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Media Sentiment and Currency Reversals

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Abstract

Analyzing 48 foreign exchange (FX) rates and 1.2 million FX-related news articles over a 35-year period, using digital textual analysis, we find that a currency reversal investment strategy that buys (sells) currencies with low (high) media sentiment offers strong positive and statistically significant returns and Sharpe ratios. The results are robust and the strategy adds value over other currency premia determinants. Analysts' forecasts systematically mispredict the reversal strategy. This is the first article to show that price reversals based on media sentiment are a well-defined feature of the FX market.

I. Introduction

Mass media, especially mainstream newspapers, contribute a large portion of public information acquired by foreign exchange (FX) investors on a daily basis. If the semi-strong form of market efficiency holds in the 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), and Fang and Peress (2009)),[1] demonstrating that financial news content is related to investor psychology. However, it is not clear whether the content of FX news drives, reinforces, or reflects investors' trading behavior in the FX market.[2] Our contribution is therefore

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[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

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 FX market. In addition, we investigate the mechanism that drives our findings.

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 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 article, we construct a novel sentiment measure for the FX market and show that it is a strong predictor of the cross section of currency returns. Chen, Han, and Pan (2021) find that skilled hedge funds try to predict and exploit sentiment changes which help them earn higher returns contributing positively to the performance of the fund.

In the FX 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 are 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 Oct. 1983 and Apr. 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. Our main analysis uses sentence-level sentiment but we also offer results for article-level sentiment; the main findings hold across the two measures.

The analysis begins with an investigation of the time-series predictive ability of FX media sentiment for currency returns. In a panel regression with currency 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

nonfundamentals). In this article, however, we use the term "news" in the more general sense of information appearing in the news media, rather than just the unanticipated component.

manner. Thus, it predicts negative price pressure followed by a mean reversion to country fundamentals within 5 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 FX market, the negative impact of FX sentiment on prices is more persistent, with mean reversion occurring over a period of 2–5 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 1 and 12 months. We develop a trading strategy that evaluates the sentiment of FX media 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. Specifically, we find that a strategy that buys currencies with low sentiment over the previous month and sells currencies with high sentiment offers an annualized return of 9.05% for all countries and 7.04% for developed countries. We hold our portfolios for 1 month. We find similar results for different holding and formation periods.

To the best of our 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. In addition, our results are robust after controlling for the sentiment index of Yu (2013).

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. Thus, a currency reversal strategy with a formation and a holding period of 1 month offers an annualized Sharpe ratio of 0.94 for the sample of all 48 countries, rising to 1.59 when the sample is limited to developed countries.

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 below (above) the median sentiment of all currencies in the sample over the formation period, with 1-month formation and holding periods, yields statistically significant annualized returns of 4.53% for the universe of all 48 countries and 4.28% for developed countries. The profitability of time-series reversals drops as the formation and holding periods are increased. We find similar results when we build a strategy that buys (sells) currencies with low (high) sentiment changes over the formation period.

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 9%. While the betas with the carry trade factor are a little higher, orthogonalizing with respect to carry still produces annualized alphas of around 9%. 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 1.9, 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 the profitability of the currency reversal strategy is concentrated among currencies with high idiosyncratic volatility and high illiquidity, while volatility, country size, and current-month return do not seem to play an important role in this strategy. In addition, we find stronger results for currencies with low past month return, which is expected for a reversal strategy.

To further investigate the underlying mechanism that drives these results, we examine an additional data set: analysts' average forecast of future spot rate changes. Each month between Oct. 1983 and Mar. 2017, and for each of the 17 currencies, we obtain analysts' average forecasts of each currency's spot exchange rate changes in the next 3 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. We also find that analysts contribute to the reversal strategy.

In addition, we proxy demand pressure with currency trading volume and we find that the overvaluation of high sentiment currencies is more pronounced for currencies accompanied by stronger trading volume. We repeat the same exercise with order imbalances and find that the overvaluation is driven by net buy positions.

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

Thus, we find that investors' preferences for high media sentiment currencies generate the relative demand and thus the upward price pressure. We also decompose the media sentiment into local and global sentiment and find that our results are driven by local media sentiment.

In what follows, we briefly discuss the effect of media news sentiment on asset prices in Section II, while Section III discusses the construction of the sentiment measures. In Section IV, we describe the data as well as the construction of the currency portfolios. Section V discusses the main empirical results of the article. Section VI offers robustness and other specification tests. Finally, in Section VII, we offer some concluding comments.

II. 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 1–12 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 are 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 article, we demonstrate that an analogous approach is also helpful in understanding the cross section of currency excess returns.

III. FX Media Sentiment

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

A. 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.

B. 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.

C. FX Media Sentiment

We measure the tone of the news articles following a "bag-of-words" approach as in Tetlock (2007) and Loughran and McDonald (2011). Our goal is to compute the sentiment of the foreign currency against the U.S. dollar. This way, the U.S. dollar sentiment is just minus the average sentiment for all other currencies. Specifically, for every sentence in an article that mentions a foreign currency and the U.S. dollar, we compute the tone of the sentence by calculating the frequency of positive and negative keywords that appeared in the tone dictionary. We use a dependency parser for every sentence to get the dependency tree of the sentence. This way, we measure the shortest paths between the foreign currencies and the U.S. dollar. If the positive or negative sentiment words in the path refer to the U.S. dollar, then our sentiment measure has a negative sign.[4] Section B of the Supplementary Material offers two examples of the calculation of the sentence-level sentiment.[5] 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

[4]We would like to thank the referee for this suggestion.

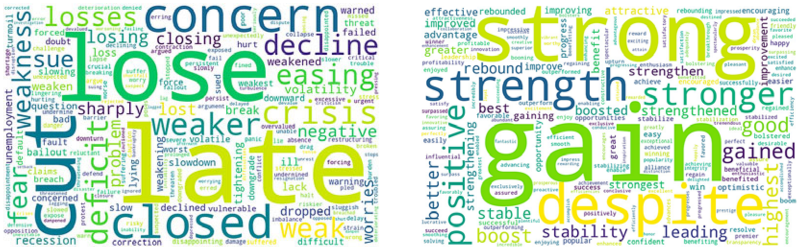
[5]We recognize that we might omit some information when we calculate the sentiment of the path of the sentences that mention the U.S. dollar. However, we obtain more accurate sentiment calculations. We offer in a later section results for the article-level sentiment. We show that both approaches provide similar results. However, the novelty of the sentence-level sentiment is that it can "sign" the sentiment more accurately based on whether it is related to the foreign currency or the U.S. dollar.

FIGURE 1

Most Frequent Negative and Positive Words

Figure 1 displays the 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 Oct. 1983 to Apr. 2019.

Graph A. Negative Words *Graph B. Positive Words*



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 more positive or less negative sentiment. Thus, the measure takes the form below:

$$\text{SENT}_{i,t} = \frac{n_{i,t}^{\text{Positive}} - n_{i,t}^{\text{Negative}}}{n_{i,t}^{\text{Sentence}}}, \tag{1}$$

where $n_{i,t}^{\text{Positive}}$ ($n_{i,t}^{\text{Negative}}$) 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 shortest path between the currencies in the sentences of the articles.[6] We focus on sentences that mention the U.S. dollar and the currency i at time t.[7]

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 FX traders to describe exchange rate fluctuations.

D. 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

[6] Our results are similar if we compute the sentiment of the whole sentence.

