# 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 shock 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.

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 important because recent research (e.g., Chen, De, Hu, and Hwang (2014)) shows that media sources beyond traditional newspapers and newswires also contain important information. Another particular advantage of the diversified media data is that they allow us to distinguish between different types of media sources from overall media coverage 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 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, our media sentiment measure can be considered as an abnormal sentiment score.

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 sentiments and sells past winners with high media sentiments yields approximately 4.8% 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. In less liquid markets, where sentiment information is more episodic, there is likely to be a smaller immediate price move when returns and sentiment agree. The dual-source positive information does eventually get incorporated into prices, but it does so more slowly, leading to initial return underreaction when returns and sentiment agree.

Consistent with this view, we find that the media reinforcement effect is predominantly concentrated among developed country currencies, equities, and large cap firms and firms with high coverage. For example, highly covered firms with high (low) returns and sentiments score over the past week tend to incur (earn) approximately -2.30% (2.33%) per annual in the subsequent ten trading days, with a *t*-statistics of -1.95 (1.68). However, the media reinforcement effect is largely absent within middle- and low-coverage groups.

If investor overreaction towards attention-grabbed reinforced signal is the underlying mechanism,[2] we expect the media reinforcement effect to be stronger among a breadth of individual readerships. Fortunately, the media data for S&P 500 firms provide us types of the media source. We group media articles in to three mutually exclusive categories based on the media source: local, specialist/professional, 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 a significant reinforcement effect only with local media sentiments, supporting our conjecture that the effect is largely driven by individual investors.

Finally, we investigate whether and how media reinforcement effect works in the emerging market. Given the inferior information environment, we expect the reinforced effect either does not work or works in the opposite direction (continuation) in the emerging market. Interestingly, we find emerging currencies exhibit short-term return continuation only when the past return and media sentiment goes in the same direction. The result indicates that investors in the emerging market do react to the reinforced signal, but it seems that they process and absorb the information sluggishly, leading to a return drift in the short-run.

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

[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.

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 concludes.

## 1. Literature Review

Our paper speaks to several strands of research. First, this study contributes to the growing literature on the role and content of media and its impact on 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. 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 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 sentiment as an additional harbinger of overreaction.

This paper also touches on the literature on information dissemination in financial market. Chan (2003) finds that firms that covered by the media experience larger subsequent drift. 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. Our paper adds to this literature by showing that the media reinforcement effect overwhelmingly concentrates in developed markets.

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 matches the formation period asset return, inducing subsequent return reversal. Our result also suggests that attention-grabbing and overreaction biases are mostly due to individuals since the media reinforcement effect is pronounced among local media readerships.

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

## 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 through the period from January 2013 to August 2016. The data is collected daily through various channels from thousands of sources for developed country currencies, equities, 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)). The data also provides us information about the number of positive and negative words for each article. To define positive/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

[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.

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.

Table 1 provides the summary statistics of the media data. Panel A reports the total number of media coverage, average tone of contents of media articles, and standard deviation of article tones of developed country currencies and equity indexes. Note that when measuring the media sentiment score of Euro Zone, we pool all the articles of each individual country within Euro Zone (nine countries in our data) together. As expected, the total number of coverage of the major countries, such as U.S., U.K., and Euro Zone, is substantially higher than that of other countries. For example, U.S. has a total of 103,750 media article mentions, while Israel has only 304 articles over the sample period. The average tone of media content is negative for all countries. U.S. and Israel have the most negative tone of media coverage, while Denmark and Sweden have the least negative tone of media coverage. The standard deviation of article tone is similar across countries, for approximately 0.5.

Panel B of Table 1 reports the sample statistics of individual S&P 500 firms. On average, each firm has approximately 3,558 media coverage with a tone of 0.08 over the sample period. In line with Fang and Peress (2009), when we break down the sample into different size (market capitalization) groups, media coverage is highly skewed towards large-size stocks. The largest 100 U.S. firms have on average more than 9,000 media article mentions, while the smallest 100 of S&P 500 firms have less than 2,000 media coverage over the three and half years. Notably, the media tone is relatively more pessimistic for large firms in contrast to small firms.

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

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

Throughout this paper, the media sentiment score is constructed daily using a weekly rolling weighted moving average, thus contents of media articles in more recent days have more weights:

$$Sentiment_{i,t} = \sum_{j=0}^{4} W_{i,t-j}\Delta Tone_{i,t-j}, \tag{2}$$

where $W_{i,t-j}$ is the weight that decays from 1 to 0.6, with a step of 0.1 each day from day *t* to day *t*-4, and $\Delta Tone_{i,t-j}$ is the log 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 (U.S. dollar as benchmark), 14 developed country equity indexes (18 indexes when we break Euro Zone into individual countries in some analyses), 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.[5]

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.

To align with the media sentiment score, the formation period asset return is 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

[5] Appendix A.1 provides details on each developed country equity index and their sources, which are mainly from Datastream.

skip one day between the formation and forecast periods. By doing so, it also mitigates the effect of the bid-ask bounce.

## 3. Media Reinforcement and Asset Returns

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 Fig. 1, 2, and 3 for developed country currencies, equity indexes, and the largest 100 U.S. individual firms, respectively. Every day for each asset class, 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. To utilize the media data, we construct the sentiment score using media coverage for both currency and equity index.[6]

Cumulative returns during the formation and event periods are plotted. Panel A and B report the effect of media sentiment on past losers (i.e., low past returns) and past winners (i.e.,

[6] In the calendar time portfolio analysis shown in next section, we show that using sentiment scores based on media coverage for either currency or equity index yields qualitatively similar results.

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. Subsequent return reversal only exhibits among past losers (winners) with low (high) media sentiment score over the same period, while the testing period price movement for losers (winners) with high (low) media sentiment is close to zero. These findings hold across asset classes, including currencies, equity indexes, and the largest 100 U.S. individual stocks. For example, currencies whose past returns match the concurrent media sentiment scores experience reversals for approximately 2.27% per annual ten-day after the formation period. However, when media sentiment points to the opposite direction of past return, currency undergoes a minimal return reversal less than 0.5% per annual ten-day post the formation period.

In Panel C, we report the cumulative profit 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 a lag of nine days. Across all asset classes, the media-reinforced strategy yields a statistically and economically significant abnormal return of 0.2% (or 4.8% per annual) after ten trading days, and its abnormal return gradually reverses over 50% of the initial profit 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 financial market.

### 3.2. FX/Country Equity Portfolio Analysis

With the event time findings 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 $\tau$---one formed in day $\tau$-1, one formed in day $\tau$ -2, and so on. The return in day $\tau$ 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 effect of media sentiment on currency and equity index return autocorrelation 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 based on the media coverage for both currency and country equity. For a more in-depth analysis, we measure sentiment score using different combinations of media sources. Panel A of Table 2 shows the result using sentiment score constructed solely on media coverage for currency. As the result shows, when currencies experience low (high) return with aligned media sentiment over the past week, it yields (incurs) 1.86% (-2.03%) annualized return in the following ten trading days, with a *t*-statistics of 1.71 (-2.06). However, when past 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 0.95% (-0.78%) annualized subsequent ten-day return, with insignificant *t*-statistics of 0.90 (-0.82). The spread of winner with high sentiment minus loser with low sentiment amounts to -3.89% (*t*-stat: -1.95), while the unconditional strategy that winner minus loser only generates a spread of -2.34% (*t*-stat: -1.56), and the unconditional strategy that high sentiment minus low sentiment has a minimal spread of 0.10% (*t*-stat: 0.10). The finding suggests that investors independent response to individual signals is overwhelmed by the response to reinforced signals.

Furthermore, the results show that media sentiment score constructed on currency media coverage also displays significant effect on other correlated asset classes, such as local-currency-denominated- and USD-denominated-equity indexes. For example, when both return and media sentiment are negative (positive) over the past week, local-currency-denominated country equities yield (incur) 2.93% (-2.38%) annualized return in the subsequent ten-day, with a *t*-statistics of 2.32 (-1.78). 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 -5.32% (*t*-stat: -2.28), which is more than twice as the spread of the single-sort return reversal strategy with approximately -2.59% (*t*-stat: -1.42).

