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JEL Classification: C38, C55, F31, G11, G41, Z13

Keywords: FX media news, digital text, currency risk premium, currency reversals

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1 Introduction

Mass media, especially mainstream newspapers, contribute a large portion of public information acquired by foreign exchange investors on a daily basis. If the semi-strong form of market efficiency holds in the foreign exchange (FX) market, one would expect that the information content of newspapers may have already been incorporated into currency prices (e.g., Fama, 1998). The question of whether media sentiment has significant predictive content for future currency returns is therefore worthy of investigation, especially given that recent literature in the equities market has shown links between media coverage and stock returns (e.g., Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Fang and Peress, 2009).[1], demonstrating that financial news content is related to investor psychology. However, it is not clear whether the content of foreign exchange news drives, reinforces, or reflects investors' trading behavior in the FX market.[2] Our contribution is therefore twofold. First, we attempt to characterize the link between the content of FX news and currency returns. We test for the presence of a currency reversal associated with media sentiment and assess its economic value in the foreign exchange market. In addition, we investigate the types of traders that try to exploit the profitability of media sentiment strategies by analyzing trading patterns of currencies with high and low media sentiment.

Our currency reversal finding is in line with a theory of market sentiment according to which short-term returns will be reversed over longer horizons. For example, a growing literature on investor sentiment demonstrates that the initial decline in equity prices due to pessimism is often temporary and reverts over longer horizons (e.g., Campbell, Grossman, and Wang, 1993). Stambaugh, Yu, and Yuan (2012) also find that investor sentiment is a strong negative predictor for the short legs of spread anomaly portfolios in the equities

[1]For example, Fang and Peress (2009) find that stocks with no media coverage tend to exhibit higher stock returns than stocks with more pronounced media coverage.

[2]There is a long-standing literature that examines the effect of unanticipated movements in fundamentals on the exchange rate, in which 'news' is defined as the unanticipated component of an announcement on fundamentals (see Taylor (1995) for a survey and Cheung, Fatum, and Yamamoto (2019) for a recent application; Dominguez and Panthaki (2006), extend the approach to consider non-fundamentals). In this paper, however, we use the term 'news' in the more general sense of information appearing in the news media, rather than just the unanticipated component.

market. Baker and Wurgler (2006, 2007) develop a sentiment index that incorporates information from six categories and shows that high investor sentiment is a negative predictor of the cross-section of stock returns. This finding appears to be stronger for stocks that are speculative and to be subject to limits to arbitrage. Baker, Wurgler, and Yuan (2012) offer international support for six major equities markets. Huang, Jiang, Tu, and Zhou (2015) employ a partial least squares (PLS) method in order to provide a less noisy version of the Baker and Wurgler (2006) sentiment index and find that sentiment is a strong predictor of the aggregate stock market. However, in this paper, we construct a novel sentiment measure for the foreign exchange market and show that it is a strong predictor of the cross-section of currency returns.

In the foreign exchange literature, Gholampour and van Wincoop (2019) construct a sentiment measure of Euro-Dollar tweets and show that it predicts the direction of the Euro-Dollar exchange rate in a statistically significant manner. The authors create a dictionary of words that is based on a financial lexicon utilized by traders in the Euro-Dollar market in order to classify the tweets as positive, negative or neutral.

In the present analysis, some 1.2 million news articles are collected that mention particular currencies between October 1983 and April 2019 from nine of the largest news providers in the world. A common word categorization ('bag of words') approach is followed in order to measure the tone of articles discussing each currency, whereby we calculate the number of positive and negative words and scale their difference with the total number of words, as in Tetlock (2007) and Loughran and McDonald (2011), so that an increase in the measure implies higher sentiment. We also construct a negativity measure, which includes only the number of negative words because investors' judgment may be asymmetrically driven mainly by negative rather than positive sentiment (e.g., Tetlock, 2007); the main findings hold across the two measures.

The analysis begins with the investigation of the time-series predictive ability of FX media sentiment for currency returns. In a panel regression with country fixed effects, FX media sentiment is found to be a strong negative predictor of currency excess returns. We also employ panel vector autoregressions (VARs) to simultaneously measure the relationship between currency excess returns and media sentiment, and find that the FX sentiment factor is a strong negative predictor of the next month's currency returns in a statistically and economically significant manner. Thus, it predicts a negative price pressure followed by a mean reversion to country fundamentals within five months. Tests reject the hypothesis of no reversal – i.e. the conjecture of currency return continuation after negative sentiment FX news. In contrast to the findings of Tetlock (2007) – who shows evidence of mean reversion in the equities market within one trading week – we observe that in the foreign exchange market, the negative impact of FX sentiment on prices is more persistent, with mean reversion occurring between three to five months.

If the news related to specific currencies contains novel information about country fundamentals, we would expect a permanent decline in prices. If the FX news contains information that is already reflected in prices, FX sentiment would not affect currency returns. Our findings are consistent with the temporary negative price pressure that is driven by investor sentiment.

To evaluate the cross-sectional predictive ability of media sentiment for currency returns, we allocate currencies into six portfolios based on their average media sentiment over formation and holding periods ranging between one and twelve months. We develop a trading strategy that evaluates the sentiment of FX articles by going long currencies with low sentiment while short-selling high sentiment currencies. We find that media sentiment is a significant *negative* predictor of the cross-section of currency returns, or in other words, of currency reversals.

To the best of the present authors' knowledge, this is the first study to examine the connection between the information dissemination of FX news and the cross-section of currency returns. In particular, we examine the cross-sectional and time-series predictability of FX media sentiment for future currency returns. The negative relationship between media sentiment and currency returns is robust even after controlling for other determinants of currency premia in Fama and MacBeth (1973) cross-sectional regressions.

The currency reversal strategy is highly economically and statistically significant for developed countries. This finding could be related to the fact that developed economies' currencies exhibit higher levels of media coverage. In other words, these currencies are under the spotlight of investor attention, exhibiting higher levels of mispricing rather than rational information processing Hillert, Jacobs, and Müller (2014). Thus, a currency reversal strategy with a formation and a holding period of one month offers annualized Sharpe ratios of 0.57 and 0.80 for the sample of all 48 countries and developed countries, respectively.

The reversal strategy is economically and statistically significant even after accounting for transactions costs calculated using either the full reported bid-ask spreads or adjusting these to reflect the view that indicative quote spreads may overestimate transactions costs (Goyal and Saretto (2009)).

A time-series currency reversal strategy that buys (sells) a particular currency based on its media sentiment being low (high) over the formation period, with one-month formation and holding periods, yields statistically significant annualized returns of 2.24% for the universe of all 48 countries and 3.39% for developed countries. The profitability of time-series reversals drops as the formation and holding periods are increased.

It is important to investigate whether media sentiment is related to more well documented currency trading strategies such as carry trade and momentum. To this end, we contemporaneously project returns to currency reversal strategies onto a dollar factor (the cross-sectional average return or 'market factor') and the carry trade (long high-interest rate currencies, short low-interest rate currencies) factor of Lustig, Roussanov, and Verdelhan (2011) or the currency momentum (long recently appreciating currencies, short recently depreciating currencies) factor of Menkhoff, Sarno, Schmeling, and Schrimpf (2012b).[3] We find that the reversal factor is orthogonal to momentum and, while there is low correlation with the dollar factor (beta of around 0.1), the orthogonalized annualized alphas are around 8%. While the betas with the carry trade factor are a little higher, at around 0.3, orthogonalizing with respect to carry still produces annualized alphas of around 4%.

[3] We offer a detailed explanation of the construction of the factors in the data section.

These results suggest that there may be significant diversification effects of combining the reversals strategy with a carry trade strategy and, indeed, when this is done it yields impressive Sharpe ratios of around 1.5, compared to Sharpe ratios for carry alone of around 0.9.

Alternative drivers of currency returns are considered in double sorts, such as country risk, volatility, illiquidity, current-month returns, and past-month returns. We find that currencies with low volatility and low illiquidity contribute to the profitability of the strategy. In contrast, idiosyncratic volatility and country size do not seem to be drivers of currency reversals. This is particularly important as it indicates that currency reversals are very different from the currency momentum strategy, which is subject to limits to arbitrage (e.g., Menkhoff et al., 2012b). We also observe more pronounced results for currencies with high current-month returns and low past-month returns, which one would expect for a reversal strategy.

The results are robust across other frequencies. Specifically, currency reversals are significant at a daily level. Currencies are sorted daily into portfolios according to their media sentiment over formation periods of 1, 5, 10, 15, and 22 days: a currency reversal strategy that goes long low sentiment currencies the previous day and shorts currencies with high sentiment over the same formation period renders a currency excess return of 14.31% per annum. The results are stronger for formation periods of 22 days.

To further investigate the underlying mechanism that drives these results, we examine an additional dataset: analysts' average forecast of future spot rate changes. Each month between October 1983 and March 2017, and for each of 17 currencies, we obtain analysts' average forecasts of each currency's spot exchange rate changes in the next three months. We sort these currency forecasts into portfolios based on their media sentiment over the formation periods (1, 3, 6, and 12 months) and calculate their portfolio average of forecasts. We find that analysts predict that foreign currencies with *low* sentiment tend to *depreciate* more than currencies with *high* sentiment, contributing *negatively* to the currency excess return of the reversal strategy. However, our findings indicate that currencies with *low* sentiment tend to *appreciate* more than currencies with *high* sentiment, contributing positively to the currency reversal strategy. Thus, analysts' forecasts cannot explain the sign and magnitude of the payoff of this strategy. This is in line with Guo, Li, and Wei (2020) who find that analyst's recommendations in the equities market contradict anomaly predictions.

In what follows, we briefly discuss the effect of media news sentiment on asset prices in section 2, while in section 3 we describe the data as well as the construction of the currency portfolios. Section 4 discusses the construction of the sentiment measures. Section 5 discusses the main empirical results of the paper. Section 6 offers robustness and other specification tests. Finally, in section 7 we offer some concluding comments.

2 The Effect of Media Sentiment on Asset Prices

Investor sentiment – the way that investors form beliefs – is a key driver of asset prices (e.g., Keynes, 1936; Barberis, Shleifer, and Vishny, 1998) based on the well-known psychological fact that investors with higher or positive (lower or negative) levels of sentiment are more likely to make optimistic (pessimistic) decisions. De Long, Shleifer, Summers, and Waldmann (1990) show theoretically that sentiment can create deviations of asset prices from their fundamental value especially for assets that are subject to limits to arbitrage. This pattern persists, moreover, even when informed investors are aware of such opportunities.

Recent empirical research shows that the impact of media sentiment on asset prices is associated with overreaction or underreaction. The underreaction theory predicts that asset prices tend to underreact to the news over horizons of 1 to 12 months while the overreaction theory implies that securities with good news, or positive sentiment over a longer period tend to be overpriced and exhibit mean-reversion in the long run (e.g., 3-5 years). Cutler, Poterba, and Summers (1991) investigate autocorrelation patterns in indices of different asset classes including stocks, bonds and exchange rates over different horizons and markets. The authors find positive autocorrelations that are consistent with the underreaction hypothesis which supports the notion that security prices incorporate the additional information slowly, creating predictable patterns in returns over short horizons.

Sentiment theories put emphasis on the timing of investor reaction to media sentiment, testing the hypothesis that low media sentiment that is related to low investor sentiment could cause downward price pressure (e.g., De Long et al., 1990). This conjecture implies that low media sentiment (e.g., high media pessimism) could forecast low currency returns at shorter horizons with a reversal to their fundamental value at longer horizons. In other words, low media sentiment could result in lower returns with subsequent higher returns in the future. However, the connection between media sentiment and investor sentiment or its relationship with past investor sentiment is not clear in the literature.

Other sentiment theories suggest that low media sentiment could reflect negative information about fundamentals that is not fully incorporated into prices. Thus, if media pessimism is a result of negative news about country fundamentals, then we should still anticipate a negative association between low media sentiment and currency returns in the short term (e.g., Tetlock, 2007).

Overall, empirical evidence and theoretical models both suggest that media sentiment matters for understanding the cross-section of stock returns. In this paper, we demonstrate that an analogous approach is helpful to understand the cross-section of currency excess returns as well.

3 Data and Currency Portfolios

In this section, we offer a detailed description of the exchange rate data we employ and the process of constructing excess returns. We also describe the FX news dataset as well as the data of currency analysts' forecast. In addition, we describe the formation of currency portfolios.