[7] We offer similar results in the Supplementary Material for article-level sentiment.

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TABLE 1

Summary Statistics of FX News Articles

Table 1 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 labeled each article by all currencies that appeared in that article. Our data contain daily series that span the period of Oct. 1983 to Apr. 2019.

Foreign Exchange News Coverage

	%_OF_CURRENCIES_COVERED									Conditional 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
1983	0.00	0.00	0.00	52.08	0.00	41.67	0.00	0.00	0.00	62.56	0.00
1984	0.00	0.00	0.00	54.17	0.00	47.92	0.00	0.00	0.00	58.89	0.00
1985	0.00	0.00	0.00	50.00	0.00	45.83	0.00	0.00	0.00	40.56	0.00
1986	27.08	0.00	0.00	52.08	35.42	50.00	2.08	0.00	0.00	64.56	1.00
1987	35.42	50.00	0.00	54.17	52.08	43.75	6.25	0.00	0.00	103.22	87.00
1988	31.25	68.75	0.00	43.75	45.83	37.50	4.17	0.00	0.00	168.67	77.00
1989	35.42	56.25	0.00	50.00	45.83	39.58	0.00	0.00	0.00	310.00	114.00
1990	39.58	83.33	0.00	45.83	52.08	33.33	0.00	0.00	0.00	349.44	188.00
1991	33.33	72.92	0.00	60.42	0.00	37.50	0.00	0.00	0.00	324.89	0.00
1992	16.67	72.92	0.00	54.17	0.00	33.33	0.00	0.00	0.00	367.22	0.00
1993	4.17	72.92	0.00	56.25	2.08	35.42	0.00	0.00	0.00	325.44	1.00
1994	22.92	89.58	0.00	72.92	0.00	45.83	0.00	0.00	0.00	401.67	0.00
1995	8.33	91.67	0.00	70.83	0.00	56.25	0.00	0.00	0.00	621.11	0.00
1996	0.00	87.50	10.42	79.17	0.00	0.00	0.00	0.00	0.00	654.44	0.00
1997	12.50	97.92	0.00	66.67	10.42	8.33	0.00	0.00	0.00	1,203.11	2.00
1998	93.75	97.92	0.00	64.58	16.67	0.00	0.00	0.00	0.00	2,972.89	0.00
1999	89.58	91.67	0.00	58.33	16.67	0.00	0.00	0.00	0.00	4,403.78	0.00
2000	45.83	91.67	16.67	66.67	64.58	14.58	0.00	0.00	0.00	3,773.44	21.00
2001	6.25	81.25	58.33	54.17	60.42	37.50	10.42	6.25	31.25	954.11	178.00
2002	27.08	87.50	54.17	64.58	62.50	31.25	20.83	4.17	41.67	1,696.22	297.00
2003	41.67	75.00	66.67	68.75	68.75	47.92	33.33	20.83	54.17	749.44	541.00
2004	56.25	83.33	62.50	70.83	60.42	43.75	29.17	33.33	66.67	948.33	560.00
2005	52.08	77.08	62.50	75.00	60.42	43.75	22.92	22.92	62.50	734.89	570.00
2006	64.58	75.00	60.42	75.00	64.58	29.17	25.00	16.67	64.58	697.56	546.00
2007	45.83	85.42	54.17	68.75	66.67	39.58	35.42	20.83	50.00	1,104.33	689.00
2008	50.00	95.83	77.08	70.83	77.08	39.58	33.33	20.83	54.17	1,983.11	601.00
2009	50.00	89.58	66.67	62.50	64.58	39.58	33.33	16.67	60.42	1,487.89	378.00
2010	70.83	93.75	64.58	68.75	58.33	47.92	33.33	20.83	62.50	1,878.56	654.00
2011	79.17	93.75	64.58	68.75	58.33	33.33	27.08	6.25	56.25	1,647.00	546.00
2012	60.42	93.75	66.67	75.00	45.83	31.25	29.17	10.42	56.25	1,180.11	507.00
2013	45.83	87.50	56.25	68.75	29.17	41.67	20.83	14.58	33.33	873.00	124.00
2014	0.00	89.58	58.33	68.75	14.58	25.00	10.42	10.42	29.17	943.89	19.00
2015	0.00	89.58	66.67	70.83	43.75	20.83	14.58	20.83	45.83	800.89	61.00
2016	0.00	85.42	58.33	62.50	47.92	18.75	22.92	6.25	29.17	581.67	77.00
2017	0.00	79.17	52.08	77.08	45.83	22.92	2.08	14.58	16.67	541.44	51.00
2018	0.00	79.17	54.17	77.08	39.58	29.17	2.08	0.00	22.92	540.33	39.00
2019*	0.00	70.83	25.00	66.67	20.83	10.42	0.00	0.00	18.75	147.00	3.00
Full	97.92	100.00	93.75	100.00	89.58	83.33	62.50	52.08	85.42	726.05	124.50

media coverage for currency assets. We also observe that the *Financial Times* and the *New York Times* offer the highest coverage in our sample. In addition, media outlets such as Dow Jones, Reuters, and the *Wall Street Journal* also offer strong coverage of currencies.[8]

IV. 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 data set as well as the data of currency analysts' forecast. In addition, we describe the formation of currency portfolios.

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

A. Exchange Rate Data

We start with daily spot and 1-month forward exchange rates against the U.S. dollar spanning the period from Oct. 1983 to Apr. 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 1-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, and the 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 Jan. 1999. Some countries entered the euro zone later than Jan. 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 Supplementary Material offers a detailed description of the construction of currency excess returns that include bid and ask spreads. Similarly to Lustig et al. (2011) and Della Corte, Riddiough, and Sarno (2016), we remove currency-time observations that exhibit large deviations from the covered interest rate parity (CIP) condition. Figure A2 in the Supplementary Material shows the number of currencies that are available each month in our sample.[9]

B. 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

[9]Section A of the Supplementary Material 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.

$$\text{RX}_{t+1} = f_t - s_{t+1}. \tag{2}$$

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., $f_t - s_t \simeq \widehat{i}_t - i_t$), where $\widehat{i}_t$ and i_t denote the foreign and domestic riskless interest rates, respectively. Therefore, the excess return could also be written as $\text{RX}_{t+1} \simeq \left(\widehat{i}_t - i_t\right) - \Delta s_{t+1}$. Thus, the currency excess returns can be approximated by the interest rate differential subtracted from the rate of depreciation of the exchange rate.[10]

C. FX News

We collect around 1.2 million news articles from Factiva, the global news-gathering service, for the period from Oct. 1983 to Apr. 2019. In particular, we search the Factiva news database for the name of each currency included in our sample.[11] 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. 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.

[10]Figure A1 in the Supplementary Material shows the number of currencies that are available every month in our sample.

[11]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.

D. Analysts' Forecasts

We obtain analysts' forecasts from the global macroeconomic survey firm, Consensus Economics. The data span the period from Oct. 1989 to Mar. 2017. This data set 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 3 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 3 months. All forecasts are expressed as foreign currency units per U.S. dollar. Specifically, the data set 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 Jan. 2016 indicate that the Australian dollar should decline by 1.1%, and Malaysian Ringgit should rise by 1.9% in April.