In Panel B of Table 2, the result with media sentiment score constructed from country equity media coverage shows mixed evidence. Surprisingly, in the FX market the media reinforcement effect is at work when the point at the opposite direction. The spread of winner with high sentiment minus loser with low sentiment is insignificant at -2.83 (*t*-stat: -1.33). In addition, while the past country equity winners with high media sentiments exhibit significant subsequent reversals for approximately 3.87% (*t*-stat: -2.13), the past losers with low media sentiments yield insignificant reversals for about 1.45 (*t*-stat: 0.72).[7] The result of USD-denominated country equities indicates a clear media reinforcement effect. Losers (winners) with high (low) past media sentiment scores experience approximately 3.01% (-4.60%) annualized subsequent ten-day return, with a *t*-statistics of 1.65 (-2.39). The spread of winners with high sentiments minus losers with low sentiments amounts to -7.61% (*t*-stat: -2.31).

Panel C of Table 2 displays the result using sentiment score constructed from both currency and equity indexes media coverage. The 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). The spread of winner with high sentiment minus loser with low sentiment in currencies, local-currency-denominated-, and USD-denominated-equity indexes is -4.81% (*t*-stat: -2.39), -5.19% (*t*-stat: -2.07), and -5.63% (*t*-stat: -2.34), respectively. Summing up the results from all panels, we find statistically and economically significant media reinforcement effect in seven of out nine scenarios,

[7] However, the untabulated analysis shows that there is a significant media reinforcement effect when past return and sentiment are low if we use a bi-weekly formation horizon. This suggests that investors may present differential sensitivity and processing time towards information from differential media sources.

suggesting that investor over-reaction is intensified when the media sentiment matches the formation period return. For brevity, we use sentiment score based on both currency and country equity media articles in the rest of the paper, given that it provides the richest sources of media coverage.

### 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. From the summary statistics, we document that firm size has an overwhelming effect on media coverage: large firms are much more likely to be covered. Therefore, we examine the media reinforcement effect by partitioning the sample into different size groups.

Panel A of Table 3 investigates the media effect among the largest 100 U.S. individual firms. The result clearly indicates that the media reinforcement effect exhibits in the cross-section of large cap stocks. Firms with high (low) returns and sentiment scores over the past week tend to incur (earn) approximately -2.92% (2.54%) per annual in the subsequent ten trading days, with a *t*-statistics of -2.82 (2.38). The media reinforced strategy that longs losers with low sentiments and shorts winners with high sentiments profits about 5.46% (*t*-stat: 2.78), which is substantially higher than the profitability of a strategy solely based on a single signal of either return or media sentiment.

Interestingly, when we examine the media effect on the rest S&P 500 firms or S&P 500 stocks as a whole in Panel B and C of Table 3, we do not observe a significant media reinforcement effect. The fact that the media reinforcement is concentrated in the large cap stocks contradicts to

Fang and Peress (2009), in which they find that no-coverage premium is strongest among small stocks. Evidence shown in their paper suggest that no-coverage premium is mainly due to stock illiquidity and risk compensation for imperfect diversification, while our finding implies that investor trading activities are significantly amplified when investors' attention is grabbed by the return-media-sentiment reinforced signal. Consistent with this view, Barber and Odean (2008) shows 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. To test this hypothesis, we partition S&P 500 individual firms based on the total number of media coverage during the formation week. We restrict our analysis among a sample of firms with non-zero (i.e., positive) media coverage over the past week since during weeks with no media coverage investors either have no media content to refer to or can only infer from stale information from previous coverage, which may induce substantial estimation noise.[8] Therefore, we divide the non-zero coverage sample into three coverage groups: high coverage, middle coverage, and low coverage, and test the relationship between media reinforcement effect and level of media coverage.

As shown in the Table 4, the media reinforcement effect is predominantly concentrated among firm with high coverage. Highly covered firms with high (low) returns and sentiments score

[8] In an untabulated analysis, we find that the result of zero-coverage group is similar to that of low-coverage group, which does not display a significant media reinforcement effect.

over the past week tend to incur (earn) approximately -2.30% (2.33%) per annual in the subsequent ten trading days, with a *t*-statistics of -1.95 (1.68). However, the media reinforcement effect is largely absent within middle- and low-coverage groups. This finding is consistent with our conjecture that investors respond to large price movement and matched media sentiment only if these firms are extensively covered in the media.

### 3.4. Performance of Media Reinforced Strategy

To investigate the media reinforcement effect over time, we form the long-short portfolios in each of the three asset classes. Using the same method, every day for each asset class 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 returns and low sentiments and shorts instruments with high returns and high sentiments. Repeating this every day yields a time series of returns for this zero-investment portfolio. Panel A, B, and C of Fig. 4 plots the cumulative returns to the media reinforced strategy in developed country currencies, equities, and the largest 100 U.S. stocks, 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 sample. The annualized Sharpe ratio of the strategy profit in developed country currencies, equities, and individual stocks is 1.10, 0.89, and 1.43, respectively. Notably, during the first three months of 2015 the media reinforced strategy in currencies and equity indexes performs poorly. The underperformance may coincide with the oil price collapse and political uncertainty between Russia and Ukraine around that time period. Panel D of Fig. 4 reports the time-series performance of the volatility-weighted portfolio by aggregating individual time-series strategy in each of the 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 4.62% per annual and an annualized Sharpe ratio of 1.72.

To evaluate the abnormal performance of the media reinforced strategy, we regress the time-series strategy returns on factors known to affect the cross-sectional of returns in different asset markets. The factors we control for are daily Fama and French (1993) three factors (MKT, SMB, and HML) and momentum factor (MOM). For currencies and country equities, we use the corresponding global factors.[9] To account for the carry trade effect, we construct two common risk factors building daily portfolio of currencies sorted on their forward discounts following Lustig, Roussanov, and Verdelhan (2011).

Panel A of Table 5 reports results in FX market. The second model considers global Fama-French three factors and momentum factor. The loadings on all the risk factors are insignificant. In the third row, we further add two carry trade factors into the model. The negative and significant

[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.

coefficient on MKT and positive and significant coefficient on DOL indicate that the media reinforced strategy in currencies has a negative exposure to the market, and a positive exposure to the dollar risk (driven by the fluctuation of the U.S. dollar against a broad basket of currencies). Nevertheless, in both cases the media reinforced strategy delivers a large and significant alpha or intercept for approximately 4.19% (4.66%) per annual with respect to models with four (six) factors, with a *t*-statistics of 2.01 (2.30).

Panel B of Table 5 repeats the regression in country equity market. Once again, the alpha of the strategy is still an impressive 4.60% per annual (*t*-stat: 1.78), after controlling for the four risk factors. Interestingly, the media reinforced strategy positively load on HML factor, suggesting that the strategy exposes to value equities. Panel C and D of Table investigate the media reinforced strategy for U.S. 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 among individual stocks. In Panel C, the strategy based on the largest 100 U.S. stocks earns an annualized alpha of 5.19% (*t*-stat: 2.58). In Panel D, we focus on the strategy based on the highly covered S&P 500 firms, and find a significant alpha of 4.46% (*t*-stat: 1.82).

### 3.5. Fama-MacBeth Regressions

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 is low and sentiment score is 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 is high and sentiment score is high, and zero otherwise. Then we multiply the past-week return (in excess of the cross-sectional mean) with each of the four dummy variables. 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). By doing so, we are able to examine the return reversal pattern in each scenario.

