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Economic policy uncertainty, short-term reversals, and investor sentiment

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Abstract

This study finds that the predictability of economic policy uncertainty on short-term reversals is stronger among stocks exposed more to the volatility (*VIX*) and economic policy uncertainty (*EPU*) indexes. In addition, the predictability of the *VIX* index on short-term reversals is stronger among stocks exposed more to this index and the Aruoba, Diebold, and Scotti business conditions index (*ADS*). Furthermore, the finding is robust after controlling for the other popular investor sentiment indexes, the Fama-French five risk factors, financial crises, and firm size.

Keywords:
Economic policy uncertainty, Return reversals, Liquidity provision, Investor sentiment

JEL classification:
G11; G12; G14

1. Introduction

Short-term reversal refers to the abnormal profits of an investment strategy that relies on past stock returns. Specifically, this strategy consists of taking a long position in the worst-performing stocks and a short position in the best-performing stocks in the prior week/month. Although prior literature shows that short-term reversal is pervasive worldwide (Griffin, Kelly, and Nardari, 2010; Cheng, Hameed, Subrahmanyam, and Titman, 2017; Chui, Subrahmanyam, and Titman, 2022), less is known about how short-term reversal varies across time. Recent studies in the U.S. stock market document that short-term reversal covariates with the Cboe volatility (*VIX*) and the economic policy uncertainty (*EPU*) indexes in the prior month (Nagel, 2012, and Chui, 2022).

When *EPU* increases, the inventory risk of liquidity providers rises. Therefore, liquidity providers require more compensation for absorbing order imbalance, leading to more significant short-term reversals.[1] On the other hand, investors' cognitive biases, such as overconfidence, tend to be more prominent in a more uncertain environment (Hirshleifer, 2001). When *EPU* increases, overconfident investors overreact to good and bad news, resulting in more stock mispricing and strengthening short-term reversals. Therefore, there is a positive relationship between *EPU* in the prior month and the short-term reversal in the current month through overconfidence and liquidity channels.

When investors overreact to the news during a high sentiment period, their trades may concentrate on a stock's buy or sell sides. Therefore, their trades not only push away a stock's price from its fair value but also generate order imbalance. Hence, a stock

[1] So and Wang (2014) find that the compensation for providing liquidity goes up with the uncertainty associated with earnings announcements. Wang, Xu, and Zhong (2019) show that an increase in economic policy uncertainty leads to a decrease in the number of liquidity providers in the credit default swap (CDS) market. Nagar, Schoenfeld, and Wellmn (2019) document that trading cost of stocks rises as economic uncertainty increases.

exposed more to investor sentiment/*EPU* tends to have more mispricing and more significant order imbalance. Since the *EPU* effect on short-term reversal goes through the overconfidence and liquidity channels, one would expect its impact on short-term reversal should be more substantial among stocks exposing more to investor sentiment/*EPU*. Hence, this study examines the relationship between *EPU* and short-term reversal conditional on stocks' exposure to *EPU* and investor sentiment indexes.

A stock's exposure to an index is constructed from this stock's beta with respect to that index. As in Bail, Brown, and Tang (2017), I use 60-month rolling regressions of stock return on an index and the Fama-French (2015) five risk factors to estimate the betas for each stock listed in the New York Stock Exchange (*NYSE*), American Stock Exchange (*AMEX*), and Nasdaq (*NASDAQ*) over the period from January 1986 to December 2018.

The indexes examined are the economic policy uncertainty (*EPU*) of Baker, Bloom, and Davis (2016), Bake-Wurgler (2007) sentiment index (*BWSENT*), the Cboe volatility index (*VIX*), Aruoba-Diebold-Scotti (2009) business conditions index (*ADS*), and the University of Michigan consumer sentiment index (*CSENT*). The latter five indexes are investor sentiment indexes. By construction, *VIX* is more related to institutional investors, and other sentiment indexes are more associated with individual investors.