E. Currency Volume

We obtain unique data on FX signed volume from the CLS FX cash settlement system via the financial data platform, Quandl. CLS is the world's largest FX settlement institution. The daily data span the period between Sept. 2012 and Apr. 2019. In total, CLS settles around 50% of daily FX trading volume. The data set captures trade count in a universe of 17 currency pairs against the U.S. dollar. In particular, the data set includes the currencies of the following countries or regions: Australia, Canada, Switzerland, Denmark, Europe, United Kingdom, Hong Kong, Hungary, Israel, Japan, South Korea, Mexico, Norway, New Zealand, Sweden, Singapore, and South Africa. It is further categorized by the type of market participant. Specifically, the data set reports transactions between banks and funds, banks and corporates, and banks and nonbank financials. We compute trading volume (VOL) as the total number of trades per currency pair.

F. Currency Reversal Portfolios

At the end of each month t, we allocate currencies into six portfolios on the basis of their FX media sentiment (SENT) 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 equal 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.

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G. Time-Series Currency Reversals

We also construct a time-series currency reversal factor that goes long currencies with sentiment below the median sentiment and short currencies with media sentiment above the median sentiment of all currencies. In particular, we define our time-series currency reversal strategy as:

$$\text{(3)} \qquad \mathrm{RX}_{i,t+1}^{\mathrm{REV}} = \begin{pmatrix} -\mathrm{RX}_{i,t+1} & \text{if } \mathrm{SENT}_{i,t} > \mathrm{MEDIAN}(\mathrm{SENT}_t) \\ \mathrm{RX}_{i,t+1} & \text{if } \mathrm{SENT}_{i,t} \leq \mathrm{MEDIAN}(\mathrm{SENT}_t), \end{pmatrix}$$

where $\mathrm{RX}_{i,t+1}$ is the currency excess return of currency i at time t. $\mathrm{SENT}_{i,t}$ represents the sentiment if currency i at time t and $\mathrm{MEDIAN}(\mathrm{SENT}_t)$ is the median sentiment of all currencies that are available at time t.[12] We also develop a similar strategy using sentiment changes and it offers similar results (presented in the Supplementary Material).

H. 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 equal weighted. Thus, we build a zero-cost carry trade portfolio (CAR) that *buys* investment currencies while short-selling funding currencies.

I. 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 equal weighted. Thus, we build a zero-cost momentum portfolio (MOM) that *buys* winner currencies while short-selling loser currencies.

V. Empirical Results

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

A. FX Media Sentiment and Currency Excess Returns

Figure A3 in the Supplementary Material 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

[12] We would like to thank the referee for the suggestion.

number of articles. Figure A4 in the Supplementary Material shows the number of articles over time.

1. Panel Regressions

We calculate the sentence-level tone (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) fixed effects of currency excess returns or exchange rate changes on FX media sentiment plus a number of control variables.[13] The regression model takes the form

$$R_{i,t} = \alpha_i + \tau_t + \beta \mathrm{SENT}_{i,t-1} + \gamma z_{i,t-1} + \varepsilon_{i,t}, \text{ for } R = \mathrm{RX} \text{ or } -\Delta s, \tag{4}$$

where $\mathrm{RX}_{i,t}$ ($\Delta s_{i,t}$) represents the currency excess return (exchange rate change) of currency i at time $t+1$ and $\mathrm{SENT}_{i,t-1}$ 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 $z_{i,t-1}$.[14] 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. 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.

2. 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 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 5 days. Thus, our model takes the form

[13]We provide a detailed description of the volatility and illiquidity measures in Section C of the Supplementary Material.

[14]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.

TABLE 2

FX Media Sentiment and Currency Returns

Table 2 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 as well as a number of control variables. The model takes the form below:

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

where $\text{RX}_{i,t}$ ($-\Delta s_{i,t}$) represents the currency excess return (exchange rate change) of currency i at time t and $\text{SENT}_{i,t-1}$ denotes the sentiment measure (see Section III 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 $\mathbf{z}_{i,t-1}$. 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 U.S. dollar. We report t-statistics in square brackets that are based on double-clustered standard errors across time and currency pairs. *, **, and *** indicate significance levels of 1%, 5%, and 10%, respectively. Our data contain monthly series that span the period of Oct. 1983 to Apr. 2019.

CURRENCY_RETURNS

	RX_t	RX_t	$-\Delta s_t$	$-\Delta s_t$
	1	2	3	4
SENTIMENT_{t-1}	−0.155***	−0.155***	−0.157***	−0.155***
	[−3.04]	[−3.06]	[−3.10]	[−3.02]
Constant	0.001	0.001***	0.001	−0.000***
	[0.83]	[248.6]	[1.31]	[−45.15]
Controls	Yes	No	Yes	No
Time FE	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes
Cluster	Currency	Currency	Currency	Currency
No. of obs.	9,269	9,269	9,269	9,269
R^2	0.409	0.409	0.452	0.449

$$(5) \qquad R_{i,t} = \alpha_i + \tau_t + \sum_{k=1}^{5} \beta_k \text{SENT}_{i,t-k} + \boldsymbol{\gamma} \mathbf{z}_{i,t-1} + \varepsilon_{i,t}, \text{ for } R = \text{RX or} - \Delta s,$$

where $\text{RX}_{i,t}$ ($\Delta s_{i,t}$) represents the currency excess return (exchange rate change) of currency i at time t and $\text{SENT}_{i,t-k}$ denotes the sentiment measure (see Section III for the construction of the measure) of each currency pair at time $t-k$ for $k = 1, \ldots, 5$. We include time (τ_t) and currency (α_i) fixed effects of currency excess returns or exchange rate changes. We also control for other determinants of currency returns such as currency volatility and illiquidity, which are included in the vector $\mathbf{z}_{i,t-1}$.

Table 3 shows the results for monthly frequencies using 5 lags of the sentiment measure and control variables.[15] The FX sentiment measure's estimated coefficients capture the dependence of currency excess returns on the sentiment factor. We observe that the t-statistic for the null hypothesis that the FX sentiment measure with 5 months lags cannot forecast currency returns is 3.09, 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-stat. = −2.95). This finding is significant in both statistical and economic terms.

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 FX market, this effect is more persistent, with mean reversion occurring in 2–5 months.

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

TABLE 3

FX Media Sentiment and Currency Returns: VAR Estimates

Table 3 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 as well as a number of control variables. The model takes the form below:

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

where $\mathrm{RX}_{i,t}$ ($\Delta s_{i,t}$) represents the currency excess return (exchange rate change) of currency i at time t and $\mathrm{SENT}_{i,t-k}$ denotes the sentiment measure (see Section III 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 $\mathbf{z}_{i,t-1}$. Columns 1 and 2 show results for monthly 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 U.S. dollar. We report t-statistics in square brackets that are based on robust standard errors. *, **, and *** indicate significance levels of 1%, 5%, and 10%, respectively. Our data contain monthly series that span the period of Oct. 1983 to Apr. 2019.