Exchange Rate Data. We start with daily spot and one-month forward exchange rates against the U.S. dollar spanning the period from October 1983 to April 2019. The data are collected from Barclays and Reuters via Datastream. In the main analysis, we consider mid quotes that are defined as the mean of the bid and ask quotes for each currency. We control for transaction costs as a robustness check. We construct an end-of-month series of daily spot and one-month forward rates as in Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011). Note that the data are not averaged over each month but represent the exchange rates on the last trading day of each month. The sample consists of the following 48 countries: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Egypt, Euro area, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Iceland, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Ukraine, United Kingdom. We label this sample as "*All Countries*". In order to guard against tradability concerns and make our analysis more robust, we also consider a smaller subsample of more liquid currencies that we label "*Developed Countries*". More specifically, the universe of *Developed Countries* comprises: Australia, Belgium, Canada, Denmark, euro area, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom.

Those currencies that were partly or completely pegged to the U.S. dollar are not excluded from the sample, since their forward contracts were available to investors. The euro area countries are excluded after the introduction of the euro in January 1999. Some countries entered the euro zone later than January 1999, and their exchange rates are excluded from the samples at the later date of entry. We also take into consideration the implementation cost of our strategies by constructing net excess returns. Section A of the Internet Appendix offers a detailed description of the construction of currency excess returns that include bid and ask spreads. Similarly to Lustig et al. (2011); Della Corte, Riddiough, and Sarno (2016), we remove currency-time observations that exhibit large deviations from the covered interest rate parity (CIP) condition. Figure A1 of the Internet Appendix shows the number of currencies that are available each month in our sample.[4]

Currency Excess Returns. We denote by s_t and f_t the logarithm of the time t spot and forward exchange rates. Each currency is quoted against the U.S. dollar such that an appreciation of the U.S. dollar reflects an increase in s_t. The log excess return (rx_{t+1}) is defined as the payoff of a strategy that buys a foreign currency in the forward market at time t and then sells it in the spot market at maturity (i.e. at time $t+1$). The excess return at time can be computed as

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

[4]Section A of the Internet Appendix discusses the exclusion of currency-time observations. Our results are not affected by the elimination of these observations. In fact, we observe improved results before the exclusion of such observations.

Therefore, the excess return can be expressed as the sum of the forward discount and the exchange rate return. The CIP condition states that the forward discount should be equal to the interest rate differentials, i.e. $f_t - s_t \simeq \hat{i}_t - i_t$, where $\hat{i}_t$ and i_t denote the foreign and domestic riskless interest rates, respectively. Therefore, the excess return could also be written as $rx_{t+1} \simeq (\hat{i}_t - i_t) - \Delta s_{t+1}$. Thus, the currency excess returns can be approximated by the interest rate differential subtracted by the rate of depreciation of the exchange rate.[5]

FX News. We collect around 1.2 million news articles from Factiva, the global news gathering service, for the period from October 1983 to April 2019. In particular, we search the Factiva news database for the name of each currency included in our sample.[6] Our analysis focuses on articles that are in English and appear under the subjects "Foreign Exchange Markets" or "Currency Options" or "Money Markets" or "Euro Zone/Currency" in Factiva, concentrating on articles from nine major media sources, namely Dow Jones, Reuters, Agence France Presse, The Financial Times, The Wall Street Journal, The New York Times, The Washington Post, USA Today and Associated Press Newswire.

We match each article to a specific currency or a set of currencies by counting the number of times that a currency is mentioned in each article. To this end, we construct a sample of news that is linked to specific currencies over time. Our initial extraction of news contains 1,461,905 articles. After the elimination of monthly exchange rate reports, we end up with a universe of 1,185,368 articles discussing the currencies contained in our search.

[5] Figure A1 of the Internet Appendix shows the number of currencies that are available every month in our sample.

[6] Specifically, we searched for GBP or British Pound or Pound sterling or CHF or Swiss Franc or JPY or Japanese Yen or CAD or Canadian dollar or AUD or Australian dollar or NZD or New Zealand dollar or SEK or Swedish Krona or NOK or Norwegian Krone or DKK or Danish Krone or EUR or Euro or DEM or Deutsche Mark or ITL or Italian lira or FRF or french franc or NLG or Dutch guilder or BEF or Belgian Franc or FIM or Finnish markka or IEP or Irish pound or HKD or Hong Kong dollar or ZAR or South African Rand or SGD or Singapore dollar or ATS or Austrian schilling or CZK or Czech koruna or GRD or Greek drachma or HUF or Hungary Forint or INR or Indian Rupee or IDR or Indonesian rupiah or KWD or Kuwaiti Dinar or MYR or Malaysian Ringgit or MXN or Mexican Peso or PHP or Philippine Peso or PLN or Polish Zloty or PTE or Portuguese escudo or SAR or Saudi riyal or KRW or South Korean won or ESP or Spanish peseta or TWD or New Taiwan dollar or THB or Thai baht or BRL or Brazilian real or EGP or Egyptian Pound or RUB or Russian ruble or SKK or Slovak koruna or HRK or Croatian kuna or CYP or Cypriot pound or ILS or Israeli new shekel or Israeli shekel or ISK or Icelandic krona or SIT or Slovenian tolar or BGN or Bulgarian lev or UAH or Ukrainian hryvni.

We check the articles that mention more than one currency and isolate the sentences that discuss each currency. Then, we calculate the sentiment for each currency that is mentioned in the article. For example, a specific article could have positive sentiment for one currency and negative sentiment for another.

Analysts' Forecasts. We obtain analysts' forecasts from the global macroeconomic survey firm, Consensus Economics. The data span the period from October 1989 to March 2017. This dataset offers the mean and standard deviation of a range of institutions' forecasts of exchange rates, inflation, unemployment, housing, and other macro variables for developed and emerging economies. The forecast horizon is three months, which matches the typical horizon that is set by policymakers. More specifically, the Consensus Economics database publishes every month the analysts' average forecasts of the percentage change of the spot rate of 27 currencies, with a forecast horizon of three months. All forecasts are expressed as foreign currency units per U.S. dollar. Specifically, the dataset includes the following countries: Australia, Brazil, Canada, Switzerland, Germany, Denmark, Egypt, Europe, United Kingdom, Hong Kong, Indonesia, Israel, India, Japan, South Korea, Mexico, Malaysia, Norway, New Zealand, Philippines, Russia, Saudi Arabia, Sweden, Singapore, Thailand, Taiwan and Ukraine. For example, the forecasts for January 2016 indicate that the Australian dollar should decline by 1.1%, and Malaysian Ringgit should rise by 1.9% in April.

Currency Reversal Portfolios. At the end of each month t, we allocate currencies into six portfolios on the basis of their FX media sentiment during the formation period (f) and hold our portfolios for a period equal to our holding period of (h) months. We consider 1, 3, 6, 9 and 12 months of formation and holding periods. To this end, the first portfolio contains currencies that are associated with pessimistic news (low sentiment) and the last portfolio consists of currencies with optimistic news (high sentiment). The currency excess returns within each portfolio are equally weighted. Thus, we build a zero-cost portfolio (i.e. REV) that buys the currencies with the lowest sentiment and short sells the currencies with the highest sentiment.

Time-Series Currency Reversals. We also construct a time-series currency reversal factor that goes long currencies with negative changes in sentiment and short currencies with positive changes in media sentiment. In particular, we define our time-series currency reversal strategy as:

$$rx_{i,t+1}^{REV} = \begin{cases} -rx_{i,t+1} & \text{if } \Delta Sentiment_t > 0, \\ rx_{i,t+1} & \text{if } \Delta Sentiment_t \leq 0. \end{cases} \quad (2)$$

where $rx_{i,t+1}$ is the currency excess return of currency i at time t. $\Delta Sentiment_t$ represents changes in sentiment at time t. We also develop a similar strategy using the negativity measure and it offers similar results (presented in the Internet Appendix).

Currency Carry Trade Portfolios. At the end of each month t, we allocate currencies into quintiles on the basis of their forward discounts ($f_t - s_t$) in month $t-1$. The first portfolio contains currencies with low interest rates and the last portfolio consists of high-interest-rate currencies. The currency excess returns within each portfolio are equally weighted. Thus, we build a zero-cost carry-trade portfolio (*CAR*) that *buys* investment currencies while short-selling funding currencies.

Currency Momentum Portfolios. At the end of each month t, we allocate currencies into quintiles on the basis of their return in month $t-1$. The first portfolio contains countries with poor past performances (e.g., *losers*) and the last portfolio consists of past winners. The currency excess returns within each portfolio are equally weighted. Thus, we build a zero-cost momentum portfolio (MOM) that *buys* winner currencies while short-selling loser currencies.

4 FX Media Sentiment

In this section we describe the construction of the sentiment measures.

Filters. We eliminate words that provide very little information, using the general list of stop words offered by Loughran and McDonald (2011). We also tokenize the list of words obtained from the news articles. Specifically, we employ Porter (1980)'s stemmer which eliminates the suffixes of every word in our sample. We thus avoid considering the same word in our sample twice.

Bag-of-Words Approach. Our textual analysis method is based on a common word categorization approach in order to measure the tone of the news articles (e.g., Loughran and McDonald, 2011). In this method, every article is characterized by a vector of word counts that comprise a term-document matrix.

FX Media Sentiment and Negativity. We measure the tone of the news articles following a 'bag-of-words' approach as in Tetlock (2007) and Loughran and McDonald (2011). Specifically, for every article we compute the tone of the document by calculating the frequency of positive and negative keywords that appeared in the tone dictionary. Loughran and McDonald (2011) show that negative words included in the widely used Harvard IV-4 Psychosociological Dictionary (e.g., the Harvard-IV-4 TagNeg (H4N) file) might not capture the tone of financial texts. For this reason, the authors recommend an alternative dictionary that is constructed based on 10-K filings and is able to capture the tone of documents with financial contexts. Therefore, we measure the tone of a document as the difference between the number of positive and negative tonal words. Intuitively, a higher tone indicates a more positive or less negative sentiment. Thus, the measure takes the form below

$$Sent_{i,t} = \frac{n_{i,t}^{Positive} - n_{i,t}^{Negative}}{n_{i,t}^{NewsArticles}}, \tag{3}$$

where $n_{i,t}^{Positive}$ ($n_{i,t}^{Negative}$) represents the total number of positive (negative) words in the FX news articles focusing on currency i at time t. Thus, the tone score is defined as the difference between positive and negative word counts divided by the total number of words in the set of articles that mention currency i at time t.

Tetlock (2007) highlights the fact that investor sentiment in the equities market is largely driven by the set of negative words in the dictionary. For this reason, we also consider a measure that only captures negative sentiment. The negative sentiment measure takes the following form:

$$Neg_{i,t} = -\frac{n_{i,t}^{Negative}}{n_{i,t}^{NewsArticles}}, \tag{4}$$

where $n_{i,t}^{Negative}$ represents the total number of negative words in FX news articles focusing on currency i at time t. We take the additive inverse of the frequency in order to make the two measures comparable and easy to read – note that our negativity measure exhibits a positive correlation with the sentiment measure by construction. More precisely, an increase in the negativity measure corresponds to fewer words with negative meaning. We obtain consistent results for both measures. For this reason, our main analysis focuses on the sentiment measure and we present our results based on negativity in the Internet Appendix. Figure 1 shows a word cloud of negative and positive words in our corpus where terms with larger sizes appear more often in our corpus. We observe that the pool of negative words includes terms such as crisis, lose, cut, weak, decline, unemployment and volatility and the positive words with higher frequencies are terms such as gain, positive, strong, stability, strengthen, rebound, boost and stable. Thus, our set of negative and positive words reflects the terminology being used among foreign exchange traders to describe exchange rate fluctuations.

Example. Figure 2 displays the process by which we eliminate stop words and calculate the sentiment and negativity measures of two articles that are included in our sample. In particular, we offer an article in May 1983 that was published in Financial Times and

Figure 1. Most Frequent Negative and Positive Words

(a) Negative Words **(b) Positive Words**

The figure displays word clouds of positive (Graph a) and negative (Graph b) words. Specifically, words with larger fonts exhibit higher frequencies in our corpus. The data span the period of October 1983 to April 2019.

discusses movements of Hong Kong dollar. We have erased the stop words and highlight with a dashed line *negative* words such as “weakened”, “breaching”, “worst”, “decline” and *positive* words such as “strengthen”.[7] At the bottom of the article, we present the sentiment and negativity measures as well as the total number of words and the set of the remaining words after eliminating the stop words from the corpus.