Since overconfident investors may overreact to both good and bad news and push share prices above or below their fair values, *EPU*/sentiment betas could be positive or negative. Besides, stocks with more positive or negative betas tend to be traded more heavily by sentiment-prone overconfident investors and have less liquidity supply (Baker and Wurgler, 2007; Shleifer and Vishny, 1997). Therefore, one can use the absolute value

of a stock's beta to measure its exposure to overconfident investors and liquidity provision. Accordingly, this study measures a stock's exposure to an index (*Exposure*) as the absolute value of its beta estimated from this index.

A stock with greater *Exposure* tends to have larger mispricing and less liquidity provision in high sentiment/EPU periods. Since economic policy uncertainty influences short-term reversals through overconfidence and liquidity channels, one may expect economic policy uncertainty to have a stronger effect on short-term reversals among stocks with greater *Exposure*. Consistent with this conjecture, this study finds that the *EPU*-reversals relationship is more profound among stocks with greater exposure to *VIX* and *EPU*. Nevertheless, economic policy uncertainty exerts similar effects on short-term reversals for stocks with different exposure to other investor sentiment indexes.

On the other hand, this study documents that the economic policy uncertainty effect on short-term reversals for portfolios sorted by *Exposure* is always positive and statistically significant. Moreover, similar to *EPU*, *VIX* is a reliable predictor of short-term reversals. In other words, both *EPU* and *VIX* explain how short-term reversals vary across time.

This study finds that *VIX* exerts a larger effect on short-term reversals among stocks with greater exposure to *VIX* and *ADS*. The effects of other sentiment indexes on short-term reversals are not robust and are usually not significant. The above findings remain even after controlling for the Fama-French five risk factors, major financial crises, and firm size. Since *VIX* is related to the sentiment and liquidity provision of institutional investors, the findings suggest the *EPU/VIX* effect on short-term reversals going through institutional investors' trading.

The paper is organized as follows. First, section 2 establishes the hypotheses. Then, section 3 describes the data. Next, section 4 presents the methodology and empirical findings. Finally, section 5 concludes the paper.

2. Hypothesis

There are two plausible explanations for short-term reversal. The first is overreaction. Investors may overreact to the news because of their sentiments. Hence, stock prices may be momentarily deviated from their fundamental values, and these pricing errors are corrected in the near future (Cooper, 1999; Mase, 1999; Subrahmanyam, 2005). The second is the liquidity effect. When liquidity providers have positive (negative) excess inventory, they tend to quote prices below (above) the fundamental value so as to encourage buy (sell) orders and discourage sell (buy) orders. Stock prices return to their intrinsic values when these inventory imbalances vanish (Jegadeesh and Titman, 1995; Campbell, Grossman, and Wang, 1993; Avramov, Chordia, and Goyal, 2006; Cheng, Hameed, Subrahmanyam, and Titman, 2017). Prior studies find evidence supporting both explanations. For example, Da, Liu, and Schaumburg (2014) find that short-term reversal is related to both effects.

Sentiment-prone investors are overconfident investors who overact to the news during high sentiment periods. Baker and Wurgler (2007) find that investor sentiment significantly affects stock prices, and this sentiment effect varies across stocks. As will be shown later, almost half of the sentiment betas, *i.e.* the correlation between stock returns and investor sentiment, are negative. This finding suggests that sentiment-prone investors overreact more to both good and bad news in high sentiment periods. In other words, overconfident investors may concentrate their buy (sell) orders in a group of stocks

during a high sentiment period, making their prices higher (lower) than their fair values leading to a positive (negative) sentiment betas. As a result, we observe short-term reversals when these pricing errors are corrected shortly. Previous research has shown that investor sentiment predicts short-term reversals (e.g. Da, Liu, and Schaumburg, 2014; Da, Engelberg, and Gao, 2014).