CURRENCY_RETURNS

	RX_t	$-\Delta s_t$
	1	2
$\mathrm{SENTIMENT}_{t-1}$	−0.186***	−0.198***
	[−2.95]	[−3.64]
$\mathrm{SENTIMENT}_{t-2}$	0.039	−0.022
	[0.50]	[−0.48]
$\mathrm{SENTIMENT}_{t-3}$	−0.025	−0.031
	[−0.37]	[−0.63]
$\mathrm{SENTIMENT}_{t-4}$	0.063	0.079
	[0.59]	[1.03]
$\mathrm{SENTIMENT}_{t-5}$	0.154***	0.134***
	[3.09]	[3.00]
Constant	−0.000	−0.000
	[−0.30]	[−0.57]
$\chi^2(5)$[Joint]	3.540	6.020
p-value	0.01	0.00
Sum 2–5	0.091	0.160
$\chi^2(1)$[Reversal]	4.07	5.01
p-value	0.01	0.00
Control	Yes	Yes
Time FE	Yes	Yes
Currency FE	Yes	Yes
Cluster	Currency	Currency
No. of obs.	5,790	5,790
R^2	0.460	0.535

Specifically, the reversal size between 2 and 5 months lags is 0.091 and is statistically different from 0 at the 1% significance level. This implies that we can reject the hypothesis of no reversal—the conjecture of currency return continuation 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 5 months. We find similar results for exchange rate changes.

B. 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.

1. FX News and Currency Reversals

In order to test our hypothesis in a nonparametric 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 the 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., $\text{REV}(1,1)$) offers an annualized excess return of 9.05% 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 ($\text{REV}(1,12)$) renders an annualized return of 3.52% per annum.[16] We also observe that the excess return

TABLE 4

Currency Reversal Portfolios

Table 4 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 square brackets that are based on Newey and West (1987) standard errors with 1 lag. *, **, and *** indicate significance levels of 1%, 5%, and 10%, respectively. Our data contain monthly series that span the period of Oct. 1983 to Apr. 2019.

	CURRENCY_EXCESS_RETURNS						EXCHANGE_RATE_CHANGES				
	Holding Period *h*						Holding Period *h*				
Panel A. ALL_COUNTRIES											
f	1	3	6	9	12	*f*	1	3	6	9	12
1	9.05***	6.59***	4.19***	3.71***	3.52***	1	9.55***	7.09***	4.11***	3.50***	3.25***
	[7.80]	[7.10]	[5.03]	[4.08]	[3.86]		[9.54]	[8.62]	[6.86]	[5.18]	[5.04]
3	5.63***	3.47***	2.25***	2.00**	2.23***	3	6.38***	3.81***	2.59***	2.34***	2.37***
	[5.82]	[3.76]	[2.59]	[2.33]	[2.74]		[8.32]	[5.10]	[3.55]	[3.51]	[3.56]
6	3.35***	1.78	0.57	0.51	0.96	6	3.68***	2.22**	1.36	1.19	1.06
	[2.81]	[1.35]	[0.44]	[0.40]	[0.89]		[3.98]	[2.14]	[1.42]	[1.33]	[1.30]
9	3.46**	1.11	0.32	0.29	0.64	9	3.45***	1.44	0.71	0.59	0.58
	[2.44]	[0.75]	[0.24]	[0.22]	[0.58]		[2.74]	[1.08]	[0.60]	[0.55]	[0.60]
12	2.67*	0.39	0.00	0.37	0.76	12	2.74*	0.46	0.13	0.21	−0.01
	[1.67]	[0.25]	[−0.00]	[0.28]	[0.69]		[1.90]	[0.34]	[0.10]	[0.18]	[−0.01]
Panel B. DEVELOPED_COUNTRIES											
f	1	3	6	9	12	*f*	1	3	6	9	12
1	7.04***	4.77***	2.94***	2.16***	2.12***	1	7.05***	4.84***	3.03***	2.27***	2.21***
	[4.41]	[4.12]	[3.59]	[3.03]	[3.44]		[4.71]	[4.49]	[4.17]	[3.56]	[4.11]
3	4.78***	2.21**	1.17	0.82	0.87	3	4.84***	2.20**	1.15*	0.81	0.86
	[3.90]	[2.32]	[1.56]	[1.23]	[1.41]		[4.19]	[2.57]	[1.73]	[1.39]	[1.58]
6	2.17*	1.11	0.58	0.35	0.40	6	2.00*	0.96	0.47	0.28	0.32
	[1.81]	[1.14]	[0.73]	[0.46]	[0.54]		[1.70]	[1.05]	[0.65]	[0.40]	[0.46]
9	2.86**	1.24	0.65	0.35	0.55	9	2.50**	0.97	0.39	0.13	0.35
	[2.25]	[1.38]	[0.77]	[0.43]	[0.71]		[2.10]	[1.14]	[0.50]	[0.18]	[0.49]
12	3.77***	1.21	0.42	0.63	0.94	12	3.42***	0.83	0.06	0.37	0.67
	[3.28]	[1.18]	[0.43]	[0.71]	[1.16]		[3.17]	[0.87]	[0.07]	[0.46]	[0.92]

[16]Note that we report positive currency excess returns of the reversal strategies (REV) because we construct low-minus-high (LMH) portfolios. Table A3 in the Supplementary Material provides the portfolio turnover of the strategy.

decreases as we increase the holding period but remains highly significant in both economic and statistical terms.[17] 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.[18] Intuitively, investors tend to overreact to currencies with very negative sentiment within the month with a subsequent reversal in the next period.

The right-hand panel of 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 U.S. 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.

2. 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 1-month formation and holding periods offers annualized Sharpe ratios of 1.59 for the universe of ALL_COUNTRIES and 0.94 for the set of DEVELOPED_COUNTRIES. The ratios are significant in both statistical and economic terms for shorter formation and holding periods. Sharpe ratios decrease when the length of the formation or holding periods increases.[19]

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

[17]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.

[18]Tables A1 and A2 in the Supplementary Material show results for emerging economies which comprises the set of 33 remaining countries after we exclude the set of Developed Countries from our full sample.

[19]Our sentiment measure uses the total number of words in a sentence as a normalization. Tables A4 and A5 in the Supplementary Material show results for a sentiment measure which uses the (#positive + #negative) words per sentence as normalization. Specifically, Table A4 in the Supplementary Material shows the average returns of currency portfolios that are sorted based on media sentiment for All Countries and Developed Countries. Table A5 in the Supplementary Material displays the Sharpe ratios of currency reversal portfolios. Our results are similar.

TABLE 5

Sharpe Ratios of Currency Reversal Portfolios

Table 5 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 square brackets that are based on a moving block bootstrap. *, **, and *** indicate significance levels of 1%, 5%, and 10%, respectively. Our data contain monthly series that span the period of Oct. 1983 to Apr. 2019.