Table 6 reports the regression result for developed country currencies and equities. We first examine the unconditional return reversal effect by running the regression of future ten-day return on past-week return. In both markets, the developed country instruments exhibit significant return reversal. Next, we test the media reinforcement 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. In both currencies and equities, when past returns and past media sentiments are both high, investors overreact to this joint signal, inducing significant return reversals in the short-term. Specifically, the coefficient of *Past_ret*×*HRHS_D* is -0.12 (-0.10) for currencies (equities), with a *t*-statistics of -2.09 (-2.23). Equities with low past returns and media sentiments exhibits similar pattern as for those with high past returns and media sentiments. The coefficient of *Past_ret*×*LRLS_D* is -0.10, with a *t*-statistics of -1.78.  However, the low return case in currencies provides mixed evidence. The coefficient of

*Past_ret*×*LRLS_D* is insignificant at -0.06, indicating that the investors' response to past return is not monotonic among currency losers even with a media reinforced signal.

Then we turn to S&P 500 individual firms. Panel A of Table 7 repeats the regression models with different size groups. Consistent with the prior portfolio finding, the media reinforcement effect is concentrated in the largest 100 U.S. individual stocks. When both returns and media sentiments are high (low), investors overreact to this joint signal, inducing significant return reversal in the short-term. Specifically, the coefficient of *Past_ret*×*HRHS_D* (*Past_ret*×*LRLS_D*) is -0.05 (-0.06), with a *t*-statistics of -2.30 (-2.44). In addition to the basic findings, another interesting observation is that the return reversal only happens in the largest 100 U.S. stocks, and is fully subsumed by our media reinforcement effect. In Panel B of Table 7, we run regression by partitioning the S&P 500 firms based on media coverage over the past week. In line with the portfolio analysis, media reinforcement effect is absent among stocks with middle or low media coverage. Among highly covered firms, investors overreact to the joint signal when both return and media sentiment are high, inducing significant return reversal in the short-term. The coefficient of *Past_ret*×*HRHS_D* is -0.04, with a *t*-statistics of -1.87. Once again, asymmetric media reinforcement effect is exhibited that the return reversal pattern among negative reinforced scenario is insignificant at 0.02.

One possible explanation for this asymmetric response between positive and negative return scenarios is that the joint effect of disposition effect on low return side and overconfidence effect on high return side. That is, investors are reluctant to sell the losers immediately to incur wealth losses even when the media sentiment is only pessimistic, while investors who hold the winners become less risk averse (more willing to cumulate positions) especially when the media sentiment confirms with the past return. If that is the case, investors who hold the losers tend to react to a less extent as opposed to those who hold the winners.

### 3.6. Differential Effect across Media Types

Our findings indicate that the media reinforcement effect is pronounced and prevalent in the financial market, which can be due to investor overreaction to attention-grabbing signals from both market (return) and media (sentiment). If this hypothesis holds, naturally we expect to observe the reinforcement phenomenon concentrated among individual investors. As argued in Barber and Odean (2008), individual investors face cognitive limits to process 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. In addition, individuals are more likely to over-react to these attention-grabbing signals in contrast to their institutional counterparts due to severe psychological bias.

Fortunately, the media data for S&P 500 firms provides us detailed information regarding the types of the media source, allowing us to investigate this hypothesis in depth. Generally, a typical media article can be grouped in to three mutually exclusive categories based on the media source: local media outlets, specialist/professional media outlets, and firm initiated media coverage (e.g., PR and news service). We then construct three measures of media sentiment scores based on different types of media sources. 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. Therefore, to minimize the errors due to no coverage (but may confound with non-zero coverage for other media types), we restrict our sample into the largest 100 U.S. firms with positive coverage for a specific media type over the past week. Then we run the Fama and MacBeth (1973) regressions separately for each media sentiment measure using the same models in Table 7.

The result shown in Table 8 supports our conjecture that the media reinforcement effect is largely driven by the individual investors. Using the sentiment score constructed from local media outlets, we find a significant reinforcement effect. When return and media sentiment are both high (low), investors overreact to this joint signal, inducing a significant return reversal in the short-term. Specifically, the coefficient of $Past\_ret \times HRHS\_D$ ($Past\_ret \times LRLS\_D$) is -0.04 (-0.06), with a *t*-statistics of -1.94 (-2.54). However, using the media sentiment constructed from specialist/professional or firm initiated media coverage, we do not find the media reinforcement effect is at work. One caveat of this 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. This is a sensible argument since institutions usually process information from their proprietary channels, specialized sources (such specialist/professional media sources), or communication directly with firms (PR and new service), while the local media outlets are to reach out a broad readership of individuals.

### 3.7. Media Effect in Emerging Market

So far, we have focused our analysis in the developed market. 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 and regression test using the data for emerging markets. After taking out the countries that do not have sufficient number of media coverage, we retain a sample of 16 emerging currencies (15 emerging country equities since we do not have equity index for Nigeria). We then obtain the corresponding emerging country currency data from Thomson Reuters World Market, and local-currency-denominated equity index prices from Datastream.[10] Panel A of Table 9 shows the calendar time portfolio result in emerging currency market. Interestingly, in contrast to developed currencies, emerging currencies exhibit short-term return continuation. That is, the spread of winner minus loser amounts to approximately 6.65% (*t*-stat: 3.42). A more striking finding is that 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) 4.94% (-3.97%)

[10] Appendix A.2 provides details on each emerging country equity index and their sources, which are mainly from Datastream.

annualized return in the subsequent ten-day, with a *t*-statistics of 2.45 (-2.47). 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 do react to the joint signal of return and media sentiment, but it seems that they process and absorb the information sluggishly, leading to a return drift in the short-run. Panel B of Table 9 reports the result in emerging country equity market. In contrast to the currency counterparts, the emerging country equity market does not exhibit either return reversal or return continuation. Furthermore, the media reinforcement effect does not work at all.

In Table 10, we then turn to the Fama and MacBeth (1973) regressions, and find consistent results with those shown in portfolio analysis. When return and media sentiment are both high (low), investors in emerging currency market underreact to this joint signal, inducing a significant return continuation in the short-term. Specifically, the coefficient of *Past_ret*×*HRHS_D* (*Past_ret*×*LRLS_D*) is 0.25 (0.17), with a *t*-statistics of 4.08 (2.56). Once again, the regression indicates that investors in emerging country equity market do not react to return movement, media sentiment, or return-sentiment joint signal.

## 4. 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, 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 actively 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

## A.1. Developed Country Equities

This table provides a list of the universe of 14 developed country equity indexes obtained from Datastream. Information for both local-currency-denominated- and USD-denominated-country equities is provided. The sample period is from 2013:01 to 2016:08.

| Country | Local-currency-denominated Equity Index | USD-denominated Equity Index |
|---|---|---|
| Australia | ASX 200 | FTSE |
| Canada | TSX | FTSE |
| Denmark | OMXC 20 | FTSE |
| Euro Zone | STOXX 50 | Dow Jones |
| Hong Kong | Hang Seng | FTSE |
| Israel | TA 100 | FTSE |
| Japan | Nikkei 225 | FTSE |
| New Zealand | NZX 50 | FTSE |
| Norway | Olso Exchange All Share | FTSE |
| Singapore | Straits Times Index | Dow Jones |
| Sweden | OMXS 30 | FTSE |
| Switzerland | Swiss Market (SMI) | FTSE |
| U.K. | FTSE 100 | FTSE |
| U.S. | S&P 500 | S&P 500 |

## A.2. Emerging Country Equities

This table provides a list of the universe of 15 emerging country equity indexes obtained from Datastream. Information for both local-currency-denominated- and USD-denominated-country equities is provided. The sample period is from 2013:01 to 2016:08.

| Country | Local-currency-denominated Equity Index | USD-denominated Equity Index |
|---|---|---|
| Argentina | Merval | FTSE |
| Brazil | Bovespa | FTSE |
| China | Shanghai SE A Share | FTSE |
| Colombia | IGBC | FTSE |
| Egypt | Hermes | FTSE |
| India | Nifty 500 | FTSE |
| Indonesia | IDX | FTSE |
| Mexico | Bolsa | Dow Jones |
| Malaysia | FTSE Bursa | FTSE |
| Philippines | PSEi | Dow Jones |
| Poland | WIG | Dow Jones |
| Russia | RTS | FTSE |
| South Africa | FTSE JSE | FTSE |
| Thailand | S.E.T | Dow Jones |
| Turkey | BIST National 100 | FTSE |

## Table 1: Summary Statistics

This table summarizes the descriptive statistics of media variables. Panel A reports the total number of media coverage, average media article tone, and standard deviation of article tone of developed country currencies and country equity indexes. Panel B reports the average total number of media coverage across S&P 500 individual firms and daily average of cross-sectional summary statistics of media variables for S&P 500 individual stocks. Summary statistics for S&P 500 stocks with different size groups are also reported. The sample period is from 2013:01 to 2016:08.