[FIGURE 2 ABOUT HERE.]

Descriptive Statistics for FX News. Table 1 shows descriptive statistics for the FX news article coverage per year. Both unconditional statistics (percentage of currencies receiving coverage) and conditional statistics (number of articles written on the currencies conditioned on coverage) are presented. We match each article with the currency that is mostly discussed in the text. We find increasing mean and median of articles mentioning currencies over time from 1983 to 2019, demonstrating increasing media coverage for currency assets. We also observe that The Financial Times and The New York Times offer the highest coverage in our sample, ranging from 50% to 89% and from 39% to 83%, respectively. In

[7] In this simple example, we have not tokenized the corpus so as to preserve the content of the article but we have tokenized the corpus in our main analysis.

addition, media outlets such as Dow Jones, Reuters and The Wall Street Journal also offer strong coverage of currencies.[8]

[TABLE 1 ABOUT HERE.]

5 Empirical Results

In this section, we present the main empirical results of our analysis.

5.1 FX Media Sentiment and Currency Excess Returns

Figure 3 displays a histogram of the distribution of currencies covered by the media, calculated separately within two groups: the top graph shows results for developed markets (15 currencies), and the bottom graph show results for emerging markets (33 currencies). The percentage is the number of articles that mention each particular currency as a percentage of the total number of articles.[9] These percentages do not add up to 100% as some articles contain more than one currency. Even in the "main currency" case – where we link an article with the currency that is mostly discussed – there are still articles with multiple currencies of the same highest frequency.

[FIGURE 3 ABOUT HERE.]

Panel Regressions. We calculate the tone of each article – as described in the previous section – in order to evaluate the predictive ability of media sentiment for currency returns. As a first attempt at understanding the relationship between FX media sentiment and currency returns, we run a predictive panel regression with time (τ_t) and currency (α_i)

[8] The coverage for 2019 is until April, which is the end of our sample.

[9] We also consider a "main currency" case, where the percentage is the number of articles with each currency as the highest frequency currency over total number of articles. Our results are similar regardless of the method being used and are available on demand.

fixed effects of currency excess returns or exchange rate changes on FX media sentiment or negativity plus a number of control variables. The regression model takes the form:

$$R_{i,t} = \alpha_i + \tau_t + \beta Sent_{i,t-1} + \boldsymbol{\gamma} \boldsymbol{z}_{i,t-1} + \varepsilon_{i,t}, \text{ for R} = rx \text{ or } -\Delta s \tag{5}$$

where $rx_{i,t}$ ($\Delta s_{i,t}$) represents the currency excess return (exchange rate change) of currency i at time $t+1$ and $Sent_{i,t-1}$ denotes the sentiment measure of each currency pair at time $t-1$. We also control for other determinants of currency returns such as currency volatility and illiquidity that are included in the vector $\boldsymbol{z_{i,t-1}}$.[10] Columns (1) and (2) of Table 2 present results for currency excess returns and Columns (3) and (4) show estimates for exchange rate changes. We report t-statistics in square brackets, based on double-clustered standard errors.

We find that the sentiment measure exhibits a strong *negative* association with currency excess returns and exchange rate changes in the following period. In other words, a *decrease* in FX media sentiment (e.g., higher media pessimism) corresponds to a *depreciation* of the U.S. dollar or an *appreciation* of the foreign currency, on average. We obtain a similar result when considering the negativity measure in Table A1 of the Internet Appendix.[11] This pattern is present even after controlling for other determinants of currency premia such as volatility and liquidity measures. This finding is consistent with the sentiment theory which predicts that short-term returns will be reversed over longer horizons.

[TABLE 2 ABOUT HERE.]

VAR Estimates. In our previous analysis, we find that media sentiment is a strong negative predictor of currency returns. Here we examine further this predictive relationship by estimating the intertemporal links between FX media sentiment and currency returns using vector autoregressions (VARs). Specifically, we employ a panel VAR with time and country

[10] Volatility is based on a GARCH(1,1) that is fitted to each series of currency excess returns and exchange rate changes. The illiquidity measure is based on bid-ask spreads for each currency pair.

[11] Recall that the negativity measure comoves with the sentiment measure by construction. For example, an *increase* in the negativity measure is associated with *fewer* negative words.

fixed effects in order to test whether FX media sentiment predicts future currency returns, and to examine potential mean reversion to fundamentals over short horizons. Tetlock (2007) shows that media pessimism forecasts downward pressure on stock market prices with mean reversion to fundamentals with a horizon of five days. Thus, our model takes the form:

$$R_{i,t} = \alpha_i + \tau_t + \sum_{k=1}^{5} \beta_k Sent_{i,t-k} + \boldsymbol{\gamma} \boldsymbol{z}_{i,t-1} + \varepsilon_{i,t}, \text{ for R} = rx \text{ or } -\Delta s \tag{6}$$

where $rx_{i,t}$ ($\Delta s_{i,t}$) represents the currency excess return (exchange rate change) of currency i at time t and $Sent_{i,t-k}$ denotes the sentiment measure (see Section 4 for the construction of the measure) of each currency pair at time $t-k$ for $k = 1, \ldots, 5$. We also control for other determinants of currency returns such as currency volatility and illiquidity, which are included in the vector $\boldsymbol{z}_{i,t-1}$.

Table 3 shows the results for daily and monthly frequencies using five lags of the sentiment measure and control variables.[12] The FX sentiment measure's estimated coefficients capture the dependence of currency excess returns on the sentiment factor. Starting with the monthly frequency, we observe that the t-statistic for the null hypothesis that the FX sentiment measure with five months lags cannot forecast currency returns is 2.67, indicating that FX sentiment exhibits a strong association with future currency returns. In addition, we observe that the FX sentiment measure demonstrates a negative effect on the next month's currency returns (t-statistic = -2.77). This finding is significant in both statistical and economic terms. We observe a similar pattern for the coefficient with two lags.

In contrast to the findings of Tetlock (2007) – who shows that there is mean reversion in the equities market within a trading week – we observe that in the foreign exchange market this effect is more persistent, with mean reversion occurring between three to five months. Specifically, the reversal size between two through five months lags is 0.593 and is statistically different from zero at the 1% significance level. This implies that we can reject the hypothesis of no reversal – the conjecture of currency return continuation

[12] Our VAR estimates are analogous to Granger causality tests.

after negative sentiment FX news. FX sentiment, which is mainly driven by negative news, exhibits a significant temporary effect on future currency returns, which is reversed within five months. On the other hand, we do not observe (in the right Panel of table 3) reversion to fundamentals at daily frequencies.

5.2 Cross-sectional Predictive Ability of FX Media Sentiment

In the previous section, we focus on the times-series predictive ability of media sentiment for future currency returns. In particular, we observe a reversal in the time series that is consistent with the evidence from the equities market (e.g., Tetlock, 2007). Here, we test whether FX media sentiment contains important information for the cross-section of currency returns.

FX News and Currency Reversals. In order to test our hypothesis in a non-parametric setting, we allocate currencies into six portfolios based on the level of media sentiment every month. Thus, high (low) sentiment portfolios comprise currencies with high (low) FX media sentiment over the previous period. We focus on the formation and holding periods of 1, 3, 6, 9 and 12 months. *Panel A* of Table 4 shows average currency excess returns of spread portfolios that go long currencies with *low* FX media sentiment (high media pessimism) while short-selling currencies with *high* media sentiment in the previous month. We find that a strategy that buys currencies with media pessimism and sells currencies with media optimism (e.g., $REV(1,1)$) offers an annualized excess return of 6.53% per annum that is persistent across different formation periods. For example, a currency reversal strategy with a formation period of 1 month and a holding period of 12 months ($REV(1,12)$) renders an annualized return of 3.52% per annum.[13] We also observe that the excess return decreases as we increase the holding period but remains highly significant in both economic and

[13] Note that we report positive currency excess returns of the reversal strategies (REV) because we construct low-minus-high (LMH) portfolios.

statistical terms.[14] Thus, we observe a very strong *negative* association between media sentiment and currency excess returns. *Panel A* shows the results for *All Countries* while *Panel B* presents the results for the sample of *Developed Countries*.[15] Intuitively, investors tend to overreact to currencies with very negative sentiment within the month with a subsequent reversal in the next period.

The right part of the Table 4 reports the corresponding spread portfolios for spot rate changes. We present the negative of the log spot exchange rate change in order to obtain returns that comove with the reversal strategy's total excess return. In other words, an increase in spot rate change is associated with a positive contribution in the currency excess return. Thus, whenever we report spot rate changes, we are indicating $-\Delta S$, so that higher values imply that the foreign currency appreciates against the US dollar. We find that the profitability of currency reversal strategies is present in spot rate changes and is less influenced by the interest rate differential that one would observe in the case of carry trades (e.g., Lustig et al., 2011). Indeed, the strategy with a 1-month formation and holding periods is driven to a significant extent by spot rate changes. Menkhoff et al. (2012b) observe a similar pattern for the currency momentum strategy.

[TABLE 4 ABOUT HERE.]

Sharpe Ratios. In order to measure the performance of our portfolios conditional on the amount of risk, we compute the corresponding Sharpe ratios. Table 5 presents annualized Sharpe ratios of currency reversals for different formation and holding periods as well as different subsamples. We report t-statistics in square brackets (based on a moving block-bootstrap). We find that a reversal strategy with one-month formation and holding periods offers annualized Sharpe ratios of 0.57 for the universe of *All Countries* and 0.80 for the set of *Developed Countries*. The ratios are significant in both statistical and economic

[14] We do not, of course, wish to imply that the longer holding periods are realistic but rather that the profitability of the reversals signal is robust to increasing the holding period even to lengths as long as 12 months.

[15] Table A1 of the Internet Appendix show results for emerging economies which comprises the set 33 remaining countries after we exclude the set of Developed Countries from our full sample.

terms for shorter formation and holding periods. Sharpe ratios decrease when the length of the formation or holding periods increases.

In contrast to the momentum strategy, the profitability of which is mainly concentrated among currencies that are less liquid and are subject to limits to arbitrage, the currency reversal strategy also presents risk-adjusted profitability – under some scenarios even higher (e.g., $REV(1,1)$) – among *Developed Countries* despite the higher return offered by the universe of *All Countries*.[16]

[TABLE 5 ABOUT HERE.]

Figure 4 shows cumulative returns of a currency reversal strategy based on FX media sentiment, $REV(1,1)$, with a formation period (f) of one month and a holding period (h) of one month. We present results with and without transaction costs on the right and left side, respectively. Shaded areas represent NBER-dated recessions. The strategy $REV(1,1)$, which buys currencies with low sentiment over the previous month while short-selling currencies that demonstrated high sentiment in the previous month and holds the portfolio for the next month, offers a Sharpe ratio of 0.36 after allowing for implementation cost. In addition, the figures show that the strategy is not affected by recessions. We observe an improvement in the performance of the strategy after 2014 until the end of our sample. This period coincides with the end of Quantitative Easing in the U.S. as well as other major economies in our sample.

[FIGURE 4 ABOUT HERE.]

Cross-Sectional Regressions. Our previous analysis tests the significance of media sentiment as a predictor of the cross-section of future currency excess returns in a nonparametric setting. This approach has the advantage of not imposing a functional form on the relation between FX media sentiment and future currency excess returns. However, there are a

[16] Specifically, the momentum strategy tends to be less profitable for the universe of developed countries as its profitability is mainly driven by political risk and other dimensions of country risk (e.g., Menkhoff et al., 2012b; Filippou, Gozluklu, and Taylor, 2018).

number of disadvantages regarding this method. For example, it ignores a significant amount of information in the cross-section due to aggregation and it is more challenging for other determinants of currency premia to be considered simultaneously. Therefore, we investigate the cross-sectional relationship between media sentiment and expected currency excess return at the currency level by running Fama and MacBeth (1973) cross-sectional regressions.