	CURRENCY_EXCESS_RETURNS						EXCHANGE_RATE_CHANGES				
	Holding Period *h*						Holding Period *h*				
f	1	3	6	9	12	*f*	1	3	6	9	12
Panel A. ALL_COUNTRIES											
1	1.59***	0.88***	0.45***	0.34***	0.30***	1	1.76***	1.00***	0.51***	0.38***	0.35***
	[8.74]	[7.32]	[4.97]	[3.61]	[2.94]		[9.95]	[8.80]	[6.87]	[5.17]	[4.75]
3	0.99***	0.51***	0.27***	0.22*	0.24**	3	1.23***	0.62***	0.32***	0.27***	0.28***
	[5.60]	[3.77]	[2.70]	[1.91]	[2.10]		[7.99]	[5.20]	[3.90]	[3.84]	[3.37]
6	0.54***	0.21	0.06	0.05	0.09	6	0.62***	0.28**	0.15***	0.13**	0.12**
	[2.81]	[1.57]	[0.72]	[0.75]	[1.06]		[3.60]	[2.32]	[2.77]	[2.36]	[1.97]
9	0.49**	0.12	0.03	0.03	0.06	9	0.52***	0.16	0.07*	0.06	0.06
	[2.53]	[1.03]	[0.74]	[0.62]	[0.83]		[2.89]	[1.48]	[1.78]	[1.36]	[1.25]
12	0.36*	0.04	−0.00	0.03	0.07	12	0.40***	0.06	0.01	0.02	−0.00
	[1.80]	[0.66]	[0.49]	[0.69]	[1.02]		[3.06]	[0.55]	[0.82]	[0.91]	[0.64]
Panel B. DEVELOPED_COUNTRIES											
1	0.94***	0.61***	0.34***	0.24**	0.25**	1	0.95***	0.63***	0.36***	0.26***	0.26***
	[4.28]	[2.68]	[2.92]	[2.20]	[2.33]		[4.49]	[3.10]	[3.79]	[3.46]	[3.90]
3	0.65***	0.30**	0.15	0.11	0.11	3	0.65***	0.30***	0.15**	0.11	0.11
	[3.91]	[2.26]	[1.52]	[1.22]	[1.17]		[4.39]	[2.69]	[1.97]	[1.43]	[1.63]
6	0.31*	0.15	0.08	0.05	0.05	6	0.29*	0.13	0.07	0.04	0.04
	[1.80]	[1.13]	[0.71]	[0.62]	[0.77]		[1.67]	[0.99]	[0.61]	[0.62]	[0.82]
9	0.39**	0.16	0.09	0.05	0.07	9	0.34*	0.13	0.05	0.02	0.04
	[2.24]	[1.42]	[0.86]	[0.55]	[0.83]		[1.96]	[1.14]	[0.59]	[0.38]	[0.74]
12	0.52***	0.16	0.05	0.08	0.11	12	0.48***	0.11	0.01	0.05	0.09
	[3.19]	[1.16]	[0.49]	[0.84]	[1.31]		[3.13]	[0.89]	[0.19]	[0.74]	[1.36]

scenarios even higher (e.g., REV(1,1))—among DEVELOPED_COUNTRIES despite the higher return offered by the universe of ALL_COUNTRIES.[20]

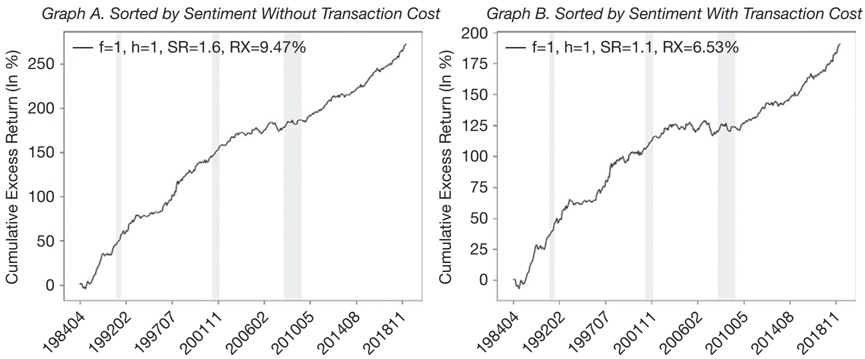
Figure 2 shows the cumulative returns of a currency reversal strategy based on FX media sentiment, REV(1,1), with a formation period (*f*) of 1 month and a holding period (*h*) of 1 month. We present results with (Graph A) and without (Graph B) transaction costs. Shaded areas represent NBER-dated recessions. 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 1.10 after allowing for implementation cost. In addition, the graphs show that the strategy is not affected by recessions. We observe an improvement in the performance of the strategy after the global financial crisis 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.

[20]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)).

FIGURE 2

Cumulative Returns

Figure 2 displays the cumulative returns of currency reversal portfolios. Graph A shows results for unadjusted excess returns and Graph B exhibits results for net excess returns with transaction costs. Shaded areas represent NBER recessions. The data contain monthly series from Oct. 1983 to Apr. 2019.



3. 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 number of disadvantages to 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 Fama and MacBeth (1973), we examine which independent variables demonstrate premiums that are different from 0 on average. To this end, we run cross-sectional regressions on a monthly basis of the following model, and nested specifications:

$$(6) \qquad R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\mathrm{SENT}_{i,t} + \lambda_{2,t}R_{i,t} + \lambda_{3,t}\mathrm{FD}_{i,t} + \varepsilon_{i,t+1}, \text{ for } R = \mathrm{RX} \text{ or } -\Delta s,$$

where $\mathrm{SENT}_{i,t}$ denotes the average media sentiment, $\mathrm{RX}_{i,t}(\Delta s_{i,t})$ is the currency excess return (exchange rate change) and $\mathrm{FD}_{i,t}$ 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,

TABLE 6

Cross-Sectional Regressions

Table 6 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 0, on average. To this end, we run cross-sectional regression on a monthly basis of the model (and nested specifications) below:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\text{SENT}_{i,t} + \lambda_{2,t}R_{i,t} + \lambda_{3,t}\text{FD}_{i,t} + \varepsilon_{i,t+1}, \text{ for } R = \text{RX or } -\Delta s,$$

where $\text{SENT}_{i,t}$ denotes the average media sentiment, $\text{RX}_{i,t}(\Delta s_{i,t})$ is the currency excess return (exchange rate change) and $\text{FD}_{i,t}$ 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 U.S. dollar. We report t-statistics in square brackets that are based on Newey and West (1987) standard errors with 1 lag. *, **, and *** indicate significance levels of 1%, 5%, and 10%, respectively. Our data contain monthly series that span the period of Oct. 1983 to Apr. 2019.

	RX_{t+1}	RX_{t+1}	RX_{t+1}	RX_{t+1}	$-\Delta s_{t+1}$	$-\Delta s_{t+1}$	$-\Delta s_{t+1}$	$-\Delta s_{t+1}$
	1	2	3	4	5	6	7	8
Panel A. ALL_COUNTRIES								
$\text{SENT}_{i,t}$	−0.018***	−0.021***	−0.0141***	−0.018***	−0.018***	−0.018***	−0.014***	−0.018***
	[−2.89]	[−4.61]	[−4.71]	[−3.96]	[−2.94]	[−4.66]	[−4.77]	[−4.10]
$\text{RX}_{i,t}$	−0.384	0.072				−0.065		
	[−1.04]	[0.60]				[−0.70]		
$\text{FD}_{i,t}$	1.027***		0.658***		−0.309*		−0.324**	
	[2.91]		[4.22]		[−1.88]		[−2.07]	
$\Delta s_{i,t}$				−0.265	−0.364			−0.241
				[−0.96]	[−0.99]			[−0.89]
Constant	0.004	0.001	0.001	0.005	0.004	0.003	0.001	0.003
	[0.96]	[0.16]	[0.93]	[1.52]	[1.01]	[1.64]	[0.90]	[0.97]
No. of obs.	9,244	9,244	9,244	9,244	9,244	9,244	9,244	9,244
R^2	0.485	0.340	0.341	0.286	0.394	0.283	0.237	0.290
Panel B. DEVELOPED_COUNTRIES								
$\text{SENT}_{i,t}$	−0.050***	−0.052***	−0.047**	−0.050***	−0.050***	−0.052***	−0.047**	−0.052***
	[−2.65]	[−3.04]	[−2.48]	[−2.90]	[−2.67]	[−3.15]	[−2.55]	[−3.09]
$\text{RX}_{i,t}$	−0.380	−0.045				−0.101		
	[−1.02]	[−0.38]				[−1.17]		
$\text{FD}_{i,t}$	1.386***		0.765**		0.158		−0.113	
	[2.70]		[2.41]		[0.38]		[−0.36]	
$\Delta s_{i,t}$				−0.268	−0.396			−0.274
				[−0.96]	[−1.07]			[−1.01]
Constant	0.002	0.000	0.001	0.004	0.002	0.004*	0.001	0.003
	[0.38]	[0.11]	[1.14]	[1.28]	[0.48]	[1.74]	[1.16]	[1.02]
No. of obs.	4,003	4,003	4,003	4,003	4,003	4,003	4,003	4,003
R^2	0.558	0.387	0.367	0.385	0.553	0.387	0.357	0.388

forward discounts cannot explain the cross section of currency returns, demonstrating the disconnect between currency reversals and currency carry trades.

