Media Reinforcement in International Financial Markets

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Abstract

We introduce the possibility of a "reinforcement effect" between past returns and media-measured sentiment. When returns and sentiment point in the same direction (either up or down), prices are in the midst of overreacting. Such evidence of overreaction should disappear when returns and sentiment disagree. We find results supporting these views from parallel tests -- across liquid individual stocks, international equity markets, and currencies -- using weekly media scores for each asset culled from extensive data on cross-asset media coverage. Interestingly, the effect is consistently stronger in relatively more liquid assets, assets for which media coverage is relatively broad, and in subsets of media coverage generated by relatively more "local" news outlets. We find that for each of these asset groups, a simple "reinforcement" strategy of buying past losers with low sentiment and selling past winners with high sentiment earns spreads of several hundred basis points annually.

Introduction

This paper explores the idea that independently constructed measures of investor optimism may be used together to extract a common component associated with overreaction in markets. We speculate that both returns and measures of media sentiment are each correlated with wide-spread investor optimism. But each measure contains considerable unrelated noise.

Returns likely reflect very well market-wide optimism when information is loud and ubiquitous–say, in the case of a Federal Reserve announcement or a large-company earnings call. However, in most assets most of the time, information is diffuse and multi-sourced and it spreads unevenly across heterogeneous investors. If a relatively small and random group of investors shows up on these less liquid days to express their views, the sampling error of returns around market-wide optimism will be large.

Media sentiment provides a similarly flawed measure of market-wide optimism. While those who are trading overlap only slightly, if at all, with professionals who are writing, most of the time in most assets there is likely to be considerable heterogeneity in media views yet relatively few sources expressing. This also suggests noise–large sampling error around the mean of market-wide sentiment.

While both returns and sentiment are flawed individual measures of market-wide optimism, they together can provide some independent parallax on a common component–a shock to market-wide optimism. That is the hypothesis that led us to the empirical tests in this paper. We reasoned that in states of nature when these two independently constructed optimism measures reinforce one another, they are more likely to reveal a shock to market-wide optimism and, in those states, there is likely to be more than the usual amount of overreaction. When these sources disagree there is likely to be less than the usual amount of market overreaction. The mechanism might be that more normally-passive investors are motivated to enter the fray and, say, buy, when they see both a positive return and a positive read in markets. This induces negative autocorrelation in returns, but not unconditionally. The negative autocorrelation is conditional, and therefore harder to measure, because it appears only when past returns and media sentiment are in agreement.

To investigate this hypothesis, our empirical analysis relies on the media data that extract articles through various channels from thousands of media sources, including major newspapers, local media outlets, PR and news services, specialized business and investing magazines, or social media platforms. This is crucial because recent research (e.g., Chen, De, Hu, and Hwang (2014)) shows that media sources beyond traditional newspapers and newswires also contain valuable information. Another particular advantage of the diversified media data is that it allows us to distinguish among different types of media sources to examine the differential effect of readership clienteles. We construct the proxy for media sentiment by counting the number of positive and negative words for each article. Given the persistence in media coverage and tone, we are careful in making sure that we do not simply pick up a spurious effect between media sentiment and return. To do so, we adjust the daily media tone by the past four same-day-of-week averages. Therefore, this measure can be considered as an abnormal change in media sentiment.

In line with our conjecture, we find that return reversal is pronounced only when media sentiment matches the formation period return, while the reversal is close to zero when media sentiment points to the opposite direction of concurrent asset return. The cumulative profit for a strategy that buys past losers with low media sentiment and sells past winners with high media sentiment yields approximately 4% to 5% per annual after ten trading days. This phenomenon is remarkably consistent across different asset classes, including developed country currencies, equity indexes, and the large cap U.S. individual stocks.

This logic seemed most sensible to us for relatively liquid markets, where it is plausible that at least some normally passive investors enter the market quickly upon observing both returns and media views. Consistent with this view, we find that the media reinforcement effect is predominantly concentrated among developed country currencies, and large cap firms and firms with high recent coverage shocks. For example, highly covered firms with high (low) returns and sentiments score over the past week tend to incur (earn) approximately -2.90% (3.35%) per annual in the subsequent ten trading days, with a *t*-statistics of -2.57 (2.22). However, the media reinforcement effect is small in magnitude and statistically insignificant within low-coverage groups.

If investor overreaction towards attention-grabbing reinforced signal is the underlying mechanism,[2] we expect the media reinforcement effect to be stronger among a breadth of

[2] Barber and Odean (2008) show that due to their cognitive limitations to process a large amount of information, individual investors tend to be net buyers of attention-grabbing stocks.

individual readerships. Fortunately, the media data for S&P 500 firms provide us detailed types of media source. We group media articles in to three mutually exclusive categories based on the media source: local, professional investing, and firm initiated (e.g., PR and news service) media outlets. We then construct three measures of media sentiment scores based on each type of media sources. We find significantly stronger media reinforcement in subsets of media coverage generated by local news outlets.

Finally, we investigate whether the reinforcement effect is driven by major news events such as the quarterly earnings and major macroeconomics announcements, because media coverage spikes surrounding the scheduled announcements and investor sentiment could also change substantially around these days. We delete the observations when an announcement occurs during the formation period and find that the announcements appear to have little impact on the media reinforcement phenomenon in all three asset markets.

These are the ideas we explore in this paper, buttressed by our attempt to test this hypothesis separately in individual stocks, currencies, and country equities. These are markets where we have been able to amass comprehensive independent databases of media items, so as to score all the media items relating to a given asset–a stock, currency or country equity market–using natural language processing and then aggregate them into an asset-specific measure of media sentiment. Independently measuring the same effect across very different groups of assets and underlying media items, enhances our sense that the reinforcement effects we find in the data are real.

The remainder of the paper is organized as follows. Section 1 provides a brief overview of how this study relates to existing literature. Section 2 describes the data and methods. Section 3 presents the main empirical results that exploit the media reinforcement effect. Section 4 examines the robustness of our findings. Section 5 concludes.

1. Literature Review

Our paper speaks to several strands of research. First, this study contributes to the growing literature on how the content and tone of media affect asset prices. Tetlock (2007) analyzes the linguistic content of the *Wall Street Journal* and finds that media pessimism predicts downward pressure and a subsequent reversal. Tetlock, Saar-Tsechansky, and Macskassy (2008) and Chen, De, Hu, and Hwang (2014) document that the negative words in the news stories and social media articles predict future stock returns and earnings surprises. Garcia (2013) finds that both the fraction of positive and negative words can predict stock returns and the predictability is concentrated in recessions. Our paper examines the impact of media content across several asset classes with consolidated news information from various sources.

The literature on short-term return autocorrelation is also relevant. Return reversal is most commonly documented at weekly and monthly frequencies, rejecting the random walk hypothesis.[3] Jegadeesh and Titman (1995) and Copper (1999), among others, suggest that the

[3] See, for example, Jegadeesh (1990) and Lehman (1990).

return reversal may reflect investor overreaction to information, while Avramov, Chordia, and Goyal (2006) document a strong relationship between return reversal strategy profits and asset illiquidity. Our findings are generally consistent with the investor overreaction view, but go further by introducing media sentiment as an additional harbinger of overreaction.

This paper is also closely related to the literature on the role of media coverage in information dissemination in financial market. Chan (2003) finds that firms that covered by the media experience larger subsequent drift. Fang and Peress (2009) document that stocks with no media coverage earn higher returns, which suggests an investor recognition explanation. Tetlock (2010) shows that public news help resolve information asymmetry, leading to substantially lower return reversal. Griffin, Hirschey, and Kelly (2011) examine the market reaction to news releases across countries, and find that emerging markets underreact to news due to inferior information environment. Hillert, Jacobs, and Müller (2014) find that firms extensively covered by the media exhibit significantly stronger momentum, lending support to the investor overreaction-based explanation. Our paper shows that the media reinforcement effect is a prevalent phenomenon in the financial market.

Finally, this paper is related to the literature on investor inattention and other behavioral biases. Barber and Odean (2008) find individual investors are the net buyers of attention-grabbing stocks. Solomon, Soltes, and Sosyura (2014) show that investors direct capitals into mutual funds whose holding are covered in the recent newspapers. We show that investor attentions are caught only if media sentiment and asset return agree, inducing subsequent return reversal.

2. Data and Methodology

The data used in this paper obtain from several sources. We begin by discussing the construction of the media sentiment score, which is the main variable used in our analysis.

2.1. Media Sentiment Scores

We obtain the media data from MKT MediaStats, LLC over the period from January 2013 to March 2017. The data is collected daily through various channels from thousands of sources for country currencies, country equity indexes, as well as the universe of S&P 500 individual firms. An example of a typical media article for S&P 500 firms can come from major newspapers, local media outlets, PR and news services, specialized business and investing magazines, or social media platforms. Including news information from various sources is important since investors learn about the financial market through multiple channels beyond traditional newspapers and newswires (Tetlock (2014)). To define positive and negative words, we follow the recent textual analysis literature to use the financial dictionary developed by Loughran and McDonald (2011).[4] Hillert, Jacobs, and Müller (2014) and García (2013) use the same methodology to classify article words. We measure the content of each article combing positive (P) and negative (N) words, i.e., (P-N)/(P+N). As a result, the measure is bounded from -1 to +1.

[4] As argued in their paper, the financial dictionary is designed to overcome the fact that standard dictionaries fail to account for the nuances of finance jargon.

Panel A of Table I reports summary statistics of media coverage in developed country currencies, equity indexes, and S&P 500 individual firms. A currency or country equity index on average has some 10,000 media article coverage over the sample period, while the average number of articles published about an S&P firm is approximately 4,742. As show in Panel B of Fig. 1, the media coverage for both country currency and country equities has soared over sample period, suggesting the increased importance of media onto the financial market. In addition, Panel A and C of Fig. 1 reveal that coverage is highly skewed towards major countries (e.g., U.S., Euro Zone, and U.K.) and large cap U.S. firms. Specifically, almost half of media coverage for S&P 500 firms is can be attributed to firms in the two largest size deciles. Panel D of Fig. 1 details the types of media outlets and their proportions of the media data for the sample of S&P 500 individual firms. The media articles from investing social media and news sites, such as Seeking Alpha and InvestorPlace, accounts for the largest proportion, at more than 60%, while local media outlets and firm initiated news each account for 7% and 11%, respectively. Note that about 10% of the media articles are classified into both investing and local media types. To minimize the confounding effect, we drop dual-type articles when analyzing the media reinforcement effect across different media types.

Panel B of Table I describes the average tone of media article contents, and standard deviation of article tones of each asset class. Note that in general the tone of media content is negative for currencies and country equity indexes, while the media sentiment is positive for S&P 500 individual firms during sample period. This pattern is aligned with the recent asset price pattern that currencies and global equity market has experienced substantial fluctuations, while U.S. stock market continues to achieve its historical peak.