**Panel A: FX and Country Equity Media**

| Country | Currency Code | Total # Articles | Mean Tone | Std Dev Tone |
|---|---|---|---|---|
| Australia | AUD | 14,026 | -0.21 | 0.45 |
| Canada | CAD | 18,210 | -0.14 | 0.46 |
| Denmark | DKK | 492 | -0.10 | 0.51 |
| Euro Zone | EUR | 76,052 | -0.22 | 0.49 |
| Hong Kong | HKD | 18,626 | -0.25 | 0.44 |
| Israel | ILS | 304 | -0.27 | 0.43 |
| Japan | JPY | 18,430 | -0.18 | 0.49 |
| New Zealand | NZD | 7,004 | -0.15 | 0.46 |
| Norway | NOK | 1,143 | -0.27 | 0.46 |
| Singapore | SGD | 9,628 | -0.13 | 0.45 |
| Sweden | SEK | 951 | -0.11 | 0.51 |
| Switzerland | CHF | 6,799 | -0.24 | 0.47 |
| U.K. | GBP | 40,162 | -0.21 | 0.49 |
| U.S. | USD | 103,570 | -0.29 | 0.48 |

**Panel B: S&P 500 Firms**

| Size Groups | Total # Articles Per | Daily Average of Cross-Sectional Summary of Sentiment | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Firm | Mean | Std Dev | Min | 25th Pctl | Median | 75th Pctl | Max |
| <=100 | 9,416 | 0.04 | 0.29 | -0.73 | -0.14 | 0.03 | 0.21 | 0.82 |
| 100-200 | 3,091 | 0.04 | 0.38 | -0.83 | -0.20 | 0.04 | 0.28 | 0.88 |
| 200-300 | 2,591 | 0.08 | 0.40 | -0.84 | -0.17 | 0.09 | 0.34 | 0.90 |
| 300-400 | 2,290 | 0.08 | 0.41 | -0.83 | -0.18 | 0.09 | 0.35 | 0.90 |
| >400 | 1,854 | 0.09 | 0.41 | -0.88 | -0.16 | 0.10 | 0.35 | 0.93 |
| All Firms | 3,558 | 0.08 | 0.10 | -0.28 | 0.02 | 0.06 | 0.30 | 0.99 |

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

This table reports the 10-day calendar-time portfolio returns based on past returns and media sentiments. Each day developed country currencies (local-currency-denominated- or USD-denominated-equities) 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 (local-currency-denominated- or USD-denominated-equities) returns over the past week. *Sentiment* is the log changes of daily media tone relative to past four same day-of-the-week averages, then weighted sum over the past week. Panel A reports results using sentiment score calculated based on currency media coverage. Panel B exhibits results using sentiment score calculated based on country equity media coverage. Panel C displays results using sentiment score calculated based on both currency and country equity media coverage. Developed countries include Australia, Canada, Euro Zone, Hong Kong, Japan, New Zealand, Norway, Sweden, Singapore, Switzerland, UK, and USA. When analyzing currency returns, we drop USA and Hong Kong. In addition, when analyzing country equity return using sentiment score based on country equity media coverage, we break Euro Zone into individual countries. 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 2016:08.

| Panel A: Forecasting Using Currency Media Coverage | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Return=FX | | | Country Equity | | | USD-denominated Country Equity | | |
| Sentiment | Past Return | | | Past Return | | | Past Return | | |
| | Low | High | Single-sort Spread | Low | High | Single-sort Spread | Low | High | Single-sort Spread |
| Low | 1.86 | -0.78 | -2.34 | 2.93 | -0.20 | -2.59 | 3.05 | 0.24 | -3.69 |
| | [1.71] | [-0.82] | [-1.56] | [2.32] | [-0.14] | [-1.42] | [2.00] | [0.17] | [-2.13] |
| High | 0.95 | -2.03 | | -0.35 | -2.38 | | 0.92 | -3.16 | |
| | [0.90] | [-2.06] | | [-0.35] | [-1.78] | | [0.64] | [-2.74] | |
| Single-sort | 0.10 | | -3.89 | -1.95 | | -5.32 | -2.40 | | -6.22 |
| Spread | [0.10] | | [-1.95] | [-1.18] | | [-2.28] | [-1.31] | | [-2.57] |

**Table 2-***Continued*

| Panel B: Forecasting Using Country Equity Media Coverage | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Return=FX | | | Country Equity | | | USD-denominated Country Equity | | |
| Sentiment | Past Return | | | Past Return | | | Past Return | | |
| | | | Single-sort | | | Single-sort | | | Single-sort |
| | Low | High | Spread | Low | High | Spread | Low | High | Spread |
| Low | 1.78 | -3.13 | -4.41 | 1.45 | 0.30 | -3.58 | 3.01 | 0.15 | -4.85 |
| | [1.47] | [-2.88] | [-2.74] | [0.72] | [0.15] | [-1.17] | [1.65] | [0.08] | [-1.66] |
| High | 2.64 | -1.05 | | 2.16 | -3.87 | | 2.24 | -4.60 | |
| | [2.28] | [-0.82] | | [0.90] | [-2.13] | | [0.87] | [-2.39] | |
| Single-sort | 1.57 | | -2.83 | -1.61 | | -5.31 | -1.70 | | -7.61 |
| Spread | [1.29] | | [-1.33] | [-1.02] | | [-1.72] | [-0.91] | | [-2.31] |

| Panel C: Forecasting Using Currency and Country Equity Media Coverage | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Return=FX | | | Country Equity | | | USD-denominated Country Equity | | |
| Sentiment | Past Return | | | Past Return | | | Past Return | | |
| | | | Single-sort | | | Single-sort | | | Single-sort |
| | Low | High | Spread | Low | High | Spread | Low | High | Spread |
| Low | 2.34 | -0.35 | -2.34 | 3.09 | -0.36 | -2.71 | 3.13 | -1.64 | -4.26 |
| | [1.93] | [-0.34] | [-1.56] | [2.06] | [-0.25] | [-1.44] | [1.99] | [-1.11] | [-2.51] |
| High | 0.47 | -2.46 | | 0.06 | -2.10 | | 1.38 | -2.50 | |
| | [0.42] | [-2.39] | | [0.05] | [-1.68] | | [1.07] | [-2.21] | |
| Single-sort | -0.67 | | -4.81 | -2.20 | | -5.19 | -2.05 | | -5.63 |
| Spread | [-0.63] | | [-2.39] | [-1.40] | | [-2.07] | [-1.15] | | [-2.34] |

## Table 3: Calendar-Time Portfolio Return, Individual Firms

This table reports the 10-day calendar-time portfolio returns based on past returns and media sentiments, at different size levels. Each day 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 log changes of daily media tone relative to past four same day-of-the-week averages, then weighted sum over the past week. Panel A reports results of largest 100 U.S. firms based on the market capitalization as of the end of 2012. Panel B exhibits results for the rest S&P 500 firm. Panel C displays results by including all 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 2016:08.