In the spirit of the Fama and MacBeth (1973), we examine which independent variables demonstrate premiums that are different from zero on average. To this end, we run cross-sectional regressions on a monthly basis of the following model, and nested specifications:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} Sent_{i,t} + \lambda_{2,t} R_{i,t} + \lambda_{3,t} fd_{i,t} + \varepsilon_{i,t+1}, \text{ for R} = rx \text{ or } -\Delta s \qquad (7)$$

where $Sent_{i,t}$ denotes the average media sentiment, $rx_{i,t}$($\Delta s_{i,t}$) is the currency excess return (exchange rate change) and $fd_{i,t}$ is the forward discount of currency i at time t. Table 6 displays time-series averages of slope coefficients from the regressions of currency excess returns and exchange rate changes at time t on the media sentiment measure at time t, with and without controls. *Panel A* (*Panel B*) of Table 6 shows results for *All Countries* (*Developed Countries*). We report results for both currency excess returns and exchange rate changes. We find that media sentiment is a strong *negative* predictor of the cross-section of future currency excess returns even after controlling for other determinants of currency premia such as lagged excess returns, lagged forward discounts and lagged exchange rate changes. Interestingly, when all controls are included in the model, forward discounts cannot explain the cross-section of currency returns, demonstrating the disconnect between currency reversals and currency carry trades.[17]

[TABLE 6 ABOUT HERE.]

[17]Table A2 of the Internet Appendix offer similar results when replacing sentiment with the negativity measure.

5.3 Time-Series Currency Reversals

In this sub-section, we investigate whether the reversal strategy is also present when considering a time-series rather than a cross-sectional strategy. In particular, we develop a strategy that invests in each currency based on the sign of the sentiment measure over the formation period. Table 7 shows average currency excess returns of equally-weighted portfolios of time-series currency reversal strategies based on different formation and holding periods. In particular, we construct a strategy that goes long currencies with *negative* sentiment change and short those with *positive* sentiment change based on a formation period f months and a holding period of h months. We compute the excess return of each currency and then construct an equally-weighted portfolio. We consider formation (holding) periods of 1, 3, 6, 9 and 12 months. *Panel A* (*Panel B*) reports results for *All Countries* (*Developed Countries*). We express currency excess returns in percentage per annum. We report t-statistics in square brackets, based on Newey and West (1987) standard errors with one lag.

We find that a reversal strategy with formation and holding periods of one month renders annualized returns of 2.24% for the universe of *All Countries* and 3.39% for *Developed Countries* that are significant in both economic and statistical terms. We also observe a deterioration of the profitability as we increase the formation and holding period, indicating a potential mean reversion in the long run, which is consistent with the sentiment theory.

[TABLE 7 ABOUT HERE.]

5.4 Underlying Mechanism

To further investigate the underlying mechanism that drives the previous findings, we examine an additional set of data: analysts' average forecast of future currency returns.

FX News and Analysts' Forecasts. In this section, we examine the link between media sentiment and analysts' forecasts in the foreign exchange market. Specifically, in each month between October 1983 and March 2017 and for each of 17 currencies, we obtain analysts' average forecasts of each currency's spot rate change in the ensuing three months. We sort these currencies into portfolios based on their media sentiment over the formation periods (1, 3, 6, and 12 months), and calculate the portfolio average of forecasts.[18] In order to be consistent with the previous findings and offer comparable results with Table 4, we report the negative of the log spot exchange rate change forecast in order to obtain returns that comove with the reversal strategy's total excess return. Therefore, whenever we mention spot rate change, we are indicating $-\Delta S$ which equals $(s_t - s_{t+1})$ instead of $(s_{t+1} - s_t)$. This implies that an increase of the exchange rate changes corresponds to an appreciation of the foreign currency.

Table 8 reports the average forecast of spot rate changes for low and high sentiment as well as the corresponding spread portfolios (e.g., LMH). We find that analysts anticipate foreign currencies with *low* sentiment to *depreciate* more than currencies with *high* sentiment, contributing *negatively* to the currency excess return of the currency reversal strategy. This finding is robust to different formation periods. In contrast to our findings, the analysts forecast that the difference between low and high sentiment portfolios should be negative rather than positive.

However, our main results – in the right panel of Table 4 – indicate that the difference in the spot rate changes between low and high sentiment is positive, as low sentiment currencies tend to *appreciate* more than high sentiment currencies. Thus, analysts' forecasts cannot explain the sign and the magnitude of the currency reversal strategy. One reason would be that the information set of analysts relies less on publicly available information. This is in line with Guo et al. (2020) who examine analysts' recommendations for stocks that are overvalued or undervalued based on different anomalies in the equities market. The authors show that analysts' recommendations in the equities market contradict anomaly predictions. In particular, they consider anomalies that represent public information that analysts could exploit in real time. Nonetheless, the authors find that analysts tend to

[18] Table A7 of the Internet Appendix shows results for forecasts of spot rate changes that are sorted based on the negativity measure.

offer more favorable recommendations to equities that are labelled as overvalued (e.g., they appear in the short leg of the anomalies); this set of equities exhibit more negative abnormal returns in the future.

[TABLE 8 ABOUT HERE.]

6 Robustness and Other Specification Tests

6.1 Double Sorts

In order to better understand the strong cross-sectional predictive ability of media sentiment for currency returns, we double-sort currencies into terciles based on different determinants of currency premia. Table 9 presents currency excess returns that are sorted into three portfolios based on country risk (CS) (*Panel A*) or volatility (V) (*Panel B*) or illiquidity (I) (*Panel C*) or current month return (CR) (*Panel D*) or past month return (PR) (*Panel E*) or idiosyncratic volatility (IV) (*Panel F*). Then, within each portfolio, we allocate currencies into terciles based on the average sentiment of news per currency over a formation period of one month and a holding period of one month. In particular, we construct a strategy that goes long *low*-sentiment portfolios while short selling *high*-sentiment currency portfolios.

We find that the profitability of the currency reversal strategy is concentrated among currencies with low volatility and low illiquidity, while idiosyncratic volatility and country size do not seem to play an important role for this strategy. We also observe more pronounced results for currencies with high current month return and low past month return, which is expected for a reversal strategy. This finding also highlights the disconnect between currency reversals and currency momentum, as the latter tends to be more profitable among currencies that are more volatile, less liquid and exhibit high idiosyncratic volatility (e.g., Menkhoff et al., 2012b).

[TABLE 9 ABOUT HERE.]

6.2 Other Currency Investment Strategies

In this sub-section, we examine the relationship between our strategy and other well-known currency investment strategies such as carry trade and momentum strategies. To this end, we regress the return of our currency reversal strategy on dollar and carry trade portfolios and on dollar and momentum portfolios. *Panel A* of Table 10 displays estimated alpha and beta coefficients and R-squares of a contemporaneous linear regression of currency reversal based on formation periods of 1 and 6 months and a holding period of one month on dollar (DOL), carry (CAR) and momentum (MOM) risk factors. The dollar factor (DOL) is defined as the cross-sectional average of all currencies each month. The momentum factor considers a one-month formation period and a holding period of one month. In particular, the regression model takes the form:

$$REV_{t+1} = \alpha + \beta_1 DOL_t + \beta_2 X_t + \varepsilon_{t+1}, \text{ for X} = CAR \text{ or } MOM \tag{8}$$

where REV denotes the currency reversal strategy. For the momentum strategy, we find low R-squares and estimated betas that are insignificantly different from zero at standard significance levels. However, the estimated annualized alphas are statistically significantly different from zero at standard significance levels and are economically sizeable, with point estimates of 0.577 and 0.700. Since all variables are in percentage monthly terms, these translate into remarkably high annualized alphas of 6.9% to 8.4%. For the carry trade risk factor, the R-squares are again small but the estimated betas are statistically significant although economically small in value, at 0.328 and 0.390 for the 1 and the 6 months formation periods, respectively. Even for carry, however, the estimated alphas, measuring the value added by the strategy over and above any residual carry features, amount to a sizeable 3.9% to 4.7% on an annualized basis. Overall, we find that the news reversal strategy exhibits very low correlations with carry trade and momentum strategies offering high annualized alphas.

The high annualized alphas that remain after orthogonalizing the signal with respect to these other strategies suggests that there may be diversification benefits from including them both in a portfolio investment strategy. To investigate this, we combine the carry trade factor (CAR) with REV(1,1) and REV(6,1), i.e. the reversal strategies with one or six months formation period and with a one month holding period. In *Panel B* of Table 10 we report summary performance statistics of the carry trade portfolio as well as the blended carry trade and reversals portfolios. We find that the annualized Sharpe ratios increase from 0.92 for the simple carry trade strategy to a very impressive 1.51 and 1.61 for the strategies that combine the carry trade and reversal strategies. This finding indicates the strong diversification benefits of the news reversal strategy for carry trade portfolios. This could be due to the fact that carry trades perform poorly in periods with low sentiment.

[TABLE 10 ABOUT HERE.]

6.3 Transaction Costs

We also consider the implementation cost of the FX media sentiment strategy. Section A of the Internet Appendix offers a detailed description of the construction of net excess returns. Table 11 shows average *net excess returns* and net spot rate changes of spread portfolios sorted based on the average sentiment of news per currency over the formation period. In particular, we report the average return of a strategy that goes long *low* sentiment portfolios while short selling *high* sentiment currency portfolios based on a formation period f months and a holding period of h months. We consider formation (holding) periods of 1, 3, 6, 9 and 12 months. *Panel A* (*Panel B*) reports results for quoted spreads (effective spreads).

One should take into account that bid–ask spreads reported from BBI/Reuters are based on indicative quotes and are in general too wide (e.g., Lyons et al., 2001) in comparison with actual effective spreads in FX markets. Thus, our results with net excess returns that consider the full, quoted bid–ask spread may be too conservative and not represent a realistic return. Hence, we also present in *Panel B* of Table 11 excess returns after allowing for transaction costs calculated as 50% and 75% of quoted spreads, as in Goyal and Saretto (2009). These results are more realistic and indicate that transaction costs do not eliminate the profitability of currency reversal strategy. This is perhaps not surprising, as our previous analysis indicates that the profitability of the currency reversal strategy is more concentrated among currencies of *Developed Countries* that tend to be more liquid. In any case, we find that currency reversals offer very positive and statistically significant net excess returns with transaction costs. In particular, the net excess return to a currency reversal strategy is 3.75% per annum when considering the quoted spread and it increases to 4.58% and 5.24% when including an effective spread of 75% and 50%, respectively. The latter returns are more realistic as they probably reflect more closely the transaction costs that investors would face in reality.

[TABLE 11 ABOUT HERE.]

6.4 Time-Variation in the Profitability of Currency Reversals

In this sub-section, we examine the stability of currency reversals over time. Figure 5 displays mean currency excess returns to the three spread currency reversal portfolios – $REV(1,1)$, $REV(6,1)$, and $REV(12,1)$, estimated based on a rolling window of 36 months. The left panel presents returns before transaction costs and the right panel displays net excess returns that consider the implementation cost of strategies. We find that the profitability of currency reversals exhibits time-variation and that currency excess returns tend to be higher over the most recent period. These results are present for both adjusted and unadjusted currency excess returns. For example, currency reversals for all three formation periods demonstrate very high returns between 2014 and 2018, offering monthly net excess returns of about 3% per month.

Another important aspect of Figure 5 is that currency reversals are not constant even over intermediate horizons, and therefore, this strategy may be more appealing to investors with longer investment horizons. This is particularly important for professional market participants and proprietary traders who are more involved in currency speculation and whose performance is usually evaluated based on short-term horizons (e.g., Lyons et al., 2001).

[FIGURE 5 ABOUT HERE.]

6.5 Daily Frequencies

Here, we investigate whether the sentiment reversal strategy is also profitable when considering daily frequencies. In particular, we examine the presence of currency reversals at a daily level. We allocate currency excess returns into portfolios based on the previous period FX sentiment per currency. Table A9 of the Internet Appendix displays average currency excess returns of spread portfolios that are sorted based on the average sentiment of news per currency over the formation period. In particular, we report the average return of a strategy that goes long *low*-sentiment portfolios while short selling *high*-sentiment currency portfolios based on a formation period of f months and a holding period of h months. We consider formation (holding) periods of 1, 5, 10, 15 and 22 days. We report results for *All countries*.

We find that a currency reversal strategy that buys currencies with low sentiment in the previous day and sells currencies with high sentiment over the same formation period offers an annualized return of 14.31%. This pattern is more pronounced for the strategy with both formation period and holding period of one day. We also find even stronger results for a formation period of 22 days that is present across different holding periods. This is in line with the sentiment theory as we observe an overpricing that persists for longer periods with a subsequent mean-reversion to the fundamental value.

6.6 Topic Modelling

Our primary analysis is based on a dictionary-based measure of tone following the methodology of Loughran and McDonald (2011), among others. Another approach would be to focus on topic modeling methods. However, such approaches suffer from hindsight bias as the estimation is based on the full sample.