Moreover, the above argument suggests that short-term reversals are related to liquidity shocks. Since sentiment-prone investors concentrate their trades on either the buy or sell sides of a stock, the order imbalance of this stock increases, generating a stronger reversal. In summary, a stock with a larger sentiment beta in absolute terms indicates that this stock's price is more affected by investor sentiment and liquidity shock.

What makes some stocks expose more to investor sentiment? There are two explanations. First, firms such as young, small, or firms with very uncertain future cash flows are more difficult for investors to determine their fair values compared to large firms with long earnings histories or stable future cash flows (Baker and Wurgler, 2007). Overconfidence is generally more substantial when investors have to value a stock with greater uncertainty (Daniel and Titman, 1999). Therefore, overconfident investors tend to overreact more to news about firms with greater valuation uncertainty. As a result, the speculative demand for stocks with high valuation uncertainty is larger than for stocks with low valuation uncertainty. Hence, high-valuation uncertainty stocks will expose more to investor sentiment than low-valuation uncertainty stocks.

Second, betting against sentiment-prone investors is costly and risky (Shleifer and Vishny, 1997).[2] This limit-to-arbitrage tends to be greater for younger, smaller, or stocks

[2] The costs of buying and short selling are not the same across stocks. Furthermore, the idiosyncratic risk in return varies across stocks. In addition, the strong speculative demand may push stock prices further

with higher return volatility (Baker and Wurgler, 2007). In a high sentiment period, arbitrageurs will find it more challenging to obtain funds to finance their investments in high limit-to-arbitrage stocks (Shleifer and Vishny, 1997). As a result, stocks with higher limit-to-arbitrage expose more to investor sentiment and have less liquidity provision. The key point is that stocks expose more to investor sentiment are usually subject to greater speculative demand and liquidity shocks.

On the other hand, why does economic policy uncertainty (*EPU*) matter for short-term reversals? Chui (2022) provides two explanations for the positive relationship between *EPU* and short-term reversals. First, increases in *EPU* raise the inventory risk of liquidity providers. Therefore, during a high *EPU* period, liquidity suppliers demand larger compensation for absorbing order imbalances by quoting prices further away from the fair values. When these imbalances in order flow disappear, stock prices return to their fundamental values. Hence, short-term reversals become more significant after high *EPU* periods. Second, cognitive biases, such as overconfidence, tend to have a greater effect on investors' decisions in a more uncertain environment (Daniel and Titman, 1999; Griffin and Tversky, 1992; Hirshleifer, 2001).[3] Therefore, overconfident investors overreact to news in high *EPU* periods, leading to more sizeable pricing errors. As a result, short-term reversals become more profound after high *EPU* periods. Similar to investor sentiment, share prices could react positively or negatively to *EPU*, and *EPU* betas, *i.e.* the correlation between stock return and *EPU*, could be positive or negative.

In summary, stocks with a larger sentiment/EPU beta in absolute terms, *i.e.* a larger *Exposure*, tend to be influenced more by overconfidence and liquidity shocks. Moreover,

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away from their fair values. In this case, arbitrageurs with short investment horizons or capital constraints have to close their positions and suffer a loss.

[3] Kumar (2009) documents that market uncertainty increases investors' overconfidence.

since the *EPU* effect on short-term reversal goes through the overconfidence and liquidity channels, one would expect its impact on short-term reversal should be more substantial among stocks with greater *Exposure*. These considerations lead to the following hypotheses.

H_1: Economic policy uncertainty (*EPU*) effect on short-term reversals is more prominent among stocks exposed more to investor sentiment.

H_2: Economic policy uncertainty (*EPU*) effect on short-term reversals is more substantial among stocks exposed more to economic policy uncertainty.