Next, we detail the process of the sentiment score construction for each instrument. The summary statistics indicate that the tone of media articles may be correlated with asset characteristics. To isolate the true impact of media sentiment and adjust for potential seasonality in media coverage, we calculate the change of media tone at daily levels relative to past four historical same day-of-the-week averages:

$$\Delta Tone_{i,t} = Tone_{i,t} - \frac{1}{4}\sum_{j=1}^{4} Tone_{i,t-j\times 7}. \tag{1}$$

Throughout this paper, the media sentiment score is constructed daily using a weekly rolling weighted moving average, thus media tone in more recent days receiver larger weights:

$$Sentiment_{i,t} = \sum_{j=0}^{6} W_{i,t-j} \Delta Tone_{i,t-j}, \tag{2}$$

where $W_{i,t-j}$ is the weight that decays from 1 to 0.4, with a step of 0.1 each day from day *t* to day *t-6*, and $\Delta Tone_{i,t-j}$ is the change of media tone in daily level calculated from Eq. (1).

2.2. Asset Price Data

Our empirical tests are carried out using 12 developed country currencies, 33 country equity indexes,[5] and S&P 500 individual firms. Daily currency forward and spot prices are obtained from Thomson Reuters World Market, daily equity index prices are from Datastream, and daily S&P 500 stock returns are from CRSP.[6] The price data for 17 emerging currencies and 14 commodities used in the robustness tests are from Thomson Reuters World Market and Bloomberg.

Following Lustig, Roussanov, and Verdelhan (2011), we calculate the log currency excess return on buying a foreign currency in the forward market and sell in the spot market next period as follows:

$$rx_{i,t+1} = f_{i,t} - s_{i,t+1}, \tag{3}$$

where *s* denotes the log of the spot exchange rate in units of foreign currency per U.S. dollar, and *f* denotes the log of the forward exchange rate, also in units of foreign currency per U.S. dollar. Given the empirical evidence that covered interest-rate parity (CIP) holds at daily or lower frequency, the log currency excess return equals approximately the interest rate differential less the rate of depreciation:

$$rx_{i,t+1} = rf_t^* - rf_{i,t} - \Delta s_{i,t+1}, \tag{4}$$

where rf_t^* and $rf_{i,t}$ denote the one-period foreign and domestic nominal risk-free rates.

[5] In analysis using country equity media, the sample contains 24 country equity indexes since we drop 9 thinly covered indexes.
[6] Appendix A provides details on each country equity index and their sources, which are obtained from Datastream.

To align with the media sentiment score, the formation period asset return is also measured weekly and is rolled over at daily frequency. Since we do not have a detailed time-stamp for each media article, it is possible that some articles are written after the exchange closure. Therefore, to minimize the potential time overlapping between the media coverage and future asset returns, we skip one day between the formation and forecast periods. By doing so, it also mitigates the effect of the bid-ask bounce.

2.3. Media Sentiment Around Political Events

Before we move forward to test our main hypothesis, it is important to validate whether the media tone derived from the data is sensible. Recent controversial and opinion-divided political events serve as perfect laboratory to show how media sentiment relates and influences the international financial market, and how it varies across countries.

Panel A of Fig. 2 indicates that media tone seems to be positive right before the Brexit referendum vote as most people believed U.K. would vote to stay. Once the striking outcome of "leaving" was announced, the media sentiment of the global financial market turned sharply negative. However, countries such as China, Russia exhibit positive sentiment shock. 2016 U.S. presidential election displays similar media sentiment reaction as that during the Brexit. Panel B of Fig. 2 shows that countries that have close relationship with U.S. experienced negative sentiment shock when Donald Trump won the election, while Russia and Turkey display positive sentiment shock. Panel C of Fig. 2 shows before the French election on April 23rd, 2017, major European countries were concerned about the chance that the far-right candidate, Marine Le Pen, could win the election primary. And consistent with this view, the media tone for the Euro country equities is widely negative. The strong performance of Emmanuel Macron, the center-leaning candidate, alleviated the concern of anti-European pressures. As a result, most countries' financial experienced a positive shock of media sentiment.

The aforementioned observation of media tone change surrounding the recent political events assure us that our media sentiment is in line with the general perception people have for these events. It also highlights the importance and necessity of taking the analysis of media impact on financial market into an international context, as assets across countries may react to the same underlying news drastically different.

3. Media Reinforcement and Asset Returns

In this section, we first examine the relationship between media sentiment score and return autocorrelation across various asset classes using an event time study for illustration. We then investigate this relationship further using calendar time portfolio and regression analyses.

3.1. Event Time Analysis

The essence of our finding is captured by the event time analysis (for visual illustration only; our statistical methods are based on calendar time) shown in Panel A, B, and C of Fig. 3 for developed country currencies, country equities, and the S&P 500 individual firms, respectively. Every day for each asset class, we divide instruments into two groups based on their past week returns. Within each of the two groups, we further sort assets into two portfolios based on their sentiment scores over the past week.[7]

Cumulative returns during the formation and event periods are plotted. In each panel, the left and middle graphs report the effect of media sentiment on past losers (i.e., low past returns) and past winners (i.e., high past return), respectively. Given that past return is the sorting variable, it is not surprising that the return patterns in the formation period are almost the same between low- and high-media-sentiment groups. However, subsequent return reversal is much more pronounced among assets whose past return and media sentiment are in agreement, while the testing period price movement for assets with disagreed return and media sentiment is minimal. This finding holds across asset classes, including currencies, equities, and the S&P 500 stocks. For example, country equities whose past returns and media sentiment agree experience reversals for approximately over 2% per annual ten-day after the formation period, while media sentiment points to the opposite direction of past return, currency undergoes a neglected return reversal less than 0.5% per annual ten-day post the formation period.

The far right graph in each panel reports the cumulative return of a portfolio that buys past losers with low media sentiment and sells past winners with high media sentiment. We refer to this strategy as "media-reinforced strategy". The dashed grey lines depict the two standard error bounds after adjusting for serial autocorrelation using the Newey and West (1987) with up to 20 lags. Across all asset classes, the media-reinforced strategy yields a statistically and economically

[7] Specifically, we construct the sentiment score using media coverage for currency. In the calendar time portfolio analysis shown in next section, we show that using sentiment scores based on combined media coverage for currency and equity yields qualitatively similar results.

significant abnormal return of approximately 0.15% to 0.2% (or 3.6% to 4.8% per annual) after ten trading days, and its abnormal return gradually reverses in one month post the formation period. Notably, in all three asset classes the media-reinforced strategy displays a similar return pattern, suggesting that the influence of media sentiment on investors is prevalent and pervasive in the financial market.

3.2. FX/Country Equity Portfolio Analysis

With the event time finding at hand, we now turn to formal statistical test using calendar time method by Jegadeesh and Titman (1993). The calendar time method overlaps portfolios instead of returns, which avoids the strongly positive serial correlation in returns while allowing all possible formation periods to be considered. Suggested by the event time study that the media reinforcement effect is most pronounced at ten trading days post formation period, we form the portfolio in event day t+1 to t+10 after calculating the weekly return and media sentiment at day t. The ten-day horizon also matches earlier papers (e.g., Tetlock, Saar-Tsechansky, and Macskassy (2008) and Tetlock (2010)). At the end of each trading day, we double-sort assets into two-by-two groups based on the latest weekly return and sentiment score, and hold the assets for ten trading days. Therefore, there are ten strategies at a given day τ---one formed in day τ-1, one formed in day τ -2, and so on. The return in day τ is the equal weighted average of these ten currently "active" portfolios. Rolling forward to the next day, one tenth of the cohort portfolios is rebalanced by dropping the oldest portfolio and adding the newest portfolio according to the most recent weekly return and sentiment score.

The baseline result of media reinforcement effect in currency and equity market is displayed in Table 2. Return is given in percentage per annual (as in the remainder of other calendar time portfolio tests). In the event time analysis, we construct the media sentiment score solely based on the currency media coverage. To investigate in a more comprehensive manner, we measure sentiment score using different combinations of media sources. Panel A of Table 2 shows the result in the FX market using sentiment score from different media sources. As the result shows, when currencies experience low (high) return with aligned currency media sentiment over the past week, it yields (incurs) 2.04% (-1.72%) annualized return in the following ten trading days, with a *t*-statistics of 1.94 (-1.92). However, when past currency media sentiment score points at the opposite direction of formation period return, the subsequent currency return reversal is insignificant. Specifically, currency losers (winners) with high (low) past media sentiment score experience only approximately 0.83% (-1.15%) annualized subsequent ten-day return, with insignificant *t*-statistics of 0.91 (-1.33). The spread of winner with high sentiment minus loser with low sentiment amounts to -3.76% (*t*-stat: -2.10), while the unconditional strategy that winner minus loser only generates a spread of -2.90% (*t*-stat: -1.90). The finding suggests that investor independent response to individual signals is overwhelmed by the response to reinforced signals.

Furthermore, result in Panel B of Table 1 shows that media sentiment score constructed on currency media coverage also displays significant effect on country equity indexes. For example, when both return and media sentiment are negative (positive) over the past week, country equities yield (incur) 2.12% (-3.01%) annualized return in the subsequent ten-day, with a *t*-statistics of 1.78 (-2.57). Similar to the result in currencies, when past media sentiment score points at the opposite direction of past return, the subsequent return reversal is minimal and insignificant. The spread of winner with high sentiment minus loser with low sentiment amounts to -5.11% (*t*-stat: -2.49), which is more than twice as the spread of the single-sort return reversal strategy with approximately -2.45% (*t*-stat: -1.56).

It is interesting that the result with media sentiment score constructed from country equity media coverage shows weaker result for both currency and country equity returns. The spread of winner with high sentiment minus loser with low sentiment is insignificant at -2.36 (*t*-stat: -1.09) and -3.23 (-1.41) for currencies and country equities, respectively.[8] The fact that the absence of media reinforcement in the currency market using country equity media sentiment suggests that the FX investors' sentiment may not be influenced by the country equity media coverage or they simply pay less attention on the coverage for global equity market.

The result using sentiment score constructed from currency and country equity combined media coverage is qualitatively similar to that using currency media coverage, suggesting the sentiment from currency media articles is the driving component. The spread of winner with high sentiment minus loser with low sentiment is -3.35% (*t*-stat: -2.00) and -4.68% (*t*-stat: -2.24) in currency and country equity market, respectively. Summing up the results from all panels, we find statistically and economically significant media reinforcement effect in in the international financial market, suggesting that investor over-reaction is intensified when the media sentiment matches the formation period return. For brevity, we use sentiment score based on currency media

[8] However, the untabulated analysis shows that there is a significant media reinforcement effect if we look at shorter horizon (e.g., 3-day) in the country equity market. This suggests that investors may present differential sensitivity and processing time towards information from differential media sources.

articles in the rest of the paper, since the aforementioned results suggest currency media seems to be the most relevant source of media sentiment in the international financial market.