C. Time-Series Currency Reversals

In this subsection, 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 whether the sentiment measure is above or below the median sentiment over the formation period. Table 7 shows the average currency excess returns of equal 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 sentiment above

TABLE 7

Time-Series Currency Reversals

Table 7 shows average currency excess returns of equal 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 that are below the median sentiment and short currencies that are below the median sentiment of all the currencies 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 equal 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 that are based on Newey and West (1987) standard errors with 1 lag. *, **, and *** indicate significance levels of 1%, 5%, and 10%, respectively. Our data contain monthly series that span the period of Oct. 1983 to Apr. 2019.

	Holding Period *h*				
f	1	3	6	9	12
Panel A. ALL_COUNTRIES					
1	4.53***	3.32***	1.84***	0.94*	0.78*
	[4.06]	[4.99]	[3.17]	[1.94]	[1.79]
3	5.27***	1.69***	1.53***	0.90**	1.06**
	[5.73]	[3.01]	[3.27]	[2.06]	[2.55]
6	4.06***	2.00***	1.01*	0.67	0.44
	[4.53]	[3.35]	[1.91]	[1.57]	[1.10]
9	2.10*	0.15	0.23	0.25	−0.01
	[1.94]	[0.17]	[0.34]	[0.46]	[−0.03]
12	3.85***	2.22***	1.10*	0.34	0.18
	[3.77]	[2.79]	[1.65]	[0.63]	[0.38]
Panel B. DEVELOPED_COUNTRIES					
1	4.28**	3.14***	2.00**	1.71***	1.02**
	[2.44]	[3.80]	[2.52]	[2.99]	[2.05]
3	5.87***	1.98***	1.08**	0.44	0.62
	[4.48]	[2.63]	[2.04]	[0.95]	[1.41]
6	3.38***	1.16	−0.52	−0.58	−0.23
	[3.28]	[1.64]	[−0.87]	[−1.14]	[−0.45]
9	2.83**	−0.11	0.00	−0.02	−0.02
	[2.02]	[−0.12]	[0.00]	[−0.03]	[−0.04]
12	2.90**	0.70	0.04	−0.79	−0.63
	[2.06]	[0.79]	[0.05]	[−1.39]	[−1.14]

the median sentiment and short those with a sentiment below the median 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 equal 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 1 lag.

We find that a reversal strategy with formation and holding periods of 1 month renders annualized returns of 4.53% for the universe of ALL_COUNTRIES and 4.28% 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.[21]

[21]Table A6 in the Supplementary Material offers an alternative time-series reversal strategy where we go long currencies with positive sentiment changes and short currencies with negative sentiment changes over the formation period. The strategy offers similar results.

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D. 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 and currency volume.

1. FX News and Analysts' Forecasts

In this section, we examine the link between media sentiment and analysts' forecasts in the FX market. Specifically, in each month between Oct. 1983 and Mar. 2017 and for each of 17 currencies, we obtain analysts' average forecasts of each currency's spot rate change in the ensuing 3 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. 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 in the exchange rate changes corresponds to an appreciation of the foreign currency.

Panel A of 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

TABLE 8

FX News and Analysts' Forecasts of Exchange Rate Changes

Table 8 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. Panel A reports 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. Panel B shows annualized excess returns of portfolios that are sorted into three portfolios based on the average 3-month forecast and within each portfolio we sort into three portfolios based on media sentiment. The last row shows the excess return of a portfolio that buys low sentiment and high depreciation forecast portfolios and shorts high sentiment portfolios with low depreciation forecast portfolios. All returns are expressed in percentage. We report *t*-statistics that are based on Newey and West (1987) standard errors with 1 lag. *, **, and *** indicate significance levels of 1%, 5%, and 10%, respectively. Our data contain monthly series that span the period of Oct. 1983 to Apr. 2019.

Panel A. Average Forecasts Based on 3-Month Forecast Horizon

f	LOW	HIGH	LMH	*t*-Stat.
1	−0.57	−0.60	0.03	0.08
3	−0.62	−0.77	0.15	0.32
6	−1.44	−0.43	−1.01*	−1.75
9	−1.22	−0.21	−1.01*	−1.83
12	−1.00	−0.03	−0.97*	−1.80

Panel B. Double Sorts on 3-Month Forecasts and Media Sentiment

	LOW	2	HIGH	LMH	*t*-Stat.
F1	11.04	14.14	10.36	0.68	0.23
F2	5.72	1.49	−2.71	8.43***	5.90
F3	−5.86	−15.24	−8.44	2.58	0.78
F1–F3	16.90***	29.38***	18.8***		
t-stat.	5.27	5.56	6.15		
F1Low–F3High				19.48***	6.15

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

We also examine if analysts contribute to currency reversals.[22] To test this hypothesis, we sort currencies into three portfolios based on the analysts' depreciation forecast and then within each portfolio we sort based on media sentiment. Panel B of Table 8 shows the currency excess returns of the portfolios. Portfolio F1 comprises currencies with the *highest* depreciation and F3 with the lowest. We develop a strategy that buys low sentiment and high depreciation forecasts (F1Low) and sells high sentiment low depreciation forecasts (F3High). The strategy offers a return of 19.48% that is statistically significant, which indicates that analysts contribute to reversal effect. We also compute a spread portfolio that buys currencies with high depreciation forecasts (F1) and sells currencies with low depreciation forecasts (F3). We find that the spreads are positive and statistically significant. The returns of these portfolios increase with media sentiment. This provides additional evidence regarding the opposite predictions of analysts and their contribution to currency reversals.

2. Impact of Currency Volume

We interpret the overvaluation of high media sentiment currencies as evidence that investors' preferences for these currencies generate the relative demand and thus the upward price pressure for high sentiment currencies. Thus, we ask whether the overvaluation of high media sentiment currencies is more pronounced when there is higher demand pressure. To this end, we proxy demand pressure with currency volume that is calculated as the total number of trades and we find that the overvaluation is more pronounced for currencies accompanied by stronger trading volume. We repeat this exercise using order imbalances and find that the overvaluation of high media sentiment currencies is stronger for net buy positions.

Table 9 displays time-series averages of currency excess returns that are double-sorted based on currency volume or order imbalances and FX media sentiment. We report the returns of a strategy that goes long low sentiment portfolios

[22]We thank the referee for the suggestion.

