table 11 shows that *Media tone*$^{\perp}$ is surprisingly not related to investor attention. Second, we find that investor attention does not predict currency excess returns. We proceed with the last step by including both *Media tone*$^{\perp}$ and *Attention* simultaneously. We find that *Media tone*$^{\perp}$ is positive and significant in contemporaneous month and month t+1 whereas *Attention* is not significant. We thus conclude *Attention* is not a channel through which *Media tone*$^{\perp}$ predicts currency excess returns.[24]

[24] When we use Google Search volume using "US dollar" term, there is no results either.

Insert Table 11 here

5.4 Uncertainty

As previous studies have found (see Section 1 and Table 2), *Uncertainty*, measured as a consumption risk, volatility, or rare disaster, plays a significant role as a determinant of currency excess returns. That is, investors should require higher returns of currency from bearing high uncertainty. For our final mechanism, we examine whether the predictability of *Media tone*$^{\perp}$ is attributed to increased financial market uncertainty. As a measure of financial market uncertainty, we use the VIX market volatility index. Table 12 lists three steps in a similar fashion as the previous three mechanisms. First, we find that uncertainty is not related to *Media tone*$^{\perp}$. This is not surprising because, unlike Table 2, Table 12 presents *Media tone*$^{\perp}$ with volatility filtered out. In Panel B, *Uncertainty* is weakly associated with the contemporaneous returns and decreases future returns slightly during the (t+1 - t+3) and (t+4 - t+6) windows. Once we include *Media tone*$^{\perp}$ and *Uncertainty* together, *Media tone*$^{\perp}$ is still significantly associated with contemporaneous returns and predicts currency excess returns during the (t+1,t+3) window. *Uncertainty* is still negative and weakly significant. Its significance and magnitude in Panel C is similar to those in Panel B, thus it is unlikely that *Uncertainty* is a channel of *Media tone*$^{\perp}$.[25]

Insert Table 12 here

5.5 *Divergence of opinion*

Our main results show after orthogonalizing the *Media tone* by macroeconomic fundamentals and currency factors, there exists a significant positive association between the positive tone in the media and currency returns. If such an association is causal, we should observe the association getting stronger during the periods when investors or analysts have disagreement in term of USD. During the times of the greatest divergence of opinion, investors should rely more on the media and thus *Media tone* should have stronger predictive power. We compute the standard deviation of the forecasts from various analysts provided in the Thomson Reuters FX Poll. We scale each of the standard deviations by the current forecast to adjust the scale. The results are random and not consistently strong, and thus it appears unlikely that divergence of opinion is a mechanism of

[25] We also examined the results for raw *Media tone*. Although the contemporaneous relationship between *Media tone* and uncertainty measures is negative and significant, when included in the same models, *Media tone* remains a significant predictor of currency returns while uncertainty does not predict returns.

media tone. Another possibility is that higher variation in *Media tone*$^{\perp}$ could induce uncertainty in forecasts. We also test this possibility, but the results indicate that divergence of *Media tone*$^{\perp}$ is not a mechanism underlying a causal relation between the tone and the returns. To save space, we do not report the results here, but they are available upon request from the authors.

6. Which aspects of *Media tone* predict the returns?

We have shown that the predictive power of *Media tone*$^{\perp}$ is based on analysts' *Forecast Errors*, which we estimate from analysts' forecasts provided by the Refinitiv. Our *Media tone*$^{\perp}$ is defined as overall positive references from TRMI from both news and social media. Another question is whether the predictive power of *Media tone*$^{\perp}$ is driven by the traditional news or social media component. Most papers present sentiment from news (to name a few, Tetlock (2007), Garcia (2013), Calomiris and Mamaysky (2019)). Meanwhile, only a few papers present sentiment from social media. TRMI provides the same measure of *Media tone* for both components, allowing us to test each component separately.[26] We orthogonalize and standardize them in a similar way as we do for *Media tone*. Table 13 shows the results for *News_Media tone*$^{\perp}$ and *Social media_Media tone*$^{\perp}$, which can be compared to Table 3 Panel A. The results indicate that the impact of *Media tone*$^{\perp}$ is driven by news more than social media, as the significance and magnitude of the coefficients are similar between *Media tone*$^{\perp}$ and *News_Media tone*$^{\perp}$. This is not surprising, as the amount of USD-related references is substantially higher for traditional news than for social media.[27] Notably, the impact of social media is in fact more pronounced than that of news, and the coefficient is larger and significant until t+4 to t+6 for both the TW and EW indices. The significance of *Social media_Media tone*$^{\perp}$ also applies to the OOS results of the (t+7 to t+12) returns. This might be related to the social media's characteristic of distributing the most important and influential news articles.

Insert Table 13 here

We posit that social media works as an echo chamber that amplifies the *Media tone*$^{\perp}$ from the most influential (predictive) news. Further, this might happen over a longer period of time since people share the news or columns only after some period, which increases the duration of the impact of

[26] As Appendix 2 explains, different text analytical models are used for different sources, and hence the lexicon used for social media sources differs partially from the one used for more traditional news.

[27] For the combined *Media tone*, the monthly average of daily references to the USD is 5096. For traditional news, the figure is 4501, and for social media it is 594.

social media. TRMI captures only the first time the news/column is written, and ignores the future when it is shared. Testing of this hypothesis is left for future research.

For consistency, we also examine text-based determinants of *Media tone*$^{\perp}$ that match the determinants in Table 2 Panel A. TRMI provides scores of various aspects of *Media tone*$^{\perp}$ using their own proprietary algorithm and lexicons. These partly overlapping constituents are filtered and standardized in a similar vein as *Media tone*$^{\perp}$. Although these constituents do not capture all the aspects TRMI considers when computing *Media tone*$^{\perp}$, the results in Table 12 allow us to understand which attributes explains *Media tone*$^{\perp}$ predictability. We find that *Optimism*$^{\perp}$ and *Price Forecast*$^{\perp}$ predict currency excess returns during t+1 to t+3, while *Price Direction*$^{\perp}$ predicts currency returns contemporaneously. Interestingly, *Uncertainty*$^{\perp}$ does not predict currency returns while *Volatility*$^{\perp}$, which captures volatility in market prices and business conditions, predicts currency returns during t+7 to t+12.[28] As *Media tone*$^{\perp}$ has predictive power up to t+3, we attribute its predictability to *Price Forecast*$^{\perp}$/*Expectation*$^{\perp}$ rather than to risk, consistent with Table 10.

7. Which media has a predictive tone?

Since the currency market is populated by sophisticated investors, we attempt to understand whether the predictability of *Media tone* is based on the media sources that most institutional investors access, such as the *Financial Times* (*FT*), *Wall Street Journal (WSJ;* Tetlock, 2007), *New York Times* (*NYT*; see Garcia 2013), *Bloomberg* (Ben-Raphael et al., 2017), and *the Economist* (Obaid and Pukthuanthong, 2020), as well as those targeting noise traders, such as *Seeking Alpha*, *StockTwits* (Cookson and Niessner, 2020), and *Twitter* (Azar and Lo, 2016). Table 14 Panel A presents the Media Tone and results of mainstream media from the full sample period of 1998–2016. When we use raw *Media tone*, the tone from *FT* and *Seeking Alpha* can predict currency returns up to six months ahead. Interestingly, we find a return reversal for *NYT* similar to the stock return reversal studied by Tetlock (2007) and Garcia (2013). This implies that the market reacts positively to the tone of *NYT* contemporaneously, and then the reaction reverts in the next month. Note that, in our main results in Table 3, we cannot detect any reversal throughout the first year. We next orthogonalize our tone in the same way as we do for other analyses and present the results in Panel B. The predictive power of the *FT* tone disappears during the first month but still exists during

[28] The definitions of *Volatility* and *Uncertainty* are murky. According to the TRMI, *Volatility* captures terms like the ones in Appendix 3, which generally refer to actions or events and events that are dramatic. *Uncertainty* relates to a lack of clarity, doubts, etc.

t+1 to t+3. Importantly, the predictability of the *Seeking Alpha* and *StockTwits* tones disappears almost completely, thereby suggesting that the *Media tone*$^{\perp}$ of these two sources is composed of fundamentals, which is surprising. For *NYT*, the tone is positively related to contemporaneous returns, although the coefficient is not significant. The market reverts with a larger and significant magnitude. The same pattern is applied for the *Economist* tone, and the returns become negative and significant at t+1. Surprisingly, the *Twitter* tone is also associated with negative returns in t+1 and t+1 to t+3, but then the returns become positive and significant during t+4 to t+6 and t+7 to t+12. We conjecture that once there is any positive tone from *Twitter*, all investors will trade based on that information, and this causes a negative reaction during t+1 to t+3. Then, the market positively reacts to that information again. Since most social media did not gain popularity until late 2000, we perform similar analyses during the sample period of 2007 to 2016.[29] For all media except for the *Economist*, the market reacts positively contemporaneously to *Media tone*$^{\perp}$, but the reaction is not significant. There is a reversal in t+17 to t+12 for *WSJ* and t+1 for *NYT* similar to what we observe from the full sample. For the *Economist,* we find that a positive tone negatively predicts currency returns in the next month. We could not detect any predictive power from the *Media tone*$^{\perp}$ of *Seeking Alpha* and *StockTwits*, which is in contrast to their power when it is unorthogonalized, especially for *Seeking Alpha*. The results from 2007 to 2016 confirm that the tone of these social media sources seems to be mainly driven by fundamentals. *Twitter* portrays the same pattern, with negative predictive power during t+1 to t+3 but positive power during t+4 to t+12.

Insert Table 14 here

Our analysis from mainstream sources for institutional investors suggests a return reversal of *Media tone*$^{\perp}$ predictability, which supports a rational explanation, whereas the tone from sources like *Twitter* has a predictive power that is hard to explain rationally. There is the limitation of testing individual sources, as there are no news about USD for every month. Thus, the data for some courses are sparse and statistical power might be low. We then aggregate the tone of major media and test. We do the same for non-major media. The tone of all major sources combined does not present the results (unreported).[30] The major sources including media and social media are those reported in the second to eleven columns. However, after aggregating nonmainstream sources

[29] Due to limited space, we do not report the results here, but they are available upon request.

shown in the last column of Table 14, the results emerge, thereby suggesting our main results shown in the first column, which show no sign of reversal, seem to be driven by the nonmainstream media sources in aggregate.

7. **Trading strategy**

Investors can apply our results and develop a trading strategy accordingly. A simple trading strategy is to invest in USD at the beginning of month t+1 for one to six months (based on our results in Table 3 and Appendix 4, showing that *Media tone*$^{\perp}$ and *Media tone* are significant up to t+6) if *Media tone*$^{\perp}$ at the end of month t. is greater than zero. Otherwise, we invest in three-month T-bills. To illustrate, we choose the top two Exchange Traded Funds (ETFs) of the USD (UUP and UDN). UUP is the Invesco DB USD Bullish fund, which has a long USD and short global basket. Figure 3 presents the total amount of investment of $1 starting from the inception of these two ETFs in January 2007 until December 2016, the end of our sample period. We present the profits of the t+1 and t+3 holding strategies, as they are the intermediate terms between t and t+6 when *Media tone* and *Media tone*$^{\perp}$ are significant. We apply both *Media Tone* and *Media Tone*$^{\perp}$. Although our main results are based on *Media Tone*$^{\perp}$, we also present the trading strategy based on *Media Tone* because it is more practical for investors to use. Table 15 shows that the results from *Media Tone* and *Media Tone*$^{\perp}$ are qualitatively similar, although the returns from *Media Tone*$^{\perp}$ are weaker, which is not surprising since *Media Tone*$^{\perp}$ filters out all possible macroeconomic variables. We find returns of 23% for the one-month strategy and 44.38% for the three-month strategy, which encompasses the return of holding UUP (2.20%) and T-bills (6%). To examine whether our strategy is robust, we also do the opposite, which is to buy T-bills in month t+1 if *Media tone* in month t is positive, and buy USD ETFs if it is negative. The holding period of the ETF can be one to six months. Similar to above, we show the strategy based on one- and three-month holding. Note that we reinvest every month using geometric average returns, as we assume that ETFs are liquid enough for investors to enter and exit at any time. The returns on investment of the opposite strategy are lower for both one and three months (-11.91% and 34.70%, respectively) than for the strategy in which ETF is purchased when *Media tone* is positive. Further, we apply UDN, which is the opposite of UUP. UDN is a product of the same company as UPN, thereby allowing us to make a reasonable comparison. UDN is the Invesco DB USD Bearish fund, which longs the global basket and shorts the USD. We expect the result from UDN to be opposite of that for UUP. Investors will obtain a higher return (or less negative returns) if they utilize the opposite strategy (i.e., buying UDN when *Media tone* is negative and T-bills otherwise.) By buying UDN when *Media tone* is positive, the returns are -15.72% for the one-month investment and -30.57% for the three-month

investment. The opposite strategy yields -1.58% for one month and -28.09% for three months. This section illustrates that investors can construct a trading strategy based on our results.[31]

Insert Table 15 here

8. Transaction costs and robustness of the results

In this section, we provide a robustness check of whether our results are sensitive to transaction costs, although it is known that transaction costs in the currency market are low. We apply currency excess returns provided by Professor Adrian Verdelhan, who generously makes the data used in Lustig et al. (2011) available on his website. Professor Verdelhan's data are suitable for robustness checks for a number of reasons: the currency set he used to form portfolios differs slightly from our set, currencies are sorted to portfolios based on interest rate differences similar to what we do, the number of portfolios is slightly different from that of our set (six for all currencies, five for developed country currencies),[32] net and gross excess returns are available (i.e., excess returns with and without bid-ask spreads), and returns have not been winsorized. Table 16 shows that there is no difference in the *Media tone* predictability of net and gross excess returns across all countries and developed markets, either with raw or *Media tone*$^{\perp}$. From the results, we can conclude that transaction costs have no material impact on the predictability of *Media tone*$^{\perp}$.

Insert Table 16 here

9. Conclusions

The foreign exchange market is regarded as one of the most efficient markets. It is highly liquid, open 24 hours a day globally, and populated by institutional investors. Although the currency market presents a challenging context for return prediction, previous studies report several foreign exchange-related anomalies. In particular, the failure of uncovered interest rate parity is well documented in the literature. As a result, the carry trade strategy has gained increasing interest in the industry and among academics.

This study provides novel evidence regarding the impacts of USD-related media content, *Media tone*, on exchange rate excess returns using 74 currencies against the USD. We find *Media tone* to be both a statistically and economically significant predictor of in-sample and out-of-sample

[31] We attempt the third largest ETF for US dollar, USDU (WisdomTree Bloomberg US Dollar Bullish), and we get the same conclusion as with UPN. We do not report the results here since USDU inception is not until December 2013. We hesitate to draw any conclusion from USDU because it has an overly short data period.

[32] Unfortunately, the data are not available for emerging market currency portfolios separately.

currency returns. The effects last for three months and are more significant for currencies that are freely floating and those with higher interest rates, inflation, volatility, and political risks as well as those with lower turnover and credit ratings and from emerging countries. The results are robust to the inclusion of bid–ask spreads, slightly different currency sets, and the number of portfolios. No consistent results can be found for momentum portfolios formed based on different return windows. We also find that currency-specific *Media tones* predict the following period's returns for the other four developed and 18 emerging market currencies.

Although the effects of *Media tone* unrelated to common currency factors are larger for currencies that are assumed to be harder to value and costlier to arbitrage, we do not observe a reversal of returns during the first 12 months. Hence, we are not able to show that *Media tone* captures sentiment, although we cannot completely reject the hypothesis that it does.

We further examine the mechanisms behind the impact of *Media tone* and find expectations (forecast error) to be the strongest candidate. Our *Media tone* captures different information than is included in the widely used Baker–Wurgler market sentiment index, and its effects are not channeled through financial market uncertainty.

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References

Akram, Q., Rime, D., Sarno, L., 2008. Arbitrage in the foreign exchange market: Turning on the microscope. Journal of International Economics 76, 237-253.

Almeida, A., Goodhart, C., Payne, R., 1998. The effects of macroeconomic news on high frequency exchange rate behavior. Journal of Financial and Quantitative Analysis 33, 383-408.

Aloosh, A., Bekaert, G. 2019. Currency factors. Unpublished working paper, Columbia University.

Antweiler, W., Frank, M.Z., 2004. Is all that talk just noise? The information content of internet stock message boards. Journal of Finance 59, 1259-1294.

Andersen, T., Bollerslev, T., Diebold, F.D., Vega, C., 2003. Micro effects of macro announcements: Real-time price discovery in foreign exchange. American Economic Review 93, 38-62.

Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259-299.

Asness, C.S., Moskowitz, T.J., Pedersen, L.H., 2013. Value and momentum everywhere. Journal of Finance 68, 929-985.

Atanasov, V., Møller, S.V., Priestley, R., 2019. Consumption fluctuations and expected returns. Forthcoming Journal of Finance.

Azar, P., Lo, A.W., 2016. The wisdom of Twitter crowds: Predicting stock market reactions to FOMC meetings via Twitter feeds. Journal of Portfolio Management 42, 123-134.

Bacchetta, P., van Wincoop, E., 2004. A scapegoat model of exchange-rate fluctuations. American Economic Review 94, 114-118.

Bacchetta, P., van Wincoop, E., 2006. Can information heterogeneity explain the exchange rate determination puzzle? American Economic Review 96, 552-576.

Bacchetta, P., van Wincoop, E., 2013. On the unstable relationship between exchange rates and macroeconomic fundamentals. Journal of International Economics 91, 18-26.

Baker, S.R., Bloom, N., Davis, J.S., 2016. Measuring economic policy uncertainty. The Quarterly Journal of Economics 131, 1543-1636.

Baker, D., Bloom, N., Davis, J.S., Kost, K., 2019. Policy news and stock market volatility. Unpublished working paper, University of Chicago.

Baker, M., Wurgler, J., 2006. Investment sentiments and the cross-section of stock returns. Journal of Finance 61, 1645-1680.

Baker, M., Wurgler, J., 2007. Investor sentiments in the stock market. Journal of Economic Perspectives 21, 129-152.

Baker, M., Wurgler, J., Yuan, Y. 2012. Global, local and contagious investment sentiments. Journal of Financial Economics 104, 271-287.

Baloria, V.P., Heese, J., 2018. The effects of media slant of firm behavior. Journal of Financial Economics 129, 184-202.

Bansal, R., Dahlquist, M., 2000. The forward premium puzzle: different tales from developed and emerging economies. Journal of International Economics 51, 115-144.

Bartram, S.M., Djuranovik, L., Garratt, A., 2019. Currency anomalies. Working paper, available at SSRN: https://ssrn.com/abstract=3194107

Ben-Rephael, A., Da, Z., Israelsen, R.D., 2017. It depends on where you search: Institutional investor attention and underreaction to news. The Review of Financial Studies 30, 3009-3047.

Ben-Rephael, Kandel S., Wohl A., 2012. Measuring investor sentiment with mutual fund flows. Journal of Financial Economics 104, 363-382.

Berg, K.A., Mark, N.C., 2018. Measures of global uncertainty and carry-trade excess returns. Journal of International Money and Finance 88, 212-227.