| Sentiment | Past Return | | |
|---|---|---|---|
| | Low | High | Single-sort Spread |
| | Panel A: Largest 100 Firms | | |
| Low | 2.54 | -0.66 | -3.54 |
| | [2.38] | [-0.65] | [-2.21] |
| High | 1.11 | -2.92 | |
| | [1.01] | [-2.82] | |
| Single-sort | -2.02 | | -5.46 |
| Spread | [-2.01] | | [-2.78] |
| | Panel B: The Rest Firms | | |
| Low | 1.82 | -0.79 | -1.57 |
| | [1.58] | [-0.67] | [-0.75] |
| High | -0.22 | -0.84 | |
| | [-0.18] | [-0.74] | |
| Single-sort | -1.22 | | -2.66 |
| Spread | [-1.32] | | [-1.20] |
| | Panel C: All Firms | | |
| Low | 1.79 | -0.66 | -1.78 |
| | [1.71] | [-0.61] | [-0.92] |
| High | -0.01 | -1.12 | |
| | [-0.01] | [-1.08] | |
| Single-sort | -1.29 | | -2.91 |
| Spread | [-1.65] | | [-1.44] |

## Table 4: Calendar-Time Portfolio Return, Media Coverage on Individual Firms

This table reports the 10-day calendar-time portfolio returns based on past returns and media sentiments, at different media coverage levels. Each day we divide our sample of S&P 500 individual firms with non-zero media coverage over the past week into three groups: high coverage, middle coverage, and low coverage. Within in each media-coverage portfolio, we sort firms 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 log changes of daily media tone relative to past four same day-of-the-week averages, then weighted sum over the past week. Results of high-, middle-, and low-coverage groups are shown in Panel A, B, and C, respectively. 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 2016:08.

| Sentiment | Past Return | | |
|---|---|---|---|
| | Low | High | Single-sort Spread |
| | Panel A: High Coverage Group | | |
| Low | 2.33 | -0.74 | -2.65 |
| | [1.68] | [-0.59] | [-1.20] |
| High | 0.76 | -2.30 | |
| | [0.63] | [-1.95] | |
| Single-sort | -1.79 | | -4.63 |
| Spread | [-1.56] | | [-1.88] |
| | Panel B: Middle Coverage Group | | |
| Low | 1.28 | -1.28 | -2.06 |
| | [1.05] | [-1.08] | [-1.00] |
| High | 0.78 | -0.78 | |
| | [0.70] | [-0.65] | |
| Single-sort | -0.04 | | -2.07 |
| Spread | [-0.04] | | [-0.89] |
| | Panel C: Low Coverage Group | | |
| Low | 0.48 | -1.40 | -1.53 |
| | [0.46] | [-1.47] | [-0.87] |
| High | 1.05 | -0.13 | |
| | [1.05] | [-0.12] | |
| Single-sort | 0.96 | | -0.61 |
| Spread | [1.15] | | [-0.31] |

## Table 5: Performance of Media Reinforced Strategy

This table reports results of time series regressions of daily return of media reinforced strategy that buys losers with low sentiments and sells winners with high sentiments on various risk factors in three asset markets. Panel A reports the results of FX 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 local-currency-denominated country equities, where Fama and French global factors (MKT, SMB, HML, and MOM) are included. Panel C reports the result of largest 100 U.S. firms, where Fama and French U.S. factors (MKT, SMB, HML, and MOM) are included. Panel D reports the result of highly covered S&P 500 firms, where Fama and French U.S. factors are included. In currency and country equity tests, we construct media sentiment score based on media coverage for both currencies and equities. 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 2016:08.

| Model | Intercept | MKT | SMB | HML | MOM | DOL | FXHML |
|---|---|---|---|---|---|---|---|
| | | | Panel A: FX (Global Factors) | | | | |
| (1) | 4.81 | | | | | | |
| | [2.39] | | | | | | |
| (2) | 4.19 | -0.02 | -0.03 | -0.03 | 0.01 | | |
| | [2.01] | [-1.45] | [-1.07] | [-0.75] | [0.32] | | |
| (3) | 4.66 | -0.03 | -0.05 | -0.04 | 0.01 | 0.09 | 0.01 |
| | [2.30] | [-1.90] | [-1.49] | [-1.00] | [0.31] | [2.41] | [0.32] |
| | | | Panel B: Country Equity (Global Factors) | | | | |
| (1) | 5.19 | | | | | | |
| | [2.07] | | | | | | |
| (2) | 4.60 | -0.01 | -0.07 | 0.12 | 0.01 | | |
| | [1.78] | [-0.47] | [-1.62] | [2.21] | [0.19] | | |
| | | | Panel C: Largest 100 Firms (U.S. Factors) | | | | |
| (1) | 5.46 | | | | | | |
| | [2.78] | | | | | | |
| (2) | 5.19 | 0.01 | -0.03 | -0.00 | -0.00 | | |
| | [2.58] | [1.23] | [-1.31] | [-0.14] | [-0.13] | | |
| | | | Panel C: Highly Covered S&P 500 Firms (U.S. Factors) | | | | |
| (1) | 4.63 | | | | | | |
| | [1.88] | | | | | | |
| (2) | 4.46 | 0.03 | -0.02 | 0.02 | -0.01 | | |
| | [1.82] | [1.91] | [-0.68] | [0.61] | [-0.29] | | |

## Table 6: Fama-MacBeth Regressions, FX/Country Equity

This table reports the Fama and MacBeth (1973) regressions of forecasting developed country currency (equity) returns based on past returns and media sentiments. Each day developed country currencies (equities) are first ranked into two groups based on their past-week return and then, within each group, we further sort the instruments into two groups based on media sentiment scores over the past week. We assign 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 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. *Past_ret* 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. Developed countries include Australia, Canada, Euro Zone, Hong Kong, Japan, New Zealand, Norway, Sweden, Singapore, Switzerland, UK, and USA. When analyzing currency returns, we drop USA and Hong Kong. We construct media sentiment score based on media coverage for both currencies and country equities. We skip 1 day between the formation and forecast period. The coefficients are 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 2016:08.

| Forecast Return=10-day | (1) FX | | (2) Country Equity | |
|---|---|---|---|---|
| Past_ret | -0.09 | | -0.06 | |
| | [-2.01] | | [-1.71] | |
| Past_ret× LRLS_D | | -0.06 | | -0.10 |
| | | [-0.70] | | [-1.79] |
| Past_ret× LRHS_D | | -0.08 | | -0.04 |
| | | [-1.11] | | [-0.86] |
| Past_ret× HRLS_D | | 0.00 | | 0.09 |
| | | [0.04] | | [1.34] |
| Past_ret× HRHS_D | | -0.12 | | -0.10 |
| | | [-2.09] | | [-2.23] |

## Table 7: Fama-MacBeth Regressions, Individual Firms

This table reports the Fama and MacBeth (1973) regressions of forecasting S&P 500 individual firm returns based on past returns and media sentiments, at different size and coverage levels. Each day 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. We assign four dummy variables to each of the two-by-two scenarios: *LRLS_D* equals one if the stock's past return and sentiment score are both low, and zero otherwise; *LRHS_D* equals one if the stock's past return is low and sentiment score is high, and zero otherwise; *HRLS_D* equals one if the stock's past return is high and sentiment score is low, and zero otherwise; *HRHS_D* equals one if the stock's past return and sentiment score are both high, and zero otherwise. *Past_ret* is the cumulative stock 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. The size ranking is determined by the market capitalization as of the end of 2012. S&P 500 Firms with non-zero media coverage over the past week are divided into three groups: high coverage, middle coverage, and low coverage. We skip 1 day between the media formation and forecast period. The coefficients are 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 2016:08.