TABLE 9

FX Trading and Media Sentiment

Table 9 displays currency excess returns that are double-sorted based on currency volume or order imbalances and FX media sentiment. We report the returns of a strategy that goes long low sentiment portfolios while short-selling high sentiment currency portfolios based on a formation period of 1 month and a holding period of 1 month for different levels of volume or order imbalance. W reports results for volume that are based on the number of trades. Currency excess returns are annualized and expressed in percentage. We report *t*-statistics that are based on Newey and West (1987) standard errors with 1 lag. *, **, and *** indicate significance levels of 1%, 5%, and 10%, respectively. Our data contain monthly series that span the period of Jan. 2012 to Apr. 2019.

	LOW	2	HIGH	LMH	*t*-Stat.
Panel A. FX Volume					
VOL1	−3.28	0.65	−1.36	−1.93	−0.46
VOL2	6.63	−2.53	−3.79	10.42***	2.98
VOL3	−1.07	−3.84	−8.73	7.66**	2.49
Panel B. FX Order Flow					
OIB1	3.07	−1.39	−2.84	5.91*	1.74
OIB2	1.60	−2.49	−7.05	8.66***	3.62
OIB3	6.54	−2.07	−6.21	12.75***	4.55

while short-selling high sentiment currency portfolios based on a formation period of 1 month and a holding period of 1 month for different levels of volume or order imbalance. Panel A (Panel B) reports results for volume (order imbalances) that are based on the number of trades. We find that the reversal strategy is highly significant when the volume is high and when we have very positive order imbalances indicating net buying activity.

Specifically, we find in Panel A of Table 9 that the average excess returns of high sentiment portfolios decreases from −1.36% to −8.73% as the currency volume increases, rendering a highly positive and statistically significant spread portfolio for medium and high volume currencies. Panel B shows the corresponding results for order imbalances. We find that high sentiment portfolios offer negative returns, on average, that decrease in a linear manner from −2.84% to −6.21% as the order imbalances increase. The high order imbalance portfolio which comprises currencies with net buy positions offers a spread portfolio with an average excess return of 12.75% that is statistically significant, while the currency reversal strategy is not significant for net sell positions. Taken together, we find that investors' preferences for high sentiment currencies generate relative demand and thus upward price pressure.[23]

VI. Robustness and Other Specification Tests

A. Other Currency Investment Strategies

In this subsection, we examine the relationship between our strategy and other well-known currency investment strategies such as carry trade and momentum

[23]In Table A7 in the Supplementary Material, we examine further the relationship between currency volume and media sentiment. We run a VAR regression of currency volume on FX media sentiment with 1–5 lags and a number of controls. We find a positive and statistically significant relationship between volume and lagged sentiment at monthly frequencies. Consistently with our previous findings, we also find that this relationship becomes negative for 2–5 lags.

TABLE 10

Robustness: Currency Reversals and Other Currency Investment Strategies

Table 10 shows alpha and beta coefficients and R^2 of a contemporaneous linear regression (Panel A) of the excess return of the currency reversal strategy based on formation periods of 1, 3, and 6 months and a holding period of 1 month on dollar (DOL), carry (CAR) and momentum (MOM) risk factors. The momentum factor considers a 1 month formation period and a holding period of 1 month. In particular, the model takes the form below:

$$\mathrm{REV}_{t+1} = \alpha + \beta_1 \mathrm{DOL}_t + \beta_2 X_t + \varepsilon_{t+1}, \text{for } X = \mathrm{CAR} \text{ or } \mathrm{MOM},$$

where REV represents the currency reversal strategy. The alphas are annualized and they are expressed in percentage. Panel B shows summary statistics such as the mean, 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 square brackets that are based on Newey and West (1987) standard errors with 1 lag. *, **, and *** indicate significance levels of 1%, 5%, and 10%, respectively. Our data contain monthly series that span the period of Oct. 1983 to Apr. 2019.

Panel A. Regressions of Currency Reversals on Currency Factors

	REV(1,1)	REV(3,1)	REV(6,1)	REV(1,1)	REV(3,1)	REV(6,1)
	1	2	3	4	5	6
Alpha	8.604***	5.832***	4.248***	8.784***	5.460***	3.552***
	[7.80]	[5.39]	[3.66]	[8.25]	[5.18]	[3.11]
DOL	−0.109**	−0.077*	−0.077	−0.126***	−0.085*	−0.083*
	[−2.40]	[−1.69]	[−1.60]	[−2.81]	[−1.85]	[−1.72]
CAR	−0.031	−0.042	−0.057			
	[−0.86]	[−1.18]	[−1.50]			
MOM				−0.063*	−0.006	0.022
				[−1.85]	[−0.17]	[0.61]
R^2	0.022	0.014	0.016	0.030	0.010	0.010

Panel B. Diversification Benefits for Carry Trade Portfolios

	CAR	CAR+REV(1,1)	CAR+REV(3,1)	CAR+REV(6,1)
	1	2	3	4
−5 Mean	8.424***	9.876***	7.614***	6.024***
t-stat.	[4.37]	[8.27]	[7.12]	[6.37]
Sharpe ratio	0.922	1.944	1.518	1.119
Skewness	−0.649	−0.192	−0.109	−0.464
Kurtosis	2.152	0.956	1.303	2.182

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^2 of a contemporaneous linear regression of currency reversal based on formation periods of 1, 3, and 6 months and a holding period of 1 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 1-month formation period and a holding period of 1 month. In particular, the regression model takes the form

$$\text{(7)} \qquad \mathrm{REV}_{t+1} = \alpha + \beta_1 \mathrm{DOL}_t + \beta_2 X_t + \varepsilon_{t+1}, \text{ for } X = \mathrm{CAR} \text{ or } \mathrm{MOM},$$

where REV denotes the currency reversal strategy. For the momentum strategy, we find low R^2 and estimated betas that are insignificantly different from 0 at standard significance levels. However, the estimated annualized alphas are statistically significantly different from 0 at standard significance levels and are economically sizeable, amount to a sizeable of 8.8%, 5.46%, and 3.55% on an annualized basis. For the carry trade risk factor, the R^2 are again small and the estimated betas are not statistically significant. 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 4.25%–8.60% 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 suggest 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), REV(3,1), and REV(6,1), that is, the reversal strategies with 1, 3, or 6 months formation period and with a 1 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 1.94, 1.52, and 1.12 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.

B. Transaction Costs

We also consider the implementation cost of the FX media sentiment strategy. Section A of the Supplementary Material offers a detailed description of the construction of net excess returns. Table A8 in the Supplementary Material 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 (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 A8 in the Supplementary Material 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 the 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 6.33% per annum when considering the quoted spread and it increases to 6.92% and 7.52% 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.

C. Other Sentiment Measures

We also control for other sentiment measures in the literature. Specifically, we control for the sentiment index of Yu (2013). This sentiment measure is different from ours as it captures the economic sentiment while ours measures the level of media pessimism for specific currencies. In addition, our sentiment measure is daily, and the Yu (2013) sentiment measure is available annually. Table A9 in the Supplementary Material shows panel regressions of currency excess returns and exchange rate changes on media sentiment, the Yu (2013) sentiment and several controls. We offer results for sentence-level and article-level sentiment.[24] In both cases, we find that the coefficient of media sentiment is negative and statistically significant after controlling for this measure.[25]

D. Additional Tests

We also conduct the analyses including double sorts (Table A10 in the Supplementary Material), time-variation in the profitability of currency reversals (Figure A5 in the Supplementary Material), distinguishing local and global sentiment (Tables A11–A14 in the Supplementary Material), topic modeling (Table A15 in the Supplementary Material),[26] and article-level sentiment (Tables A16–A18 in the Supplementary Material). The results from those analyses further confirm our main conclusion. We detail those five analyses and present the results in the Supplementary Material.