3. Data

3.1 The stock sample

The stock sample consists of all common stocks listed on the *NYSE*, *AMEX*, and *NASDAQ* exchanges from January 1986 through January 2019. This sample starts from January 1986 because the Cboe volatility (*VIX*) index is not available before 1986. In addition, this sample ends in January 2019 because the Baker-Wurgler (2007) sentiment (*BWSENT*) index is unavailable after 2018. Our tests are based on monthly stock returns because estimation bias owing to the bid-ask spread and infrequent trading on short-term return reversals are small when monthly returns are employed (Jegadeesh, 1990). Stock data are collected from the Center for Research in Security Prices (*CRSP*). To avoid any market microstructure effects that may contaminate the findings, I follow prior literature and remove those stocks with a monthly closing price of less than 5 dollars from the sample (e.g. Da et al. 2014, and Cheng et al. 2017).

3.2 The indexes

The Baker, Bloom, and Davis (2016) economic policy uncertainty index (*EPU*) is collected from the Economic Policy Uncertainty website. This index is a weighted average of the number of words relating to uncertainty and government policies that appeared in major U.S. newspapers.[4] The higher this index is, the larger the economic policy uncertainty is. This index is widely used in the business literature (Nagar, Schoenfeld, and Wellman, 2019). For instance, Brogaard and Detzel (2015) find that *EPU* predicts stock market returns and Nagar et al. (2019) document that *EPU* raises bid-ask spreads and reduces stock price sensitivity to earnings surprise.

This study includes several investor sentiment indexes that are frequently used in prior literature. Monthly Baker and Wurgler (2007) investor sentiment index (*BWSENT*) is collected from the website of Jeffrey Wurgler. This index is based on the first principal component of five sentiment proxies. These proxies are value-weighted dividend premium, first-day returns on IPOs, IPO volume, close-end fund discount, and equity share in new issues. The higher this index, the greater investor sentiment. Baker and Wurgler (2006) document that *BESENT* significantly affects the cross-section of stock returns. Shen, Yu, and Zhao (2017) find that *BESENT* is a crucial factor in determining the return spread between high- and low-risk portfolios.

Daily Cboe implied volatility index is obtained from the Chicago Board Options Exchange website. This index starts in January 1986.[5] Nagel (2012) suggests this index as a measure of liquidity provision, and Da, Engelberg, and Gao (2015) find that it is related to investor fear sentiment. The higher this index, the larger the fear sentiment and

[4] The raw U.S. economic uncertainty index is scaled by the mean calculated over the periods from 1995 to 2009.
[5] The Cboe volatility index used in this study is based on the old method.

the smaller the liquidity provision of investors. The Cboe volatility index (*VIX*) in a given month is calculated as the mean of the daily volatility index in that month.

The monthly University of Michigan consumer sentiment index (*CSENT*) is obtained from the Federal Reserve Bank of St. Louis. The *CSENT* index is a survey-based consumer confidence index, and the index scores are computed based on five questions. Qiu and Welch (2004) argue that investors who are bullish about the economy also tend to be bullish about the stock market. Since *CSENT* reflects investors' expectations of business condition, this index could be a proxy for investor sentiment. The higher this index, the larger investor sentiment. Qiu and Welch (2004) find that the *CSENT* index is better than the closed-end fund discount in measuring investor sentiment. Schmeling (2009) uses *CSENT* as a proxy for individual investor sentiment and shows that it negatively predicts stock market returns. Lemmon and Portniaguina (2006) find that *CSENT* forecasts the returns on small and low institutional ownership stocks. Mclean and Zhao (2014) document that external finance costs are higher in low *CSENT* sentiment periods.

Another frequently used measure for the business condition is the Aruoba, Diebold, and Scotti (2009) business conditions index (*ADS*) (e.g. Gao, Ren, and Zhang 2020; Barunik, Bevilacqua, and Tunaru 2022). Therefore, I use *ADS* as a proxy for investor sentiment. Daily data on *ADS* is collected from the Federal Reserve Bank of Philadelphia. This index is built on several seasonally adjusted macroeconomic variables of various frequencies, such as weekly initial jobless claims, monthly payroll employment, and quarterly GDP. A more positive index value indicates progressively better-than-average conditions, while a more negative index value indicates progressively worse-than-average

conditions. Gao, Ren, and Zhang (2020) show that *ADS* positively affects stock returns. Similar to *VIX*, the *ADS* business conditions index (*ADS*) in a given month is calculated as the mean of the daily Aruoba, Diebold, and Scotti (2009) business conditions index in that month.