Bhattacharya, U., Galpin, N., Ray, R., Yu, X., 2009. The Role of the media in the Internet IPO bubble. Journal of Financial and Quantitative Analysis 44, 657-682.

Bilson, J., 1981. The "speculative efficiency" hypothesis. The Journal of Business 54, 435-451.

Bork, L., Møller, S., Pedersen, T., 2019. A new index of housing sentiment. Forthcoming Management Science.

Brown, G., Cliff, M., 2004. Investor sentiment and the near-term stock market. Journal of Empirical Finance 11, 1-27.

Brunnermeier, M.K., Nagel, S., Pedersen, L.H., 2009. Carry trades and currency crashes. NBER Macroeconomics Annual 2008, 313-347.

Burnside, C., Eichenbaum, M., Kleshechelski, I., Rebelo, S., 2011. Do peso problems explain the returns to the carry trade? Review of Financial Studies 24, 859-891.

Burnside, C., Eichenbaum, M., Rebelo, S., 2009. Understanding the forward foreign premium puzzle: A microeconomic approach. American Economic Journal: Macroeconomics 1, 127-154.

Burnside, C., Eichenbaum, M., Rebelo, S., 2011. Carry trade and momentum in currency markets Annual Review of Financial Economics 3, 511-535.

Calomiris, C.W., Mamaysky, H., 2019. How news and its contents drive risk and returns around the world, Journal of Financial Economics 133, 299-336.

Cenedese, G., Sarno, L., Tsiakas, I., 2014. Foreign exchange risk and the predictability of carry trade returns, Journal of Banking and Finance 42, 302-313.

Chen, H., De, P., Hu, Y., Hwang, B-H., 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. Review of Financial Studies 27, 1367-1403.

Cheung, Y.-W., Chinn, M.D., 2001. Currency traders and exchange rate dynamics: a survey of the US market, Journal of International Money and Finance 20, 439-471.

Chong, Y.Y., Hendry, D.F., 1986. Econometric Evaluation of Linear Macro-Economic Models. Review of Economic Studies 53, 671-690.

Christiansen, C.A., Ranaldo, A., Söderlind, P., 2011. The time-varying systematic risk carry trade strategies. Journal of Financial and Quantitative Analysis 4, 1107-1125.

Clark, T., West, K., 2007. Approximately normal test for equal predictive accuracy in nested models. Journal of Econometrics 138, 291-311.

Cookson, J.A., Niessner, M., 2020. Why don't we agree? Evidence from a social network of investors. Forthcoming Journal of Finance.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. Journal of Finance 66, 1461-1499.

Da, Z., Engelberg, J., Gao, P., 2015. The sum of all fears: Investor sentiment and asset prices. Review of Financial Studies 28, 1-32.

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

Dougal, C., Engelberg, J., García, D., Parsons, C.A., 2012. Journalists and the stock market. Review of Financial Studies 25, 639-679.

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

Evans, M.D.D., Lyons, R.K., 2002. Order flow and exchange rate dynamics. Journal of Political Economy 110, 170-180.

Fama, E.F., 1984. Forward and spot exchange rates. Journal of Monetary Economics 14, 319-338.

Farhi, E., Gabaix, X., 2016. Rare disasters and exchange rates. Quarterly Journal of Economics 131, 1-52.

Frankel, J.A., Froot, K.A., 1987. Using survey data to test standard propositions regarding exchange rate expectations. The American Economic Review 77, 133-153.

Frankel, J.A., Froot, K.A., 1990. Chartists, fundamentalists, and trading in the foreign exchange market. American Economic Review, 80, 181-185.

Fratzscher, M., Rime, S., Sarno L., Zinna, G., 2015. The scapegoat theory of exchange rates: the first tests. Journal of Monetary Economics 70, 1-21.

Gao, L., Süss, S., 2015. Market sentiment in commodity futures returns. Journal of Empirical Finance 33, 84-103.

Garcia, D., 2013. Sentiment during recessions. Journal of Finance 68, 1267-1300.

Glasserman, P., Mamaysky, H., 2019. Does unusual news forecast market stress? Journal of Financial and Quantitative Analysis 54, 1937-1974.

Gurun, U.G., Butler, A.W., 2012. Don't believe the hype: Local media slant, local advertising, and firm value. Journal of Finance 67, 561-597.

Hansen, L.P., Hodrick, R.J., 1983. Risk averse speculation in the forward foreign exchange market: An econometric evaluation of linear models, in Jeffrey Frankel, ed. Exchange Rates and International Macroeconomics, University of Chicago Press.

Hillert, A., Jacobs, H., Müller, S., 2014. Media makes momentum. Review of Financial Studies 27, 3467-3501.

Hillert, A., Jacobs, H., Müller, S., 2018. Journalist disagreement. Journal of Financial Markets 41, 57-76.

Huang, D., Fuwei, J., Tu, J., Zhou, G., 2015. Investor sentiment aligned: A powerful predictor of stock returns. Review of Financial Studies 28, 791-837.

Ilzetzki, E., Reinhart, C., Rogoff, K.S., 2017. The country chronologies to exchange rate arrangements into the 21st century: Will the anchor currency hold?, NBER Working Papers 23135.

Ismailov, A., Rossi, B., 2018. Uncertainty and deviations from uncovered interest rate parity. Journal of International Money and Finance 88, 242-259.

Jegadeesh, N., Wu, D., 2013. Word power: A new approach for content analysis. Journal of Financial Economics 110, 712-729.

Jiang, F., Lee, J., Martin, X., Zhou, G., 2019. Manager sentiment and stock returns. Journal of Financial Economics 132, 126-149.

Jordá, Ó., Taylor, A. M., 2012. The carry trade and fundamentals: Nothing to fear but FEER itself. Journal of International Economics 88, 74-90.

Korajczyk, R.A., 1985. The pricing of forward contracts for foreign exchange. Journal of Political Economy 93, 346-368.

Kumar, A., Lee, C.M., 2006. Retail investor sentiment and return comovements. Journal of Finance 61, 2451–2486.

Lettau, M., Maggiori, M., Weber, M., 2014. Conditional risk premium in currency market and the asset classes. Journal of Financial Economics 114, 147-225.

Levich, R., 1989. Is the foreign exchange market efficient? Oxford Review of Economic Policy 5, 40-60.

Londono, J. M., Zhou, H., 2017. Variance risk premiums and the forward premium puzzle. Journal of Financial Economics 124, 415-440.

Loughran, T., McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. Journal of Finance 66, 35-65.

Loughran, T., McDonald, B., 2016. Textual analysis in accounting and finance: A survey. Journal of Accounting Research 54, 1187-1230.

Lustig H., Verdelhan, A., 2007. The cross section of foreign currency risk premia and consumption growth risk. American Economic Review 97, 89-117.

Lustig, H., Roussanov, N., Verdelhan, A., 2011. Common risk factors in currency markets. Review of Financial Studies 24, 3731-3777.

Mark, N.C., 1995. Exchange rate and fundamentals: Evidence on long-horizon predictability. American Economic Review 85, 201-218.

Mark, N.C., Wu, Y., 1998. Rethinking deviations from uncovered interest parity: The role of covariance risk and noise. The Economic Journal 108, 1686-1706.

Meese R., Rogoff, K., 1983. Empirical exchange rate models of the seventies. Journal of International Economics 14, 3-24.

Menkhoff, L., Rebitzky, R.R., 2008. Investor sentiment in the US-dollar: Long-term, non-linear orientation on PPP. Journal of Empirical Finance 15, 455-457.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012a. Carry trades and global foreign exchange volatility. Journal of Finance 67, 681-718.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012b. Currency momentum strategies. Journal of Financial Economics 106, 660-684.

Moskowitz, T., Ooi, Y.H., Pedersen, L.H., 2012. Times series momentum. Journal of Financial Economics 104, 228-250.

Obaid, K., Pukthuanthong, K., 2020. A picture is worth a thousand words: measuring investor sentiment by combining machine learning and photos from news. Unpublished working paper, University of Missouri.

Peress, J., 2014. The Media and the diffusion of information in financial markets: Evidence from newspaper strikes. Journal of Finance 69, 2007-2043.

Pukthuanthong, K., Levich, R.M., Thomas, L.R., 2007. Do foreign exchange markets still trend? Journal of Portfolio Management 34, 114-118.

Rapach, D.E., Strauss, J.K, Zhou, G., 2013. International stock return predictability: What is the role of the United States? Journal of Finance 68, 1633-1662.

Rossi, B., 2013. Exchange rate predictability. Journal of Economic Literature 51, 1064-1119.

Schmeling, M., 2009. Investor sentiment and stock returns: Some international evidence. Journal of Empirical Finance 16, 394–408.

Shiller R., 2017. Narrative Economics. Cowles Foundation discussion paper no. 2069.

Soo, C. K., 2018. Quantifying sentiment with news media across local housing markets. Review of Financial Studies 31, 3689-3719.

Stambaugh, R.F., Yu, J., Yuan Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104, 288-302.

Tetlock, P.C., 2007. Giving content to investor sentiment: The role of media in the stock market. Journal of Finance 62, 1139–1168.

Tetlock, P.C., Saar-Tsechansky, M., Macskassy, S., 2008. More than words: Quantifying language to measure firm's fundamentals. Journal of Finance 63, 1437-1467.

Veldkamp, L., 2006. Media frenzies in markets for financial information. American Economic Review 96, 577-601.

Verdelhan, A., 2010. A habit-based explanation of the exchange rate risk premium. Journal of Finance 65, 123-145.

Yu, J., 2013. A sentiment based evaluation of the forward premium puzzle. Journal of Monetary Economics 60, 474-491.

Yu, J., Yuan, Y., 2011. Investor sentiments and the mean variance relation. Journal of Financial Economics 100, 367-381.

Wolf, C.C.P., 1987. Forward foreign exchange rates. Expected spot returns, and premium. Journal of Finance 42, 345-406.

Table 1. Descriptive statistics

In Panel A, $MediaTone$ is the text-based TRMI USD *Media tone*, and Filtered $MediaTone$, $MediaTone^{\perp}$, is the same index orthogonalized with respect to the variables included in Specification 3 of Panel B Table 2. Panel B shows excess returns of the broad TW index, the trade-weighted currency index, and the broad EW index to the equal-weighted currency index for the 25 largest trading partners of the US. The portfolios in Panel C refer to the excess returns (in %) of currency portfolios in month t+1 formed based on exchange rate behavior or macroeconomic characteristics in month t. Portfolio 1 (Portfolio 5) refers to currencies with the lowest (highest) values for the characteristic in question. P5–P1 refers to a portfolio formed as a difference between Portfolio 5 and Portfolio 1 returns. Portfolios are formed using all the available currencies and excluding the periods of high inflation. ***, **, and * denote ,1%, 5% and 10% statistical significance levels, respectively. See Appendix 3 for variable descriptions and sources.

Portfolio	Mean	STD	Q1	Median	Q3	Skew	Kurt	Min	Max
Panel A: Media tone									
$MediaTone$	-0.05	0.04	-0.08	-0.06	-0.03	0.06	-0.28	-0.16	0.04
$MediaTone^{\perp}$	0.00	0.03	-0.02	0.00	0.02	-0.04	0.15	-0.09	0.09
Panel B: Currency indices excess returns (%)									
Broad TW index	-0.05	1.62	-0.94	-0.17	0.90	0.31	1.36	-4.80	6.48
Broad EW index	-0.17	1.79	-1.19	-0.27	0.84	0.42	1.78	-5.89	6.82
Panel C: Excess returns of currency portfolios formed in month t from characteristics in month t									
Characteristics:									
C.1 Interest rate difference portfolios									
P1	0.20	1.56	-0.85	0.21	1.30	-0.02	-0.16	-3.67	4.22
P2	0.01	1.45	-0.76	-0.01	0.91	-0.07	0.77	-3.97	4.26
P3	-0.19	1.59	-1.13	-0.27	0.82	0.10	0.28	-4.40	4.25
P4	-0.11	1.78	-1.11	-0.16	1.11	0.19	0.14	-3.89	5.17
P5	-0.90	2.05	-2.30	-0.96	0.46	0.06	0.25	-6.79	6.12
P5-P1	-1.09***	1.74	-2.16	-1.09	0.03	-0.14	0.08	-5.88	3.46
C.2 Inflation portfolios									
P1	-0.17	1.55	-1.10	-0.23	0.87	0.07	0.98	-5.27	5.08
P2	-0.20	1.68	-1.22	-0.19	0.86	0.01	0.17	-4.53	5.21
P3	-0.14	1.75	-1.28	-0.22	0.80	0.29	0.13	-4.19	5.37
P4	-0.20	1.74	-1.32	-0.32	1.05	0.08	-0.17	-5.18	4.52
P5	-0.37	1.82	-1.55	-0.41	0.90	-0.15	0.21	-6.32	4.87
P5-P1	-0.20**	1.47	-1.00	-0.20	0.74	-0.20	1.20	-5.04	4.73
C.3 Currency turnover portfolios									
P1	-0.36	1.84	-1.54	-0.45	0.84	0.04	-0.13	-5.50	4.29
P2	-0.28	1.67	-1.40	-0.39	0.75	0.20	-0.11	-4.21	4.87
P3	-0.12	2.18	-1.51	-0.32	1.57	0.13	-0.32	-5.54	6.02
P4	-0.19	1.92	-1.36	-0.28	1.12	0.22	0.22	-4.39	5.84
P5	0.00	1.82	-1.27	0.02	1.32	-0.17	-0.52	-4.38	3.92
P5-P1	0.36***	1.58	-0.65	0.33	1.23	0.33	0.56	-4.24	4.90
C.4 1-month Momentum portfolios									
P1	-0.54	2.05	-1.77	-0.50	0.72	-0.03	-0.11	-6.04	4.31
P2	-0.17	1.63	-0.93	-0.20	0.77	-0.24	0.73	-5.06	3.77
P3	-0.13	1.46	-0.90	-0.12	0.74	-0.01	0.24	-3.76	4.49
P4	-0.05	1.70	-1.04	-0.11	0.76	0.45	1.00	-4.60	5.13
P5	0.16	2.00	-0.97	0.09	1.23	0.24	0.57	-4.93	6.59
P5-P1	0.70***	2.06	-0.49	0.56	2.01	0.07	0.00	-5.18	6.16
C.5 6-month Momentum portfolios									
P1	-0.62	2.02	-1.93	-0.53	0.34	0.13	0.68	-6.47	5.95
P2	-0.16	1.62	-1.00	-0.12	0.78	-0.08	0.92	-4.79	5.11

P3	-0.09	1.61	-1.10	-0.13	0.86	0.21	0.02	-3.96	4.29
P4	-0.04	1.70	-1.01	-0.12	0.84	0.08	0.54	-4.88	4.63
P5	0.04	2.01	-1.00	0.01	1.30	-0.13	0.34	-5.52	5.27
P5-P1	0.67***	2.13	-0.60	0.75	2.10	-0.27	-0.29	-4.64	6.19
C.6 12-month Momentum portfolios									
P1	-0.62	2.06	-1.70	-0.62	0.30	0.14	0.89	-6.91	5.94
P2	-0.22	1.63	-1.02	-0.27	0.72	-0.01	0.74	-5.07	5.01
P3	-0.08	1.64	-1.06	0.02	1.01	-0.19	0.20	-5.04	4.51
P4	-0.05	1.63	-1.00	-0.13	0.76	0.15	0.59	-4.26	5.55
P5	-0.03	1.99	-1.13	-0.02	1.31	-0.14	0.43	-5.58	5.61
P5-P1	0.59***	2.20	-1.07	0.77	2.21	-0.05	-0.45	-4.65	6.28
C.7 12-month exchange rate volatility portfolios									
P1	-0.07	0.27	-0.17	-0.07	0.05	1.10	10.10	-1.22	1.67
P2	-0.11	1.22	-0.95	-0.14	0.63	0.17	0.78	-4.62	3.50
P3	-0.16	1.96	-1.42	-0.21	1.10	0.05	-0.21	-5.57	4.98
P4	-0.19	2.24	-1.64	-0.02	1.26	-0.08	-0.32	-4.91	5.46
P5	-0.51	2.56	-2.45	-0.55	1.19	0.18	-0.36	-5.80	6.40
P5-P1	-0.44***	2.47	-2.35	-0.38	1.18	0.19	-0.32	-5.79	6.38
C.8 Previous month's exchange rate volatility portfolios									
P1	-0.11	0.22	-0.21	-0.10	0.01	-0.06	1.82	-0.89	0.64
P2	-0.22	1.24	-0.95	-0.25	0.50	-0.03	0.46	-3.95	3.31
P3	-0.21	1.87	-1.29	-0.26	1.07	-0.02	-0.01	-5.20	4.81
P4	-0.16	2.23	-1.66	-0.22	1.42	0.11	-0.43	-4.96	5.04
P5	-0.31	2.54	-2.10	-0.33	1.36	0.10	-0.38	-5.55	6.65
P5-P1	-0.20	2.47	-1.97	-0.12	1.49	0.13	-0.36	-5.33	6.76
C.9 Credit rating portfolios									
P1	-0.68	2.18	-2.26	-0.88	0.85	0.14	-0.34	-5.84	5.46
P2	-0.12	2.00	-1.35	-0.26	1.05	0.25	0.21	-4.87	5.87
P3	-0.16	1.93	-1.44	-0.16	1.16	0.19	0.09	-4.41	5.85
P4	-0.05	1.66	-1.17	0.06	1.08	-0.13	-0.38	-4.59	4.17
P5	-0.02	2.08	-1.29	-0.06	1.38	-0.15	-0.40	-4.87	4.61
P5-P1	0.66***	2.04	-0.58	0.60	1.83	0.36	0.79	-4.57	8.01
C.10 Political risk portfolios									
P1	-0.13	2.14	-1.41	-0.14	1.40	-0.15	-0.37	-4.99	4.52
P2	-0.10	1.73	-1.26	-0.16	1.09	-0.03	-0.55	-4.59	4.10
P3	-0.08	1.58	-1.24	-0.13	1.00	0.16	0.01	-4.49	4.22
P4	-0.18	1.40	-0.98	-0.15	0.59	0.09	0.89	-4.18	4.57
P5	-0.53	1.68	-1.48	-0.56	0.45	-0.12	0.35	-5.70	4.32
P5-P1	-0.41***	-1.94	0.88	-0.45	-1.79	-0.24	-0.54	4.73	-8.00

Table 2. Determinants and predictors of USD *Media tone*

This table present the determinants of USD *Media tone*. Panel A shows the determinants that are related to *Media tone* and the USD. Panel B shows the determinants that are currency factors proposed by the extant literature and business cycle variables. See Appendix 3 for variable descriptions. ***, **, and * denote ,1%, 5% and 10% statistical significance levels, respectively.