3.3. Individual Firm Portfolio Analysis

We then conduct the calendar time portfolio analysis using a sample of S&P 500 individual firms. Each day, we divide the stocks into two-by-two groups based on media sentiment score and return over the past week. The result in Table 3 clearly indicates that the media reinforcement effect exists in the cross-section of large cap stocks. Firms with low (high) returns and sentiment scores over the past week tend to earn (incur) approximately 2.25% (-2.32%) per annual in the subsequent ten trading days, with a *t*-statistics of 2.01 (-2.07). The media reinforced strategy that longs losers with low sentiments and shorts winners with high sentiments profits about 4.57% (*t*-stat: 2.09), which is substantially higher than the profitability of a strategy solely based on a single signal of either return or media sentiment.

The overall result shown in the calendar time portfolio is in line with that in the event time analysis. That is, across all three asset classes, when both asset returns and media sentiments are negative (positive), assets tend to outperform (underperform).

3.4. Media Reinforcement around the Brexit Vote

Recall that when we attempt to check our media data quality, we verify it by examining the media tone surrounding recent political events. It is also crucial to visualize the media reinforcement effect in a political event time frame. Specifically, we compare the price movement of currencies and equity indexes of U.K. and Euro Zone with their corresponding media sentiment score pattern two weeks surrounding the Brexit vote.

The graphs in Fig. 4 suggest that two countries' currencies and equities both appreciated leading up to the voting date, and daily rolling one-week sentiment score exhibits similar trends. The surprising outcome shook the market as well as the media sentiment, leading to a drastic decline. If the media reinforcement is at work, we expect to observe a quick reversal in the short-run. Consistent with our conjecture, the asset prices of these two countries quickly bounced back when the past return and media sentiment were in agreement.

3.5. Media Reinforcement: Risk-Adjusted Returns

To investigate the media reinforcement effect over time, we form the long-short portfolios in each of the three asset classes. In each asset class, every day we divide instruments into two groups based on their past week returns. Within each of these two groups, we further sort assets into two portfolios based on their sentiment scores over the past week. We then compute the ten-day calendar time portfolio return on a zero-investment portfolio that longs instruments with low return and low sentiment and shorts instruments with high return and high sentiment. Repeating this every day yields a time series of returns for this zero-investment portfolio. Panel A, B, and C of Fig. 5 plots the monthly portfolio returns and cumulative returns to the media reinforced strategy in developed country currencies, country equities, and S&P 500 individual firms, respectively. As the figures show, the strategy performance over time provides a relatively steady stream of positive return despite that the strategy in latter sample outperforms that in earlier one. The annualized

Sharpe ratio of the strategy profit in developed country currencies, equities, and individual stocks is 1.02, 1.11, and 1.05, respectively. Notably, the media reinforced strategy has experienced extreme performance during the period between late 2015 and early 2016. This phenomenon may coincide with the oil price collapse and geopolitical uncertainty around the world which lead to increased uncertainty thus investor sentiment can fluctuate considerably from day to the next. Panel D of Fig. 5 reports the time-series performance of the volatility-weighted portfolio by combining all three markets. We set the position size of each asset class portfolio to be inversely proportional to the time-series media reinforced strategy volatility. From Moskowitz, Ooi, and Pedersen (2012), volatility adjustment is to mitigate the noise when we aggregate strategies across asset classes with differential volatility levels. As expected, the aggregate strategy exhibits a more smooth and pronounced time-series trend. The time-series value-weighted media reinforced strategy has a statistically significant profit of 4.42% per annual and an annualized Sharpe ratio of 1.62.

We then regress the time-series portfolio returns on factors known to affect the cross-sectional of returns in different asset markets, including daily Fama and French (1993) three factors (MKT, SMB, and HML) and momentum factor (MOM). For tests with currencies and country equities, we use corresponding global factors.[9] We build daily portfolio of currencies sorted on their forward discounts to construct two carry trade factors following Lustig, Roussanov, and Verdelhan (2011).

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[9] We thank Ken French for making data for both U.S. and global factors available on his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Panel A of Table 4 reports shows that the media reinforced strategy in currency market delivers a large and significant alpha or intercept for approximately 3.54% (3.82%) per annual with respect to models with four (six) factors, with a *t*-statistics of 1.89 (2.05). The negative and significant coefficient on SMB and positive and significant coefficient on DOL indicate that the media reinforced strategy in currencies has a positive exposure to the size effect and the dollar risk (driven by the fluctuation of the U.S. dollar against a broad basket of currencies). Panel B of Table 4 repeats the regression in country equity market. Once again, the alpha of the strategy is still an impressive 5.71% per annual (*t*-stat: 2.68), after controlling for the four global risk factors. Panel C of Table 4 investigates the media reinforced strategy for S&P 500 individual firms with the U.S. factors in place of the global factors. Similarly, traditional risk factors do not absorb the significance of the media reinforced strategy, achieving an annualized alpha of 4.53% (*t*-stat: 2.19).

3.6. Size, Coverage Intensity and Media Types (S&P 500 firms)

In the sample of S&P 500 individual firms, we are able to analyze the media reinforcement effect in more depth given the sufficient number of securities in the cross section. From the summary statistics, we observe that media coverage is highly correlated with firm size: large firms are much more likely to be covered. Therefore, we examine the media reinforcement sorted by size. Panel A of Table 5 shows that the media reinforcement effect is concentrated among the largest 100 U.S. stocks, while we observe a weaker effect in the rest 400 firms. Evidence shown in Fang and Peress (2009) suggest that no-coverage premium is mainly due to stock illiquidity and risk compensation for imperfect diversification, while our finding implies that investor reaction are significantly amplified when investors' attention is grabbed by the return-media-sentiment reinforced signal, which is in line with Barber and Odean (2008) that attention-driven buying by individuals is as strong for large cap stocks as for small stocks.

One possible interpretation for our finding is that large firms are more likely to catch investors' attention than those small firms because large firms are extensively covered in the news, while information flow of small firms is much thinner and reaches to investors sluggishly. To investigate this conjecture, we sort S&P 500 firms into subsamples of differential coverage intensity. To account for the strong persistence and highly skewness in media coverage, we construct the coverage intensity as the natural logarithm changes of daily media article coverage relative to past four same day-of-the-week averages, then weighted sum over the past week. Each day we partition S&P 500 individual firms based on the media coverage intensity during the formation week, and then test the media reinforcement effect in each of the coverage intensity subsample.

As shown in the Panel B of Table 5, the media reinforcement effect predominantly concentrates among firms with high coverage intensity. Highly covered firms with high (low) returns and sentiments score over the past week tend to incur (earn) approximately -2.90% (3.35%) per annual in the subsequent ten trading days, with a *t*-statistics of -2.22 (2.57). However, the media reinforcement effect is largely absent within the low coverage intensity group. This finding is consistent with our conjecture that investors intensively respond more to large price movement and matched media sentiment when these firms are extensively covered in the media.

In a related vein, as argued in Barber and Odean (2008), individual investors face cognitive limits and psychological bias when processing a large amount of information, thus tend to choose assets that catch their attentions. Their attentions can be caught if a firm recently experiences an extreme price movement or volume shock, is covered by the mass media, or both. With the detailed information regarding the media source types of S&P 500 firms, we examine the hypothesis that the media reinforcement phenomenon would be stronger using sentiment scores constructed from local media outlets. We group media articles into three mutually exclusive categories based on the media source: local media outlets, investing media outlets, and firm initiated media coverage (e.g., PR and news service). We then construct three measures of media sentiment scores based on articles in each media source type. Given that media coverage of each type is only a subset of all media articles, there is a substantial amount of firm-day observations that experience zero coverage for each media type. Nevertheless, the result shown in Panel C of Table 5 lends support to our hypothesis that the media reinforcement effect is stronger using local media sentiment. Specifically, media reinforced strategy that longs losers with low local media sentiments and shorts winners with high local media sentiments profits about 4.15% (*t*-stat: 1.79), while using the media sentiment constructed from investing or firm initiated media outlet coverage the reinforcement effect is smaller, yield about 3.51% (*t*-stat: 1.73) and 3.67% (*t*-stat: 1.89) per annual, respectively. One caveat of the result is that we do not directly observe individual trading activities, but can only infer that the local media coverage is a reasonable proxy for individual attentions. We believe this is a sensible argument since institutions usually process information from their proprietary channels, specialized sources (such specialist/professional media sources), or communicate directly with firms (PR and new service), while the local media outlets are mainly to reach out a broad readership of individuals.

3.7. Announcement Analysis

In this subsection, we examine whether the media reinforcement is driven by the quarterly earnings and major macroeconomics announcements, since media coverage spike surrounding the scheduled announcement and investor sentiment could also change substantially around these days. To rule out the possibility that our finding is largely driven by those events, we delete the observations when an announcement happens during the formation period.[10] The result shown in Table 6 alleviates our concern, since the announcements appear to have little impact on the media reinforcement phenomenon in all three asset markets.

3.8. Media Reinforcement: Fama-MacBeth Regression

We continue to examine the robustness of the media reinforcement effect using Fama and MacBeth (1973) cross-sectional regressions. To mimic the calendar time portfolio analysis, we construct four dummy variables to each of the two-by-two scenarios: *LRLS_D* equals one if the instrument's past return and sentiment score are both low, and zero otherwise; *LRHS_D* equals one if the instrument's past return is low and sentiment score is high, and zero otherwise; *HRLS_D* equals

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[10] Quarterly earnings announcement dates are obtained from the Compustat and CPI and PPI announcement dates are from the Bloomberg. The reason to choose CPI and PPI as proxy for macroeconomic announcements is that they have been shown to be important macroeconomic factors to affect a country's financial market. In addition, we could retain a testable sample after deleting the announcement days.

one if the instrument's past return is high and sentiment score is low, and zero otherwise; *HRHS_D* equals one if the instrument's past return and sentiment score are both high, and zero otherwise. The dependent variable in the regression is the future ten-day cumulative return in excess of the cross-sectional mean. We suppress the intercept and adjust autocorrelation of standard errors using the Newey and West (1987). The result shown in Table 8 confirms the finding in calendar time portfolio study and event time analysis. Specifically, the two reinforced dummies (*LRLS_D* and *HRHS_D*) are statistically significant in developed country currencies, country equities, as well as S&P 500 individual firms, while the non-reinforced dummies are largely insignificant. The only exception is that the coefficient of *HRHS_D* is insignificant in the country equity regression. However, the economic magnitude of this coefficient is still large and comparable to those in the currency and stock market regressions.

We examine further about the return reversal pattern in each of the four scenarios. To do so, we multiply the past-week return (in excess of the cross-sectional mean) with each of the four dummy variables. Model (2) of Table 7 shows the unconditional return reversal effect by running the regression of future ten-day return on past-week return. As expected, developed currencies, country equities and large cap stocks exhibit strong return reversal. Model (3) of Table 7 tests the within-dummy-group return reversal effect by running the regression of future ten-day return on four interaction terms. Consistent with the prior finding, investors do not react to past return when it does not match the concurrent media sentiment. While the reinforced dummy interaction variables are short of significance in certain cases, the overall results suggest that the return reversal, if any, predominately comes from the situations when past return and media sentiment point to the same direction.