| Panel A: Size Grouping | | | | | | |
|---|---|---|---|---|---|---|
| Forecast Return=10-day | (1) Largest 100 Firms | | (2) Rest Firms | | (3) S&P 500 Firms | |
| Past_ret | -0.04 | | 0.00 | | -0.00 | |
| | [-2.11] | | [0.12] | | [-0.09] | |
| Past_ret× LRLS_D | | -0.06 | | 0.01 | | 0.01 |
| | | [-2.44] | | [0.44] | | [0.24] |
| Past_ret× LRHS_D | | -0.02 | | 0.03 | | 0.03 |
| | | [-0.70] | | [1.01] | | [0.88] |
| Past_ret× HRLS_D | | -0.02 | | -0.03 | | -0.03 |
| | | [-0.80] | | [-1.68] | | [-1.81] |
| Past_ret× HRHS_D | | -0.05 | | -0.01 | | -0.02 |
| | | [-2.30] | | [-0.89] | | [-0.97] |
| Panel B: Coverage Grouping | | | | | | |
| Forecast Return=10-day | (1) High Coverage | | (2) Middle Coverage | | (3) Low Coverage | |
| Past_ret | -0.01 | | -0.00 | | -0.01 | |
| | [-0.60] | | [-0.18] | | [-0.68] | |
| Past_ret× LRLS_D | | 0.02 | | -0.00 | | -0.01 |
| | | [1.01] | | [-0.06] | | [-0.24] |
| Past_ret× LRHS_D | | -0.01 | | 0.02 | | -0.01 |
| | | [-0.25] | | [0.79] | | [-0.51] |
| Past_ret× HRLS_D | | -0.02 | | -0.02 | | -0.04 |
| | | [-1.39] | | [-1.00] | | [-1.79] |
| Past_ret× HRHS_D | | -0.04 | | -0.01 | | -0.00 |
| | | [-1.87] | | [-0.51] | | [-0.15] |

## Table 8: Fama-MacBeth Regressions, Media Types

This table reports Fama and MacBeth (1973) regressions of forecasting largest 100 U.S. individual firm returns based on past returns and media sentiments. Each day 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. We assign four dummy variables to each of the two-by-two scenarios: *LRLS_D* equals one if the stock's past return and sentiment score are both low, and zero otherwise; *LRHS_D* equals one if the stock's past return is low and sentiment score is high, and zero otherwise; *HRLS_D* equals one if the stock's past return is high and sentiment score is low, and zero otherwise; *HRHS_D* equals one if the stock's past return and sentiment score are both high, and zero otherwise. *Past_ret* is the cumulative stock 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. The size ranking is determined by the market capitalization as of the end of 2012. We construct media sentiment score based on three mutually exclusive sources of media coverage: local media outlets, specialist/professional media outlets, and firm initiated media (PR and news services). We restrict firm-day observations with positive coverage over the past week. We skip 1 day between the formation and forecast period. The coefficients are 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 2016:08.

| Forecast Return=10-day | (1) Local | | (2) Specialist/Professional | | (3) PR and News Service | |
|---|---|---|---|---|---|---|
| Past_ret | -0.04 | | -0.03 | | -0.06 | |
| | [-2.05] | | [-1.27] | | [-2.15] | |
| Past_ret× LRLS_D | | -0.06 | | -0.01 | | -0.02 |
| | | [-2.54] | | [-0.13] | | [-0.58] |
| Past_ret× LRHS_D | | -0.03 | | -0.01 | | -0.08 |
| | | [-0.89] | | [-0.35] | | [-1.77] |
| Past_ret× HRLS_D | | -0.03 | | 0.02 | | -0.04 |
| | | [-1.18] | | [0.50] | | [-0.96] |
| Past_ret× HRHS_D | | -0.04 | | -0.02 | | -0.09 |
| | | [-1.94] | | [-0.61] | | [-1.16] |

## Table 9: Calendar-Time Portfolio Return, Emerging FX/Country Equity

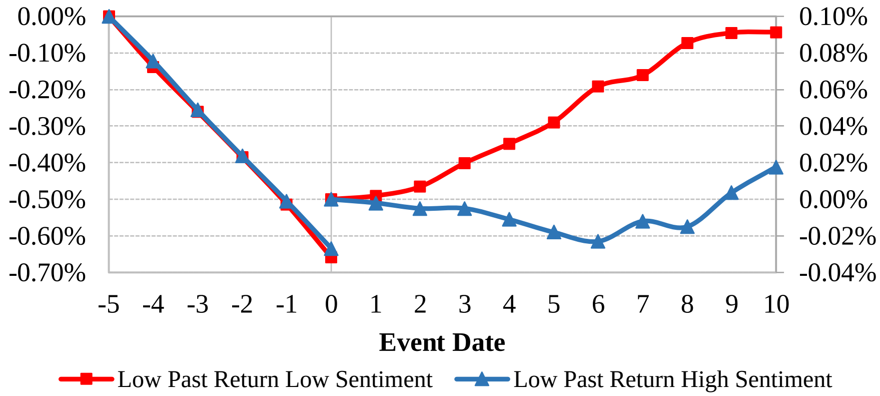
This table reports the 10-day calendar-time portfolio returns based on past returns and media sentiments in the emerging market. Each day emerging country currencies (equities) are first ranked into two groups based on their past-week returns and then, within each group, we further sort the instruments into two groups based on media sentiment scores over the past week. *Past Return* is the cumulative excess emerging country currency (equity) returns over the past week. *Sentiment* is the log changes of daily media tone relative to past four same day-of-the-week averages, then weighted sum over the past week. Results for emerging country currencies and equities are reported in Panel A and B, respectively. Emerging countries include Argentina, Brazil, China, Colombia, Egypt, India, Indonesia, Mexico, Malaysia, Nigeria (no equity index), Philippines, Poland, Russia, Thailand, Turkey, and South Africa. We construct media sentiment score based on media coverage for both currencies and equities. 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 2016:08.

| Sentiment | Past Return | | |
|---|---|---|---|
| | Low | High | Single-sort Spread |
| | Panel A: FX | | |
| Low | -3.97 | 1.61 | 6.65 |
| | [-2.47] | [1.21] | [3.42] |
| High | -2.59 | 4.94 | |
| | [-1.50] | [2.45] | |
| Single-sort Spread | 1.98 | | 8.91 |
| | [1.50] | | [3.30] |
| | Panel B: Country Equity | | |
| Low | 3.86 | -0.62 | -2.44 |
| | [1.53] | [-0.25] | [-0.82] |
| High | -0.62 | -1.66 | |
| | [-0.29] | [-0.77] | |
| Single-sort Spread | -0.94 | | -5.52 |
| | [-0.32] | | [-1.37] |

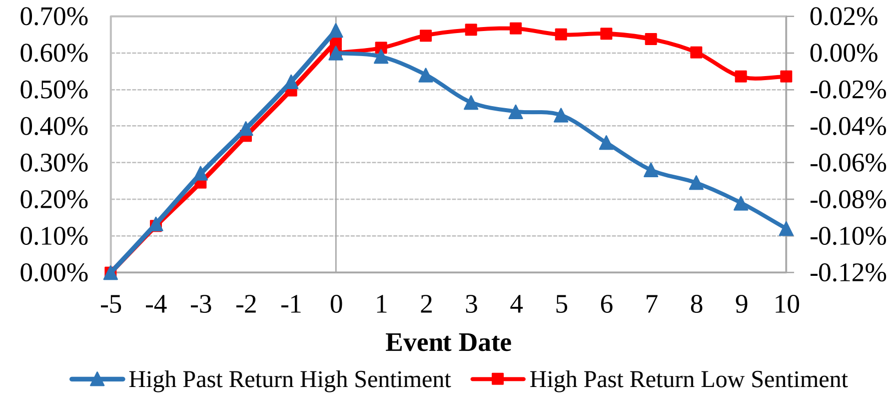
## Table 10: Fama-MacBeth Regressions, Emerging FX/Country Equity

This table reports the Fama and MacBeth (1973) regressions of forecasting currency (equity) returns based on past returns and media sentiments in the emerging market. Each day emerging country currencies (equities) 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. We assign 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 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 high, and zero otherwise; *Past_ret* 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. Emerging countries include Argentina, Brazil, China, Colombia, Egypt, India, Indonesia, Mexico, Malaysia, Nigeria (no equity index), Philippines, Poland, Russia, Thailand, Turkey, and South Africa. We construct media sentiment score based on media coverage for both currencies and equities. We skip 1 day between the formation and forecast period. The coefficients are 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 2016:08.