Panel A: The determinants of *Media tone*

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: *Media tone*$_t$					
FX_t	0.32***					0.36***
	[6.74]					[3.87]
S&P500Return$_t$		0.36***				0.05***
		[6.29]				[3.89]
US Equity Market Volatility$_t$			-0.22***			-0.11*
			[-4.29]			[-1.70]
VIX$_t$				-0.16***		-0.08
				[-2.96]		[-1.53]
USD Expectation$_t$					-0.39***	-0.16**
					[-8.31]	[-2.02]
Media tone$_{t-1}$	0.59***	0.43***	0.59***	0.59***	0.61***	0.53***
	[12.12]	[7.33]	[11.55]	[11.13]	[13.14]	[11.54]
Adj R^2(%)	49.26	48.13	43.59	41.26	53.78	60.90

Panel B: USD *Media tone*, currency factors and business cycle components

	(1)	(2)	(3)
	Dependent variable: *Media tone*$_t$		
Currency factors:			
Dollar$_t$	0.50***		0.46***
	[6.95]		[7.07]
Carry$_t$	-0.07		-0.01
	[-0.99]		[-0.15]
Momentum$_t$	-0.16**		-0.13*
	[-2.02]		[-1.74]
Volatility$_t$	-0.24***		-0.25***
	[-3.61]		[-3.62]
Value$_t$	0.07		0.04
	[0.91]		[0.49]
Commodity$_t$	-0.09		-0.04
	[-1.16]		[-0.54]
World Equity$_t$	0.27***		0.17**
	[3.42]		[2.37]
Business cycle:			
IndProd$_t$		-0.40***	-0.29***
		[-3.38]	[-2.66]
Durable$_t$		0.10	0.10
		[1.20]	[1.16]
NonDurable$_t$		0.00	-0.08
		[-0.02]	[-0.87]
Services$_t$		0.06	0.14*
		[0.73]	[1.72]
Employment$_t$		0.53***	0.36***
		[5.76]	[4.05]
Recession$_t$		-0.10	0.05
		[-1.10]	[0.57]
Interest rate$_t$		-0.34***	-0.30***
		[-4.45]	[-4.32]
Adj R^2(%)	22.91	22.61	38.64

Table 3. Predicting USD returns using *Media tone*$^{\perp}$

This table reports the coefficient values, corresponding t-values, and R^2s from the regression

$$FX_{(t+k,t+l)} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \varepsilon_{(t+k,t+l)}.$$

In Panel A, $FX_{(t+k,t+l)}$ is the geometric average currency excess return for trade-weighted (left side) and equal-weighted (right side) currency indices for periods t, $(t+1)$, $(t+1, t+3)$, $(t+4, t+6)$, and $(t+7, t+12)$. In Panel B, the dependent variables are the cumulative currency excess returns for periods from $t+1$ to $t+l$, where $l = 3, 6, 9,$ and 12. The broad TW index refers to the trade-weighted currency index, and the broad EW index refers to the equal-weighted currency index for the 25 largest trading partners of the US. $MediaTone_t^{\perp}$ refers to the standardized and filtered TRMI USD *Media tone*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. R^2_{OOS} (%) provides a recursively estimated out-of-sample R^2 and compares the predictability of the *Media tone* variable to the predictability performance of the historical average using Clark and West's (2007) MSFE test. Newey–West standard errors with 12 lags are used to account for heteroscedasticity and autocorrelation. Panel C presents the results of the forecast encompassing test. See Section 3.3 for a methodology description and Appendix 3 for variable descriptions. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively.

Panel A: Average excess returns

	Broad TW Index				Broad EW Index			
FX Return	β_1	t-value	R^2(%)	R^2_{OOS} (%)	β_1	t-value	R^2(%)	R^2_{OOS} (%)
FX(t)	0.29**	2.11	2.76		0.34**	2.15	3.28	
FX(t+1)	0.14	1.36	0.34	1.47**	0.25**	2.11	1.51	2.94**
FX(t+1, t+3)	0.20***	2.79	3.89	7.65*	0.26***	2.96	4.97	10.09**
FX(t+4, t+6)	0.08	0.95	0.21	-0.12	0.14	1.36	1.10	3.67**
FX(t+7, t+12)	-0.04	-0.37	-0.22	-11.22	0.02	-0.18	-0.40	-11.31

Panel B: Cumulative excess returns

	Broad TW Index				Broad EW Index			
FX(t+3)	0.63***	2.94	4.20	9.32**	0.79***	3.06	5.20	11.12**
FX(t+6)	0.87**	2.14	3.63	7.18*	1.19**	2.40	5.30	11.21**
FX(t+9)	0.76	1.31	1.68	7.06*	1.16	1.53	2.91	11.28**
FX(t+12)	0.66	0.80	0.74	0.06	1.07	1.01	1.62	3.59

Panel C: Forecast encompassing test

	Broad TW Index				Broad EW Index			
Variable j	$\widehat{FX}_{t+1}^{MediaTone}$	t-stat	$\widehat{FX}_{t+1}^{i}$	t-stat	$\widehat{FX}_{t+1}^{MediaTone}$	t-stat	$\widehat{FX}_{t+1}^{i}$	t-stat
InterestRate3M	0.99**	2.23	0.01	0.03	0.99***	2.86	0.01	0.03
Dollar	0.96**	2.00	0.04	0.08	1.00**	2.65	0.00	0.01
Carry	0.69*	1.84	0.31	0.84	0.70**	2.39	0.30	1.01
MOM	1.00**	2.23	0.00	-0.01	1.00***	2.86	0.00	-0.01
Volatility	1.01**	2.23	-0.01	-0.01	0.99***	2.80	0.01	0.03
Value	0.84**	2.08	0.16	0.39	0.85**	2.67	0.15	0.48
Commodity	0.53	1.55	0.47	1.36	0.64**	2.20	0.36	1.22
World Equity	1.00**	2.23	0.00	0.00	0.96***	2.81	0.04	0.12
FX(t-1)	1.01**	2.06	-0.01	-0.02	0.89**	2.39	0.11	0.29

Table 4. Predicting USD using *Media tone*$^{\perp}$ during post-crisis period
The table reports the coefficient values, corresponding t-values and R^2s from the following regression

$$FX_{(t+k,t+l)} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \beta_2 PostCrisis + \beta_3 MediaTone_t^{\perp} * PostCrisis + \varepsilon_{(t+k,t+l)}.$$

$FX_{(t+k,t+l)}$ is the currency excess return for trade-weighted currency indices for periods t, $(t+1)$, $(t+1, t+3)$, $(t+4, t+6)$ and $(t+7, t+12)$. Return periods refer to geometric average returns for each corresponding period. Broad TW index refers to trade weighted currency index and Broad EW index to equally weighted currency index for the 25 largest trading partners of the US. Panel A shows the results for the trade-weighted and Panel B for the equal weighted broad index. $MediaTone_t^{\perp}$ refers to the standardized and filtered TRMI USD *Media tone*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. $PostCrisis$ captures the period after the collapse of Lehmann Brothers. $PostCrisis$ -dummy variable gets a value of 1 for the periods during and after 9/2008 and 0 otherwise. $MediaTone_t^{\perp} * PostCrisis$ is the interaction of the TRMI USD *Media tone* and $PostCrisis$ -dummy capturing the impact of *Media tone* during and after the Global Financial Crisis period. Newey-West standard errors with 12 lags are used to account for heteroscedasticity and autocorrelation. See Appendix 3 for variable descriptions. ***, **, and * denote 1%, 5% and 10% statistical significance levels, respectively.

Panel A: Broad TW Index							
FX return	β_1	t-value	β_2	t-value	β_3	t-value	R^2
FX(t)	0.46***	3.74	0.17	0.92	-0.49*	-1.8	4.08
FX(t+1)	0.22*	1.91	0.12	0.54	-0.23	-0.86	-0.01
FX(t+1, t+3)	0.29***	3.14	0.07	0.29	-0.25*	-1.68	4.5
FX(t+4, t+6)	0.06	0.63	0.12	0.44	0.02	0.11	-0.24
FX(t+7, t+12)	-0.04	-0.3	0.30	1.58	-0.09	-0.48	3.08
Panel B: Broad EW Index							
FX return	β_1	t-value	β_2	t-value	β_3	t-value	R^2
FX(t)	0.59***	4.07	0.18	0.88	-0.68**	-2.25	5.75
FX(t+1)	0.39***	3.43	0.13	0.51	-0.40	-1.41	1.88
FX(t+1, t+3)	0.38***	3.75	0.09	0.33	-0.34**	-2.13	6.31
FX(t+4, t+6)	0.15	1.12	0.11	0.37	-0.07	-0.32	0.52
FX(t+7, t+12)	-0.03	-0.18	0.32	1.35	-0.07	-0.35	2.22

Table 5. Predicting non-USD returns using *Media tone*$^{\perp}$
The table reports the coefficient values, corresponding t-values and R^2s from the following regression

$$FX_{t+k} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \varepsilon_{t+k}.$$

FX_{t+k} is the trade-weighted nominal average return of each currency against its most important trading partners and $k = 0, 1$. The trade weights are three-year average trade weights, updated every three years. The information of trading amount and each country's trading partners are available from BIS. Broad indices comprise of 48-60 economies (conditional to the existence of the Eurozone) and are available as monthly averages. $MediaTone_t^{\perp}$ refers to the standardized and filtered TRMI local currency *Media tone*. The filtering variables are the currency factors included in Specification 1 of Panel B Table 2. ***, **, and * denote 1%, 5% and 10% statistical significance levels, respectively. See Appendix 3 for variable descriptions.

	Dependent: FX(t)			Dependent: FX(t+1)		
	Developed country currencies					
Country/Area	β_1	t-value	R^2	β_1	t-value	R^2
Australia	1.04***	7.00	19.79	0.31*	1.94	1.34
Canada	0.67***	6.43	16.2	0.11	1.21	-0.01
Eurozone	0.53***	4.11	12.91	0.08	0.80	-0.11
Hong Kong	0.13**	2.31	0.96	0.10	1.45	0.42
Japan	1.02***	4.46	16.42	0.57**	2.51	4.87
New Zealand	0.84***	5.15	15.25	0.39**	2.45	2.84
Norway	0.30**	2.56	3.89	0.11	1.50	0.17
Singapore	0.18***	3.03	6.59	0.03	0.48	-0.24
Sweden	0.21***	3.21	1.99	0.03	0.34	-0.40
Switzerland	0.24***	2.90	2.43	0.04	0.50	-0.37
UK	0.70***	5.17	20.74	0.34***	4.53	4.43
USA	0.80***	8.52	40.03	0.54***	7.72	18.37
	Emerging country currencies					
Country/Area	β_1	t-value	R^2	β_1	t-value	R^2
Argentina	0.78*	1.90	2.51	0.67	1.52	1.71
Brazil	1.90***	5.97	22.77	1.05***	4.15	6.60
Chile	0.78***	5.94	12.99	0.46***	3.13	4.19
China	0.15	1.28	1.13	0.26***	2.90	4.24
Colombia	1.11***	5.48	16.87	0.65***	3.66	5.52
Czech Republic	0.38***	2.81	5.65	0.20**	2.15	1.23
Hungary	0.73***	5.33	15.18	0.31***	3.01	2.34
India	0.61***	5.02	16.23	0.34***	3.62	4.66
Indonesia	1.83***	3.24	10.99	0.48	1.64	0.70
Israel	0.67***	5.74	14.12	0.37***	3.50	4.10
Malaysia	0.44***	3.41	6.00	0.14	1.03	0.35
Mexico	1.00***	7.20	19.03	0.43**	2.52	3.13
Peru	0.08	1.63	0.10	0.02	0.26	-0.42
Philippines	0.73***	7.27	18.00	0.39***	4.04	5.95
Poland	0.91***	5.56	17.95	0.29**	2.10	1.44
Romania	0.81***	4.63	17.50	0.57***	3.09	8.41
Russia	1.41***	2.60	7.63	1.17**	2.22	5.12
Saudi Arabia	0.00	0.04	-0.44	0.19***	2.82	2.01
South Africa	1.57***	7.29	21.82	0.73***	3.03	4.32
South Korea	0.89***	7.72	14.12	0.50**	2.53	4.46
Thailand	0.31**	2.25	1.79	-0.12	-0.69	-0.04
Turkey	1.49***	6.41	15.61	0.76***	2.85	3.73
UAE	0.07	0.74	-0.19	0.05	0.51	-0.31
Venezuela	0.89**	2.36	3.05	0.57*	1.91	0.98

Table 6. Predictability of USD returns using *Media tone*$^{\perp}$ across different characteristic portfolios.
The table reports the coefficient values, corresponding t-values, and R^2s from the following regression:

$$FX_{t+1} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \varepsilon_{t+1}.$$

FX_{t+1} is the currency excess return. For each currency in a portfolio, we calculate the excess returns for each moment as the change in each exchange rate against the USD minus the interest rate differential. The excess return of a portfolio is a cross-sectional equal-weighted average of these currencies for each period. $MediaTone_t^{\perp}$ refers to the standardized and filtered TRMI USD *Media tone*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. Portfolio 1 (Portfolio 5) refers to currencies with the lowest (highest) values for the characteristic in question. P5–P1 refers to a portfolio formed as a difference between Portfolio 5 and Portfolio 1 returns. R^2_{OOS} (%) provides a recursively estimated out-of-sample R^2 and compares the predictability of the *Media tone* variable to the predictability performance of the historical average using Clark and West's (2007) MSFE test. Newey–West standard errors with 12 lags are used to account for heteroscedasticity and autocorrelation. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively. See Appendix 3 for variable descriptions.

	P1	P2	P3	P4	P5	P5-P1
Panel A: Interest rate difference portfolios						
β_1	0.07	0.09	0.13	0.13	0.48***	0.41***
t-value	0.63	1.03	1.20	1.17	3.23	2.99
R^2	-0.26	-0.06	0.20	0.09	4.98	5.07
R^2_{OOS} (%)	0.40	0.96	0.97	0.69	8.51***	10.02***
Panel B: Inflation portfolios						
β_1	0.17**	0.09	0.20*	0.18	0.33**	0.16*
t-value	2.07	0.81	1.73	1.45	2.58	1.89
R^2	0.71	-0.17	0.88	0.62	2.8	0.78
R^2_{OOS} (%)	1.29*	-0.29	1.96**	1.69*	5.08**	1.00
Panel C: Currency turnover portfolios						
β_1	0.35**	0.18	0.24*	0.18	0.09	-0.26**
t-value	2.49	1.59	1.67	1.45	0.82	-2.27
R^2	3.23	0.70	0.78	0.47	-0.19	2.26
R^2_{OOS} (%)	4.50**	1.90**	1.24*	1.83**	0.20	-2.51
Panel D: 1M Momentum portfolios						
β_1	0.28	0.03	0.17*	0.19**	0.24*	-0.04
t-value	1.60	0.30	1.85	2.12	1.95	-0.24
R^2	1.35	-0.41	1.01	0.83	0.97	-0.41
R^2_{OOS} (%)	3.94**	-2.59	2.20**	1.31	0.91	-0.06
Panel E: 6M Momentum portfolios						
β_1	0.43***	0.09	0.06	0.16	0.17	-0.27
t-value	2.74	0.68	0.62	1.58	1.40	-1.58
R^2	4.03	-0.17	-0.31	0.51	0.25	1.09
R^2_{OOS} (%)	4.85***	-0.08	0.33	1.84**	0.96	0.64
Panel F: 12M Momentum portfolios						
β_1	0.41**	0.20*	0.05	0.16	0.09	-0.32*
t-value	2.56	1.75	0.51	1.47	0.79	-1.80
R^2	3.57	1.01	-0.33	0.51	-0.24	1.70
R^2_{OOS} (%)	5.32***	2.65***	-0.01	1.64*	0.62	2.38*
Panel G: 12-month exchange rate volatility portfolios						
β_1	0.03**	0.12	0.19	0.22	0.34**	0.30*

t-value	2.38	1.44	1.31	1.56	2.04	1.91
R^2	1.21	0.56	0.46	0.56	1.29	1.06
R^2_{OOS} (%)	-12.35	2.51**	1.18	1.29	1.63*	1.80*
Panel H: Previous month's exchange rate volatility portfolios						
β_1	0.02**	0.16	0.20	0.19	0.31*	0.28*
t-value	2.40	1.59	1.64	1.30	1.88	1.77
R^2	0.76	1.32	0.71	0.25	1.03	0.88
R^2_{OOS} (%)	-5.63	2.95**	1.86	0.91	1.66*	1.72*
Panel I: Credit rating portfolios						
β_1	0.54***	0.12	0.15	0.15	0.10	-0.44***
t-value	3.26	0.87	1.35	1.41	0.70	-2.65
R^2	5.66	-0.09	0.19	0.33	-0.23	4.26
R^2_{OOS} (%)	9.71***	0.40	0.72	1.56*	-0.14	10.90***
Panel J: Political risk portfolios						
β_1	0.18	0.16	0.07	0.14*	0.36**	0.18
t-value	1.31	1.51	0.68	1.70	2.46	1.08
R^2	0.26	0.36	-0.23	0.61	4.07	0.39
R^2_{OOS} (%)	1.25	1.35*	0.10	0.82	7.53***	-2.63

Table 7. Predicting USD using *Media tone*$^{\perp}$ across developed and emerging country currency portfolios
The table reports the coefficient values, corresponding t-values and R^2s from the following regression

$$FX_{t+1} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \varepsilon_{t+1}.$$

FX_{t+1} is the currency excess return for developed (left side) and emerging (right side) country currency portfolios formed based on past currency return behavior and macroeconomic environment. See Table 6 of how we compute FX_{t+1}. $MediaTone_t^{\perp}$ is a text analysis based filtered and standardized TRMI USD *Media tone*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. R^2_{OOS} % provides a recursively estimated out-of-sample R^2 and compares the predictability of the *Media tone* variable to the predictability performance of the historical average using Clark and West (2007) mean square forecast error test. High inflation periods are excluded from the data. P1,…, P5 refer to currency portfolios where P1 has the currencies with lowest values for a variable in question and P5 the highest values. P3-P1 (for developing countries) and P5-P1 (for emerging countries) are the excess return difference between portfolios P3 and P1; and P5 and P1, respectively. Newey–West standard errors with 12 lags are used to account for heteroscedasticity and autocorrelation. ***, **, and * denote 1%, 5% and 10% statistical significance levels, respectively. See Appendix 3 for variable descriptions. R^2 and R^2_{OOS} are in %.