To examine whether the media reinforcement effect is robust to other asset characteristics, we continue the multivariate analysis in the sample of S&P 500 firms by adding firm level characteristics into the regressions. Specifically, we construct two dummy variables to denote the two reinforcement scenarios: *Reinfoce_L* equals one if *LRLS_D* is non-zero, and zero otherwise; *Reinfoce_H* equals one if *HRHS_D* is non-zero, and zero otherwise. The firm level control variables include Amihud (2002) illiquidity variable and daily return volatility measured over the past year, size measured at the end of prior calendar year, and last quarter's institutional ownership ratio. The results shown in Table 9 indicate that adding control variables have little impact on the media reinforcement effect.

4. Robustness

In this section, we conduct a number of robustness checks on the baseline results presented in Table 2 and 3. In particular, we try to alleviate the concern that the media reinforcement effect could be driven by the measure of media sentiment or the portfolio sorting method. We then investigate the possibility of media reinforcement in emerging markets.

4.1. Alternative Sentiment Measure

So far, our sentiment measure focuses on the positive and negative words ((P-N)/(P+N)). While it makes the measure bounded from -1 to +1, the caveat is that two articles could have different length while still obtaining same score. To incorporate the effect of article length, we construct an alternative measure as the difference between the number of positive and negative words, and then divided by the total number of article words. Panel A of Table 9 indicates that the alternative sentiment measure has minimal impact on our main finding. The media reinforcement effect amounts to approximately -4.37% (*t*-stat: -1.99) in the sample of S&P 500 individual firms.

4.2. Independent Portfolio Sorting

In the baseline analysis, the assets are first sorted on past return, and then within each group instruments are further sorted on media sentiment. The reason of doing so is to ensure equal number of assets in each portfolio given that there is limited number of instruments in asset classes such as developed currency and country equity markets. In this subsection, we attempt to validate our main finding using independent portfolio sorting method using the sample S&P 500 individual firms. Panel B of Table 9 shows that result using independent sort is essentially the same as that with dependent sort. The media reinforcement effect using independent sort is about -4.59% (*t*-stat: -2.08) contrasting to -4.57% (*t*-stat: -2.09) in the dependent sort scenario.

4.3. Media Effect in Alternative Asset Markets

Last, we investigate the media reinforcement in the alternative asset market in which the short-run return pattern usually exhibits continuation. In addition, given that emerging and developed markets differ systematically in terms of information environment, it is also interesting to investigate whether and how media coverage influences the emerging financial market. Griffin, Hirschey, and Kelly (2011) find that emerging market stock prices react to news to a lesser extent and slowly. They argue this is due to the slow speed and quality of news dissemination and severe information asymmetry (insider trading). Along this line of reasoning, we expect the media reinforcement effect either does not work or works in the opposite direction (continuation) in the emerging market.

We reproduce the portfolio analysis using the data for emerging currencies and commodities. After taking out the countries that do not have sufficient number of media coverage, we retain a sample of 17 emerging currencies and 14 commodities. As expected, both markets show significant short-run return continuation. Panel A of Table 10 indicates that the media reinforcement is not at work in the emerging currency market, while Panel B of Table 10 suggests that in the commodity market the return continuation pattern is only pronounced when the past return and media sentiment goes in the same direction. When past-week returns and media sentiments are both high (low), emerging currencies continue to earn (incur) 8.55% (-8.87%) annualized return in the subsequent five-day, with a *t*-statistics of 2.05 (-1.98). However, when media sentiment score points at the opposite direction of return, the subsequent return continuation is insignificant. This result indicates that investors in the emerging market seem that they process and absorb the information sluggishly, leading to a return drift in the short-run. The event time figures plotted in Fig. 6 indicate that a reversal is followed by the initial return continuation in both markets. Furthermore, the reinforced signals in the commodity market leads to sharper return reversal afterwards.

5. Conclusion

Using data from thousands of media sources, we provide new evidence to the short-term return reversal, one of the most prominent return anomalies in the finance literature. We find that the subsequent return reversal is pronounced only when media sentiment matches the formation period return, suggesting that investors independent response to individual signals is overwhelmed by the response to reinforced signals. Furthermore, we show this media reinforcement effect is remarkably robust across different asset classes, including developed country currencies, country equities, and large cap U.S. individual firms.

The overall results that the reinforced effect is most pronounced among assets with extensive media coverage and sentiment from local media outlets support the idea that individual investors overreact to attention-grabbed reinforced signal, inducing a significant subsequent return reversal. Evidence in the emerging market indicates that investors under inferior information environment also react to the reinforced signal but in the opposite direction (short-term return continuation) since they process and absorb the information sluggishly.

Our findings suggest that investors consolidate all kinds of information in the financial market and intensively react to the joint signals, thus treating individual information signals separately may lead to biased or incomplete conclusion. Thus the evidence presented in this paper shed light on current research in better understanding the information dissemination and investor behavior.

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Appendix A. Data sources

This table provides a list of the universe of 33 country equity indexes (denominated in local currency) obtained from Datastream. The sample period is from 2013:01 to 2017:03.

Country	Equity Index
Argentina	Merval
Australia	ASX 200
Brazil	Bovespa
Canada	TSX
Chile	IGPA
China	Shanghai SE A Share
Colombia	IGBC
Denmark	OMXC 20
Egypt	Hermes
Euro Zone	STOXX 50
Hong Kong	Hang Seng
Hungary	BUX
India	Nifty 500
Indonesia	IDX
Israel	TA 100
Japan	Nikkei 225
Mexico	Bolsa
Malaysia	FTSE Bursa
New Zealand	NZX 50
Nigeria	Nigeria All Share
Norway	Olso Exchange All Share
Philippines	PSEi
Poland	WIG
Russia	RTS
Singapore	Straits Times Index
South Africa	FTSE JSE
South Korea	KOSPI
Sweden	OMXS 30
Switzerland	Swiss Market (SMI)
Thailand	S.E.T
Turkey	BIST National 100
U.K.	FTSE 100
U.S.	S&P 500

Table 1: Summary Statistics

This table summarizes the descriptive statistics of media variables across asset classes, including developed country currencies, country equity indexes, and S&P 500 individual firms. Panel A reports the summary statistics of media coverage, including the average number of media articles, standard deviation, and the median across instruments within in each asset class. Panel B depicts the summary statistics of average daily media article tone across instruments within in each asset class. The sample period is from 2013:01 to 2017:03.

Panel A: Media Coverage					
Asset Class	Mean	Std Dev	25th Pctl	Median	75th Pctl
FX	10,201	9,946.52	1562.00	7646.50	17262.50
Country Equity	11,397.43	21,774.80	722.50	3031.00	9288.50
S&P 500 Firms	4,742.17	5,662.57	2,110.50	3168.00	5103.50
Panel B: Media Tone					
Asset Class	Mean	Std Dev	25th Pctl	Median	75th Pctl
FX	-0.186	0.060	-0.246	-0.192	-0.130
Country Equity	-0.205	0.102	-0.269	-0.221	-0.132
S&P 500 Firms	0.067	0.089	0.020	0.072	0.114

Table 2: Calendar-Time Portfolio Return, FX/Country Equity

This table reports the 10-day calendar-time portfolio returns based on past return and media sentiment. Each day currencies (equity indexes) are first ranked into two groups based on their past-week returns and then, within each group, we further sort the instruments into two groups based on media sentiment scores over the same formation period. *Past Return* is the cumulative excess currency (equity) returns over the past week. *Sentiment* is the difference between daily media tone and past four same day-of-the-week averages, then weighted sum over the past week. Panel A reports results of developed currencies using sentiment score calculated based on currency media coverage, country equity media coverage, and combined media coverage, respectively (from left to right). Panel B exhibits results in country equity markets accordingly. When analyzing currency market, we drop USA (benchmark) and Hong Kong (pegged). We skip 1 day between the formation and forecast period. The return is annualized and denoted in percentage. The Newey and West (1987) autocorrelation robust *t*-statistics are reported in square brackets. The sample is over the period from 2013:01 to 2017:03.

Panel A: FX						
Media Source=	FX		Country Equity		FX/Country Equity Combined	
	Past Return		Past Return		Past Return	
	Low	High	Low	High	Low	High
Low Sentiment	2.04	-1.15	0.23	-0.54	1.38	-0.92
	[1.94]	[-1.33]	[0.15]	[-0.39]	[1.50]	[-1.02]
High Sentiment	0.83	-1.72	2.43	-2.13	1.52	-1.98
	[0.91]	[-1.92]	[1.26]	[-2.05]	[1.67]	[-2.09]
Reversal	-2.90		-2.67		-2.90	
	[-1.91]		[-1.50]		[-1.91]	
Reinforcement	-3.76		-2.36		-3.35	
	[-2.10]		[-1.09]		[-2.00]	

Table 2-*Continued*

Panel B: Country Equity						
Media Source=	FX		Country Equity		FX/Country Equity Combined	
	Past Return		Past Return		Past Return	
	Low	High	Low	High	Low	High
Low Sentiment	2.12	0.57	1.81	-1.41	2.21	0.02
	[1.78]	[0.44]	[1.36]	[-1.11]	[1.79]	[0.01]
High Sentiment	0.31	-3.01	1.02	-1.42	0.25	-2.47
	[0.27]	[-2.57]	[0.88]	[-1.11]	[0.22]	[-2.22]
Reversal	-2.45		-2.83		-2.45	
	[-1.56]		[-1.73]		[-1.56]	
Reinforcement	-5.11		-3.23		-4.68	
	[-2.49]		[-1.41]		[-2.24]	

Table 3: Calendar-Time Portfolio Return, S&P 500 Firms

This table reports the 10-day calendar-time portfolio returns based on past return and media sentiment. Each day S&P 500 individual firms are first ranked into two groups based on their past-week returns and then, within each group, we further sort the stocks into two groups based on media sentiment scores over the past week. *Past Return* is the cumulative stock returns over the past week. *Sentiment* is the difference between daily media tone and past four same day-of-the-week averages, then weighted sum over the past week. We skip 1 day between the formation and forecast period. The return is annualized and denoted in percentage. The Newey and West (1987) autocorrelation robust *t*-statistics are reported in square brackets. The sample is over the period from 2013:01 to 2017:03.

	Past Return	
	Low	High
Low Sentiment	2.25	-1.02
	[2.01]	[-1.03]
High Sentiment	1.09	-2.32
	[1.00]	[-2.07]
Reversal	-3.34	
	[-1.75]	
Reinforcement	-4.57	
	[-2.09]	

Table 4: Media Reinforcement: Risk-Adjusted Returns

This table reports results of time series regressions of daily return of media reinforced strategy that buys loser with low sentiment and sells winner with high sentiment on various risk factors in three asset markets. Panel A reports the results of developed currency market, where Fama and French global factors (MKT, SMB, HML, and MOM) and two carry trade factors (DOL, FXHML) based on Lustig, Roussanov, and Verdelhan (2011) are included. Panel B reports the result of all country equities, where Fama and French global factors (MKT, SMB, HML, and MOM) are included. Panel C reports the result of S&P 500 firms, where Fama and French U.S. factors (MKT, SMB, HML, and MOM) are included. In currency and country equity tests, we construct media sentiment score based on currency media coverage. When analyzing currency returns, we drop USA (benchmark) and Hong Kong (pegged). We skip 1 day between the formation and forecast period. The intercept is annualized and denoted in percentage. The Newey and West (1987) autocorrelation robust *t*-statistics are reported in square brackets. The sample is over the period from 2013:01 to 2017:03.