One potential shortcoming of our approach might be that tone changes could proxy for specific topics discussed in the news. For example, if tone changes reflect negative information for a particular topic such as trade wars and positive information for another topic such as monetary policy, then such changes would proxy for specific topics rather than independent information.

To guard against this issue, we employ the Latent Dirichlet Allocation (LDA) method of Blei, Ng, and Jordan (2003) to estimate the topics of our corpus. This approach has been implemented in the macro literature in an attempt to examine the effects of information released by central banks on the market and key economic variables (e.g., Hansen, McMahon, and Prat, 2017; Hansen and McMahon, 2016; Schmeling and Wagner, 2019). In the foreign exchange literature, Filippou, Gozluklu, Nguyen, and Taylor (2020) apply dictionary-based and probabilistic topic modeling methods such as LDA in order to construct a textual measure that captures U.S. populist rhetoric, which is found to be a strong predictor of the cross-section of currency returns.

The LDA method allocates words into groups based on the co-existence of such words across articles. Each article is a mixture of topics that are determined by the LDA. The labeling of the topics involves subjective judgment. In our setting, we do not label the topics because we test whether the FX tone measure reflects general information over and above the one contained in the topics.

We fit an LDA model with five topics.[19] Following Schmeling and Wagner (2019), we estimate the likelihood of each topic for each article and construct dummy variables for each topic. Specifically, we construct a dummy variable per topic that takes a value of one on news months that the LDA indicates that this topic dominates the article and zero otherwise. We augment the panel regression of equation 3 with the topic dummies $2, \ldots, 5$ (we eliminate the dummy variable of topic one because of collinearity). In particular, we run a panel regression of currency excess returns and exchange rate changes on sentiment or negativity measures, our set of control variables, and the topic dummies. Table A10 of the Internet Appendix displays coefficient estimates of the sentiment and the negativity measure after controlling for the topic dummies. *Panel A* of Table A10 shows results for currency excess returns, and *Panel B* displays results for spot exchange rate changes. We find that the sentiment measures' slope coefficients are highly statistically and economically significant in all specifications. This finding implies that it is unlikely that the sentiment or negativity measures are proxies for specific topics.

7 Conclusion

Media sentiment that reflects positively on a currency is a strong *negative* predictor of currency returns, as it is associated with a currency reversal strategy that robustly renders strong and significant annualized returns and Sharpe ratios, as demonstrated by the research reported in this paper – an empirical analysis involving 1.2 million FX-related news articles and the exchange rates of 48 currencies over a 35-year period.

These results are robust even after controlling for the implementation costs of the strategy or when considering daily rebalancing. In addition, the currency reversal strategy is orthogonal to a number of well-known currency investment strategies, such as carry trades and momentum, and yields higher returns and Sharpe ratios for portfolios combining

[19] In the LDA algorithm, the researcher can define the number of topics. As it is highlighted by Hansen et al. (2017), in probabilistic topic modeling, researchers face a trade-off between the interpretability of the topics and the goodness-of-fit of the model. The authors emphasize that it is easier to interpret a smaller number of topics.

reversal and carry trade strategies than either of the strategies yields alone. The profitability of currency reversals cannot be explained by country size and idiosyncratic volatility, and is more concentrated among currencies with low volatility, low illiquidity, high current-month return and low past-month return. Similarly, currency reversals following media sentiment tend not to be foreseen by market experts: analysts make positive return forecasts for currencies with high media sentiment, which cannot account for the negative relation between sentiment and currency returns.

Our currency reversal finding is in line with a theory of financial market sentiment according to which short-term returns will be reversed over longer horizons (e.g., Campbell et al., 1993; Stambaugh et al., 2012). The research reported in the present paper, however, is the first to show that price reversals based on media sentiment are a well-defined feature of the foreign exchange market.

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Table 1. Summary Statistics of FX News Articles

This table presents summary statistics for the news article coverage of our sample currencies. Both unconditional statistics (percentage of currencies receiving coverage) and conditional statistics (number of articles written on the currencies conditioned on coverage) are presented. We first filtered out the news from major presses, and then labelled each article by all currencies that appeared in that article. Our data contain daily series that span the period of October 1983 to April 2019.

Foreign Exchange News Coverage											
Year	Dow Jones	Reuters	Agence France Presse	Financial Times	The Wall Street Journal	The New York Times	The Washington Post	USA Today	Associated Press Newswires	Mean	Median
	% of Currencies Covered									*Conditional Coverage*	
1983	0%	0%	0%	65%	0%	39%	0%	0%	0%	43.72	2.00
1984	0%	0%	0%	61%	0%	46%	0%	0%	0%	46.50	3.00
1985	2%	0%	0%	59%	7%	39%	0%	0%	0%	33.30	1.00
1986	17%	0%	0%	61%	39%	39%	15%	0%	0%	59.89	3.50
1987	33%	65%	0%	50%	54%	43%	26%	0%	0%	82.78	7.50
1988	30%	70%	0%	50%	41%	37%	24%	0%	0%	114.91	8.50
1989	35%	74%	0%	57%	41%	37%	28%	0%	0%	166.67	17.50
1990	54%	80%	0%	54%	43%	30%	20%	2%	0%	196.22	28.50
1991	24%	76%	0%	59%	0%	28%	0%	0%	0%	171.26	24.50
1992	39%	80%	0%	61%	20%	48%	0%	0%	0%	217.96	56.00
1993	20%	87%	0%	63%	22%	43%	0%	0%	0%	207.70	44.50
1994	30%	91%	0%	70%	9%	43%	0%	0%	0%	206.04	74.50
1995	11%	96%	0%	80%	15%	52%	0%	0%	0%	338.41	156.00
1996	15%	96%	15%	80%	4%	0%	2%	0%	0%	356.22	177.00
1997	26%	98%	0%	68%	30%	15%	17%	0%	0%	642.72	379.00
1998	98%	98%	0%	74%	43%	0%	0%	0%	0%	2797.30	1438.00
1999	95%	97%	0%	63%	32%	0%	0%	0%	0%	3506.82	1765.00
2000	87%	100%	29%	63%	74%	24%	0%	0%	3%	2324.55	1082.50
2001	68%	92%	50%	74%	74%	34%	18%	13%	50%	605.87	130.50
2002	81%	92%	73%	73%	81%	38%	24%	5%	59%	1043.68	283.00
2003	84%	95%	70%	78%	81%	51%	27%	30%	62%	984.24	356.00
2004	92%	97%	68%	78%	73%	51%	22%	32%	76%	1551.14	548.00
2005	92%	89%	65%	84%	68%	35%	22%	19%	70%	1506.49	357.00
2006	89%	89%	73%	84%	73%	22%	19%	16%	68%	1453.05	587.00
2007	89%	97%	69%	81%	69%	33%	25%	11%	69%	1561.50	290.50
2008	94%	97%	83%	78%	78%	36%	19%	19%	72%	1972.50	400.00
2009	86%	94%	78%	72%	83%	33%	14%	14%	53%	1624.42	310.50
2010	81%	94%	64%	75%	81%	50%	28%	22%	56%	2782.86	748.00
2011	89%	94%	72%	75%	81%	31%	31%	14%	56%	3498.36	1040.50
2012	86%	92%	69%	75%	86%	50%	36%	14%	58%	2565.67	512.00
2013	92%	97%	50%	81%	83%	47%	22%	6%	36%	1379.47	300.50
2014	86%	94%	64%	78%	75%	36%	14%	14%	42%	1217.53	260.50
2015	94%	94%	69%	89%	81%	28%	25%	19%	44%	1584.64	487.50
2016	89%	94%	58%	81%	81%	31%	17%	19%	33%	1313.28	473.50
2017	83%	89%	58%	72%	69%	22%	8%	19%	25%	1421.61	306.50
2018	86%	91%	49%	80%	66%	29%	11%	0%	29%	954.34	237.00
2019*	77%	83%	17%	34%	37%	6%	6%	0%	20%	163.71	43.00
Full Sample	100%	100%	79%	100%	98%	85%	58%	44%	73%	1027.05	170.00

Table 2. FX Media Sentiment and Currency Returns

This table presents coefficient estimates of predictive panel regressions with time (e.g., τ_t) and currency (e.g., α_i) fixed effects of currency excess returns or exchange rate changes on FX media sentiment or negativity as well as a number of control variables. The model takes the form below:

$$R_{i,t} = \alpha_i + \tau_t + \beta Sent_{i,t-1} + \boldsymbol{\gamma} \boldsymbol{z}_{i,t-1} + \varepsilon_{i,t}, \text{ for R} = rx \text{ or } -\Delta s$$

where $rx_{i,t}$ ($-\Delta s_{i,t}$) represents the currency excess return (exchange rate change) of currency i at time t and $Sent_{i,t-1}$ denotes the sentiment measure (see Section 4 for the construction of the measure) of each currency pair at time $t-1$. We also control for other determinants of currency returns such as currency volatility and illiquidity that are included in the vector $\boldsymbol{z_{i,t-1}}$. Columns (1) and (2) show results for currency excess returns and columns (3) and (4) show estimates for exchange rate changes. We have multiplied the exchange rate change (ΔS) by minus one so that higher values correspond to an appreciation of the foreign currency against the US dollar. We report t-statistics in squared brackets that are based on double-clustered standard errors across time and currency pairs. *, **, *** indicate significance levels of 1%, 5% and 10% respectively. Our data contain monthly series that span the period of October 1983 to April 2019.

	Currency Returns			
	(1)	(2)	(3)	(4)
	rx_t	rx_t	$-\Delta s_t$	$-\Delta s_t$
Sentiment$_{t-1}$	-0.143***	-0.102***	-0.120***	-0.0695***
	[-4.55]	[-4.23]	[-4.19]	[-2.75]
Constant	-0.002**	0.001	-0.002***	-0.001**
	[-2.39]	[1.33]	[-5.16]	[-2.25]
Controls	Yes	No	Yes	No
Time FE	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes
Cluster	Currency	Currency	Currency	Currency
Observations	4,620	10,915	4,620	10,915
R-squared	0.499	0.398	0.530	0.436

Table 3. FX Media Sentiment and Currency Returns: VAR Estimates

This table presents coefficient estimates of predictive panel VAR with time (e.g., τ_t) and currency (e.g., α_i) fixed effects of currency excess returns or exchange rate changes on FX media sentiment or negativity as well as a number of control variables. The model takes the form below:

$$R_{i,t} = \alpha_i + \tau_t + \sum_{k=1}^{5} \beta_k Sent_{i,t-k} + \boldsymbol{\gamma z}_{i,t-1} + \varepsilon_{i,t}, \text{ for R} = rx \text{ or } -\Delta s$$

where $rx_{i,t}$ ($\Delta s_{i,t}$) represents the currency excess return (exchange rate change) of currency i at time t and $Sent_{i,t-k}$ denotes the sentiment measure (see Section 4 for the construction of the measure) of each currency pair at time $t-k$ for $k = 1, \ldots, 5$. We also control for other determinants of currency returns such as currency volatility and illiquidity that are included in the vector $\boldsymbol{z_{i,t-1}}$. Columns (1) and (2) show results for monthly currency excess returns and exchange rate changes and columns (3) and (4) show estimates for daily currency excess returns and exchange rate changes. We have multiplied the exchange rate change by minus one so that higher values correspond to an appreciation of the foreign currency against the US dollar. We report t-statistics in squared brackets that are based on robust standard errors. *, **, *** indicate significance levels of 1%, 5% and 10% respectively. Our data contain monthly series that span the period of October 1983 to April 2019.