	Developed country currency portfolios				Emerging country currency portfolios					
	P1	P2	P3	P3-P1	P1	P2	P3	P4	P5	P5-P1
Panel A: Interest rate difference portfolios										
β_1	0.05	0.17	0.20	0.15	0.04	0.15*	0.09	0.17	0.65***	0.61***
t-value	0.37	1.38	1.56	1.45	0.55	1.79	0.91	1.41	3.25	3.26
R^2	-0.37	0.31	0.29	0.32	-0.36	0.92	-0.11	0.32	6.62	6.69
R^2_{OOS}	-1.08	1.77*	1.24**	0.55	0.19	1.79**	0.56	0.01	17.27***	25.00***
Panel B: Inflation portfolios										
β_1	0.12	0.07	0.23	0.11	0.26**	0.15	0.21*	0.30*	0.30**	0.04
t-value	1.11	0.64	1.64	1.16	2.59	1.41	1.66	1.95	2.51	0.30
R^2	-0.02	-0.31	0.73	-0.01	1.94	0.28	0.86	1.76	2.06	-0.41
R^2_{OOS}	-0.78	-0.15	2.41**	-1.59	3.59**	0.96	3.03**	2.00	4.38**	-0.63
Panel C: Currency turnover portfolios										
β_1	0.31**	0.17	0.15	-0.16	0.30***	0.40**	0.19	0.26*	0.22	-0.08
t-value	2.52	1.26	1.35	-1.64	2.63	2.33	1.53	1.90	1.31	-0.55
R^2	3.14	0.31	0.27	1.46	2.26	2.83	0.65	0.82	0.46	-0.30
R^2_{OOS}	4.86***	1.00	1.53*	-0.63**	1.89*	7.88***	2.57**	1.63*	2.10**	-2.90
Panel D: 1M Momentum portfolios										
β_1	0.00	0.17	0.24*	0.24**	-0.03	0.04	0.22*	0.24**	0.22	0.26
t-value	-0.02	1.50	1.96	2.13	-0.18	0.36	1.84	1.99	1.64	1.37
R^2	-0.44	0.26	0.92	1.60	-0.42	-0.4	0.64	0.87	0.51	0.72
R^2_{OOS}	-2.85	0.61	1.80*	-4.90	-3.08	-1.92	1.17	2.02*	1.14	-3.96
Panel E: 6M Momentum portfolios										
β_1	0.20	0.11	0.10	-0.10	0.27*	0.11	0.12	0.03	0.20	-0.07
t-value	1.41	0.85	0.86	-0.85	1.74	0.76	0.95	0.23	1.58	-0.49
R^2	0.47	-0.16	-0.19	-0.13	0.92	-0.18	-0.14	-0.42	0.36	-0.35
R^2_{OOS}	1.00	0.38	0.20	-1.18	1.65*	0.83	-0.39	-0.27	0.89	0.16
Panel F: 12M Momentum portfolios										
β_1	0.16	0.12	0.13	-0.03	0.29**	0.11	0.04	0.18	0.08	-0.21
t-value	1.15	0.90	1.07	-0.25	2.10	0.76	0.26	1.33	0.63	-1.42
R^2	0.13	-0.12	-0.04	-0.41	1.18	-0.18	-0.41	0.27	-0.31	0.38
R^2_{OOS}	0.40	-0.01	1.06	-0.42	2.02**	-0.85	-1.25	1.42*	0.17	-0.08
Panel G: 12-month exchange rate volatility portfolios										

β_1	0.08	0.13	0.21	0.13	0.01	0.11*	0.37**	0.20	0.42**	0.41**
t-value	1.06	0.93	1.35	1.21	0.62	1.94	2.30	1.25	2.47	2.44
R^2	-0.10	-0.08	0.31	0.21	-0.27	1.32	3.27	0.29	1.61	1.57
R^2_{OOS}	0.03	0.43	1.28	0.59	-1.63	2.54**	4.27**	1.18*	2.28*	2.91**
Panel H: Previous month's exchange rate volatility portfolios										
β_1	0.09	0.08	0.23	0.14	0.00	0.10*	0.35**	0.22	0.38**	0.38**
t-value	1.13	0.62	1.51	1.42	-0.16	1.85	2.22	1.47	2.04	2.03
R^2	0.04	-0.30	0.43	0.23	-0.43	1.06	3.01	0.48	1.10	1.12
R^2_{OOS}	0.34	-0.63	1.71*	-0.29	0.07	2.80**	4.91**	1.61*	2.38*	2.92**
Panel I: Credit rating portfolios										
β_1	-0.07	0.24*	0.09	0.09	0.91***	0.22*	0.19	0.08	0.12	-0.79***
t-value	-0.73	1.87	0.65	0.72	3.28	1.71	1.34	0.52	0.99	-2.62
R^2	-0.23	0.90	-0.27	-0.25	6.94	0.71	0.29	-0.33	0.03	5.33
R^2_{OOS}	-3.44	1.73*	-0.35	0.56	13.08***	1.11	1.18**	-0.33	0.13	5.85***
Panel J: Political risk portfolios										
β_1	0.07	0.13	0.20	0.13	0.16	0.13	0.17*	0.14	0.55**	0.39*
t-value	0.83	1.03	1.30	1.26	1.22	1.29	1.84	1.43	2.53	1.67
R^2	-0.20	0.04	0.18	0.17	0.15	0.24	0.83	0.44	5.22	1.89
R^2_{OOS}	-0.13	0.42	1.22*	0.63	1.09	1.15*	0.75	0.59	15.85***	-0.09*

Table 8. Predicting USD using *Media tone*$^{\perp}$ across currency regimes

The table reports the coefficient values, corresponding t-values and R^2s from the following regression

$$FX_{t+1} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \varepsilon_{t+1}.$$

FX_{t+1} is the currency excess return for portfolios formed based on previous period's interest rate difference with the US interest rate for various currency regimes where regimes are defined using the classification by Ilzetzki et al. (2017): Floating have a classification code 13, managed floating currencies have codes from 6 to 12 and fixed have codes from 2 to 5. On the left side, $MediaTone_t^{\perp}$is a text analysis based filtered and standardized TRMI USD *Media tone*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. High inflation periods are excluded from the data. Newey–West standard errors with 12 lags are used to account for heteroscedasticity and autocorrelation. ***, **, and * denote 1%, 5% and 10% statistical significance levels, respectively. See Appendix 3 for variable descriptions.

IR differential portfolios	β_1	t-value	R^2(%)
		Freely floating	
	0.20*	1.72	0.51
		Managed floating	
Lowest	0.09	0.82	-0.16
Medium	0.13	1.11	0.13
Highest	0.39***	2.72	3.64
		Fixed	
Lowest	0.07	0.85	-0.17
Medium	0.00	-0.02	-0.44
Highest	0.11	1.26	0.11

Table 9. Baker–Wurgler market sentiment as a possible channel of the predictive power of *Media tone*$^{\perp}$
Panel A reports the coefficient values, corresponding t-values, and R^2s from the following regression:

$$BW_t = \alpha + \beta * MediaTone_t^{\perp}.$$

Panel B examines the relationship between the optimism and the broad USD index returns as follows:

$$FXRet_{t+i} = \alpha + \beta * BW_t.$$

Panel C presents the regression:

$$FX_{t+i} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \beta_2 BW_t + \varepsilon_{t+i}.$$

FX_{t+i} is the geometric average currency excess return for trade-weighted (TW) and equally weighted (EW) currency indices for the periods t, $(t+1)$, $(t+1, t+3)$, $(t+4, t+6)$, and $(t+7, t+12)$ of the broad index consisting of 25 major trading partners of the US. $MediaTone_t^{\perp}$ is a text analysis-based filtered and standardized TRMI USD *Media tone*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. BW is the Baker–Wurgler investor sentiment, *Sent*$^{\perp}$. *Media tone*$^{\perp}$ and both sentiment measures are standardized. Newey–West standard errors with 12 lags are used to account for heteroscedasticity and autocorrelation. Return periods refer to geometric average returns for each corresponding period. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively. See Appendix 3 for variable descriptions.

Panel A: *BW* and *Media tone*$^{\perp}$

t	β	t-stat	adjR^2
0	0.08	0.52	0.26

Panel B: *BW* and returns

i	β	t-stat	adjR^2	R^2_{OOS} (%)	t+i	β	t-stat	adjR^2	R^2_{OOS} (%)
				Broad TW index					
0	0.16**	2.23	0.52						
1	0.16**	2.00	0.55	-0.64					
3	0.14*	1.82	0.36	-1.00	(t+1 - t+3)	0.15**	2.06	2.01	-1.67
6	0.11	1.20	0.04	-0.96	(t+4 - t+6)	0.13	1.43	1.38	-2.15
12	-0.01	-0.16	-0.46	0.07	(t+7 - t+12)	0.02	0.25	-0.38	-1.82
				Broad EW index					
0	0.26***	3.03	1.75						
1	0.26***	2.74	1.72	-1.28					
3	0.26**	2.57	1.77	-1.27	(t+1 - t+3)	0.26***	2.82	5.07	-2.93
6	0.18*	1.66	0.71	-1.53	(t+4 - t+6)	0.22**	1.98	3.75	-3.55
12	0.03	0.27	-0.44	-0.80	(t+7 - t+12)	0.08	0.79	0.40	-6.38

Panel C: *Media tone*$^{\perp}$ and returns after controlling *BW*

i	β_1	t-stat	β_2	t-stat	adjR^2	t+i	β_1	t-stat	β_2	t-stat	adjR^2
					Broad TW index						
0	0.28**	2.02	0.14*	1.78	3.03						
1	0.13	1.16	0.15*	1.83	0.75						
3	0.19*	1.87	0.13	1.57	1.23	(t+1 - t+3)	0.19***	2.72	0.13*	1.80	5.37
6	0.03	0.28	0.11	1.12	-0.37	(t+4 - t+6)	0.07	0.85	0.12	1.32	1.42
12	-0.10	-0.79	-0.01	-0.06	-0.55	(t+7 - t+12)	-0.04	-0.40	0.02	0.29	-0.57
					Broad EW index						
0	0.32**	2.07	0.24***	2.68	4.61						
1	0.22*	1.85	0.24***	2.62	2.91						
3	0.17*	1.67	0.24**	2.53	2.25	(t+1 - t+3)	0.24***	3.14	0.24***	2.73	0.24
6	0.07	0.53	0.18	1.57	0.42	(t+4 - t+6)	0.12	1.38	0.21*	1.87	0.12
12	-0.12	-0.91	0.04	0.37	-0.43	(t+7 - t+12)	-0.03	-0.25	0.08	0.80	-0.03

Table 10. *Forecast Errors* as a possible channel of the predictive power of *Media tone*$^{\perp}$
Panel A reports the coefficient values, corresponding t-values and R^2s from the following regression:

$$Forecast\ Errors_t = \alpha + \beta * MediaTone_t^{\perp}$$

Panel B examines the relationship between the optimism and the broad USD index returns as follows:

$$FXRet_{t+i} = \alpha + \beta * Forecast\ Errors_t$$

Panel C presents the regression:

$$FX_{t+i} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \beta_2 Forecast\ Errors_t + \varepsilon_{t+i}.$$

FX_{t+i} is the geometric average currency excess return for trade-weighted (TW) and equally weighted (EW) currency indices for the periods t, $(t+1)$, $(t+1, t+3)$, $(t+4, t+6)$ and $(t+7, t+12)$. Broad index consists of 25 major trading partners of the US. $MediaTone_t^{\perp}$is a text analysis based filtered and standardized TRMI USD *Media tone*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. *Forecast Errors* is ln of forecasted USD at t+i subtracted by ln of USD actual value at t+i. Both *Media tone*$^{\perp}$ and *Forecast Errors* are standardized. Newey–West standard errors with 12 lags are used to account for heteroscedasticity and autocorrelation. ***, **, and * denote 1%, 5% and 10% statistical significance levels, respectively.

Panel A: *Forecast Errors* and *Media tone*$^{\perp}$

i	β	t-value	R^2
1	-0.13*	-1.84	1.13
3	-0.19**	-2.55	3.11
6	-0.18*	-1.70	2.81
12	-0.09	-0.63	0.36

Panel B: *Forecast Errors* and returns

i	β	t-stat	adjR²	R^2_{OOS} (%)	t+i	β	t-stat	adjR²	R^2_{OOS} (%)
				Broad TW index					
0	-0.94***	-10.51	35.22						
1	-0.91***	-12.24	33.42	25.66***					
3	-0.71***	-7.09	19.68	14.72***	(t+1 - t+3)	-0.69***	-8.72	53.36	38.43***
6	-0.53***	-6.25	11.06	10.01***	(t+4 - t+6)	-0.55***	-6.90	33.22	27.43**
12	-0.38***	-4.34	5.33	3.23*	(t+7 - t+12)	-0.43***	-6.91	37.03	28.60**
				Broad EW index					
0	-0.92***	-7.99	29.85						
1	-0.90***	-8.47	28.40	19.85***					
3	-0.76***	-6.57	19.94	12.68***	(t+1 - t+3)	-0.72***	-6.88	46.45	28.71**
6	-0.63***	-6.76	13.56	9.50***	(t+4 - t+6)	-0.63***	-6.84	35.16	22.48**
12	-0.48***	-4.57	7.82	4.25*	(t+7 - t+12)	-0.54***	-7.72	42.84	33.39**

Panel C: *Media tone*$^{\perp}$ and returns after controlling *Forecast Errors*

i	β_1	t-stat	β_2	t-stat	adjR²	t+i	β_1	t-stat	β_2	t-stat	adjR²
						Broad TW index					
0	0.10	0.88	-0.93***	-9.82	35.28						
1	-0.01	-0.10	-0.92***	-11.81	33.10						
3	0.06	0.60	-0.70***	-6.78	19.42	(t+1 - t+3)	0.13**	2.18	-0.70***	-6.76	47.71
6	-0.07	-0.70	-0.55***	-5.75	10.84	(t+4 - t+6)	0.03	0.40	-0.63***	-6.42	34.91
12	-0.17	-1.55	-0.40***	-4.12	5.95	(t+7 - t+12)	-0.07	-0.88	-0.55***	-7.15	43.34
						Broad EW index					
0	0.13	1.02	-0.91***	-7.40	30.12						
1	0.10	1.07	-0.89***	-8.07	28.39						
3	0.07	0.63	-0.75***	-6.47	19.71	(t+1 - t+3)	0.06	1.54	-0.68***	-8.71	53.59
6	-0.04	-0.34	-0.64***	-6.16	13.20	(t+4 - t+6)	-0.01	-0.22	-0.55***	-6.52	32.92
12	-0.19	-1.66	-0.50***	-4.23	8.56	(t+7 - t+12)	-0.09	-1.17	-0.44***	-6.67	38.22

Table 11. *Attention* as a possible channel of the predictive power of *Media tone*$^{\perp}$
Panel A reports the coefficient values, corresponding t-values and R^2s from the following regression:

$$Attention_t = \alpha + \beta * MediaTone_t^{\perp}$$

Panel B examines the relationship between the optimism and the broad USD index returns as follows:

$$FXRet_{t+i} = \alpha + \beta * Attention_t$$

Panel C presents the regression:

$$FX_{t+i} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \beta_2 Attention_t + \varepsilon_{t+i}.$$

FX_{t+i} is the geometric average currency excess return for trade-weighted (TW) and equally weighted (EW) currency indices for the periods t, $(t+1)$, $(t+1, t+3)$, $(t+4, t+6)$ and $(t+7, t+12)$. Broad index consists of 25 major trading partners of the US. $MediaTone_t^{\perp}$is a text analysis based filtered and standardized TRMI USD *Media tone*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. $Attention$ is number of media mentions (Buzzes) in media and social media. Both *Media tone*$^{\perp}$ and *Attention* are standardized. Newey–West standard errors with 12 lags are used to account for heteroscedasticity and autocorrelation. ***, **, and * denote 1%, 5% and 10% statistical significance levels, respectively.

Panel A: *Attention* and *Media tone*$^{\perp}$

i	β	t-value	R^2
0	0.10	0.78	0.58

Panel B: *Attention* and returns

					Broad TW index				
i	β	t-stat	adjR²	R^2_{OOS} (%)	t+i	β	t-stat	adjR²	R^2_{OOS} (%)
0	0.02	0.14	-0.43						
1	0.11	1.00	-0.02	0.25					
3	0.16	1.13	0.59	1.83*	(t+1 - t+3)	0.15	1.35	2.06	6.93**
6	0.01	0.07	-0.45	-0.74	(t+4 - t+6)	0.12	1.11	1.15	3.28
12	0.01	0.05	-0.47	-1.31	(t+7 - t+12)	0.03	0.28	-0.34	1.33
					Broad EW index				
0	-0.02	-0.15	-0.43						
1	0.05	0.39	-0.37	-2.17					
3	0.19	1.17	0.71	2.18**	(t+1 - t+3)	0.14	1.07	1.08	4.05**
6	0.04	0.31	-0.40	-0.78	(t+4 - t+6)	0.13	0.94	0.97	3.15
12	0.01	0.06	-0.47	-1.42	(t+7 - t+12)	0.05	0.42	-0.13	3.57

Panel C: *Media tone*$^{\perp}$ and returns after controlling *Attention*

i	β_1	t-stat	β_2	t-stat	adjR²	t+i	β_1	t-stat	β_2	t-stat	adjR²
						Broad TW index					
0	0.29**	2.15	0.00	0.01	2.33						
1	0.13	1.26	0.10	1.05	0.28						
3	0.18	1.61	0.19	1.44	1.96	(t+1 - t+3)	0.19**	2.40	0.17*	1.73	6.37
6	0.04	0.35	0.00	0.04	-0.84	(t+4 - t+6)	0.07	0.78	0.13	1.24	1.67
12	-0.10	-0.83	0.02	0.20	-0.53	(t+7 - t+12)	-0.04	-0.40	0.03	0.33	-0.50
						Broad EW index					
0	0.35**	2.21	-0.03	-0.30	2.88						
1	0.24**	2.12	0.04	0.39	1.12						
3	0.17	1.37	0.21	1.46	1.81	(t+1 - t+3)	0.25***	2.74	0.15	1.40	6.35
6	0.08	0.59	0.03	0.23	-0.62	(t+4 - t+6)	0.13	1.20	0.14	1.03	2.22
12	-0.12	-0.88	0.03	0.20	-0.45	(t+7 - t+12)	-0.03	-0.22	0.06	0.50	-0.38

Table 12. *Uncertainty* as a possible channel of the predictive power of *Media tone*$^{\perp}$
Panel A reports the coefficient values, corresponding t-values and R^2s from the following regression:

$$Uncertainty_t = \alpha + \beta * MediaTone_t^{\perp}$$

Panel B examines the relationship between the optimism and the broad USD index returns as follows:

$$FXRet_{t+i} = \alpha + \beta * Uncertainty_t$$

Panel C presents the regression:

$$FX_{t+i} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \beta_2 Uncertainty_t + \varepsilon_{t+i}.$$

FX_{t+i} is the geometric average currency excess return for trade-weighted (TW) and equally weighted (EW) currency indices for the periods t, $(t+1)$, $(t+1, t+3)$, $(t+4, t+6)$ and $(t+7, t+12)$. Broad index consists of 25 major trading partners of the US. $MediaTone_t^{\perp}$is a text analysis based filtered and standardized TRMI USD *Media tone*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. $Uncertainty$ is VIX index. Both *Media tone*$^{\perp}$ and Uncertainty are standardized. Newey–West standard errors with 12 lags are used to account for heteroscedasticity and autocorrelation. ***, **, and * denote 1%, 5% and 10% statistical significance levels, respectively.