Model	Intercept	MKT	SMB	HML	MOM	DOL	FXHML
Panel A: FX (Global Factors)							
(1)	3.76						
	[2.10]						
(2)	3.54	-0.01	-0.04	-0.04	-0.01		
	[1.89]	[-0.72]	[-1.72]	[-1.04]	[-0.74]		
(3)	3.82	-0.02	-0.04	-0.04	-0.01	0.07	0.02
	[2.05]	[-1.11]	[-1.80]	[-1.19]	[-0.51]	[2.35]	[0.74]
Panel B: Country Equity (Global Factors)							
(1)	5.11						
	[2.49]						
(2)	5.71	-0.01	-0.11	0.00	0.01		
	[2.68]	[-0.56]	[-3.64]	[0.12]	[0.80]		
Panel C: S&P 500 Firms (U.S. Factors)							
(1)	4.57						
	[2.09]						
(2)	4.53	0.01	-0.02	-0.01	-0.02		
	[2.19]	[0.55]	[-0.56]	[-0.44]	[-1.49]		

Table 5: Media Reinforcement by Size, Coverage Intensity, and Media Source Type

This table reports the 10-day calendar-time portfolio returns based on past return and media sentiment, in subsamples of firms sorted on firm size (Panel A), media coverage intensity (Panel B), and source of media type (Panel C). Within in each subsample, we sort firms into two groups based on their past-week returns and then, we further sort the stocks into two groups based on media sentiment scores over the past week. *Past Return* is the cumulative stock returns over the past week. *Sentiment* is the difference between daily media tone and past four same day-of-the-week averages, then weighted sum over the past week. *Size* is measured at the end of prior calendar year and media *coverage intensity* is the log changes of daily media article coverage relative to past four same day-of-the-week averages, then weighted sum over the past week. We skip 1 day between the formation and forecast period. The return is annualized and denoted in percentage. The Newey and West (1987) autocorrelation robust *t*-statistics are reported in square brackets. The sample is over the period from 2013:01 to 2017:03.

	Panel A: Size				Panel B: Coverage Intensity				Panel C: Source of Media Type					
	S&P 100		Rest 400		High		Low		Local		Investing		PR News	
Sentiment	Past Return		Past Return		Past Return		Past Return		Past Return		Past Return		Past Return	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
Low	1.94	-1.22	2.10	-0.61	3.35	-0.93	1.44	-1.24	1.97	-1.17	1.80	-1.63	2.17	-1.84
	[1.76]	[-1.22]	[1.34]	[-0.53]	[2.57]	[-0.84]	[1.34]	[-1.26]	[1.65]	[-1.15]	[1.72]	[-1.56]	[2.17]	[-1.62]
High	1.50	-2.23	0.12	-1.61	0.49	-2.90	1.66	-1.86	1.34	-2.18	1.54	-1.71	1.17	-1.50
	[1.59]	[-2.01]	[0.09]	[-1.20]	[0.38]	[-2.22]	[1.61]	[-1.67]	[1.28]	[-1.81]	[1.43]	[-1.61]	[0.92]	[-1.45]
Reversal	-3.46		-2.21		-3.83		-3.09		-3.34		-3.34		-3.34	
	[-2.03]		[-1.01]		[-1.80]		[-1.68]		[-1.75]		[-1.75]		[-1.75]	
Reinforcement	-4.17		-3.70		-6.25		-3.29		-4.15		-3.51		-3.67	
	[-2.00]		[-1.43]		[-2.49]		[-1.59]		[-1.79]		[-1.73]		[-1.89]	

Table 6: Reinforcement Effect: Earnings and Macroeconomics Announcements

This table reports the 10-day calendar-time portfolio returns based on past return and media sentiment after taking out the effect of quarterly earnings (S&P 500 firms) and macroeconomics (currencies and country equities) announcements. Each day assets are first ranked into two groups based on their past-week returns and then, within each group, we further sort them into two groups based on media sentiment scores over the past week. *Past Return* is the cumulative asset returns over the past week. *Sentiment* is the difference between daily media tone and past four same day-of-the-week averages, then weighted sum over the past week. We delete the asset-day where earnings (macroeconomics) are announced in the portfolio formation period. Panel A, B, and C report the results of developed country currencies, country equities, and S&P 500 firms, respectively. The earnings announcements dates are from Compustat and CPI and PPI announcement dates are from Bloomberg. In currency and country equity tests, we construct media sentiment score based on currency media coverage. When analyzing currency returns, we drop USA (benchmark) and Hong Kong (pegged). We skip 1 day between the formation and forecast period. The return is annualized and denoted in percentage. The Newey and West (1987) autocorrelation robust *t*-statistics are reported in square brackets. The sample is over the period from 2013:01 to 2017:03.

	Panel A: FX		Panel B: Country Equity		Panel C: S&P 500 Firms	
	Past Return		Past Return		Past Return	
	Low	High	Low	High	Low	High
Low Sentiment	1.92	-0.64	2.34	-0.21	2.63	-0.87
	[2.01]	[-0.74]	[1.58]	[-0.14]	[2.39]	[-0.84]
High Sentiment	0.19	-1.48	0.93	-3.06	1.00	-2.76
	[0.19]	[-1.66]	[0.67]	[-2.18]	[0.94]	[-2.45]
Reversal	-2.17		-3.26		-3.63	
	[-1.57]		[-1.70]		[-1.88]	
Reinforcement	-3.40		-5.40		-5.39	
	[-2.04]		[-2.13]		[-2.48]	

Table 7: Media Reinforcement in Fama-MacBeth Regressions

This table reports the Fama and MacBeth (1973) regressions of forecasting asset returns on quartile dummies based on past return and media sentiment. We assign four dummy variables to each of the two-by-two scenarios every day: *LRLS_D* equals one if the instrument's past week's return and sentiment score are both low, and zero otherwise; *LRHS_D* equals one if the instrument's past return is low and sentiment score is high, and zero otherwise; *HRLS_D* equals one if the instrument's past return is high and sentiment score is low, and zero otherwise; *HRHS_D* equals one if the instrument's past return and sentiment score are both high, and zero otherwise. *Pret* is the cumulative instrument return in excess of the cross-sectional mean over the past week. Forecast return is the cumulative 10-day future return in excess of cross-sectional mean. Panel A, B, and C report the results of developed country currencies, country equities, and S&P 500 firms, respectively. We also examine the subsamples of firms sorted on firm *Size* (measured at the end of prior calendar year). In currency and country equity tests, we construct media sentiment score based on FX media coverage. We skip 1 day between the formation and forecast period. The Newey and West (1987) autocorrelation robust *t*-statistics are reported in square brackets. The sample is over the period from 2013:01 to 2017:03.

	Panel A: FX			Panel B: Country Equity			Panel C: S&P 500 Firms								
							Full Sample			Largest 100			The Rest		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
LRLS_D	0.066			0.104			0.097			0.079			0.079		
	[1.66]			[1.84]			[2.38]			[1.86]			[1.64]		
LRHS_D	0.027			0.062			0.012			0.057			0.003		
	[0.76]			[1.00]			[0.28]			[1.57]			[0.07]		
HRLS_D	-0.033			0.038			-0.034			-0.045			-0.003		
	[-1.01]			[0.58]			[-0.83]			[-1.16]			[-0.72]		
HRHS_D	-0.060			-0.079			-0.074			-0.090			-0.050		
	[-1.73]			[-1.25]			[-1.78]			[-2.20]			[-1.07]		
Pret		-0.067			-0.032			-0.000			-0.036			-0.000	
		[-1.72]			[-1.33]			[-0.03]			[-2.40]			[-0.05]	
Pret× LRLS_D			-0.073			-0.073			0.000			-0.037			0.008
			[-0.99]			[-1.96]			[0.05]			[-1.86]			[0.32]
Pret× LRHS_D			-0.058			-0.055			0.018			-0.017			0.029
			[-0.94]			[0.69]			[0.69]			[-0.71]			[1.10]
Pret× HRLS_D			-0.024			0.037			-0.023			-0.031			-0.021
			[-0.36]			[0.79]			[-1.59]			[-1.63]			[-1.42]
Pret× HRHS_D			-0.096			-0.040			-0.018			-0.063			-0.013
			[-1.79]			[-0.85]			[-1.25]			[-3.35]			[-0.85]

Table 8: Fama-MacBeth Regressions, Controlling for Firm Characteristics (S&P 500 Firms)

This table reports the Fama and MacBeth (1973) regressions of forecasting asset returns on quartile dummies based on past return and media sentiment. We assign two dummy variables to each of the two reinforced scenarios every day: *Reinforce_L* equals one if the instrument's past week's return and sentiment score are both low, and zero otherwise; *Reinforce_H* equals one if the instrument's past week's return and sentiment score are both high, and zero otherwise; *Pret* is the cumulative instrument return in excess of the cross-sectional mean over the past week. Forecast return is the cumulative 10-day future return in excess of cross-sectional mean. Firm level control variables include *Amihud* (2002) illiquidity, *Size* (log of market capitalization calculated at the end of prior calendar year), last year's return volatility (*VOL*), as well as the institutional ownership ratio (*IRO*). Panel A reports results of all S&P 500 firms as of the end of 2012. Panel B exhibits results of the largest 100 U.S. firms based on the market size measured at the end of prior calendar year. Panel C displays results for the rest S&P 500 firms. We skip 1 day between the formation and forecast period. The return is annualized and denoted in percentage. The Newey and West (1987) autocorrelation robust *t*-statistics are reported in square brackets. The sample is over the period from 2013:01 to 2017:03.