While the *BWSENT* and *VIX* indexes are constructed from stock market data, the *CSENT* is based on survey data. The *ADS* index reflects investor sentiment that stems from the macroeconomic environment. Since index options are mainly traded by institutional investors, the *VIX* index is more related to the sentiment and liquidity provision of institutional investors. The construction of *BWSENT*, *ADS*, and *CSENT* indexes makes them more relevant to the sentiment and liquidity provision of individual investors. However, the liquidity supply of institutional investors is expected to be more prominent than individual investors.

Panels A & B of Table 1 present the descriptive statistics of these indexes and the excess market returns (value-weighted market return minus risk-free rate, *EMKTR*). While the *EPU* index is positively related to the *VIX* index, it is negatively associated with the *EMKTR*, *BWSENT*, *ADS*, and *CSENT* indexes. The correlation coefficients among them are statistically significant at the 5% level. This finding indicates that *EPU* is positively related to institutional investor sentiment and negatively related to individual investor sentiment.

The *EMKTR* is positively associated with the *ADS* index and negatively related to the *BWSENT* and *VIX* indexes. Moreover, the relationship between *EMKTR* and the *CSENT* index is flat. On the other hand, the correlations among the sentiment indexes are strong. While the *VIX* index is positively related to the *BWSENT* index, it is negatively

associated with the *ADS* and *CSENT* indexes. As expected, since *ADS* and CSENT are business condition measures, they have a strong positive association.

[Insert Table 1 here]

Panel C of Table 1 shows the contemporaneous correlations among the excess market returns (*EMKTR*), *EPU* index, sentiment indexes, and a short-term reversal factor (*ST_Rev*) collected from the Ken French data library.[6] The finding indicates that only *EMKTR* and *BWSENT* have a strong positive contemporaneous relationship with *ST_Rev*. The contemporaneous relationships between *ST_Rev* and other indexes are weak. Panel D of Table 1 reveals that only *EPU* and *VIX* indexes in the prior month can predict *ST_Rev* in the current month. The higher *EPU/VIX*, the larger *ST_Rev*. *EMKTR*, *BWSENT*, *ADS*, and *CSENT* cannot predict *ST_Rev*.

3.3 EPU and sentiment betas

I use a methodology similar to that of Bail, Brown, and Tang (2017) to estimate the *EPU* and sentiment betas. Individual stock returns are regressed on the *EPU*/sentiment index and the Fama-French (2015) five risk factors. Specifically, I estimate the following regression for each firm in each month:

$$R_{jt} = \alpha_j + \beta_{i,j} Index_t + \beta_{Mkt,j} EMKTR_t + \beta_{SMB,j} SMB_t + \beta_{HML,j} HML_t + \beta_{RMW,j} RMW_t + \beta_{CMA,j} CMA_t + e_{jt}, \quad (1),$$

where R_{jt} is the stock return of firm j in month t and e_{jt} is the error term. $Index_t$ is either the natural logarithm of the *EPU* index (*LnEPU*), the *BWSENT* index, the natural logarithm of the *VIX* index (*LnVIX*), the *ADS* index, or the natural logarithm of the *CSENT* index (*LnCSENT*) in month *t*. Other explanatory variables are a market factor

[6] The short term reversal factor (*ST_Rev*) is constructed from six portfolios formed on two firm size groups (small and big) and three prior month return groups (low, medium, and high). *ST_Rev* is the difference in mean returns on the two low-prior month return and the two high-prior month return portfolios.

based on excess market return (*EMKTR*), a size factor based on firm size (small minus big, *SMB*), a book-to-market factor based on the book-to-market ratio (high minus low, *HML*), a profitability factor based on operating profitability (robust minus weak, *RMW*), and an investment factor based on total assets growth (conservative minus aggressive, *CMA*).