Panel A: *Uncertainty* and *Media tone*$^{\perp}$

t	β	t-stat	adjR^2
0	-0.09	-0.97	0.32

Panel B: *Uncertainty* and returns

				Broad TW index					
i	β	t-stat	adjR^2	R^2_{OOS} (%)	t+i	β	t-stat	adjR^2	R^2_{OOS} (%)
0	0.27*	1.98	2.33						
1	-0.19	-1.37	0.92	2.28**					
3	-0.14	-1.45	0.34	1.46*	(t+1 - t+3)	-0.19*	-1.98	3.47	8.56***
6	-0.29**	-2.51	2.85	4.44**	(t+4 - t+6)	-0.22**	-2.40	4.54	11.33***
12	-0.08	-1.07	-0.18	0.88*	(t+7 - t+12)	-0.12*	-1.69	2.47	8.92**
				Broad EW index					
0	0.31*	1.95	2.65						
1	-0.18	-1.17	0.65	1.47**					
3	-0.13	-1.13	0.13	1.22*	(t+1 - t+3)	-0.19*	-1.66	9.89	1.46*
6	-0.30**	-2.18	2.56	3.72**	(t+4 - t+6)	-0.21*	-1.90	3.40	4.44**
12	-0.07	-0.72	-0.27	0.24	(t+7 - t+12)	-0.13	-1.44	2.13	0.88*

Panel C: *Media tone*$^{\perp}$ and returns after controlling *Uncertainty*

i	β_1	t-stat	β_2	t-stat	adjR^2	t+i	β_1	t-stat	β_2	t-stat	adjR^2
					Broad TW index						
0	0.32**	2.30	0.30**	2.25	5.69						
1	0.13	1.25	-0.18	-1.34	1.11						
3	0.19*	1.74	-0.13	-1.34	1.25	(t+1 - t+3)	0.19***	2.68	-0.18*	-1.91	6.83
6	0.02	0.18	-0.29	-2.50	2.43	(t+4 - t+6)	0.06	0.79	-0.21**	-2.39	4.52
12	-0.10	-0.90	-0.09	-1.15	-0.21	(t+7- t+12)	-0.04	-0.48	-0.12	-1.71	2.42
					Broad EW index						
0	0.37**	2.35	0.35**	2.27	6.61						
1	0.23**	2.02	-0.16	-1.10	1.94						
3	0.18	1.45	-0.12	-1.04	0.77	(t+1 - t+3)	0.25***	2.76	-0.17	-1.57	6.95
6	0.06	0.46	-0.29**	-2.13	2.25	(t+4 - t+6)	0.12	1.22	-0.20*	-1.85	4.16
12	-0.12	-0.94	-0.08	-0.80	-0.23	(t+7 - t+12)	-0.03	-0.27	-0.13	-1.47	1.81

Table 13**:** Which constituent of *Media tone*$^{\perp}$ explains its predictability?
This table reports the coefficient values, corresponding t-values and R^2s from the following regression:

$$FX_{(t+k,t+l)} = \beta_0 + \beta_1 Constituents_t^{\perp} + \varepsilon_{(t+k,t+l)}.$$

$FX_{(t+k,t+l)}$ is the geometric average currency excess return for trade-weighted (left side) and equal-weighted (right side) currency indices for the periods t, $(t+1)$, $(t+1, t+3)$, $(t+4, t+6)$, and $(t+7, t+12)$. The broad TW index refers to the trade-weighted currency index, and the broad EW index refers to the equal-weighted currency index for the 25 largest trading partners of the US. $Constituents_t^{\perp}$ refers to the standardized and filtered TRMI USD constituents of *Media tone*, including *News_Media Tone*, *Social_Media Tone*, *Optimism*, *Uncertainty*, *Long Short*, *Long Short Forecast*, *Price Direction*, *Price Forecast*, *Volatility*, and *Price Momentum*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. R^2_{OOS} (%) provides a recursively estimated out-of-sample R^2 and compares the predictability of the *Constituents* variable to the predictability performance of the historical average using Clark and West's (2007) MSFE test. Newey–West standard errors with 12 lags are used to account for heteroscedasticity and autocorrelation. See Section 4.3 for a methodology description. See Appendix 3 for variable descriptions. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively.

FX Return	Broad TW Index				Broad EW Index			
	Constituents$^{\perp}$	t-value	R^2	R^2_{OOS} (%)	Constituents$^{\perp}$	t-value	R^2	R^2_{OOS} (%)
				News_Media Tone$^{\perp}$				
FX(t)	0.28	2.01**	2.55		0.33	2.06**	2.89	
FX(t+1)	0.12	1.27	0.12	1.04*	0.21	1.96*	0.93	2.34**
FX(t+1 - t+3)	0.18	2.73***	3.03	5.95**	0.22	2.88***	3.45	7.74**
FX(t+4 - t+6)	0.06	0.77	-0.08	-1.46	0.11	1.14	0.49	1.50*
FX(t+7 - t+12)	0.03	0.33	-0.28	-9.20	0.02	0.19	-0.40	-9.75
				Social_Media Tone$^{\perp}$				
FX(t)	0.28	2.65**	2.60		0.37	2.55**	3.97	
FX(t+1)	0.09	0.89	-0.12	0.38	0.12	0.92	0.04	0.59
FX(t+1 - t+3)	0.17	2.34**	2.59	6.89***	0.21	1.98*	3.03	8.29***
FX(t+4 - t+6)	0.20	2.56**	3.96	10.91***	0.29	3.18***	6.73	15.49***
FX(t+7 - t+12)	0.05	0.53	0.04	4.22***	0.08	0.70	0.57	7.29***
				Optimism$^{\perp}$				
FX(t)	0.18	1.58	0.78		0.20*	1.69	0.86	
FX(t+1)	0.14	1.49	0.27	1.28*	0.20*	1.77	0.84	2.61**
FX(t+1 - t+3)	0.18**	2.26	3.15	9.08***	0.23**	2.24	3.85	10.34***
FX(t+4 - t+6)	0.10	1.31	0.62	2.76**	0.16	1.85	1.58	5.44***
FX(t+7 - t+12)	0.02	0.29	-0.37	-10.04	0.02	0.17	-0.43	-9.09
				Uncertainty$^{\perp}$				
FX(t)	-0.08	-0.92	-0.20		-0.06	-0.68	-0.31	
FX(t+1)	0.01	0.08	-0.44	-0.56	0.03	0.36	-0.41	-0.40
FX(t+1 - t+3)	0.07	1.09	0.04	-0.23	0.05	0.71	-0.26	-0.46
FX(t+4 - t+6)	0.04	0.75	-0.27	-0.38	0.06	0.86	-0.13	-0.04
FX(t+7 - t+12)	0.02	0.51	-0.36	-0.10	0.04	0.60	-0.27	-0.46
				Long Short$^{\perp}$				
FX(t)	0.05	0.61	-0.34		0.04	0.43	-0.40	
FX(t+1)	0.08	1.13	-0.21	-0.39	0.11	1.46	-0.06	-0.25
FX(t+1 - t+3)	0.06	1.05	-0.09	-0.85	0.05	0.92	-0.25	-0.59
FX(t+4 - t+6)	0.03	0.55	-0.33	-0.42	0.04	0.54	-0.34	-0.59
FX(t+7 - t+12)	0.01	0.23	-0.43	-0.73	0.02	0.28	-0.41	-0.48
				Long Short Forecast$^{\perp}$				
FX(t)	-0.04	-0.50	-0.39		-0.03	-0.36	-0.42	
FX(t+1)	0.02	0.20	-0.44	-0.26	0.01	0.15	-0.44	-0.30

FX(t+1 - t+3)	0.03	0.52	-0.34	0.23	0.06	0.86	-0.16	0.93***
FX(t+4 - t+6)	0.01	0.28	-0.44	-0.30	0.03	0.73	-0.36	0.08
FX(t+7 - t+12)	0.01	0.15	-0.46	-0.09	0.01	0.22	-0.45	-0.22
				Price Direction$^{\perp}$				
FX(t)	0.28**	2.09	2.63		0.31**	1.95	2.56	
FX(t+1)	0.01	0.13	-0.44	-0.29	0.04	0.40	-0.38	-0.11
FX(t+1 - t+3)	0.10	1.31	0.54	2.53**	0.10	1.26	0.44	2.49**
FX(t+4 - t+6)	0.06	0.81	-0.08	-8.88	0.04	0.50	-0.29	-7.94
FX(t+7 - t+12)	0.11	1.11	1.99	-14.48	0.15	1.26	2.67	-20.36
				Price Forecast$^{\perp}$				
FX(t)	0.19	1.53	0.87		0.21	1.60	0.99	
FX(t+1)	0.16	1.50	0.51	1.81**	0.22**	2.25	1.10	2.23**
FX(t+1 - t+3)	0.17**	2.52	2.61	6.75***	0.20**	2.73	2.99	7.30***
FX(t+4 - t+6)	0.09	1.24	0.40	2.03**	0.11	1.39	0.63	2.76***
FX(t+7 - t+12)	0.00	0.03	-0.46	-3.21	0.00	0.03	-0.46	-3.62
				Volatility$^{\perp}$				
FX(t)	-0.03	-0.45	-0.41		0.02	0.29	-0.43	
FX(t+1)	0.03	0.21	-0.42	-0.45	0.05	0.40	-0.36	-0.58
FX(t+1 - t+3)	0.08	1.04	0.20	0.30	0.14	1.51	1.13	1.25
FX(t+4 - t+6)	0.12	1.36	0.98	3.09*	0.15	1.64	1.33	4.57**
FX(t+7 - t+12)	0.13**	2.05	3.07	7.71***	0.17**	2.17	3.97	9.15***
				Price Momentum$^{\perp}$				
FX(t)	-0.22*	-1.70	1.33		-0.23*	-1.69	1.27	
FX(t+1)	0.09	0.85	-0.17	-0.39	0.07	0.67	-0.27	-0.51
FX(t+1 - t+3)	0.03	0.43	-0.35	-1.20	0.01	0.12	-0.44	-1.44
FX(t+4 - t+6)	0.03	0.52	-0.34	-5.87	0.02	0.26	-0.42	-6.07
FX(t+7 - t+12)	0.11	1.10	1.89	-11.70	0.13	1.18	2.20	-15.16

Table 14: Which source has predictive Media Tone

The table presents the predictive power *Media Tone* and *Media Tone*$^{\perp}$ from different media sources. The setup is similar to the one in Table 3. FT, WSJ, NYT, and SMB stand for Financial Times, Wall Street Journal, New York Times, and Yahoo! Finance stock message boards. Please see Appendix 3 for variable descriptions.

	All sources	FT	WSJ	NYT	Forbes	Bloomberg	Economist	Reuters	CNBC	CNN	Washington Post	Morningstar	Yahoo Finance	Market Watch	Seeking Alpha	Stock Twits	Twitter	SMB	All Sources Excl Large
Independent variable: *Media Tone*																			
Broad EW index																			
FX(t)	0.69***	0.37***	0.46***	0.38***	0.45***	0.51***	0.03	0.57***	0.53***	0.51***	0.35**	0.38**	0.49*	0.54***	0.63***	0.83***	0.21	0.61***	0.54***
FX(t+1)	0.33***	0.24**	0.13	-0.22*	0.16	0.13	-0.23	0.19*	0.40***	0.14	0.35***	0.21*	0.23*	0.03	0.35***	-0.24	-0.29	0.21*	0.34***
FX(t+1,t+3)	0.35***	0.24***	0.10	0.01	0.15	0.12	0.00	0.15	0.22**	-0.01	0.13	0.19**	0.06	0.17	0.24**	-0.18	0.16	0.22**	0.26***
FX(t+4,t+6)	0.23**	0.17*	-0.01	0.13	0.18*	0.07	0.06	-0.01	0.05	-0.14	0.18	-0.01	0.01	-0.02	0.17	0.06	0.43***	0.27***	0.11
FX(t+7,t+12)	0.11	0.03	-0.08	0.03	-0.08	-0.14	-0.05	-0.02	-0.23	-0.19*	0.04	0.04	-0.02	-0.37**	-0.09	0.00	0.17***	0.10	0.10
Broad TW index																			
FX(t)	0.66***	0.37***	0.51***	0.37***	0.40***	0.50***	0.03	0.58***	0.56***	0.48***	0.30**	0.36**	0.48**	0.55***	0.63***	0.76***	0.18*	0.55***	0.54***
FX(t+1)	0.24**	0.22**	0.08	-0.19**	0.13	0.07	-0.23*	0.15	0.36***	0.13	0.29**	0.16	0.25**	0.01	0.34***	-0.25	-0.36	0.16	0.28***
FX(t+1,t+3)	0.28***	0.17***	0.09*	0.01	0.16*	0.05	-0.03	0.13	0.22**	-0.01	0.10	0.17**	0.05	0.13	0.26***	-0.15	0.08	0.18**	0.24***
FX(t+4,t+6)	0.17*	0.13*	-0.05	0.07	0.18*	0.11	0.06	-0.02	0.08	-0.12	0.18	0.01	-0.01	-0.02	0.20*	0.06	0.44***	0.18**	0.08
FX(t+7,t+12)	0.09	0.03	-0.05	0.02	-0.04	-0.06	-0.02	0.01	-0.19	-0.13	0.04	0.06	-0.02	-0.27	-0.04	-0.01	0.14***	0.06	0.10
# of obs	228	219	223	219	140	84	118	169	117	142	142	114	90	87	118	102	49	228	228
Independent variable: *Media Tone*$^{\perp}$																			
Broad EW index																			
FX(t)	0.34**	0.15	0.15	0.13	0.1	0.19	0.01	0.23	0.07	0.07	0.10	0.06	0.12	0.06	0.12	0.09	0.03	0.20*	0.31***
FX(t+1)	0.25**	0.17	0.09	-0.22**	0.05	0.16	-0.21**	0.16	0.38**	0.18	0.23*	-0.03	0.23*	0.08	0.22*	-0.19	-0.56***	0.12	0.33***
FX(t+1,t+3)	0.26***	0.15**	0.06	0.00	0.01	0.02	-0.03	0.04	0.11	-0.03	-0.06	-0.04	-0.06	0.09	0.06	-0.16	-0.09	0.12	0.20***
FX(t+4,t+6)	0.14	0.14	-0.04	0.16*	0.04	-0.05	0.09	-0.11	-0.02	-0.14	0.02	-0.25**	-0.02	-0.06	0.03	0.14	0.25*	0.22***	0.01
FX(t+7,t+12)	-0.02	-0.02	-0.11	0.06	-0.21*	0.00	-0.01	-0.02	-0.15	-0.12	-0.10	-0.02	-0.1	-0.18**	-0.13	0.06	0.10**	0.04	-0.02
Broad TW index																			
FX(t)	0.29**	0.13	0.21**	0.12	0.06	0.12	-0.01	0.18	0.11	0.04	0.07	0.05	0.11	0.05	0.16	0.11	0.06	0.15	0.27**
FX(t+1)	0.14	0.15	0.03	-0.19**	0.00	0.06	-0.23**	0.09	0.32**	0.14	0.17	-0.07	0.25*	0.07	0.19*	-0.23	-0.59***	0.06	0.25**
FX(t+1,t+3)	0.20***	0.09*	0.05	0.01	0.03	-0.06	-0.06	0.01	0.09	-0.04	-0.05	-0.05	-0.06	0.07	0.08	-0.15	-0.13**	0.08	0.19***
FX(t+4,t+6)	0.08	0.10	-0.08	0.10	0.03	-0.05	0.09	-0.13	-0.02	-0.15	0.05	-0.24**	-0.03	-0.08	0.03	0.13	0.27**	0.14*	-0.04
FX(t+7,t+12)	-0.04	-0.03	-0.09	0.03	-0.19*	0.01	0.01	-0.01	-0.15	-0.09	-0.09	-0.02	-0.09	-0.13*	-0.14	0.03	0.11**	0.01	-0.04
# of obs	228	219	223	219	140	84	118	169	117	142	142	114	90	87	118	102	49	228	228

Table 15: Trading strategy based on *Media tone*$^{\perp}$

This table presents returns on a $1 investment in ETFs from their inception in January 2007. The strategy is to buy USD ETF at the end of month t and reinvest every month for three months (or hold it for one month) if *Media tone*$^{\perp}$ in month t is positive. If it is negative, we invest in three-month T-bills for one month, and we revise the strategy based on *Media tone*$^{\perp}$ in month t+1. UUP and UDN are Invesco DB USD Bullish and Bearish funds, respectively. UUP longs the USD and shorts the global basket, while UDN longs the global basket and shorts the USD. T-bill is 3-month T-bill.

Strategy	Investing period of ETFs	Return	Return of the opposite strategy
	Strategy without using *Media Tone*		
UUP		2.20%	
UDN		-21.75%	
T -bill		6.00%	
	Strategy using *Media Tone*		
UUP and T-bill	1 month	22.98%	-11.91%
UUP and T-bill	3 months	44.38%	34.70%
UDN and T-bill	1 month	-15.72%	-1.58%
UDN and T-bill	3 months	-30.57%	-28.09%
	Strategy using *Media Tone*$^{\perp}$		
UUP and T-bill	1 month	12.55%	-3.74%
UUP and T-bill	3 months	17.95%	5.59%
UDN and T-bill	1 month	-19.95%	3.62%
UDN and T-bill	3 months	-26.67%	3.05%

Table 16. The ability of *Media tone*$^{\perp}$ to predict gross and net currency excess returns

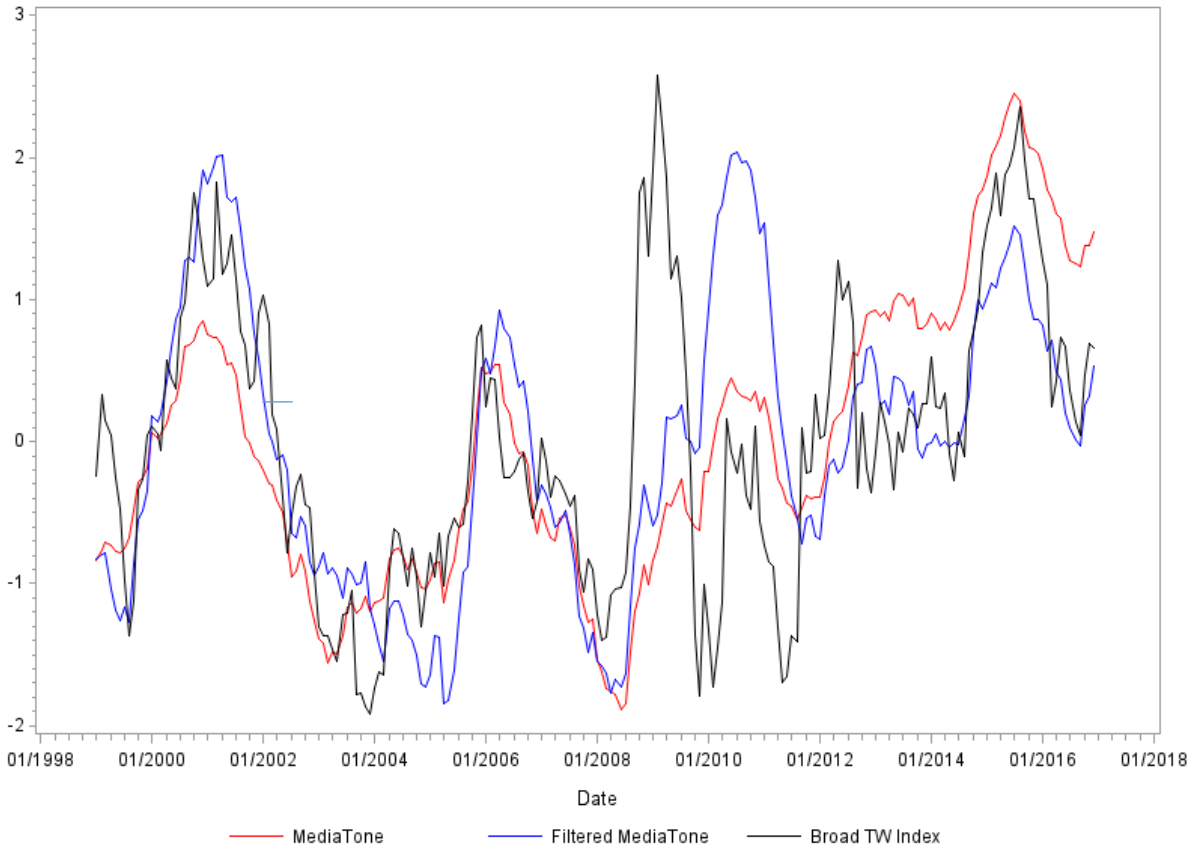
This table presents the ability of *Media tone* and *Media tone*$^{\perp}$ to predict gross and net currency excess returns, provided by Professor Adrian Verdelhan and used in Lustig, Roussanov and Verdelhan (2011), as follows:

$$FX_{(t+k,t+l)} = \beta_0 + \beta_1 MediaTone_t^{\perp} + \varepsilon_{(t+k,t+l)}.$$

$FX_{(t+k,t+l)}$ is gross or net currency excess returns computed similarly to Equation (1) for developed and emerging countries. $MediaTone_t^{\perp}$ is a text analysis-based filtered and standardized TRMI USD *Media tone*. The filtering variables are the variables included in Specification 3 of Panel B Table 2. The currency excess returns are sorted by interest rate differentials into five portfolios. P1 is the portfolio with the lowest interest rate differentials while P6 has the highest differentials for all countries. P5 has the highest differentials for developed countries. HML refers to high minus low portfolios. Gross returns are net returns added by transaction costs. ***,**, and * indicate 1%, 5%, and 10% significance levels, respectively. See the definition of variables in Appendix 3.