Currency Returns					
	(1)	(2)		(3)	(4)
	rx_t	$-\Delta s_t$		rx_t	$-\Delta s_t$
	Monthly Returns			*Daily Returns*	
Sentiment$_{t-1}$	-0.119***	-0.082**	Sentiment$_{t-1}$	-0.007**	-0.007**
	(-2.77)	(-2.09)		(-2.28)	(-2.31)
Sentiment$_{t-2}$	-0.123***	-0.0325	Sentiment$_{t-2}$	0.000	0.001
	(-2.71)	(-0.75)		(-0.027)	(0.302)
Sentiment$_{t-3}$	0.085*	-0.013	Sentiment$_{t-3}$	-0.006*	-0.005
	(1.81)	(-0.29)		(-1.96)	(-1.64)
Sentiment$_{t-4}$	-0.002	-0.014	Sentiment$_{t-4}$	-0.006*	-0.003
	(-0.05)	(-0.35)		(-1.84)	(-1.11)
Sentiment$_{t-5}$	0.099***	0.062*	Sentiment$_{t-5}$	0.001	0.003
	(2.67)	(1.69)		(0.48)	(0.86)
Constant	-0.002**	-0.003***	Constant	-0.001***	-0.000**
	(-2.28)	(-2.78)		(-7.59)	(-1.96)
$\chi^2(5)[Joint]$	5.42	1.98	$\chi^2(5)[Joint]$	4.07	2.59
p-value	0.00	0.08	*p-value*	0.00	0.04
Sum 2 to 5	0.593	0.003	Sum 2 to 5	-0.167	-0.011
$\chi^2(1)[Reversal]$	3.89	0.85	$\chi^2(1)[Reversal]$	2.24	1.14
p-value	0.00	0.49	*p-value*	0.06	0.33
Controls	Yes	Yes		Yes	Yes
Currency FE	Yes	Yes	Currency FE	Yes	Yes
Time FE	Yes	Yes	Time FE	Yes	Yes
Observations	2,421	2,509	Observations	33,864	33,864
R-squared	0.611	0.526	R-squared	0.401	0.434

Table 4. Currency Reversal Portfolios

This table shows average currency excess returns (rx) and exchange rate changes ($-\Delta S$) of low minus high (LMH) spread portfolios sorted based on the average sentiment of news per currency over the formation period. In particular, we report the average return of a strategy that goes long *low* sentiment portfolios while short selling *high* sentiment currency portfolios based on a formation period f months and a holding period of h months. We consider formation (holding) periods of 1, 3, 6, 9 and 12 months. *Panel A* (*Panel B*) reports results for All countries (Developed countries). All returns are annualized and expressed in percentage. We report t-statistics in squared brackets that are based on Newey and West (1987) standard errors with one lag. *, **, *** indicate significance levels of 1%, 5% and 10% respectively. Our data contain monthly series that span the period of October 1983 to April 2019.

Panel A: All Countries

	Currency Excess Returns						Exchange Rate Changes				
	Holding Period h						*Holding Period h*				
f	1	3	6	9	12	f	1	3	6	9	12
1	6.53***	5.38***	4.29**	3.81**	3.52**	1	4.29***	3.24**	1.91*	1.83*	1.71**
	[4.44]	[3.12]	[2.54]	[2.33]	[2.14]		[2.86]	[2.21]	[1.73]	[1.94]	[2.24]
3	8.37***	6.68***	5.22***	4.36**	4.14**	3	2.80*	2.60*	2.04*	2.03**	1.90**
	[4.45]	[3.15]	[2.72]	[2.39]	[2.43]		[1.70]	[1.86]	[1.86]	[2.21]	[2.40]
6	8.53***	6.63***	4.95**	3.88**	3.73**	6	2.73	2.12	1.77	1.86*	1.61*
	[3.72]	[2.91]	[2.42]	[2.14]	[2.22]		[1.64]	[1.47]	[1.56]	[1.90]	[1.80]
9	6.69***	5.13**	3.45*	2.91	2.74*	9	2.91	2.69*	2.18*	1.89*	1.82*
	[2.89]	[2.29]	[1.77]	[1.60]	[1.68]		[1.63]	[1.80]	[1.74]	[1.72]	[1.88]
12	6.18***	4.23**	3.34*	2.71	2.15	12	2.69	2.66*	1.86	1.59	1.42
	[2.98]	[2.09]	[1.80]	[1.63]	[1.41]		[1.61]	[1.74]	[1.54]	[1.52]	[1.51]

Panel B: Developed Countries

	Currency Excess Returns						Exchange Rate Changes				
	Holding Period h						*Holding Period h*				
f	1	3	6	9	12	f	1	3	6	9	12
1	4.70***	1.77**	1.26**	0.58	0.61	1	2.24**	0.89	-0.08	0.21	-0.14
	[5.25]	[2.16]	[2.01]	[1.11]	[1.14]		[2.20]	[0.97]	[-0.11]	[0.37]	[-0.27]
3	2.38**	1.39*	0.91	0.76	0.81	3	1.60	0.44	0.17	0.05	-0.23
	[2.54]	[1.67]	[1.24]	[1.29]	[1.47]		[1.26]	[0.40]	[0.21]	[0.08]	[-0.41]
6	1.44	0.82	0.96	0.72	0.67	6	1.35	0.73	-0.11	0.10	-0.10
	[1.43]	[0.96]	[1.24]	[1.04]	[1.04]		[1.26]	[0.76]	[-0.14]	[0.14]	[-0.16]
9	1.14	0.87	0.74	0.64	0.61	9	1.30	0.66	0.29	0.30	0.17
	[1.10]	[0.86]	[0.82]	[0.80]	[0.79]		[0.99]	[0.57]	[0.28]	[0.32]	[0.19]
12	0.71	0.46	0.19	0.36	0.39	12	1.01	0.86	0.58	0.40	0.30
	[0.61]	[0.46]	[0.21]	[0.43]	[0.49]		[0.82]	[0.80]	[0.58]	[0.44]	[0.37]

Table 5. Sharpe Ratios of Currency Reversal Portfolios

This table shows Sharpe ratios that are based on currency excess returns (rx) and exchange rate changes ($-\Delta S$) of low minus high (LMH) spread portfolios sorted based on the average sentiment of news per currency over the formation period. In particular, we construct a strategy that goes long *low* sentiment portfolios while short selling *high* sentiment currency portfolios based on a formation period f months and a holding period of h months. We consider formation (holding) periods of 1, 3, 6, 9 and 12 months. *Panel A* (*Panel B*) reports results for All countries (Developed countries). Sharpe ratios are annualized. We report t-statistics in squared brackets that are based on a moving block-bootstrap. *, **, *** indicate significance levels of 1%, 5% and 10% respectively. Our data contain monthly series that span the period of October 1983 to April 2019.

Panel A: All Countries

	Currency Excess Returns						Exchange Rate Changes				
	Holding Period h						*Holding Period h*				
f	1	3	6	9	12	f	1	3	6	9	12
1	0.57***	0.43**	0.35*	0.31*	0.29	1	0.54***	0.35**	0.25*	0.27*	0.31**
	[3.53]	[2.27]	[1.85]	[1.70]	[1.60]		[3.24]	[2.30]	[1.91]	[1.67]	[1.99]
3	0.46***	0.37*	0.32*	0.25	0.29*	3	0.30**	0.30*	0.27*	0.33*	0.36**
	[2.73]	[1.92]	[1.68]	[1.48]	[1.65]		[2.02]	[1.93]	[1.89]	[1.92]	[2.04]
6	0.42***	0.34*	0.29	0.24	0.27	6	0.30*	0.23	0.23	0.27*	0.25*
	[2.60]	[1.71]	[1.59]	[1.58]	[1.62]		[1.68]	[1.48]	[1.46]	[1.76]	[1.68]
9	0.44**	0.35*	0.27*	0.22	0.22	9	0.27*	0.26**	0.24**	0.24*	0.26**
	[2.37]	[1.78]	[1.78]	[1.49]	[1.36]		[1.91]	[2.06]	[2.04]	[1.84]	[1.97]
12	0.46***	0.35*	0.29*	0.23	0.20	12	0.26*	0.25**	0.21*	0.21*	0.21*
	[2.69]	[1.96]	[1.74]	[1.47]	[1.25]		[1.86]	[1.97]	[1.78]	[1.67]	[1.68]

Panel B: Developed Countries

	Currency Excess Returns						Exchange Rate Changes				
	Holding Period h						*Holding Period h*				
f	1	3	6	9	12	f	1	3	6	9	12
1	0.80***	0.33**	0.39**	0.20	0.18	1	0.34**	0.15	-0.02	0.07	-0.04
	[6.13]	[2.29]	[2.27]	[1.29]	[1.24]		[2.35]	[1.08]	[0.20]	[0.93]	[-0.01]
3	0.35**	0.26**	0.18	0.13	0.14	3	0.20	0.07	0.04	0.02	-0.07
	[1.96]	[1.99]	[1.47]	[0.83]	[0.99]		[1.13]	[0.48]	[0.25]	[0.07]	[-0.77]
6	0.31**	0.17	0.20	0.12	0.10	6	0.20	0.14	-0.03	0.03	-0.03
	[2.47]	[1.05]	[1.13]	[0.71]	[0.71]		[1.34]	[0.84]	[-0.08]	[0.11]	[-0.34]
9	0.32*	0.22	0.12	0.07	0.06	9	0.17	0.10	0.05	0.06	0.034
	[1.88]	[1.18]	[0.60]	[0.51]	[0.39]		[0.99]	[0.59]	[0.29]	[0.31]	[0.12]
12	0.26	0.15	0.02	0.01	0.01	12	0.13	0.14	0.11	0.08	0.06
	[1.38]	[0.86]	[-0.00]	[0.13]	[0.10]		[0.81]	[0.87]	[0.65]	[0.38]	[0.29]

Table 6. Cross-Sectional Regressions

This table displays time-series averages of slope coefficients from the regressions of currency excess returns and exchange rate changes at time $t+1$ on the media sentiment measure at time t with and without controls. In the spirit of the Fama and MacBeth (1973) regression, we examine which independent variables demonstrate premium that is different from zero, on average. To this end, we run cross-sectional regression on a monthly basis of the model - and nested specifications - below:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} Sent_{i,t} + \lambda_{2,t} R_{i,t} + \lambda_{3,t} fd_{i,t} + \varepsilon_{i,t+1}, \text{ for R} = rx \text{ or } \Delta s$$

where $Sent_{i,t}$ denotes the average media sentiment, $rx_{i,t}(\Delta s_{i,t})$ is the currency excess return (exchange rate change) and $fd_{i,t}$ is the forward discount of currency i at time t. *Panel A* (*Panel B*) reports results for All countries (Developed countries). We have multiplied the exchange rate change by minus one so that higher values correspond to an appreciation of the foreign currency against the US dollar. We report t-statistics in squared brackets that are based on Newey and West (1987) standard errors with one lag. *, **, *** indicate significance levels of 1%, 5% and 10% respectively. Our data contain monthly series that span the period of October 1983 to April 2019.

Panel A: All Countries								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}	$-\Delta s_{t+1}$	$-\Delta s_{t+1}$	$-\Delta s_{t+1}$	$-\Delta s_{t+1}$
$Sent_{i,t}$	-0.042**	-0.085***	-0.051**	-0.083***	-0.035*	-0.050**	-0.045**	-0.044**
	[-2.19]	[-3.78]	[-2.36]	[-3.37]	[-1.83]	[-2.37]	[-2.16]	[-1.98]
$rx_{i,t}$	0.095***	0.203***				0.049*		
	[3.24]	[7.00]				[1.90]		
$fd_{i,t}$	0.380***		0.471***		-0.452***		-0.451***	
	[3.17]		[3.40]		[-4.03]		[-3.28]	
$\Delta s_{i,t}$				0.095***	0.079***			0.072**
				[3.17]	[2.73]			[2.48]
Constant	0.000	0.000	0.000	0.00	0.000	-0.000	0.000	-0.000
	[0.25]	[0.12]	[0.17]	[1.12]	[0.36]	[-0.54]	[0.10]	[-0.33]
R-square	0.388	0.257	0.255	0.210	0.294	0.204	0.151	0.213

Panel B: Developed Countries								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	rx_{t+1}	rx_{t+1}	rx_{t+1}	rx_{t+1}	$-\Delta s_{t+1}$	$-\Delta s_{t+1}$	$-\Delta s_{t+1}$	$-\Delta s_{t+1}$
$Sent_{i,t}$	-0.121***	-0.123***	-0.111***	-0.117***	-0.119***	-0.126***	-0.107***	-0.124***
	[-2.95]	[-3.04]	[-2.68]	[-2.90]	[-2.93]	[-3.20]	[-2.64]	[-3.14]
$rx_{i,t}$	0.038	0.067**				0.033		
	[1.17]	[2.11]				[1.04]		
$fd_{i,t}$	0.793		0.963		-0.002		0.196	
	[0.99]		[1.31]		[-0.00]		[0.28]	
$\Delta s_{i,t}$				0.050	0.024			0.034
				[1.54]	[0.74]			[1.06]
Constant	-0.001	-0.000	-0.001	-0.000	-0.00	-0.00	-0.001	-0.00
	[-0.91]	[-0.33]	[-0.60]	[-0.20]	[-0.93]	[-0.93]	[-0.60]	[-0.85]
R-squared	0.474	0.293	0.308	0.288	0.464	0.294	0.289	0.295

Table 7. Time-Series Currency Reversals

This table shows average currency excess returns of equally-weighted portfolios of time-series currency reversal strategies based on different formation and holding periods. In particular, we construct a strategy that goes long *negative* sentiment currencies and short *positive* sentiment based on a formation period f months and a holding period of h months. We compute the excess return of each currency and then construct an equally-weighted portfolio. We consider formation (holding) periods of 1, 3, 6, 9 and 12 months. *Panel A* (*Panel B*) reports results for All countries (Developed countries). We express currency excess returns in percentage per annum. We report t-statistics in squared brackets that are based on Newey and West (1987) standard errors with one lag. *, **, *** indicate significance levels of 1%, 5% and 10% respectively. Our data contain monthly series that span the period of October 1983 to April 2019.