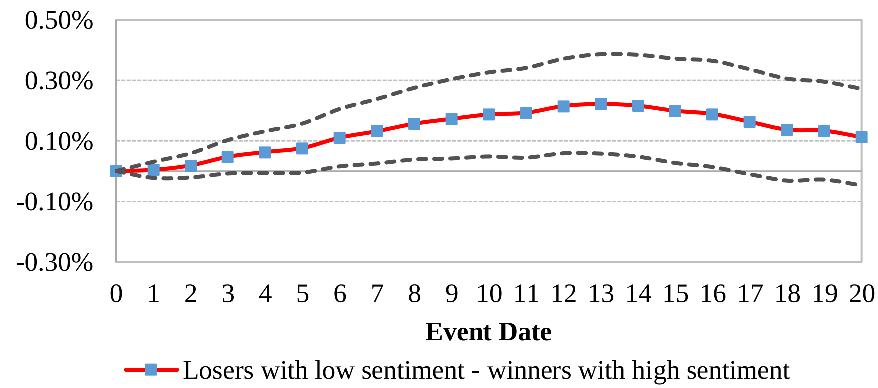
| Forecast Return=10-day | (1) FX | | (2) Country Equity | |
|---|---|---|---|---|
| Past_ret | 0.15 | | -0.01 | |
| | [3.85] | | [-0.26] | |
| Past_ret× LRLS_D | | 0.17 | | -0.03 |
| | | [2.56] | | [-0.55] |
| Past_ret× LRHS_D | | 0.09 | | -0.03 |
| | | [1.49] | | [-0.59] |
| Past_ret× HRLS_D | | 0.05 | | -0.01 |
| | | [0.71] | | [-0.19] |
| Past_ret× HRHS_D | | 0.25 | | -0.04 |
| | | [4.08] | | [-0.57] |




**Panel A: Low Past Return**

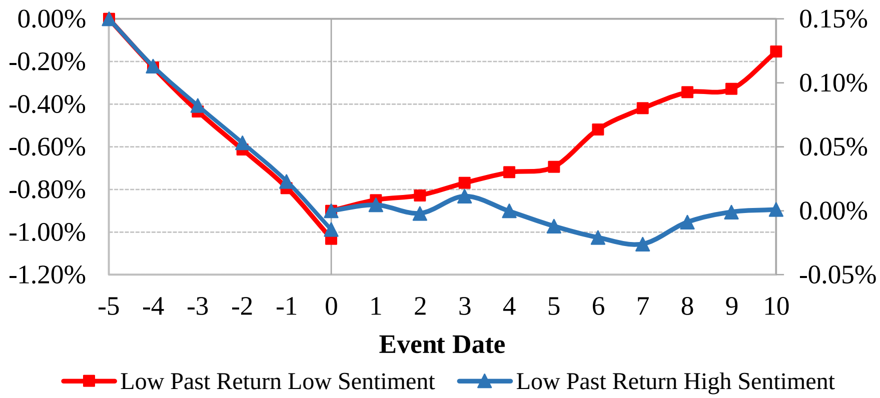



**Panel B: High Past Return**

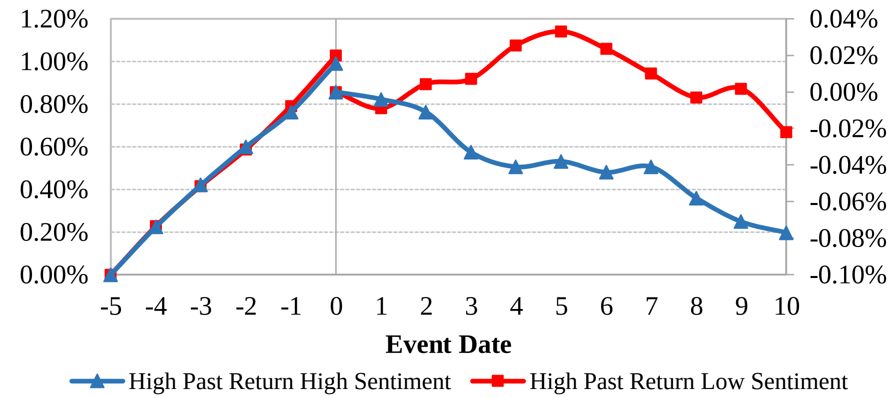



**Panel C: Low-High Past Return-Sentiment Portfolio Spread**

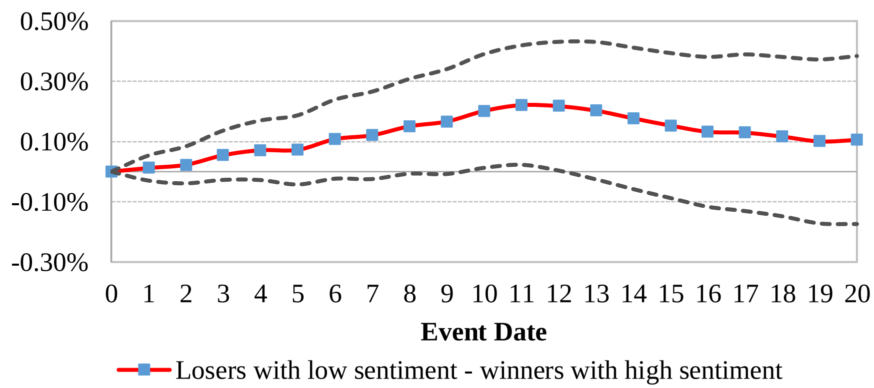
**Figure 1. Event time patterns of developed currencies.** This figure plots the average cumulative excess returns surrounding the formation of portfolios sorted on past returns and media sentiments over the past week. Each day developed currencies are first ranked into two groups based on their past-week returns and then, within each group, we further sort the currencies into two groups based on media sentiment scores over the past week. Panel A illustrates the sentiment effect in currencies with low past returns. Panel B illustrates the sentiment effect in currencies with high past returns. Panel C exhibits 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). We construct media sentiment score based on media coverage for both currencies and equities. We skip 1 day between the formation and forecast period. The sample is over the period from 2013:01 to 2016:08.