		Media tone				$MediaTone_t^{\perp}$			
		All countries		Developed. countries		All countries		Developed countries	
		Gross	Net	Gross	Net	Gross	Net	Gross	Net
P1	β_1	0.11	0.11	0.13	0.14	-0.02	-0.02	0.03	0.03
	t-stat	0.88	0.92	0.88	0.90	-0.14	-0.13	0.22	0.22
	R^2	-0.15	-0.12	-0.17	-0.15	-0.44	-0.44	-0.43	-0.43
P2	β_1	0.20**	0.20**	0.19	0.18	0.09	0.09	0.03	0.03
	t-stat	2.27	2.21	1.22	1.20	0.82	0.79	0.20	0.20
	R^2	0.91	0.8	0.06	0.04	-0.17	-0.19	-0.43	-0.43
P3	β_1	0.07	0.06	0.29*	0.28*	-0.01	-0.02	0.03	0.03
	t-stat	0.64	0.6	1.72	1.66	-0.13	-0.15	0.18	0.14
	R^2	-0.32	-0.34	0.76	0.67	-0.44	-0.44	-0.43	-0.43
P4	β_1	0.31**	0.32**	0.38**	0.38**	0.18	0.19	0.28	0.28
	t-stat	2.49	2.49	2.24	2.25	1.30	1.32	1.57	1.60
	R^2	1.86	1.91	1.37	1.35	0.32	0.37	0.55	0.59
P5	β_1	0.22*	0.22*	0.39**	0.38**	0.06	0.06	0.34	0.34
	t-stat	1.87	1.86	2.28	2.26	0.39	0.4	1.58	1.62
	R^2	0.54	0.52	0.89	0.85	-0.38	-0.37	0.55	0.58
P6	β_1	0.49***	0.44***			0.39**	0.36**		
	t-stat	2.88	2.70			2.22	2.13		
	R^2	2.50	1.96			1.42	1.25		
HML	β_1	0.38***	0.33**	0.26*	0.25*	0.40***	0.38***	0.30	0.31*
	t-stat	2.73	2.42	1.88	1.80	3.03	2.96	1.61	1.66
	R^2	2.11	1.45	0.28	0.22	2.41	2.16	0.56	0.60

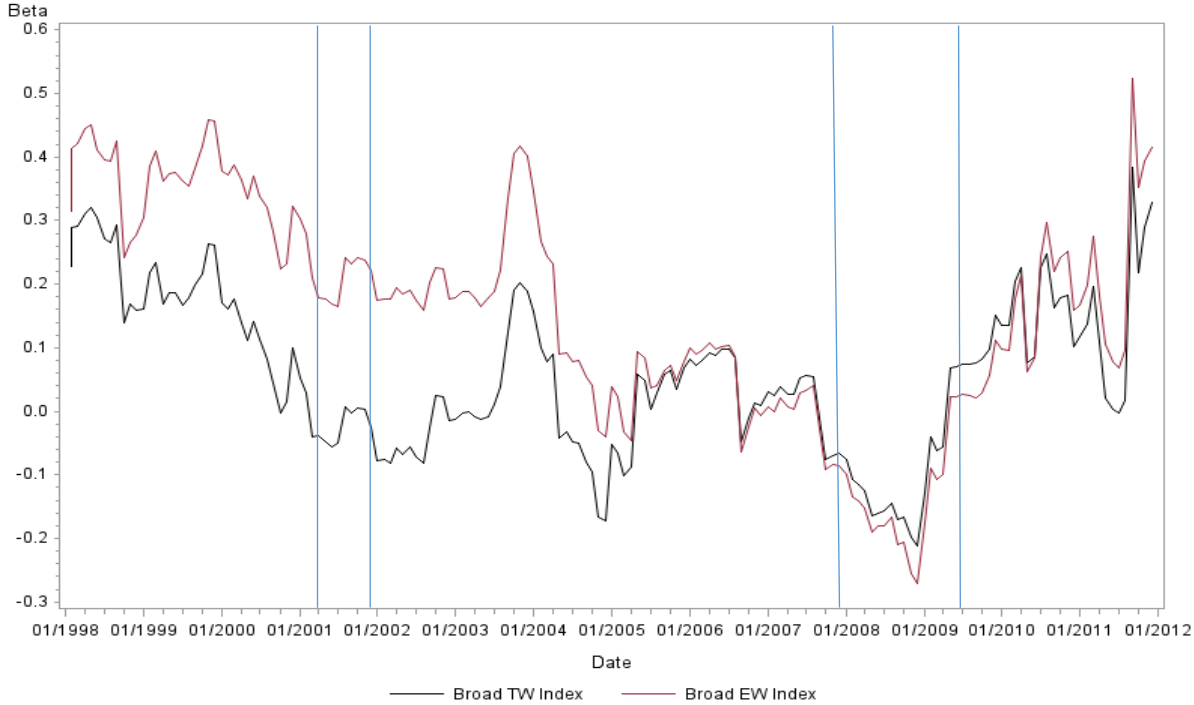
Figure 1: *Media tone*, *Media tone*$^{\perp}$ and broad TW index returns



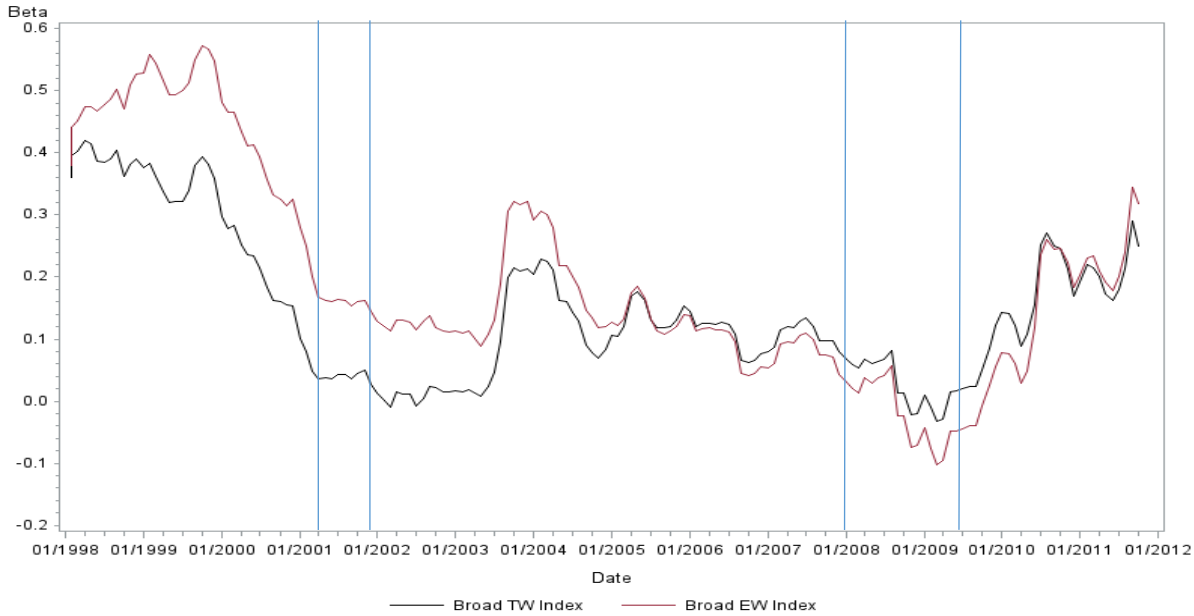
This figure presents the time-series of *Media tone*, *Media tone*$^{\perp}$ and the excess returns of broad trade-weighted USD currency index. Time-series are standardized 12-month moving averages. $MediaTone$ is the text-based TRMI USD *Media tone* and *Media tone*$^{\perp}$ is the same index orthogonalized with respect to the variables included in Specification 3 of Panel B Table 2. Broad TW index refers to trade weighted currency index for the 25 largest trading partners of the US.

Figure 2: Rolling betas of predictive regression of USD excess returns on *Media tone*$^{\perp}$

Panel A: USD excess Return is at t+1 (FX_{t+1})



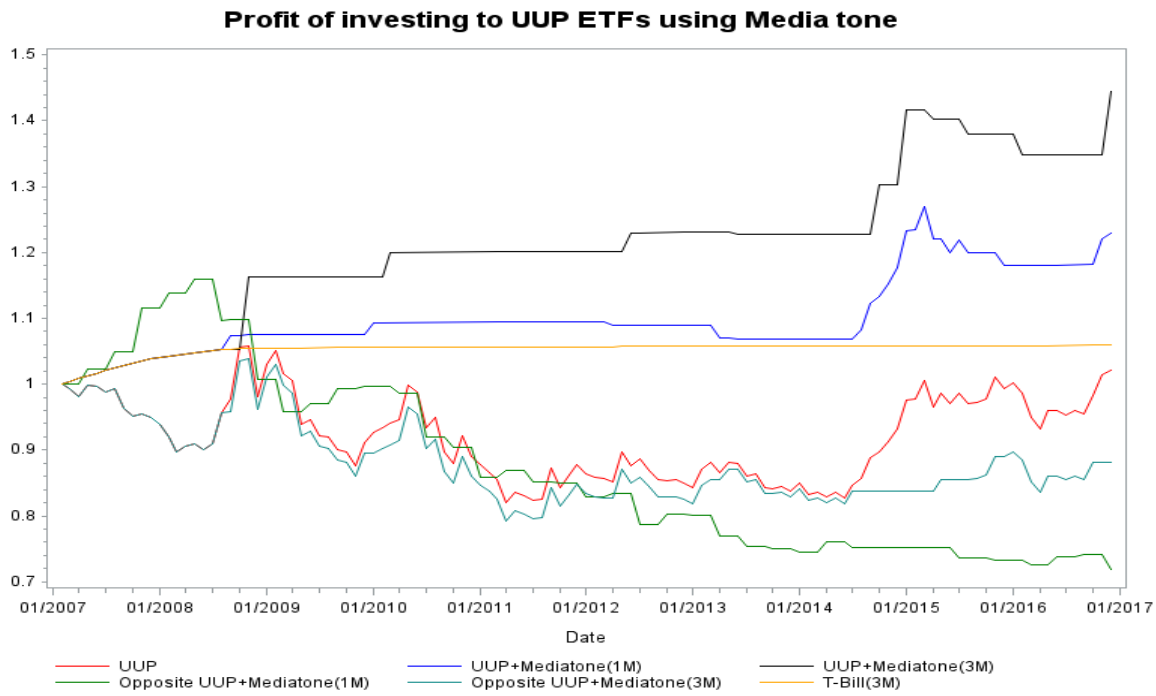
Panel B: USD excess Return is for the period (t+1 – t+3) ($FX_{t+1,t+3}$)

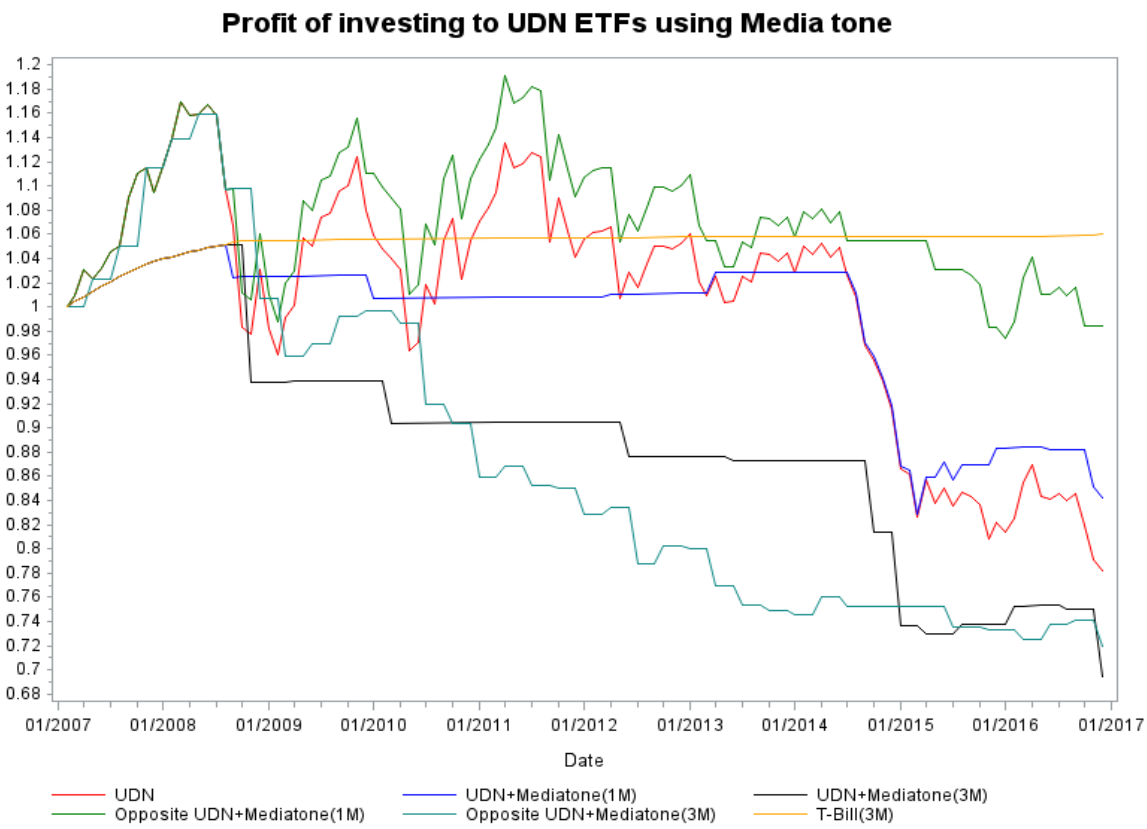


Panel A (B) presents rolling betas of regressing USD excess returns in month t+1 (t+1 to t+3) on filtered USD *Media tone* in month t. The beta is estimated every month from the 60-month rolling windows. The first and last two vertical lines present the NBER recession periods from March 2001 to November 2001 and from December 2007 to June 2009, respectively.

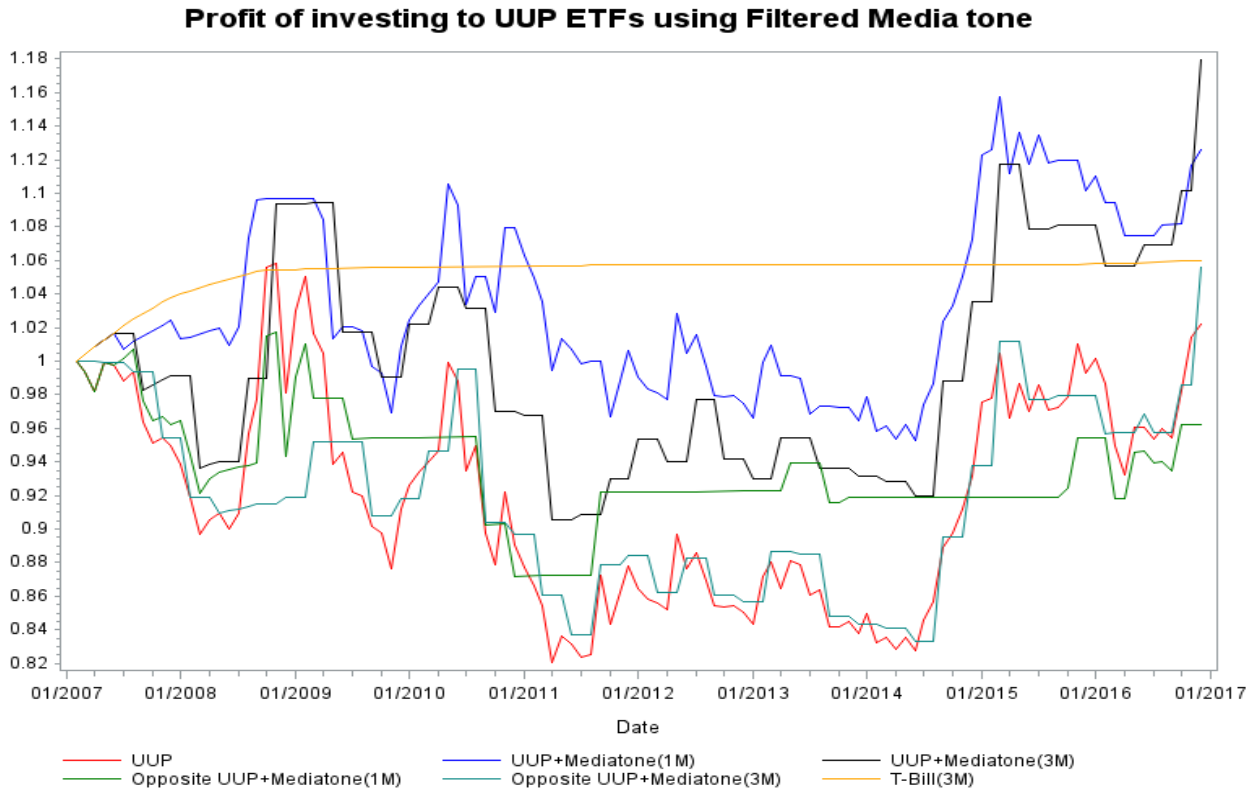
Figure 3: Trading strategy based on *Media tone* and *Media tone*$^{\perp}$