Panel A: All Countries					
	Holding Period h				
f	1	3	6	9	12
1	2.24***	0.99***	0.38*	0.21	0.11
	[2.79]	[2.71]	[1.66]	[0.96]	[0.60]
3	0.72	0.26	0.35	0.20	-0.11
	[0.97]	[0.65]	[1.07]	[0.76]	[-0.49]
6	0.66	1.15*	0.78	0.09	-0.12
	[0.80]	[1.79]	[1.55]	[0.23]	[-0.36]
9	0.66	1.10**	0.49	0.09	-0.07
	[0.90]	[1.97]	[1.01]	[0.20]	[-0.21]
12	0.13	-0.03	-0.42	-0.55	-0.39
	[0.16]	[-0.05]	[-0.87]	[-1.32]	[-1.06]
Panel B: Developed Countries					
	Holding Period h				
f	1	3	6	9	12
1	3.39***	1.32**	0.70**	0.28	0.15
	[3.20]	[2.15]	[2.11]	[1.08]	[0.68]
3	0.64	0.39	0.85**	0.22	0.04
	[0.68]	[0.68]	[2.26]	[0.71]	[0.14]
6	1.41*	1.26*	1.16**	0.50	0.18
	[1.70]	[1.90]	[2.23]	[1.17]	[0.49]
9	1.34	0.45	0.63	0.11	0.00
	[1.39]	[0.72]	[1.25]	[0.25]	[0.01]
12	0.51	0.24	-0.03	-0.19	-0.09
	[0.54]	[0.37]	[-0.06]	[-0.41]	[-0.23]

Table 8. FX News and Analysts' Forecasts of Exchange Rate Changes

This table shows average 3-month forecasts of exchange rate changes that are sorted into portfolios based on the average sentiment of news per currency over the formation period. In particular, we report the average forecast of currency returns of a strategy that goes long *low* sentiment portfolios while short selling *high* sentiment currency portfolios based on a formation period f months and a holding period of h months. We consider formation (holding) periods of 1, 3, 6, 9 and 12 months. All returns are expressed in percentage. We report t-statistics that are based on Newey and West (1987) standard errors with one lag. *, **, *** indicate significance levels of 1%, 5% and 10% respectively. Our data contain monthly series that span the period of October 1983 to April 2019.

Average Forecasts based on 3-month forecast horizon				
f	Low	High	LMH	t-stat
1	-1.77	-1.20	-0.59	-1.55
3	-2.09	-1.13	-0.98***	-2.73
6	-2.36	-0.85	-1.53***	-3.76
9	-2.49	-0.65	-1.85***	-4.27
12	-2.58	-0.57	-2.02***	-4.68

Table 9. Double Sorts

This table shows currency excess returns that are sorted into three portfolios based on country risk (CS) (*Panel A*) or volatility (V) (*Panel B*) or illiquidity (I) (*Panel C*) or current month return (CR) (*Panel D*) or past month return (PR) (*Panel E*) or idiosyncratic volatility (IV) (*Panel F*). Then within each portfolio we allocate currencies into terciles based on the average sentiment of news per currency over a formation period of one month and a holding period of one month. In particular, we construct a strategy that goes long *low* sentiment portfolios while short selling *high* sentiment currency portfolios. Currency excess returns are annualized and expressed in percentages. We report t-statistics that are based on Newey and West (1987) standard errors with one lag. *, **, *** indicate significance levels of 1%, 5% and 10% respectively. Our data contain monthly series that span the period of October 1983 to April 2019.

Panel A: Country Size

	Low	2	High	LMH	t-stat
CS1	0.58	1.29	0.88	-0.30	-0.26
CS2	1.58	-1.53	-5.46	7.03***	2.95
CS3	3.97	1.04	1.83	2.14	1.54

Panel B: Volatility

	Low	2	High	LMH	t-stat
V1	6.46	2.51	0.32	6.14***	4.93
V2	2.35	-0.25	-0.70	3.05***	2.99
V3	-1.65	1.03	-4.08	2.43	1.56

Panel C: Illiquidity

	Low	2	High	LMH	t-stat
I1	2.01	0.97	-2.20	4.21**	2.56
I2	1.28	-1.06	-0.70	1.98**	2.33
I3	2.82	1.68	0.06	2.76*	1.74

Panel D: Current Month Return

	Low	2	High	LMH	t-stat
CR1	-24.22	-24.52	-25.82	1.60	0.89
CR2	1.50	-0.25	0.74	0.76**	2.01
CR3	28.92	27.74	24.86	4.06***	4.77

Panel E: Past Month Return

	Low	2	High	LMH	t-stat
PR1	0.66	0.10	-5.37	6.03***	2.67
PR2	2.41	0.23	0.18	2.22**	1.97
PR3	4.39	3.48	2.85	1.54	1.45

Panel F: Idiosyncratic Volatility

	Low	2	High	LMH	t-stat
IV1	2.69	1.61	0.34	2.36**	2.02
IV2	3.25	-1.02	-1.66	4.92***	3.38
IV3	1.52	-0.30	-3.79	5.31***	3.09

Table 10. Robustness: Currency Reversals and Other Currency Investment Strategies

This table shows alpha and beta coefficients and R-squares of a contemporaneous linear regression (*Panel A*) of the excess return of the currency reversal strategy based on formation periods of 1 and 6 months and a holding period of one month on dollar (DOL), carry (CAR) and momentum (MOM) risk factors. The momentum factor considers a one month formation period and a holding period of one month. In particular, the model takes the form below:

$$REV_{t+1} = \alpha + \beta_1 DOL_t + \beta_2 X_t + \varepsilon_{t+1}, \text{ for X} = CAR \text{ or } MOM$$

where REV represents the currency reversal strategy. *Panel B* shows summary statistics such as the mean, standard deviation (std), Sharpe ratio, skewness and kurtosis of carry trade portfolios as well as portfolios that combine the carry trade strategy with currency reversals. The mean, standard deviation and Sharpe ratios are annualized. We report t-statistics in squared brackets that are based on Newey and West (1987) standard errors with one lag. *, **, *** indicate significance levels of 1%, 5% and 10% respectively. Our data contain monthly series that span the period of October 1983 to April 2019.

Panel A: Regressions of Currency Reversals on Currency Factors

	(1) REV(1,1)	(2) REV(6,1)	(3) REV(1,1)	(4) REV(6,1)
Alphas	0.328**	0.390***	0.577***	0.700***
	[2.31]	[2.72]	[4.25]	[4.95]
DOL	0.0328	0.0853	0.0770	0.152**
	[0.49]	[1.25]	[1.12]	[2.13]
HML	0.248***	0.352***		
	[4.18]	[5.87]		
MOM			-0.0296	0.0649
			[-0.52]	[1.07]
R-squared	0.063	0.132	0.005	0.021

Panel B: Diversification Benefits for Carry Trade Portfolios

	(1) CAR	(2) CAR+REV(1,1)	(3) CAR+REV(6,1)
Mean	8.062***	9.240***	10.273***
t-stat	[4.37]	[6.03]	[5.28]
std	30.308	21.171	22.127
Sharpe Ratio	0.921	1.512	1.608
Skewness	-0.648	0.781	0.758
kurtosis	2.171	3.059	2.517

Table 11. Robustness: FX Media Sentiment and Currency Portfolios: *Net Excess Returns*

This table shows average *net excess returns* (rx) and net spot rate changes ($-\Delta S$) of low minus high (LMH) spread portfolios sorted based on the average sentiment of news per currency over the formation period. In particular, we report the average return of a strategy that goes long *low* sentiment portfolios while short selling *high* sentiment currency portfolios based on a formation period f months and a holding period of h months. We consider formation (holding) periods of 1, 3, 6, 9 and 12 months. *Panel A* (*Panel B*) reports results for quoted spreads (effective spreads). All returns are annualized and expressed in percentage. We report t-statistics in squared brackets that are based on Newey and West (1987) standard errors with one lag. *, **, *** indicate significance levels of 1%, 5% and 10% respectively. Our data contain monthly series that span the period of October 1983 to April 2019.

Panel A: Quoted Spreads

	Net Excess Returns						Net Spot Rate Changes				
	Holding Period h						*Holding Period h*				
f	1	3	6	9	12	f	1	3	6	9	12
1	3.75***	2.97*	2.32	2.14	1.86	1	2.85*	1.66	0.52	0.39	0.29
	[2.60]	[1.72]	[1.38]	[1.27]	[1.09]		[1.92]	[1.16]	[0.46]	[0.41]	[0.36]
3	5.74***	4.29**	3.02	2.54	2.17	3	1.36	1.01	0.48	0.44	0.31
	[3.09]	[2.04]	[1.53]	[1.29]	[1.14]		[0.85]	[0.74]	[0.43]	[0.47]	[0.37]
6	5.92***	4.30*	2.65	1.95	1.77	6	1.29	0.53	0.23	0.22	-0.05
	[2.63]	[1.88]	[1.23]	[0.97]	[0.91]		[0.74]	[0.36]	[0.20]	[0.22]	[-0.05]
9	4.06*	2.81	1.38	1.09	0.99	9	1.09	1.04	0.57	0.26	0.16
	[1.77]	[1.25]	[0.67]	[0.54]	[0.53]		[0.62]	[0.74]	[0.46]	[0.24]	[0.16]
12	3.58*	2.06	1.28	0.89	0.55	12	1.02	0.99	0.30	0.08	-0.20
	[1.75]	[1.01]	[0.65]	[0.47]	[0.32]		[0.60]	[0.66]	[0.25]	[0.07]	[-0.22]

Panel B: Effective Spreads and Net excess Returns

	Effective Spread of 75%						Effective Spread of 50%				
	Holding Period h						*Holding Period h*				
f	1	3	6	9	12	f	1	3	6	9	12
1	4.58***	3.83**	3.04*	2.82*	2.52	1	5.24***	4.33**	3.57**	3.37**	3.07*
	[3.16]	[2.21]	[1.80]	[1.67]	[1.47]		[3.59]	[2.49]	[2.11]	[1.99]	[1.78]
3	6.55***	5.16**	3.78*	3.27*	2.88	3	7.17***	5.70***	4.35**	3.85*	3.47*
	[3.51]	[2.44]	[1.90]	[1.67]	[1.52]		[3.83]	[2.68]	[2.18]	[1.96]	[1.83]
6	6.74***	5.13**	3.41	2.67	2.45	6	7.35***	5.67**	3.98*	3.25	3.04
	[2.98]	[2.24]	[1.58]	[1.32]	[1.26]		[3.23]	[2.47]	[1.84]	[1.60]	[1.56]
9	4.88**	3.63	2.17	1.85	1.70	9	5.48**	4.18*	2.74	2.43	2.29
	[2.11]	[1.60]	[1.05]	[0.91]	[0.90]		[2.37]	[1.83]	[1.32]	[1.19]	[1.21]
12	4.37**	2.85	2.03	1.62	1.27	12	4.98**	3.41*	2.60	2.19	1.86
	[2.12]	[1.39]	[1.02]	[0.86]	[0.72]		[2.41]	[1.65]	[1.31]	[1.16]	[1.05]

Figure 2. Example of Sentiment Calculations

By Robert Cottrell

19 May 1983

Financial Times, Page 4

~~THE~~ Hong Kong dollar weakened yesterday ~~to~~ touch HKDollars 7 ~~to~~ ~~the~~ US dollar shortly ~~before~~ ~~the~~ close ~~of~~ local trading, setting ~~a~~ record low ~~for~~ ~~the~~ currency ~~and~~ breaching ~~an~~ important psychological barrier.