	Panel A: Full Sample				Panel B: Largest 100				Panel C: Rest Firms			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Reinforce_L	0.097	0.101			0.079	0.087			0.079	0.084		
	[2.38]	[1.92]			[1.86]	[1.92]			[1.64]	[1.70]		
Reinforce_H	-0.074	-0.041			-0.090	-0.075			-0.050	-0.005		
	[-1.78]	[-1.10]			[-2.20]	[-1.72]			[-1.07]	[-0.13]		
Pret× Reinforce_L			0.000	0.009			-0.037	-0.044			0.008	0.015
			[0.05]	[0.53]			[-1.86]	[-2.03]			[0.32]	[0.70]
Pret× Reinforce_H			-0.018	-0.020			-0.063	-0.059			-0.013	-0.012
			[-1.25]	[-1.37]			[-3.35]	[-2.97]			[-0.85]	[-0.75]
Amihud		-0.570		-0.414		-9.303		-10.925		-0.270		-0.344
		[-0.30]		[-0.23]		[-0.57]		[-0.68]		[-0.15]		[-0.20]
Size		-0.010		-0.009		-0.007		-0.006		-0.011		-0.010
		[-0.85]		[-0.81]		[-0.55]		[-0.47]		[-0.84]		[-0.73]
VOL		-4.397		-2.399		4.593		5.032		-3.759		-3.695
		[-0.26]		[-0.14]		[0.24]		[0.27]		[-0.21]		[-0.21]
IRO		-0.187		0.298		-0.547		-0.660		0.343		0.336
		[-0.33]		[1.93]		[-0.34]		[-0.41]		[2.11]		[2.06]

Table 9: Robustness: Alternative Sentiment Measure, and Sorting Methods

This table reports the 10-day calendar-time portfolio returns based on past return and media sentiment by applying alternative sentiment measure calculation and sorting method. In Panel A, the article media tone calculated as the difference between the number of positive and negative words, and then divided by the total number of article words. In Panel B, each day S&P 500 individual firms are *independently* sorted into two groups based on their return and media sentiment over the past week. *Past Return* is the cumulative stock returns over the past week. *Sentiment* is the difference between daily media tone and past four same day-of-the-week averages, then weighted sum over the past week. We skip 1 day between the formation and forecast period. The return is annualized and denoted in percentage. The Newey and West (1987) autocorrelation robust *t*-statistics are reported in square brackets. The sample is over the period from 2013:01 to 2017:03.

Panel A: Alternative Sentiment Measure		
	Past Return	
	Low	High
Low Sentiment	2.27	-1.24
	[2.00]	[-1.23]
High Sentiment	1.08	-2.10
	[0.99]	[-1.89]
Reversal	-3.34	
	[-1.75]	
Reinforcement	-4.37	
	[-1.99]	

Panel B: Independent Portfolio Sort		
	Past Return	
	Low	High
Low Sentiment	2.44	-1.17
	[2.12]	[-1.18]
High Sentiment	0.88	-2.15
	[0.84]	[-1.95]
Reversal	-3.34	
	[-1.75]	
Reinforcement	-4.59	
	[-2.08]	

Table 10: Robustness: Alternative Asset Classes: Emerging Currencies and Commodities

This table reports the 5-day calendar-time portfolio returns based on past return and media sentiment in emerging country currency (Panel A) and commodity (Panel B) markets. Each day assets are first ranked into two groups based on their past-week returns and then, within each group, we further sort them into two groups based on media sentiment scores over the past week. *Past Return* is the cumulative stock returns over the past week. *Sentiment* is the difference between daily media tone and past four same day-of-the-week averages, then weighted sum over the past week. We skip 1 day between the formation and forecast period. The return is annualized and denoted in percentage. The Newey and West (1987) autocorrelation robust *t*-statistics are reported in square brackets. The sample is over the period from 2013:01 to 2017:03.

Panel A: Emerging Currencies		
	Past Return	
	Low	High
Low Sentiment	-0.78	1.27
	[-0.47]	[0.72]
High Sentiment	-1.31	0.82
	[-0.74]	[0.54]
Reversal	2.06	
	[0.97]	
Add Sentiment	1.60	
	[0.57]	
Panel B: Commodities		
	Past Return	
	Low	High
Low Sentiment	-8.87	4.81
	[-1.98]	[1.18]
High Sentiment	-4.49	8.55
	[-1.24]	[2.05]
Reversal	13.02	
	[2.03]	
Add Sentiment	17.42	
	[2.20]	

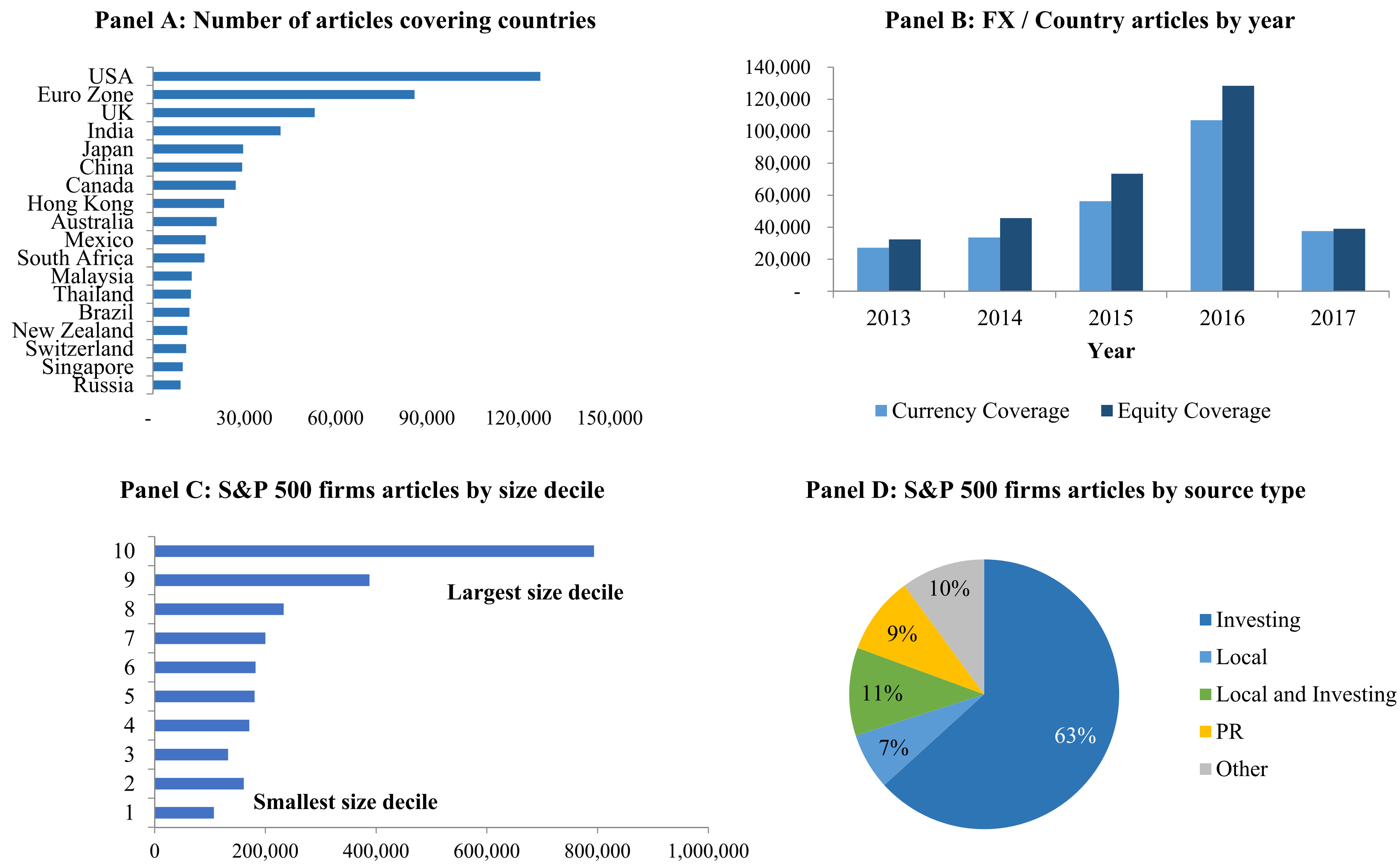
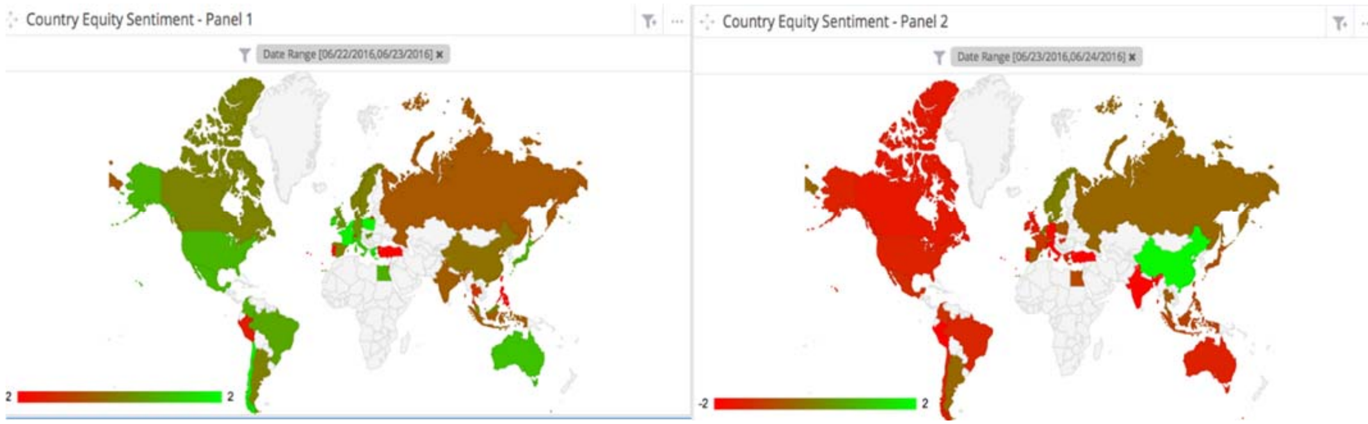


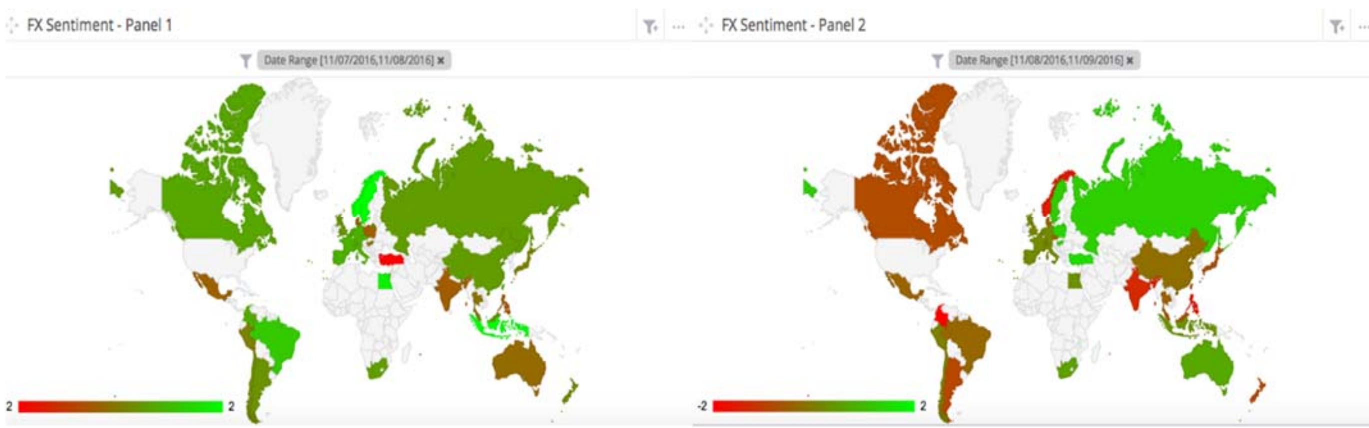
Figure 1. Data summary. This figure summarizes media data. Panel A ranks the total number of media coverage for a country's currency and equity index (18 most covered countries listed). Panel B reports yearly trend of media coverage for country currency and equity index. Note 2017 only contains media coverage up to March. Panel C depicts the daily media coverage for the S&P 500 firms within different size deciles, and Panel D details the proportion of each media source type for S&P 500 firms. The sample is over the period from 2013:01 to 2017:03.