The estimation period is sixty months prior to each month in the testing period, and each stock is required to have at least twenty-four observations in the estimation period. Since the return data in this study begins in January 1986, the first set of beta estimates is available in December 1987. Accordingly, the testing period of this study spans from January 1988 to January 2019. The $\hat{\beta}_{EPU,j}$ (*i.e.* i = *EPU*) is the *EPU*-beta estimate corresponding to the *EPU* index of firm *j*. Similarly, $\hat{\beta}_{i,j}$ is the sentiment-beta estimate associated with the *i*th investor sentiment index of firm *j*, and *i* equals *BWSENT*, *VIX*, *ADS*, or *CSENT*. Table 2 shows that about half of the *EPU* or sentiment beta estimates are negative. This finding indicates that almost half of the stock returns are positively related to the indexes, and the other half are negatively associated with these indexes. Since this study is interested in the exposure of stock returns to the indexes, I measure a stock's exposure (*Exposure*) to *EPU*/sentiment index as the absolute value of its *EPU*/sentiment beta estimate. In other words, a stock with a larger *Exposure* could be exposed more positively or negatively to sentiment/*EPU*.

[Insert Table 2 here]

4. Methodology and findings

4.1 Short-term reversals and Exposure

This section discusses how short-term reversal (*LMW*), the targeted variable of this study, is measured. In each month *t*, stocks are allocated into quantiles based on their exposure to EPU/investor sentiment index (*Exposure*) in month *t-1*, from low (bottom 20%) to high (top 20%). Then, stocks are sorted independently into five equal groups based on their returns in month *t-1* from loser (bottom 20%) to winner (top 20%). The 25 *Exposure*-return sorted portfolios are the intersections of the five *Exposure*-sorted groups and the five return-sorted groups. Equal-weighted returns (%) on these 25 portfolios are measured in month *t*. A reversal portfolio consists of buying the loser stocks and shorting the winner stocks. Therefore, short-term reversal (*LMW*) for a given *Exposure*-sorted group in month *t* is the difference in returns between the loser and winner portfolios in that group. Since this study includes five indexes, there are 125 *Exposure*-return sorted portfolios. Accordingly, there are five reversal portfolios for each index, and this study's analyses focus on the returns on these 25 reversal portfolios.

4.2 Portfolio analysis

The hypotheses indicate that the predictability of *EPU* on short-term reversal is stronger among stocks exposed more to investor sentiment and *EPU*. As a preliminary test, I examine how short-term reversal (*LMW*) in each *Exposure*-sorted group behaves in more- and less- uncertainty periods classified by *EPU*. The whole testing period from January 1988 to January 2019 is divided into two sub-periods based on the *EPU* scores. The current month *t* is classified as the More (Less) uncertainty period when the *EPU* index score in month *t-1* is higher than (lower than or equal to) the median score of this

index calculated from December 1987 to December 2018. I computed the average short-term reversals for each *Exposure*-sorted group in each sub-period. Table 3 reports the findings. Short-term reversals in the more *EPU* uncertainty period are unanimously more significant than in the less *EPU* uncertainty period. *EPU* strongly predicts short-term reversals even after controlling for stocks' exposure to investor sentiment/*EPU*.

[Insert Table 3 here]

The differences in short-term reversals between more and less uncertainty periods for the five High-*Exposure*-sorted groups are larger than their counterparts for the five Low-*Exposure*-sorted groups. This result is consistent with the hypotheses that the predictability of *EPU* for short-term reversals is stronger among stocks exposed more to investment sentiment or economic policy uncertainty.