VII. 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 article—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

[24]We observe that the coefficients of the two measures are opposite. This is not surprising because Yu (2013) constructs sentiment measures that are similar to the measures of Baker and Wurgler (2006) and Baker et al. (2012) which are computed based on stock data. To this end, the Yu (2013) sentiment measure is a strong predictor of stock returns. Thus, the opposite signs in the coefficients could reflect the negative correlations between stock and currency returns (Hau and Rey (2006)).

[25]We would like to thank the referee for the suggestion.

[26]Filippou, Gozluklu, Nguyen, and Taylor (2020) and Filippou, Gozluklu, Nguyen, and Viswanath-Natraj (2021) employ similar methods in order to examine the role of political risk in the foreign exchange market.

Sharpe ratios for portfolios combining 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 article, however, is the first to show that price reversals based on media sentiment are a well-defined feature of the FX market.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000534.

References

Baker, M., and J. Wurgler. "Investor Sentiment and the Cross-Section of Stock Returns." *Journal of Finance*, 61 (2006), 1645–1680.

Baker, M., and J. Wurgler. "Investor Sentiment in the Stock Market." *Journal of Economic Perspectives*, 21 (2007), 129–152.

Baker, M.; J. Wurgler; and Y. Yuan. "Global, Local, and Contagious Investor Sentiment." *Journal of Financial Economics*, 104 (2012), 272–287.

Barberis, N.; A. Shleifer; and R. Vishny. "A Model of Investor Sentiment." *Journal of Financial Economics*, 49 (1998), 307–343.

Burnside, C.; M. Eichenbaum; I. Kleshchelski; and S. Rebelo. "Do Peso Problems Explain the Returns to the Carry Trade?" *Review of Financial Studies*, 24 (2011), 853–891.

Campbell, J. Y.; S. J. Grossman; and J. Wang. "Trading Volume and Serial Correlation in Stock Returns." *Quarterly Journal of Economics*, 108 (1993), 905–939.

Chen, Y.; B. Han; and J. Pan. "Sentiment Trading and Hedge Fund Returns." *Journal of Finance*, 76 (2021), 2001–2033.

Cheung, Y.-W.; R. Fatum; and Y. Yamamoto. "The Exchange Rate Effects of Macro News after the Global Financial Crisis." *Journal of International Money and Finance*, 95 (2019), 424–443.

Cutler, D. M.; J. M. Poterba; and L. H. Summers. "Speculative Dynamics." *Review of Economic Studies*, 58 (1991), 529–546.

De Long, J. B.; A. Shleifer; L. H. Summers; and R. J. Waldmann. "Noise Trader Risk in Financial Markets." *Journal of Political Economy*, 98 (1990), 703–738.

Della Corte, P.; S. J. Riddiough; and L. Sarno. "Currency Premia and Global Imbalances." *Review of Financial Studies*, 29 (2016), 2161–2193.

Dominguez, K. M., and F. Panthaki. "What Defines 'News' in Foreign Exchange Markets?" *Journal of International Money and Finance*, 25 (2006), 168–198.

Fama, E. F. "Market Efficiency, Long-Term Returns, and Behavioral Finance." *Journal of Financial Economics*, 49 (1998), 283–306.

Fama, E. F., and J. D. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, 81 (1973), 607–636.

Fang, L., and J. Peress. "Media Coverage and the Cross-Section of Stock Returns." *Journal of Finance*, 64 (2009), 2023–2052.

Filippou, I.; A. E. Gozluklu; M. T. Nguyen; and M. P. Taylor. US Populist Rhetoric and Currency Returns. Available at SSRN (2020).

Filippou, I.; A. E. Gozluklu; M. T. Nguyen; and G. Viswanath-Natraj. The Information Content of Trump Tweets and the Currency Market. Available at SSRN 3754991 (2021).

Filippou, I.; A. E. Gozluklu; and M. P. Taylor. "Global Political Risk and Currency Momentum." *Journal of Financial and Quantitative Analysis*, 53 (2018), 2227–2259.

Galati, G. "Settlement Risk in Foreign Exchange Markets and Cls Bank." *BIS Quarterly Review*, 4 (2002), 55–65.

Gholampour, V., and E. van Wincoop. "Exchange Rate Disconnect and Private Information: What Can we Learn from Euro-Dollar Tweets?" *Journal of International Economics*, 119 (2019), 111–132.

Goyal, A., and A. Saretto. "Cross-Section of Option Returns and Volatility." *Journal of Financial Economics*, 94 (2009), 310–326.

Guo, L.; F. W. Li; and K. J. Wei. "Security Analysts and Capital Market Anomalies." *Journal of Financial Economics*, 137 (2020), 204–230.

Hasbrouck, J., and R. M. Levich. "FX Market Metrics: New Findings Based on Cls Bank Settlement Data." NBER Working Paper No. 23206 (2017).

Hau, H., and H. Rey. "Exchange Rates, Equity Prices, and Capital Flows." *Review of Financial Studies*, 19 (2006), 273–317.

Huang, D.; F. Jiang; J. Tu; and G. Zhou. "Investor Sentiment Aligned: A Powerful Predictor of Stock Returns." *Review of Financial Studies*, 28 (2015), 791–837.

Keynes, J. M. *The General Theory of Employment, Interest, and Money*. London, UK: MacMillan (1936).

Kos, D., and R. M. Levich. Settlement Risk in the Global FX Market: How Much Remains? Available at SSRN 2827530 (2016).

Loughran, T., and B. McDonald. "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *Journal of Finance*, 66 (2011), 35–65.

Lustig, H.; N. Roussanov; and A. Verdelhan. "Common Risk Factors in Currency Markets." *Review of Financial Studies*, 24 (2011), 3731–3777.

Lyons, R. K. *The Microstructure Approach to Exchange Rates*, Vol. 333. University Park, PA: Citeseer (2001).

Menkhoff, L.; L. Sarno; M. Schmeling; and A. Schrimpf. "Currency Momentum Strategies." *Journal of Financial Economics*, 106 (2012b), 660–684.

Newey, W. K., and K. D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), 703–708.

Porter, M. F. "An Algorithm for Suffix Stripping." *Program*, 14 (1980), 130–137.

Stambaugh, R. F.; J. Yu; and Y. Yuan. "The Short of It: Investor Sentiment and Anomalies." *Journal of Financial Economics*, 104 (2012), 288–302.

Taylor, M. P. "The Economics of Exchange Rates." *Journal of Economic Literature*, 33 (1995), 13–47.

Tetlock, P. C. "Giving Content to Investor Sentiment: The Role of Media in the Stock Market." *Journal of Finance*, 62 (2007), 1139–1168.

Tetlock, P. C.; M. Saar-Tsechansky; and S. Macskassy. "More than Words: Quantifying Language to Measure Firms' Fundamentals." *Journal of Finance*, 63 (2008), 1437–1467.

Yu, J. "A Sentiment-Based Explanation of the Forward Premium Puzzle." *Journal of Monetary Economics*, 60 (2013), 474–491.