Panel A: Brexit vote



Pre-event **Post-event**

Panel B: 2016 U.S. presidential election



Pre-event **Post-event**

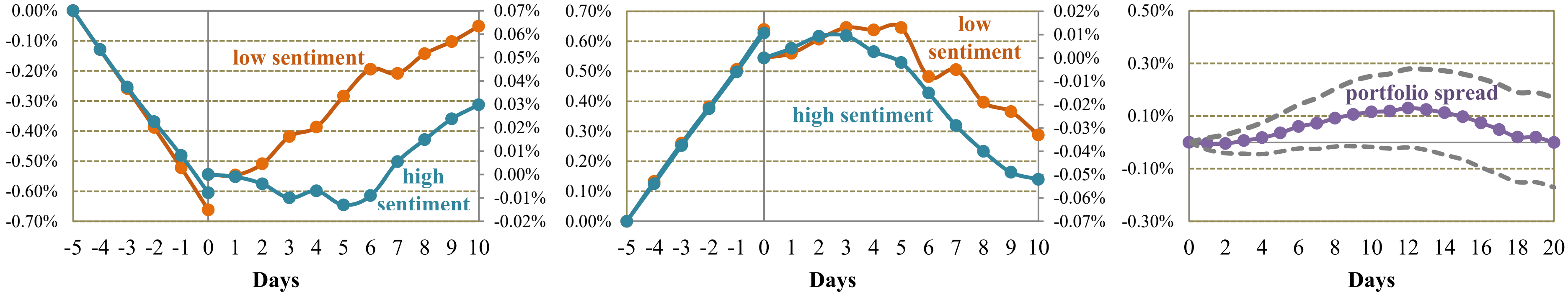
Panel C: 2017 French presidential election

Pre-event

Post-event

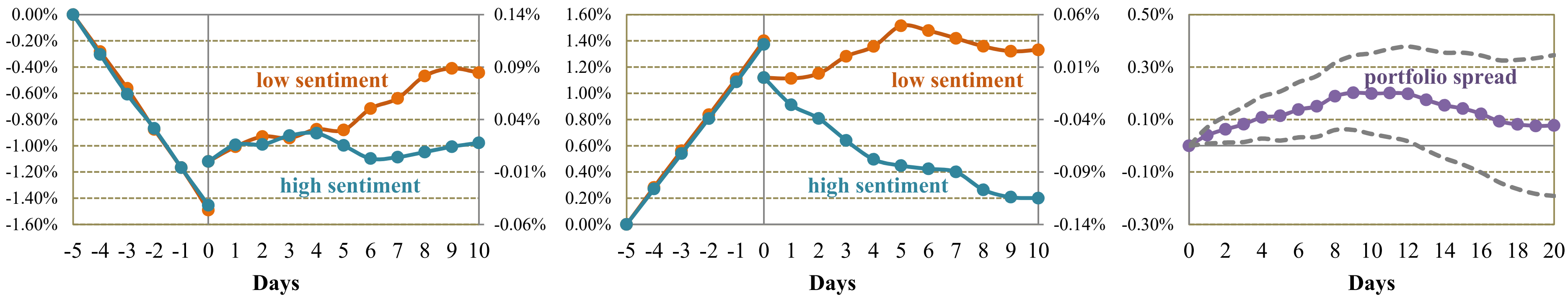
Figure 2. Media tone surrounding major political events. This figure plots the average media article tone for the major country currencies and country equity indexes surrounding the global political events. Panel A illustrates the media tone of country equity indexes at the day before and after the Brexit vote (June 23, 2016). Panel B reports media tone of currencies at the day before and after the 2016 U.S. presidential election (November 8, 2016). Panel C plots media tone of major European country equity indexes at the day before and after the 2017 French presidential election (April 23, 2017).

Panel A: Currency



Low past return | High past return | Portfolio spread

Panel B: Country equity



Low past return | High past return | Portfolio spread

Panel C: S&P 500 firms

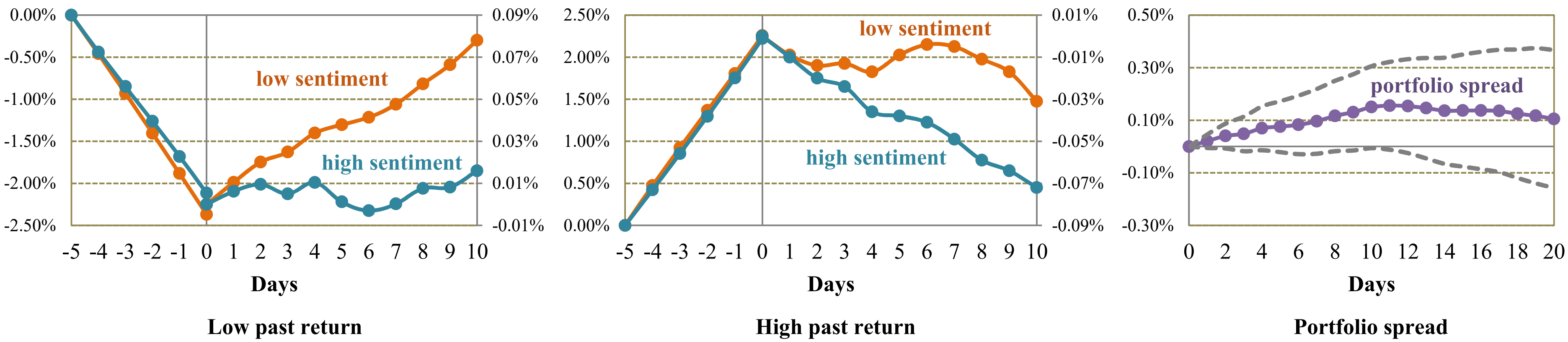


Figure 3. Event time patterns of currencies and country equities. This figure plots the average cumulative excess returns surrounding the formation of portfolios sorted on past return and media sentiment over the past week. Each day assets are first ranked into two groups based on their past-week returns and then, within each group, we further sort the currencies into two groups based on media sentiment scores over the past week. In each row from left to right, we plot the sentiment effect of portfolios with low past returns, portfolios with high past returns, and the cumulative return of the media reinforced strategy that buys losers with low sentiments and sells winners with high sentiments along with the two-standard-error bounds, which are adjusted by the Newey and West (1987). Panel A, B, and C report the results in developed country currencies, country equities, and S&P 500 individual firms, respectively. In currency and country equity tests, we construct media sentiment score based on currency media coverage. When analyzing currency returns, we drop USA (benchmark) and Hong Kong (pegged).We skip 1 day between the formation and forecast period. The sample is over the period from 2013:01 to 2017:03.

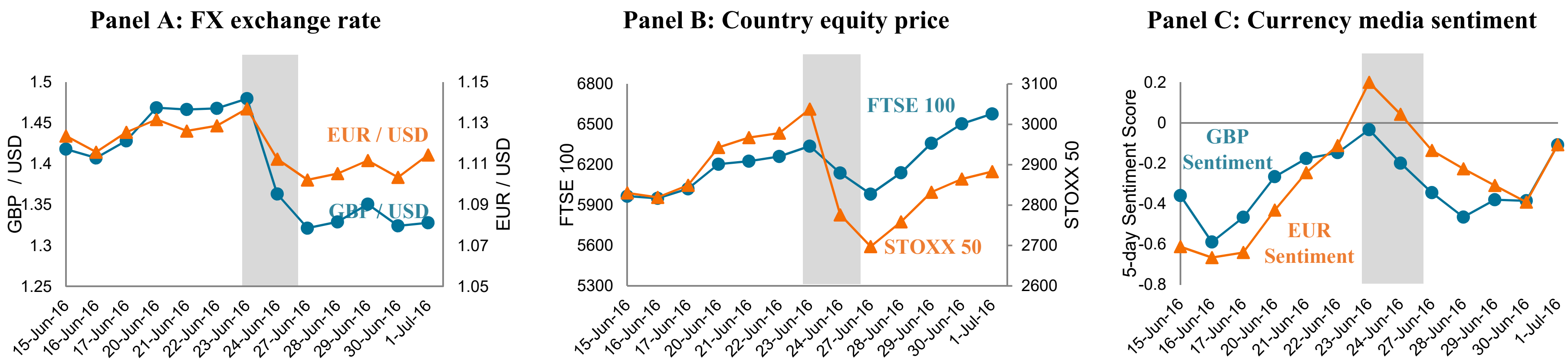
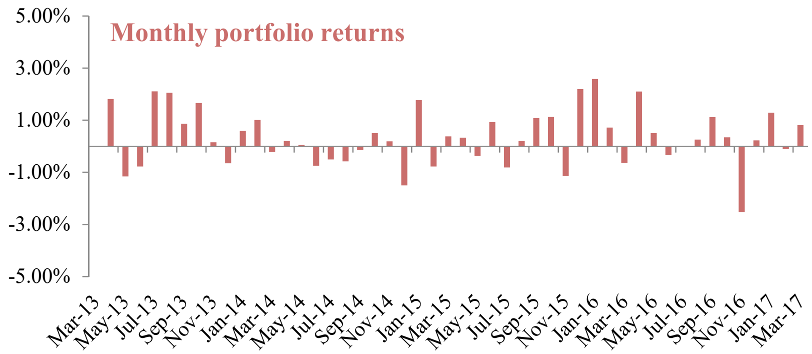
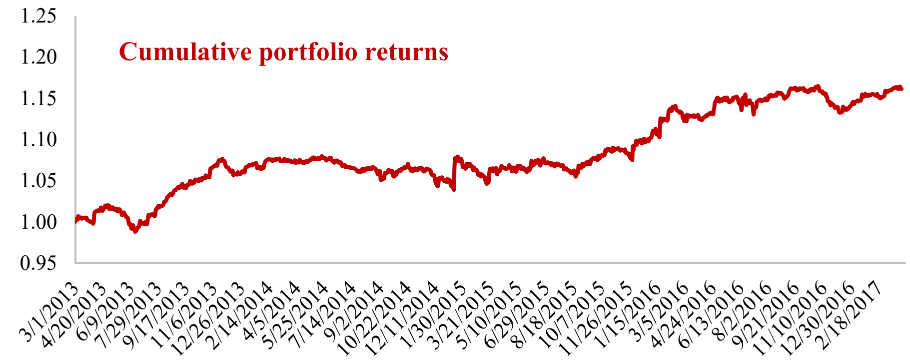


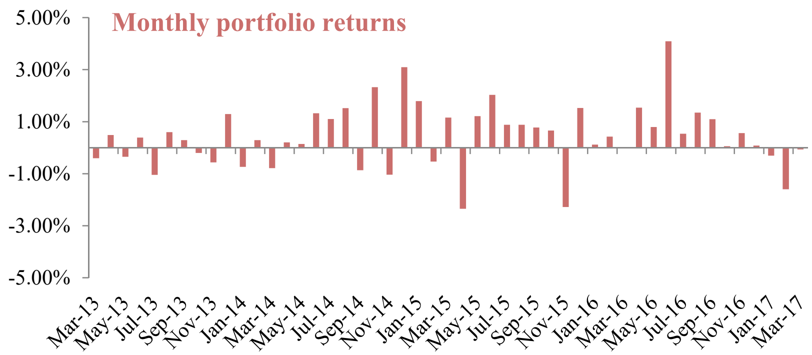
Figure 4. Reinforcement effect surrounding Brexit vote. This figure plots the media sentiment score and price pattern for the currencies and country equity indexes of UK and Euro Zone surrounding the Brexit vote. Panel A reports the exchange rate pattern of GBP and EUR two weeks surrounding the Brexit vote, while Panel B reports the price movement of FTSE 100 and STOXX 50 two weeks surrounding the Brexit vote. Panel C depicts the daily sentiment score pattern constructed from past week surrounding the Brexit vote.