4.3 The baseline model

The finding in the previous section could be driven by the strong correlations between *EPU* and *EMKTR*/other investor sentiment indexes. Besides, investor sentiment is an important determinant of short-term reversal (Nagel 2012, Da, Liu, and Schaumburg, 2014, Da, Engelberg, and Gao, 2015). Therefore, when we investigate the relationship between lagged *EPU* and short-term reversal, we need to control for the effects of *EMKTR* and other investor sentiment indexes on short-term reversal. To address this concern, I estimate the following time-series regression model, which is this study's baseline model.

$$LMW_{jt}^{i}\left(or\ Hi\_Lo_{t}^{i}\right) = \alpha + \beta_1 LMW_{jt-1}^{i}\left(or\ Hi\_Lo_{t-1}^{i}\right) + \beta_2 LnEPU_{t-1} + \beta_3 EMKTR_{t-1} + \beta_4 BWSENT_{t-1} + \beta_5 LnVIX_{t-1} + \beta_6 ADS_{t-1} + \beta_7 LnCSENT_{t-1} + \varepsilon_{jt}^{i}\ , \quad (2),$$

where LMW_{jt}^{i} is the short-term reversal of the *j*th *Exposure*-sorted group (j = Low to High) of the *i*th index (i = *BWSENT*, *VIX*, *ADS*, *CSENT*, or *EPU*) in month *t*. $LnEPU_{t-1}$, $EMKTR_{t-1}$, $BWSENT_{t-1}$, $LnVIX_{t-1}$, ADS_{t-1}, and $LnCSENT_{t-1}$ are the natural logarithm of the economic policy uncertainty index, the excess market return, the Bake-Wurgler sentiment index, the natural logarithm of the volatility index, the business conditions index and the natural logarithm of consumer sentiment index in month *t-1*, respectively. The variable ε_{jt}^{i} is the error term. The variable $Hi\_Lo_{t}^{i}$ is the short-term reversal of the high-*Exposure* group minus that of the low-*Exposure* group of the *i*th index in month *t*. I include $LMW_{jt-1}^{i}(Hi\_Lo_{t-1}^{i})$ in the regression model to control for possible lead-lag effect in short-term reversals. Since the empirical model includes lagged terms, the estimation period is from February 1988 to January 2019. The hypotheses suggest that the estimated coefficient on $LnEPU_{t-1}$ ($\widehat{\beta_2}$) is positive for each *Exposure*-sorted group, and it is larger for High-*Exposure* stocks than Low-*Exposure* stocks.

When *LMW* is the dependent variable, all but two estimated coefficients on $LnEPU_{t-1}$ ($\widehat{\beta_2}$) are positive and statistically significant at the 5% level. The other two coefficients are positive and statistically significant at the 10% level. These findings strongly suggest that lagged economic policy uncertainty index ($LnEPU_{t-1}$) positively predicts short-term reversals. I also find that lagged volatility ($LnVIX_{t-1}$) and lagged Bake-Wurgler sentiment ($BWSENT_{t-1}$) indexes can positively predict short-term reversals. However, the predictability of these indexes is weaker than the economic policy uncertainty index. Eighteen (Nineteen) out of twenty-five estimated coefficients on $LnVIX_{t-1}$ ($BWSENT_{t-1}$) are statistically significant at the 10% level, and among them, sixteen (thirteen) are significant at the 5% level. The estimated coefficients on $EMKTR_{t-1}$,

ADS_{t-1}, and $LnCSENT_{t-1}$ are usually statistically insignificant. The lead-lag effect on short-term reversals is negative and weak. These results suggest that the market returns and investor sentiment indexes do not subsume the predictability of economic policy uncertainty on short-term reversals. Table 4 displays the findings.