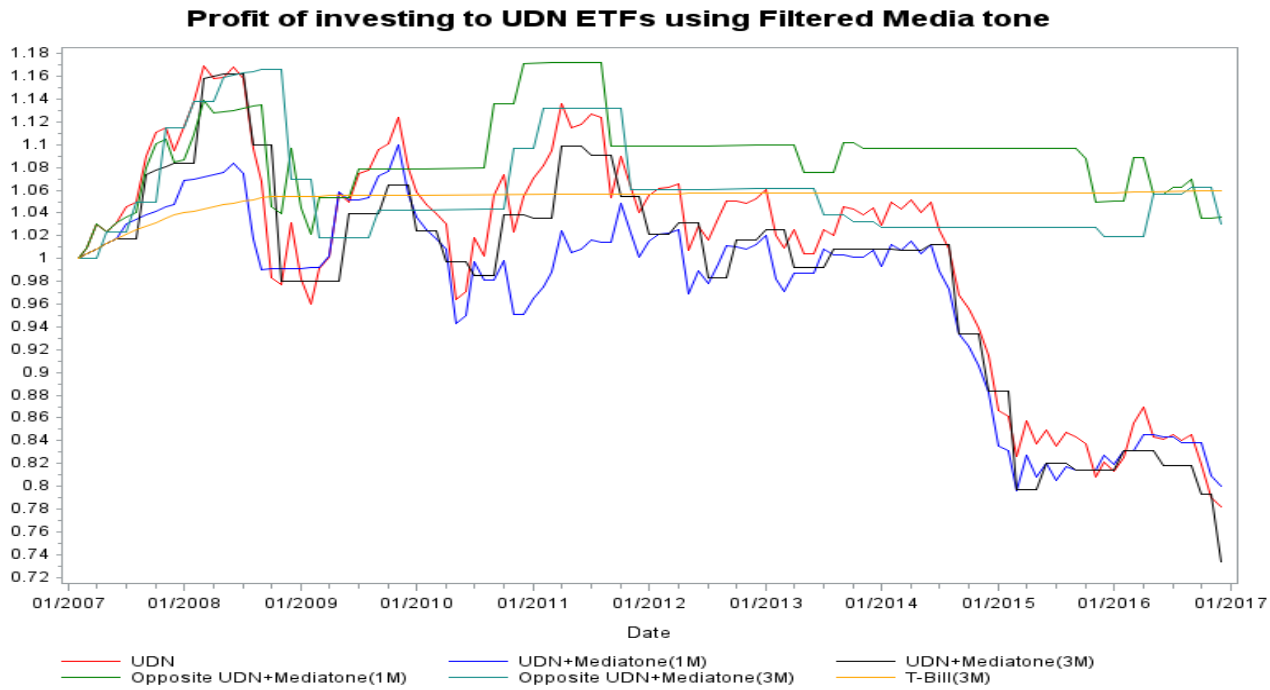
Panel A: Trading strategy based on *Media tone*





Panel B: Trading strategy based on *Media tone*$^{\perp}$





This figure shows the total return of a $1 investment in January 2007, the inception of USD ETFs (UUP and UDN). Our trading strategy is to invest in USD ETFs in month t for one month (or hold it for three months) if *Media tone*$^{\perp}$ in month t is greater than zero. We invest in three-month T-bills otherwise. Another strategy is to do the opposite, that is, to long three-month T-bills in month t for one month (or hold it for three months) if *Media tone*$^{\perp}$ in month t is greater than zero. Otherwise, we invest in USD ETFs. Our USD ETFs include the top two USD ETFs traded in the US market, UUP (Invesco DB USD Index Bullish Fund, which longs the USD and shorts the global basket) and UDN (Invesco DB USD Index Bearing Fund, which longs the global basket and shorts the USD). The notations "UUP," "UDN," and "three-month T-bill" in the figures refer to when we invest in only UUP, UDN, and three-month T-bills, respectively. In all our computations, we assume that investors reinvest monthly using geometric average returns. For the three-month strategy, investors buy the asset in month t and receive returns in month t+1, t+2, and t+3 compounded. They reinvest again at the end of month t+3 based on the *Media tone*$^{\perp}$ information in month t+3.

Appendix 1. Currencies

This appendix presents the currencies we use in our study. In detail, it shows the start and ending period, when the country joined the Euro zone, whether it is developed market, and used to construct our broad index, whether the data are provided by BIS, and whether there is any data for political risk and credit rating available.

Country	Currency	Start	End	Eurozone since	Developed	Broad index	BIS	Political Risk	Credit rating
Argentina	Peso	03/2004	12/2016			x	x	x	x
Australia	Dollar	12/1997	12/2016		x	x	x	x	x
Austria	Schilling	12/1997	12/1998	1999	x		x	x	x
Belgium	Franc	12/1997	12/1998	1999	x		x	x	x
Botswana	Pula	07/2011	12/2016					x	
Brazil	Real	07/2000	12/2016			x	x	x	x
Bulgaria	Lev	03/2004	12/2016					x	x
Canada	Dollar	12/1997	12/2016		x	x	x	x	x
Chile	Peso	03/2004	12/2016			x	x	x	x
China	Renminbi	02/2002	12/2016			x	x	x	x
Colombia	Peso	03/2004	12/2016			x	x	x	
Croatia	Kuna	03/2004	12/2016					x	x
Cyprus	Pound	03/2004	12/2007	2008				x	
Czech Republic	Koruna	12/1997	12/2016					x	x
Denmark	Krone	12/1997	12/2016		x		x	x	x
Egypt	Pound	03/2004	12/2016					x	
Estonia	Kroon	03/2004	12/2010	2011				x	
Eurozone	Euro	12/1998	12/2016		x	x		x	x
Finland	Markka	12/1997	12/1998	1999	x		x	x	x
France	Franc	12/1997	12/1998	1999	x			x	x
Germany	Mark	12/1997	12/1998	1999	x		x	x	x
Ghana	Cedi	07/2011	12/2016					x	
Greece	Drachma	12/1997	12/2000	2001			x	x	x
Hong Kong	Dollar	12/1997	12/2016		x	x	x	x	x
Hungary	Forint	12/1997	12/2016					x	x
Iceland	Krona	03/2004	12/2016					x	
India	Rupee	12/1997	12/2016			x		x	x
Indonesia	Rupiah	12/1997	12/2016			x		x	x
Ireland	Punt	12/1997	12/1998	1999	x		x	x	x
Israel	New shekel	03/2004	12/2016			x	x	x	
Italy	Lira	12/1997	12/1998	1999	x		x	x	x
Japan	Yen	12/1997	12/2016		x	x	x	x	x
Jordania	Dinar	03/2004	12/2016					x	
Kazakshtan	Tenge	03/2004	12/2016						
Kenya	Shilling	03/2004	12/2016					x	
Kuwait	Dinar	12/1997	12/2016					x	
Latvia	Lat	03/2004	12/2013	2014			x	x	
Lithuania	Lita	03/2004	12/2014	2015			x	x	
Malaysia	Ringgit	04/2006	12/2016			x	x	x	x
Malta	Lira	03/2004	12/2007	2008				x	
Mexico	Peso	12/1997	12/2016			x		x	x
Morocco	Dirham	03/2004	12/2016					x	
Netherlands	Guilder	12/1997	12/1998	1999	x		x	x	x
New Zealand	Dollar	12/1997	12/2016		x		x	x	
Norway	Krone	12/1997	12/2016		x		x	x	x
Oman	Rial	03/2004	12/2016					x	
Pakistan	Rupee	03/2004	12/2016					x	
Peru	Sol	03/2004	12/2016				x	x	
Philippines	Piso	12/1997	12/2016			x		x	x
Poland	Zloty	02/2002	12/2016				x	x	x

Portugal	Escudo	12/1997	12/1998	1999	x		x	x	x
Qatar	Rial	03/2004	12/2016					x	
Romania	Leu	03/2004	12/2016					x	x
Russia	Rouble	03/2004	12/2016			x	x	x	x
Saudi Arabia	Riyal	12/1997	12/2016			x		x	
Serbia	Dinar	07/2011	12/2016						
Singapore	Dollar	12/1997	12/2016		x	x	x	x	x
Slovakia	Koruna	02/2002	12/2008	2009				x	x
Slovenia	Tolar	03/2004	12/2006	2007				x	
South Africa	Rand	12/1997	12/2016				x	x	x
South Korea	Won	02/2002	12/2016			x	x	x	x
Spain	Peseta	12/1997	12/1998	1999	x		x	x	x
Sri Lanka	Rupee	07/2011	12/2016					x	
Sweden	Krona	12/1997	12/2016		x	x	x	x	x
Switzerland	Franc	12/1997	12/2016		x	x	x	x	x
Taiwan	New dollar	12/1997	12/2016			x		x	x
Thailand	Baht	12/1997	12/2016			x		x	x
Tunisia	Dinar	03/2004	12/2016					x	
Turkey	Lira	12/1997	12/2016					x	x
UAE	Dirham	12/1997	12/2016					x	
UK	Pound	12/1997	12/2016		x	x	x	x	x
Uganda	New shilling	07/2011	12/2016					x	
Vietnam	Dong	07/2011	12/2016					x	
Zambia	Kwacha	07/2011	12/2016					x	

Appendix 2. TRMI data formation

TRMI data are based on word recognition techniques which aim to extract economics, finance, business and psychological relevant information from financial news, social media, conference calls transcripts and executive interviews. Data are available for more than 7,750 companies from over 30 countries and index level data are available to the 15 largest markets from 1998 onwards. Data are also available for 130 countries. Only text written in English is used in the analysis.
Data analysis

Previous studies mostly use a lexical analysis method where an article text is compared to pre-specified context relevant lexicon and their frequencies are subsequently counted. The most significant limitation of this method is that it concentrates only on one dimension of *Media tone* (positive vs. negative) and ignores other, partly interrelated, dimensions. Also, some open-source *Media tone* dictionaries might misclassify business-and finance-related terms. TRMI word recognition technique uses extensive customization and curation of lexicons and aims to identify and score hundreds of *Media tone* dimensions using different grammatical frameworks to different text sources based on their special traits and also considers the structure of the sentences and articles. When applied to text, the confluence of the various text processing described below generates over 400 psychological variables (PsychVars), each with the potential to be applied to a different entity. It should be emphasized that the method aims to identify word interrelationships and calculates the score based these, instead of using frequency analysis on individual words. The following goes through the methods used for word recognition and content quantifying method used in the data formation.

Source type differences

TRMI data are extracted from both traditional news media and from social media sources which creates challenging environment for word recognition techniques. Thus, the data analysis is customized for each source due to differences in communication styles between social and news media.

Unlike news media, which uses standardized terms and appropriate tone in its contents, social media contains substantial amounts of sarcasm and irony, colloquial meanings, incomplete thoughts, misplaced punctuation, misspellings, non-standard grammar, case insensitivity and crude language. The expressions of emotions between news and social media also vary. In social media, authors tend to use nationally and regionally developed emoticons (e.g. ":)") and acronyms (e.g. "LOL") to express themselves.

In addition, unlike journalists of traditional news media, who are trained to offer multiple perspectives on the underlying story and go through editorial process, authors in social media have a tendency to express their own opinions and emotional states more directly. In the news, the role of journalists is to describe the emotional states of those they are reporting on. As a result, information obtained from social media is typically less inclusive of contrary viewpoints and more emotionally expressive from the first-person perspective than news information.

As a result of all these differences, text analytical models are used to calibrate the text analytics by source type and different models are used for news, social media forums, tweets, SEC filings and earnings conference call transcripts.

Entity identification

Entities are identified with a list containing more than 60 000 entity names and their aliases which include e.g. different language specific writing forms of locations and firms.

TRMI uses anti-correlate filters to exclude irrelevant entities. For example, gold and silver are typically mentioned every two years during the Olympic Games but they are not related to gold and silver commodities. Similarly, references to South Korean Won could be either used to refer to victories achieved by South Korean athletes or to South Korea's currency. Also, the entities should have a correct co-references. For example, "breakfast oats" are not counted as a correct reference to commodity Oats unless it is accompanied with key identification correlates such as "prices" or "futures".

Timing

TRMI has several variables referring to expectations. The text-analytics software is calibrated to identify verb tenses in every phrase and is able to recognize when the references are future-oriented and hence related to expectations. For example, "Optimism" is a difference between references to future-oriented positive and negative comments and for example to "Uncertainty", any references to past uncertainties are excluded from the analysis.

Modifiers and negations

Modifier words change the meaning or tone of a phrase or sentence by modifying its impact. For example, words or phrases that increase the significance of an adjective, such as "large", (e.g. "large loss") are multiplicative on the weighting of the modified word whereas minimizers like "a little" and "a handful" multiply the meaning score by 0.5. Modifiers can either increase (maximizers) or decrease (minimizers) the score of a key term and thus affect the scoring of textual meaning. In cases of frequent meanings based on simple word relationships, like the word "new", a multiplier is used to minimize the weight of the meaning. For example, in the case of "new" the multiplier is 0.1 when that meaning is used in the Innovation index.

Data also takes into account the differences between news headlines and article bodies. Headlines have a multiplicative weight of 3, subtitles a weight of 2 and bodies a weight of 1 in the data formation.

In addition to the maximizing and minimizing operations, the data formation takes into account negations. For example, the phrase "I'm not worried about the earnings release" connotes that the author is not afraid, and as a result, the extracted fear score is negated (-1).

Source texts

The TRMI measures are from two groups of sources, news and social media, and the data consists of three feeds: news feed, social media feed and an aggregate feed of combined news and social media content. TRMI processes more than two million articles daily and the data are updated minutely. Each minutely value is an average of the past 24 hours of observations about the target entity.

As sources, TRMI uses data from the largest and most important news organizations, global internet news coverage, and a broad and credible range of social media sources. The TRMI news indices are derived from content delivered in Thomson Reuters News Feed Direct and two Thomson Reuters news archives: a Reuters-only one from 1998 to 2002 and one with Reuters and select third-party wires from 2003 onwards. In 2005, Moreover Technologies aggregate news feed was incorporated to the data adding 50 000 internet news sites to the sources. In addition, hundreds of financial news sites and finance specific sources widely read by professional investors are also included in the data. MarketPsych social media content has been downloaded from public social media sites from 1998 onwards and the data from Moreover Technologies' aggregate social media feed, which is derived from more than four million social media sites, was incorporated to TRMI in 2009.

Quantifying the articles

Each TRMI variable constitutes of a combination of minor components called PsychVars. To form a TRMI variable, the absolute values of PsychVars are first determined using 24 hours of observations. These absolute values are then summed for all constituents to get the Buzz-variable. More specifically, Buzz is calculated as follows:

$$Buzz_t(a) = \sum_{c \in C(a), p \in P} |PsychVar_{c,p,t}|$$

where t denotes time, a is the entity, $C(a)$ is the set of all constituents of a (for example, for indices, $C(a)$ consists of all individual assets comprising the index) and $P(s)$ is the set of all PsychVars relevant to a particular TRMI variable s.

For the other TRMI variables, the values are calculated as follows:

$$TRMI_{s,t}(a) = \frac{\sum_{c \in C(A), p \in P(s)} \left(I_t(s,p) * PsychVar_{p,t}(c) \right)}{Buzz_t(a)}$$

where $I_t(s,p)$ defines whether a PsychVar $p \in P(s)$ is additive or subtractive to a TRMI variable s at time t:

$$I_t(s,p) = \begin{cases} +1, if\ additive\ at\ time\ t \\ -1, if\ subtractive\ at\ time\ t \end{cases}$$

A single PsychVar can contribute to multiple TRMI variables. For example, EarningsUp_f PsychVar (see below for an example) is a constitute of all, EarningsForecast, Sentiment, Optimism and FundamentalStrength TRMI variables.

Sentence-level Example

The following shows an example of the TRMI data generating process using the above mentioned principles. Consider the following sentence:

"Analysts expect Mattel to report much higher earnings next quarter"

The language analyzer performs the following sequence:

1. Associates ticker symbol MAT with entity reference "Mattel."
2. Identifies "earnings" as an Earnings word in the lexicon.
3. Identifies "expect" as a future-oriented word and assigns future tense to the phrase.
4. Identifies "higher" as an Up-Word (positive reference).
5. Multiplies "higher" by 2 due to presence of the modifier word "much."
6. Associates "higher" (Up-Word) with "earnings" (Earnings) due to proximity.

The analysis algorithm will report:

Date Time Ticker PsychVar Score

20110804 15:00.123 MAT EarningsUp_f 2

In the example above, 2 is the raw score produced for EarningsUp_f.

Specific examples of how *Media tone* is scored

This section illustrates how TRMI scores *Media tone*. We use the three examples below and ask the TRMI to score them. The tables in the next page shows how they come up with the score.