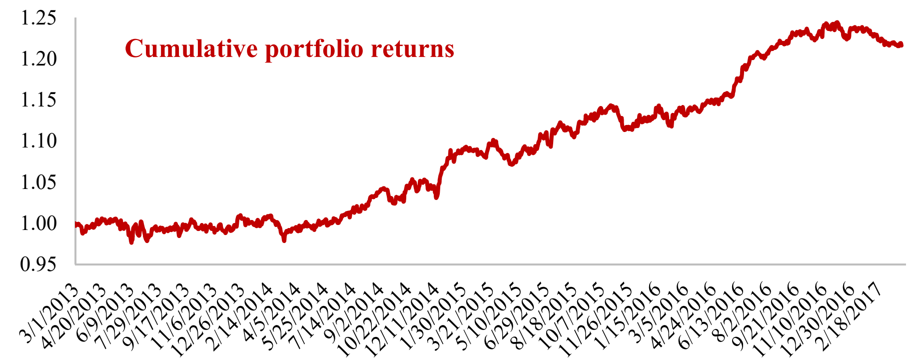
Panel A: Currency



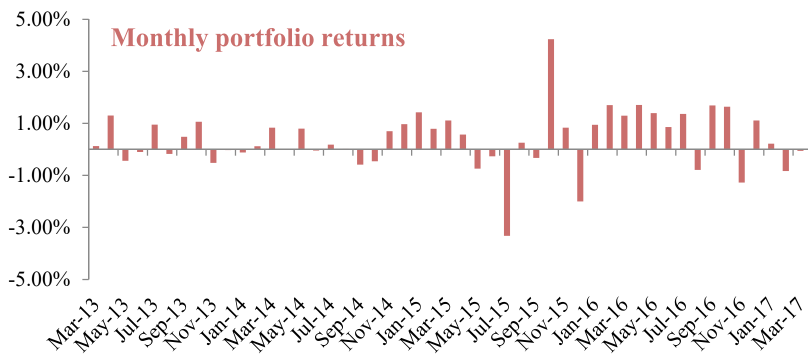


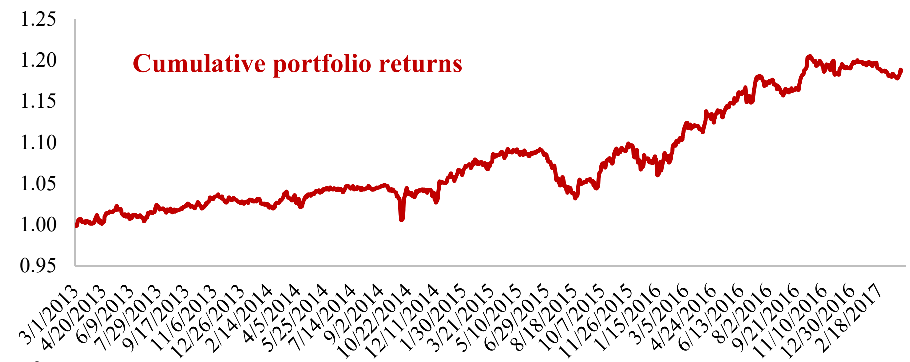
Panel B: Country equity





Panel C: S&P 500 firms





Panel D: Volatility-weighted combination

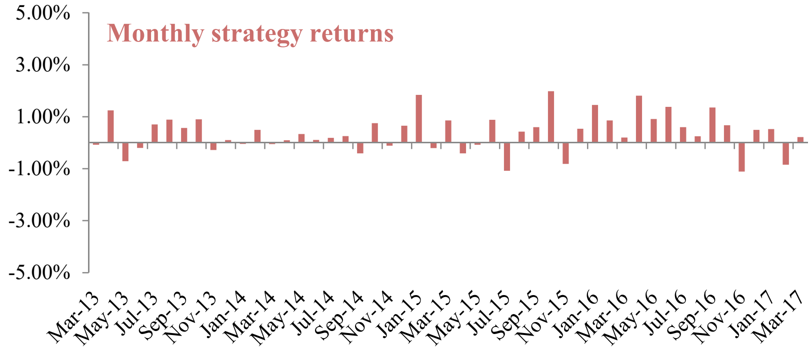


Figure 5. Time series media reinforcement portfolio returns. This figure plots the figure plots the returns of time series media reinforced portfolio that buys losers with low sentiments and sells winners with high sentiments. Every day instruments in each asset class are first ranked into two groups based on their past-week returns and then, within each group, we further sort the instruments into two groups based on media sentiment scores over the past week. The left graph reports the monthly media reinforcement portfolio returns, while the right graph shows the cumulative media reinforcement portfolio returns over the sample period. Results of currencies, country equities, and the S&P 500 individual firms are plotted in Panel A, B, and C, respectively. Panel D displays the time-series returns of the volatility-weighting portfolios combing all three asset classes. We skip 1 day between the formation and forecast period. The sample is over the period from 2013:01 to 2017:03.

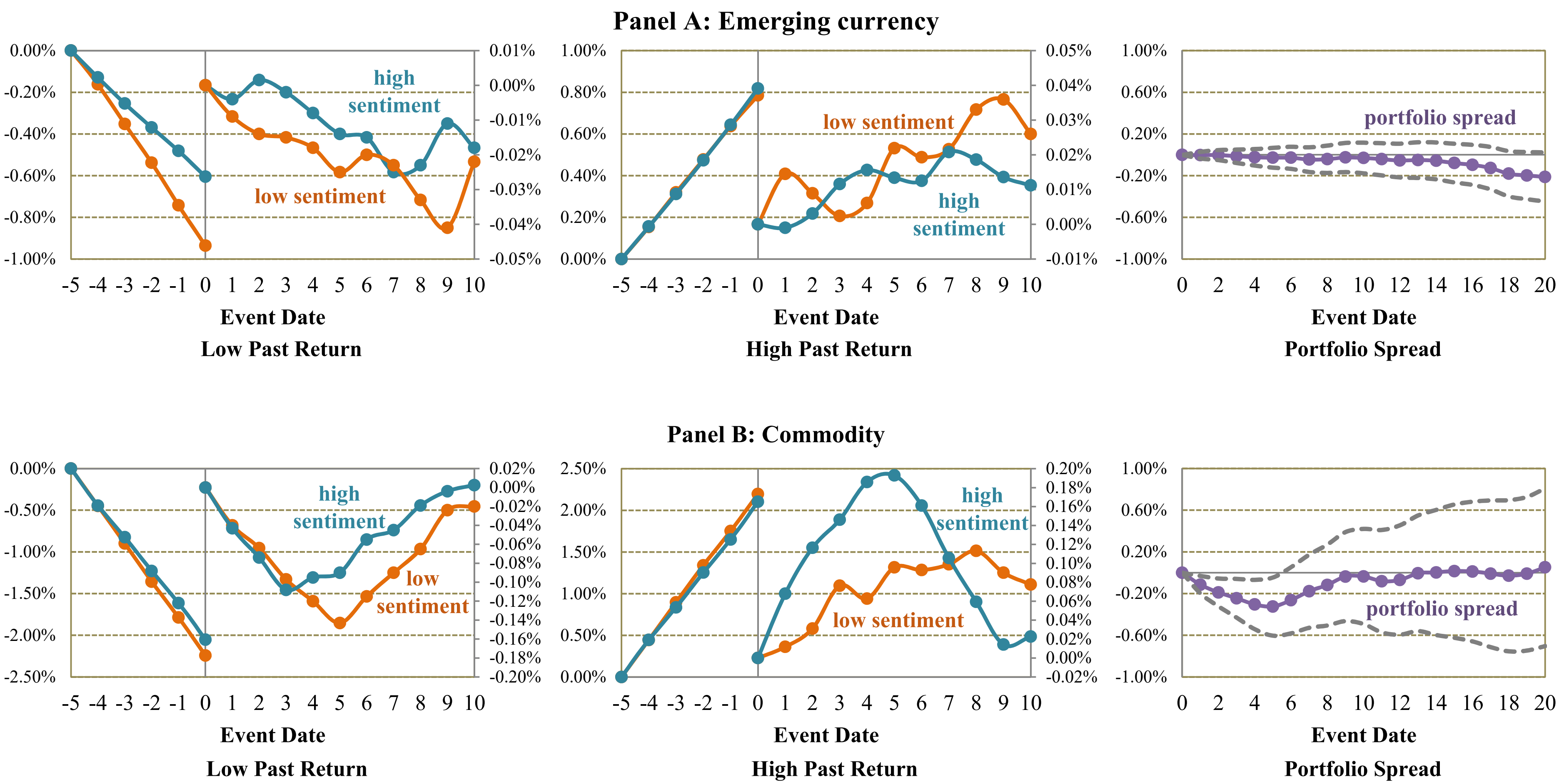


Figure 6. Event time patterns of emerging currencies and commodities. This figure plots the average cumulative excess returns surrounding the formation of portfolios sorted on past return and media sentiment over the past week. Each day assets are first ranked into two groups based on their past-week returns and then, within each group, we further sort the currencies into two groups based on media sentiment scores over the past week. In each row from left to right, we plot the sentiment effect in groups with low past returns, with high past returns, and the cumulative return of the media reinforced strategy that buys losers with low sentiments and sells winners with high sentiments along with the two-standard-error bounds, which are adjusted by the Newey and West (1987). Panel A reports the results in emerging currencies, while Panel B shows the result in commodity market. In currency test, we construct media sentiment score based on currency media coverage. We skip 1 day between the formation and forecast period. The sample is over the period from 2013:01 to 2017:03.