**Panel A: Low Past Return**

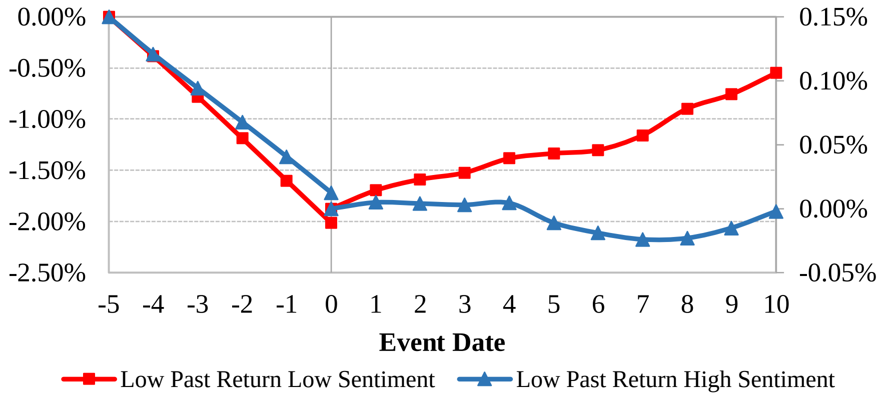



**Panel B: High Past Return**

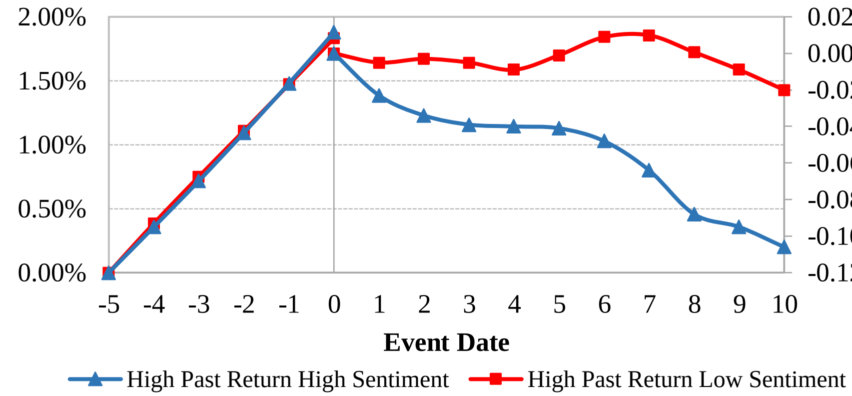



**Panel C: Low-High Past Return-Sentiment Portfolio Spread**

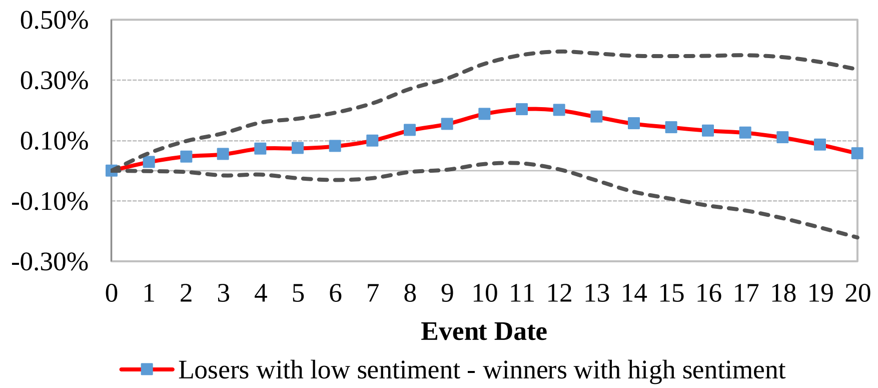
**Figure 2. Event time patterns of developed country equity.** This figure plots the average cumulative excess returns surrounding the formation of portfolios sorted on past returns and media sentiments over the past week. Each day developed country equities are first ranked into two groups based on their past-week returns and then, within each group, we further sort the country equities into two groups based on media sentiment scores over the past week. Panel A illustrates the sentiment effect in country equities with low past returns. Panel B illustrates the sentiment effect in country equities with high past returns. Panel C exhibits the cumulative return of 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). We construct media sentiment score based on media coverage for both currencies and equities. We skip 1 day between the formation and forecast period. The sample is over the period from 2013:01 to 2016:08.




**Panel A: Low Past Return**




**Panel B: High Past Return**




**Panel C: Low-High Past Return-Sentiment Portfolio Spread**

**Figure 3. Event time patterns of largest U.S. 100 individual firms.** This figure plots the average cumulative excess returns surrounding the formation of portfolios sorted on past returns and media sentiments over the past week. Each day largest 100 U.S. individual firms are first ranked into two groups based on their past-week returns and then, within each group, we further sort the firms into two groups based on media sentiment scores over the past week. Panel A illustrates the sentiment effect in stocks with low past returns. Panel B illustrates the sentiment effect in stocks with high past returns. Panel C exhibits the cumulative return of 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). The largest 100 U.S. individual firms are determined based on the market capitalization as of the end of 2012. We skip 1 day between the formation and forecast period. The sample is over the period from 2013:01 to 2016:08.

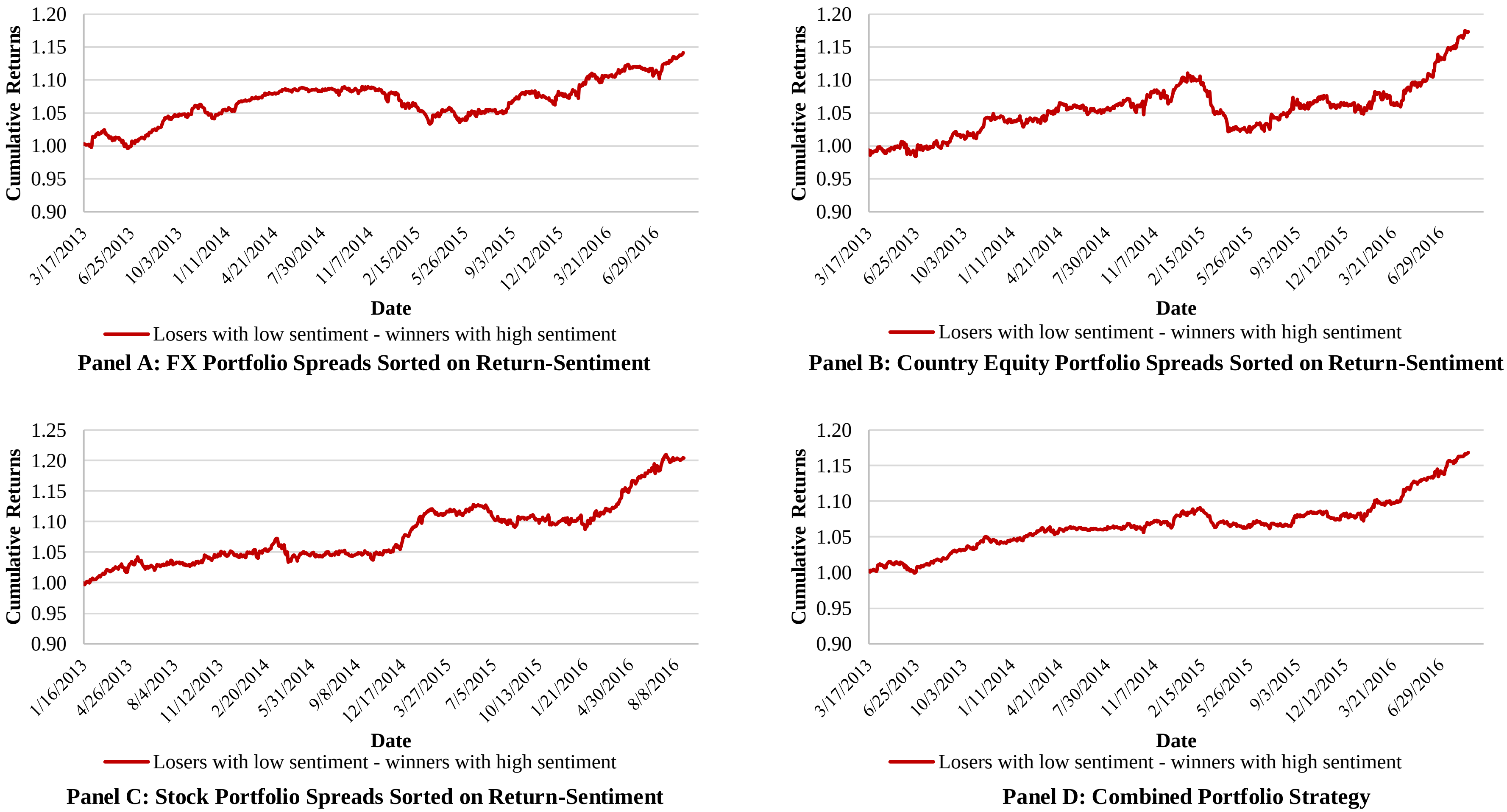



**Figure 4. Cumulative return of time series media reinforcement strategy.** This figure plots the cumulative returns of time series media reinforced strategy that buys losers with low sentiments and sells winners with high sentiments. Every day instruments in each asset class are first ranked into two 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. Results of currencies, country equities, and the largest 100 U.S. individual firms are plotted in Panel A, B, and C, respectively. Panel D displays the cumulative returns of time series value-weighted media reinforced strategy by aggregating three asset classes. The largest 100 U.S. individual firms are determined based on the market capitalization as of the end of 2012. We skip 1 day between the formation and forecast period. The sample is over the period from 2013:01 to 2016:08.