Japanese Yen and USD

https://www.fxempire.com/forecasts/article/usd-jpy-price-forecast-us-dollar-falls-against-japanese-yen-7-628064

Noun	Geo	Meaning	Tense	Quantity	Position	Phrase
USD	USA	BearVerbs	future	3	8	USD Falls
USD	USA	Negative	future	3	8	USD Falls
Japan Yen	USA	BearVerbs	past	2	16	Yen The USD pulled back
Japan Yen	USA	Negative	past	2	16	Yen The USD pulled back
Japan Yen	Japan	Negative	past	2	22	Yen The USD pulled back against the Japanese yen rather stringently
USD	USA	BearVerbs	past	1	50	USD has pulled back
USD	USA	Negative	past	1	50	USD has pulled back
USD	USA	Negative	normal	1	59	USD has pulled back significantly during the trading session on Thursday , breaking
USD	USA	Negative	normal	1	60	USD has pulled back significantly during the trading session on Thursday , breaking below

USD	Positive	Negative	Media tone
	0	10	-1
YEN	Positive	Negative	Media tone
	0	6	-1

Chinese Yuan

https://markets.businessinsider.com/news/stocks/china-currency-wuhan-outbreak-yuan-erase-gains-effect-manipulator-us-2020-1-1028843403

Noun	Geo	Meaning	Tense	Quantity	Position	Phrase
Yuan	China	Negative	past	3	6	China ‘s currency stumbles amid Wuhan virus
Yuan	China	Negative	past	3	7	China ‘s currency stumbles amid Wuhan virus outbreak
Yuan	China	BearVerbs	past	3	9	China ‘s currency stumbles amid Wuhan virus outbreak after losing
Yuan	China	Negative	past	3	9	China ‘s currency stumbles amid Wuhan virus outbreak after losing
Yuan	China	Negative	past	3	10	China ‘s currency stumbles amid Wuhan virus outbreak after losing manipulator
Yuan	China	BearVerbs	normal	1	19	Chinese currency markets are the latest to tumble
Yuan	China	Negative	normal	1	19	Chinese currency markets are the latest to tumble
Yuan	China	Negative	normal	1	22	Chinese currency markets are the latest to tumble amid Wuhan virus
Yuan	China	Negative	normal	1	23	Chinese currency markets are the latest to tumble amid Wuhan virus fears
Yuan	China	BearVerbs	past	1	26	weakeness comes after a period of strength for China
Yuan	China	Negative	past	1	26	weakeness comes after a period of strength for China
Yuan	China	Positive	past	1	32	strength for China ‘s currency
Yuan	China	Negative	past	1	49	China from the currency manipulators
Yuan	China	Negative	conditional	1	66	the yuan closes for the next week , markets fear
Yuan	China	Positive	conditional	1	73	the yuan closes for the next week , markets fear travel related to Lunar New Year celebrations
Yuan	China	Negative	conditional	1	79	yuan closes for the next week , markets fear travel related to Lunar New Year celebrations could heighten transmission of the illness

Positive	Negative	Media tone
2	24	-0.85

USD

https://www.dailyfx.com/forex/fundamental/daily_briefing/session_briefing/daily_fundamentals/2019/12/10/us-dollar-primed-for-cpi-fomc-as-gbp-usd-gbpusd-rally-continues-js56.html

Noun	Geo	Meaning	Tense	Quantity	Position	Phrase
USD	USA	BullVerbs	past	1	28	US DOLLAR / HOLDS RESISTANCE / AHEAD OF THE / FED The fourth quarter of this year has been of interest for USD price action . The Greenback gained
USD	USA	Negative	normal	1	50	the Fed and the two rate cuts
USD	USA	Negative	past	1	74	the Fed and the two rate cuts that were seen ahead of the October open . But all was not well in that bullish trend as buyers were much more shy
USD	USA	Negative	past	1	112	the Fed and the two rate cuts that were seen ahead of the October open . But all was not well in that bullish trend as buyers were much more shy at or around highs than they were at lows or around support , leading to the build of a rising wedge pattern that was looked at coming into Q4 . The month of October is when that broke
USD	USA	Positive	past	2	28	US DOLLAR / HOLDS RESISTANCE / AHEAD OF THE / FED The fourth quarter of this year has been of interest for USD price action . The Greenback gained
USD	USA	Positive	past	-0.5	67	the Fed and the two rate cuts that were seen ahead of the October open . But all was not well in that bullish
USD	USA	Positive	past	1	194	the Fed and the two rate cuts that were seen ahead of the October open . But all was not well in that bullish trend as buyers were much more shy at or around highs than they were at lows or around support , leading to the build of a rising wedge pattern that was looked at coming into Q4 . The month of October is when that broke and sellers made a re-appearance , driving price action in the currency for most of the month as a fresh low was set at the November open . November brought a range , as prices retraced 50 % of that October sell-off , Rnding resistance at a key area on the chart running from 9833-98.50 . Sellers showed up again around the December open and pushed-lower for most of last week . A quick counter-trend move showed around last week 's blowout

Positive	Negative	Media Tone
3.5	3.0	0.08

British Pound

https://www.marketwatch.com/story/british-pound-rises-further-ahead-of-uk-election-2019-12-10

Noun	Geo	Meaning	Tense	Quantity	Position	Phrase
Pound	UK	BullVerbs	future	1	29	British pound climbed on Tuesday , with the U.K . currency extending gains on the expectation the Conservatives will win

Pound	UK	Positive	future	1	29	British pound climbed on Tuesday , with the U.K . currency extending gains on the expectation the Conservatives will win

Positive	**Negative**	**Media Tone**
2	0	1.00

Appendix 3: Variable description

Dependence variable	
Broad equal-weighted index returns	The returns of equal- weighted indices of the 25 largest US trading partners. See Appendix 1 for these 25 countries and the sample period available. The indices are defined similarly as the broad and major currency indices available in the Federal Reserve Bank of St. Louis' Federal Reserve Economic Data (FRED) database. The exception is that for Broad index, we exclude Venezuela as its currency values do not change at all for the shorter periods. The index is calculated utilizing end of the month currency excess returns from bilateral exchange rates.
Broad value-weighted index returns	The returns of trade- weighted indices of the 25 largest US trading partners. See Appendix 1 for these 25 countries and the sample period available. Trade weights used for the calculations are from FRED's database. https://www.federalreserve.gov/releases/h10/weights/default.htm The index is calculated utilizing end of the month currency excess returns from bilateral exchange rates.
Independent variable	
Media tone	The monthly average of daily TRMI Sentiment capturing the positive net of negative tone of the news and social media related to USD. See Appendix B for variable construction
$MediaTone^{\perp}$	Filtered *Media tone* derived as the residuals from regressing *Media tone* on currency factors including Currency Carry Factor, Currency volatility, Currency Value, Global Dollar factor, one- month Currency Momentum, Commodity factor and World equity factor, and business cycle components including inflation, GDP growth, and 3-month Treasury bill interest rate.
Determinants of *Media tone*	
FX	USD return if the Broad value weighted index.
S&P500 return	The return of S&P500 index from Datastream
Interest rate	US 3-month T-bill rate from Federal Reserve Bank of St. Louis
US Equity Market Volatility Index	A newspaper-based Equity Market Volatility (EMV) tracker that moves with the CBOE Volatility Index (VIX) and with the realized volatility of returns on the S&P 500. The measure is developed by Baker et al. (2019) Source: https://www.policyuncertainty.com/EMV_monthly.html
VIX	Chicago Board Options Exchange (CBOE) volatility index (VIX) measures the expectations on stock market volatility while Equity Uncertainty in US (US Equity Uncertainty) is constructed using the newspaper articles containing terms related to equity market uncertainty.

	http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data
USD expectations	Reuters FX polls data from the Eikon for 1 month mean GBP/USD, EUR/USD and JPY/USD exchange rates. Data for other currencies are available only for shorter periods. Since these are the largest and most important currencies globally, these data should capture the expectations of the USD movements with them. Data for 1-month forecasts starts from 1/1999 and the monthly mean number of forecasters is about 55 for each of the bilateral exchange rates. We compute Expectations as $ln[E_t[S_{t+1}]]$ - $ln[S_t]$ where S_t is quoted as 1 unit of USD per foreign currency.
Variables used to filter raw *Media tone*	
1. Currency carry factor	
Dollar	The global dollar factor by Verdelhan (2018). For the data, please see Professor Adrian Verdelhan's website here: http://web.mit.edu/adrienv/www/Data.html
Carry	Currency carry factor by Lustig et al. (2011); For the data, please see Professor Adrian Verdelhan's website here: http://web.mit.edu/adrienv/www/Data.html
Momentum	One-month currency momentum calculated similarly as in Menkhoff et al. (2012b).
Volatility	Currency volatility by Menkhoff et al (2012a). We use all the currencies we have (except Venezuela), which is similar to Aloosh and Bekaert (2019).
Value	The methodology to compute this factor and the currencies included are similar to what Aloosh and Bekaert (2019) use i.e., the 27 OECD countries
Commodity	Monthly return of the CRB Spot Commodity Index Raw Industrials sub-index
World equity	Monthly return of MSCI World index; data are from Datastream.
2. Business cycle variables	
IndProd	Industrial production index; Source: Federal Reserve Bank St. Louis
Durable	Change in real values of consumer durables; Source: Federal Reserve Bank in St. Louis
Nondurable	Change in real values of consumer non-durables; Source: Federal Reserve Bank in St. Louis
Services	Change in real values of consumer services; Source: Federal Reserve Bank in St. Louis
US unemployment rate	Change in employment; Source: Federal Reserve Bank in St. Louis
Recession	NBER recession dummy variable; Source: Federal Reserve Bank in St. Louis
Inflation	Inflation is measured as a yearly change in seasonally adjusted consumer price index for each month. For Australia and New Zealand, only quarterly data are available and thus we use it for the

	all the months of the quarter. For Taiwan and Argentina, we use data from the Datastream and for Oman, data from the Global Finance Data. For other countries, data are from International Monetary Fund's International Financial Statistics database.
GDP growth	GDP is seasonally adjusted and measured with constant prices. GDP growth is calculated as an annual change in GDP. Since the data are at quarterly frequency, we use the previous growth for the missing periods.
3-month Treasury bill interest rate	Federal reserve bank
Hard-to-value characteristics	
Interest rate differential	Interest rate difference is calculated as a difference between 1-month forward rate and the spot exchange rate.
Inflation	Inflation is measured as mentioned above.
Currency turnover	Daily averages (in billions of USDs) for every April on "net-net" basis (every transaction includes two currencies) for the period 1995-2016. They are available for 49 of the currencies in our sample (36 when the Eurozone countries are excluded). We use previous year's values for missing years. the data are from the table: OTC foreign exchange turnover by currency in April 1995 - 2016, "net-net" basis. ***Triennial*** Survey of foreign exchange and OTC derivatives trading: https://www.bis.org/statistics/derstats3y.htm Information about the most recent survey and some general info can be found from here: https://www.bis.org/statistics/rpfx19_fx.htm
1M, 6M, and 12M Momentum portfolios	Momentum portfolios are calculated similarly as in Menkhoff et al. (2012b). For each currency, a bilateral return with the USD is calculated for previous month, past 6 and 12 months. Further, portfolio returns are calculated for portfolios which are formed based on these 1M, 6M and 12M return periods.
12M exchange rate volatility portfolios	The volatility of the monthly returns of exchange rate against USD for the past 12 months.
Previous month's exchange rate volatility portfolios	The volatility of the daily returns of exchange rate per USD for the past month.
Credit rating portfolios	We use ***quarterly*** updated sovereign credit ratings to measure creditworthiness and general macroeconomic performance of the country. Credit ratings are measured at 20 points scale where the highest value refer to AAA rating and lower values refer to weaker investment environments. Source of the data is *Oxford Economics*.

Political risk portfolios	The ***annual*** data by International Country Risk Guide (ICRG) which calculates political risk as a sum of 12 subcomponents: Government stability, External conflicts, Internal conflicts, Ethnic tensions, Military in politics, Religion in politics, Socioeconomic conditions, Investment profile, Bureaucracy quality, Corruption, Law and order, and Democratic accountability. Higher values mean higher political risks.
Channels of *Media tone*	
BW	Baker and Wurgler orthogonalized sentiment measure collected from Professor Jeffrey Wurgler's website here: http://people.stern.nyu.edu/jwurgler/
Forecast error	Every month, banks receive a questionnaire from Refinitiv asking them to submit their forecast on currency values USD/GBP, USD/EUR and USD/JPY. About 50 answers are given each month for each currency pair. No FX retail brokers or money transfer companies are asked to provide forecasts. We examine the forecast error of these analyst forecast, which is defined as cross-sectional average of $ln[E_t[S_{t+1}]] - ln[S_{t+1}]$.
VIX	See the definition above under Determinants of *Media tone.*
Uncertainties	See the definition of VIX under Determinants of *Media tone.*
Attention	Search Volume Index of USD from Google Search.
Constituents of *Media Tone*	
Buzz	Sum of all references to the USD. In detail, Buzz represents a sum of entity-specific words and phrases used in TRMI computations. It can be non-integer when any of the words/phrases are described with a "minimizer", which reduces the intensity of the primary word or phrase. For example, in the phrase "less concerned" the score of the word "concerned" is minimized by "less". Additionally, common words such as "new" may have a minor but significant contribution to the Innovation TRMI. As a result, the scores of common words/phrases with minor TRMI contributions can be minimized. See Appendix 2 for Buzz's formula.
Optimism	Optimism, net of references to pessimism
Uncertainty	Uncertainty and confusion
Long short	Buying, net of references to shorting or selling
Long short forecast	Forecasts of buying, net of references to forecasts of shorting or selling
Price Direction	Price increases, net of references to price decreases
Price Forecast	Forecasts of asset price rises, net of references to forecasts of asset price drops

Volatility	Volatility in market prices or business conditions includes, for example, activate, wobble, whirlwind, went bananas, vibrate, vary, vacillate, U-turn, uneven, unrest, unwind
Price momentum	Currency price trend strength, net of references to trend weakness

Appendix 4: The predictability of unfiltered *Media tone*

The table presents the test similar to Tables 3 Panel A and B, rather than using $MediaTone^{\perp}$, we use unfiltered *Media tone*. See Appendix 2 for *Media tone* construction and Appendix 3 for variable definitions.

Panel A: Geometric average excess returns

	Broad Index (TW)				Broad Index (EW)			
FX Return	*Media tone*	t-value	R^2(%)	R^2_{OOS} (%)	*Media tone*	t-value	R^2(%)	R^2_{OOS} (%)
FX(t)	0.66***	11.22	16.09		0.69***	9.71	14.36	
FX(t+1)	0.24**	2.57	1.73	2.72*	0.33***	3.27	3.08	2.86*
FX(t+1 - t+3)	0.28***	4.00	7.65	14.23**	0.35***	4.46	9.37	15.75**
FX(t+4 - t+6)	0.17*	1.74	2.54	8.74***	0.23**	2.07	3.80	11.90**
FX(t+7 - t+12)	0.08	0.69	1.00	1.92	0.10	0.68	1.13	4.18
Panel B: Cumulative excess returns								
	Broad Index (TW)				Broad Index (EW)			
FX(t+3)	0.86***	4.19	8.09	15.78**	1.05***	4.59	9.58	16.21**
FX(t+6)	1.30***	2.86	8.81	24.50**	1.68***	3.31	10.97	27.61**
FX(t+9)	1.40*	1.78	6.69	21.67**	1.87**	1.99	8.3	27.92**
FX(t+12)	1.74	1.57	7.86	22.84**	2.24*	1.69	8.66	27.48**

Appendix 5: The impact of interest rate differentials

This Appendix demonstrates that the results with and without interest rate differentials are similar. Panel A replicates Panels A and B of Table 3. In contrast to those panels, Panel A of this Appendix forms trade-weighted and equal-weighted broad indices based on exchange rate returns (excluding interest rate differentials). Panels B replicates Table 6 Panels A but decomposes currency excess returns into changes in spot rate (Δs_{t+1}) and interest rate differentials ($f_t - s_t$). We perform the following regression: $FX_{t+1} = \beta_0 + \beta_1 MediaTone^{\perp} + \varepsilon_{t+1}$. FX_{t+1} is the currency excess return, ($FX_{t+1} = s_{t+1} - f_t$) presented in columns (3) and (6), Δs_{t+1} in columns (4) and (7), and ($f_t - s_t$) in columns (5) and (8). $MediaTone^{\perp}$refers to the standardized and filtered TRMI USD *Media tone*. P1 to P5 present portfolios sorted by interest rate differentials. P1 has the lowest while P5 has the highest differentials. ***, **, and * indicate 1%, 5%, and 10% significance levels.

Panel A: FX_{t+1} excluding interest rate differentials

Independent variable: $MediaTone$

	β_1	t-value	(%)	β_1	t-value	(%)
	Broad Index (TW)			Broad Index (EW)		
FX(t)	0.65***	12.69	15.95	0.64***	10.78	12.56
FX(t+1)	0.24**	2.46	1.74	0.29***	2.77	2.3
FX(t+1, t+3)	0.28***	4.02	7.66	0.31***	4.09	7.5
FX(t+4, t+6)	0.18*	1.8	2.67	0.20*	1.93	2.89
FX(t+7, t+12)	0.08	0.63	0.82	0.07	0.45	0.23

Independent variable: $MediaTone^{\perp}$

	β_1	t-value	(%)	β_1	t-value	(%)
	Broad Index (TW)			Broad Index (EW)		
FX(t)	0.27*	1.94	2.33	0.26*	1.67	1.81
FX(t+1)	0.13	1.16	0.2	0.18	1.54	0.69
FX(t+1, t+3)	0.19**	2.53	3.44	0.19**	2.26	2.8
FX(t+4, t+6)	0.08	0.97	0.24	0.09	1.04	0.32
FX(t+7, t+12)	-0.04	-0.39	-0.19	-0.06	-0.59	0.16

Panel B: Decomposing US excess returns

		Independent variable: *Media tone*					
		Not excluding high inflation periods			Excluding high inflation periods		
		Dependent variable			Dependent variable		
		FX_{t+1}	Δs_{t+1}	$f_t - s_t$	FX_{t+1}	Δs_{t+1}	$f_t - s_t$
P1	Coef	0.13	0.17*	0.04	0.17*	0.19*	0.02
	t-stat	1.27	1.76	0.98	1.69	1.93	1.6
	R^2	0.13	0.83	-0.22	0.74	1.14	0.67
P2	Coef	0.15*	0.15*	0.00	0.13*	0.14*	0.00
	t-stat	1.78	1.79	0.53	1.66	1.68	0.51
	R^2	0.56	0.62	-0.18	0.38	0.43	-0.22
P3	Coef	0.24**	0.26**	0.01	0.22**	0.24**	0.01
	t-stat	2.36	2.47	1.43	2.21	2.3	1.33
	R^2	1.83	2.13	1.99	1.52	1.76	1.46
P4	Coef	0.13	0.15	0.03*	0.14	0.16	0.02
	t-stat	1.24	1.45	1.94	1.27	1.41	1.44
	R^2	0.07	0.31	3.98	0.2	0.39	2.07

P5	Coef	0.59***	0.43***	-0.16	0.56***	0.41***	-0.14
	t-stat	3.91	3.58	-1.29	3.52	3.31	-1.37
	R^2	8.08	5.2	3.62	6.94	4.35	4.05
P5-P1	Coef	0.45***	0.26**	-0.20*	0.39**	0.22*	-0.17*
	t-stat	2.97	2.38	-1.65	2.46	1.94	-1.68
	R^2	4.94	2.24	3.05	4.44	1.46	5.65

		Independent variable: $MediaTone^{\perp}$					
		Not excluding high inflation periods			Excluding high inflation periods		
		Dependent variable			Dependent variable		
		FX_{t+1}	Δs_{t+1}	$f_t - s_t$	FX_{t+1}	Δs_{t+1}	$f_t - s_t$
P1	β_1	0.10	0.06	-0.03	0.07	0.06	-0.01
	t-stat	0.93	0.6	-1.05	0.63	0.58	-0.42
	R^2	-0.15	-0.29	-0.25	-0.26	-0.29	-0.38
P2	β_1	0.10	0.10	-0.01	0.09	0.09	0.00
	t-stat	1.18	1.1	-0.77	1.03	0.96	-0.62
	R^2	0.06	0.01	0.1	-0.06	-0.09	-0.09
P3	β_1	0.14	0.14	0.00	0.13	0.12	0.00
	t-stat	1.25	1.2	-0.23	1.2	1.14	-0.41
	R^2	0.28	0.27	-0.4	0.2	0.16	-0.31
P4	β_1	0.12	0.12	0.00	0.13	0.13	0.00
	t-stat	1.16	1.14	0.28	1.17	1.14	-0.11
	R^2	-0.01	0.02	-0.37	0.09	0.08	-0.43
P5	β_1	0.56***	0.36***	-0.20**	0.48***	0.33**	-0.15*
	t-stat	4.2	2.77	-2.2	3.23	2.46	-1.89
	R^2	7.54	3.63	6.29	4.98	2.54	4.55
P5-P1	β_1	0.47***	0.30***	-0.17*	0.41***	0.26**	-0.15*
	t-stat	3.86	3.16	-1.74	2.99	2.47	-1.83
	R^2	5.41	3.32	2.14	5.07	2.37	4.14