~~The~~ currency also registered ~~a~~ record low ~~of~~ 74.9 ~~on~~ ~~its~~ trade-weighted index. ~~In~~ London ~~the~~ currency finished ~~above~~ ~~its~~ worst ~~at~~ HKDollars 6.9945.

Dealers ~~in~~ Hong Kong said trading ~~was~~ relatively thin, ~~with~~ little sign ~~of~~ government intervention.

~~The~~ steady decline ~~of~~ ~~the~~ Hong Kong dollar ~~over~~ ~~the~~ past year ~~is~~ partially attributable ~~to~~ political worries ~~over~~ ~~the~~ future ~~of~~ ~~the~~ colony. Britain's lease ~~over~~ much ~~of~~ Hong Kong expires ~~in~~ 1997, ~~and~~ China ~~has~~ declared ~~its~~ intention ~~to~~ resume sovereignty.

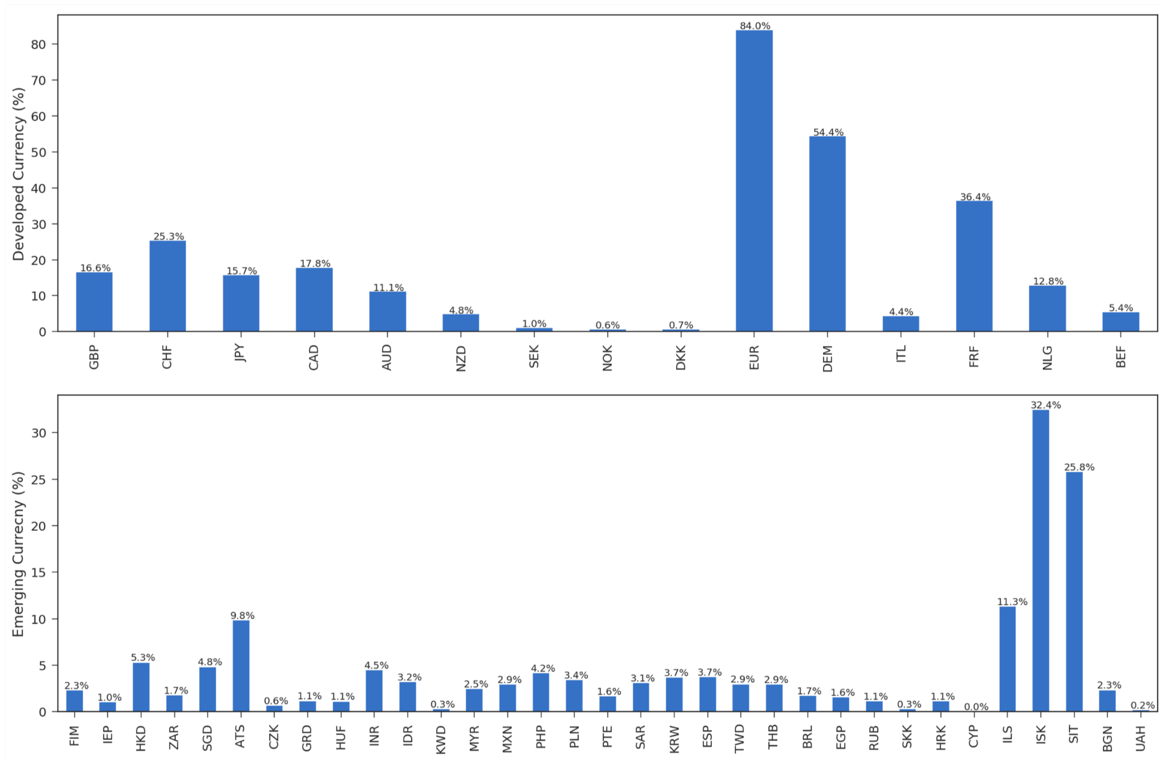
~~The~~ dollar's weakness also reflects leads-and-lages ~~in~~ Hong Kong's trade. Manufacturers ~~are~~ seeing order books lengthen ~~as~~ Hong Kong pulls ~~out~~ ~~of~~ recession, ~~and~~ ~~they~~ ~~are~~ buying foreign currency ~~to~~ finance raw material imports.

~~Some~~ analysts expect ~~the~~ Hong Kong dollar ~~to~~ strengthen ~~in~~ coming months ~~as~~ ~~these~~ raw material imports ~~are~~ translated ~~into~~ export receipts.

Total Words	167	**Non-Stopwords**	109
Positive Words	1	**Negative Words**	7
Sentiment	-5.50%	**Negativity**	-6.42%

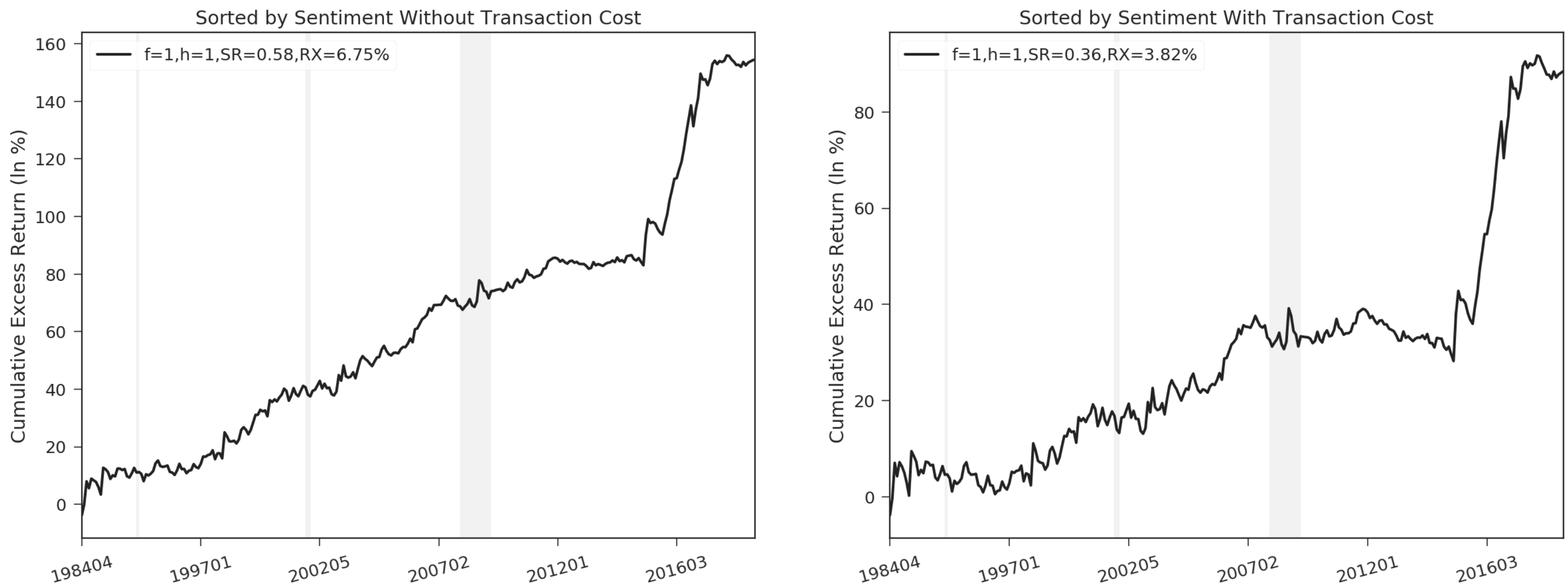
The figure displays one example of an FX article and the way that sentiment and negativity is calculated. The article appeared in Financial Times in May 1983.

Figure 3. Distribution of Articles Per Currency



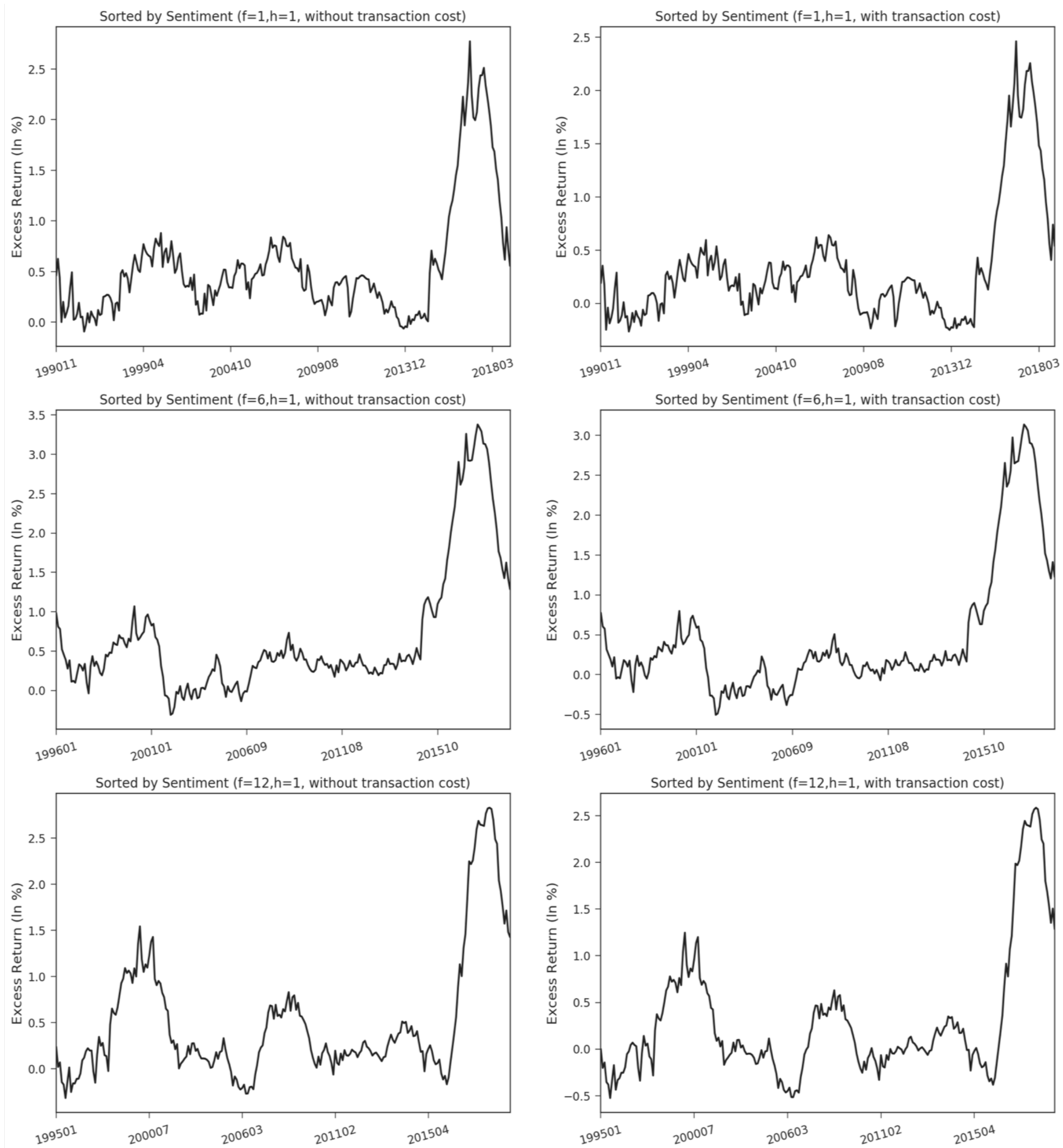
The figure displays the percentage of articles per currency in our sample. The data contain monthly series from October 1983 to April 2019.

Figure 4. Cumulative Returns



The figure displays cumulative returns of currency reversal portfolios. The left part shows results for unadjusted excess returns and the right part exhibits results for net excess returns with transaction costs. Shaded areas represent NBER recessions. The data contain monthly series from October 1983 to April 2019.

Figure 5. Rolling Currency Returns of Currency Reversal Portfolios



The figure displays average currency excess returns of FX news reversal portfolios based on a 36-month rolling window. We consider formation periods (f) of 1, 6, and 12 months and a holding period (h) of 1 month. The left part of the figure shows results for unadjusted currency excess returns and the right part of the figure shows net excess returns that include transaction costs. Shaded areas represent NBER recessions. The data contain monthly series from October 1983 to April 2019.