[Insert Table 4 here]

I find that the economic policy uncertainty effect on short-term reversals in the High-*Exposure* groups is larger than that in the Low-*Exposure* groups. To examine if this difference in *EPU* effect on short-term reversals is statistically significant, I use Hi_Lo_t as the dependent variable and replace LMW_{t-1} with Hi_Lo_{t-1} in the baseline model. Hi_Lo_t is the difference in returns on the High-*Exposure* and Low-*Exposure* reversal portfolios in month *t* of the *i*th index. I estimate the baseline model after these modifications. The last row in each panel of Table 4 shows the results. All five estimated coefficients on $LnEPU_{t-1}$ are positive, and two are statistically significant at the 5% level. These two coefficients are from the *Exposure (VIX)*-sorted and *Exposure (EPU)*-sorted portfolios. These findings show that the *EPU* effect on short-term reversals is stronger among stocks that expose more to volatility (*VIX*) and economic policy uncertainty (*EPU*) indexes.

On the other hand, using Hi_Lo_t as the dependent variable in the baseline model, I also find that the estimated coefficients on $LnVIX_{t-1}$ for the *Exposure (VIX)*-sorted and *Exposure (ADS)*-sorted portfolios are positive and statistically significant at the 5% level. This result indicates that the predictability of *VIX* on short-term reversals is more profound among stocks exposed more to volatility and business condition indexes. The estimated coefficients on other explanatory variables are statistically insignificant.

The above evidence is consistent with the second hypothesis, which states that the *EPU* effect on short-term reversals is more substantial among stocks exposed more to economic policy uncertainty. On the contrary, evidence supporting the first hypothesis is mixed. Since *VIX* is more related to institutional investors and other sentiment indexes are more connected to individual investors, the findings indicate that the *EPU* effect on short-term reversals is only related to the sentiment and liquidity provision of institutional investors. This result is consistent with the liquidity channel of the *EPU* effect on short-term reversals. Relative to individual investors, institutional investors play a more prominent role in providing liquidity to the market (Cheng et al., 2017). Since the *EPU* effect on short-term reversals goes through the liquidity channel, one would expect that this effect is more significant among stocks exposed more to the liquidity provision of the institutional investors that is measured by *VIX*.

To sum up, the *EPU* effect on short-term reversals is more significant among stocks exposed more positively or negatively to volatility (*VIX*) and economic policy uncertainty (*EPU*) indexes. On the other hand, the *VIX* effect on short-term reversals is more pronounced for stocks exposed more positively or negatively to volatility (*VIX*) and business condition (*ADS*) indexes.

4.4 Do risks matter?

To investigate if the above findings are affected by common risk factors, as in Liu, Stambaugh, and Yuan (2019), I include the Fama-French five factors in the baseline model. Specifically, I estimate the following time-series regression model.

$$\begin{aligned} LMW_{jt}^{i}\left(or\ Hi\_Lo_{t}^{i}\right) = \alpha + \ & \beta_1 LMW_{jt-1}^{i}\left(or\ Hi\_Lo_{t-1}^{i}\right) + \beta_2 LnEPU_{t-1} \\ & + \beta_3 EMKTR_{t-1} + \beta_4 BWSENT_{t-1} + \beta_5 LnVIX_{t-1} \\ & + \beta_6 ADS_{t-1} + \beta_7 LnCSENT_{t-1} + \gamma_1 EMKTR_t \\ & + \gamma_2 SMB_t + \gamma_3 HML_t + \gamma_4 RMW_t \\ & + \gamma_5 CMA_t + \varepsilon_{jt}^{i}\ , \end{aligned} \qquad (3),$$

where $EMKTR_t$, SMB_t, HML_t, RMW_t, and CMA_t are, respectively, the market factor, size factor, book-to-market factor, profitability factor, and investment factor in month *t*. Other variables in Equation (3) are defined in the previous section. Table 5 displays the findings.

The results after controlling for risks are similar to those reported in Table 4. The lagged economic policy uncertainty continues to exert a positive and significant impact on short-term reversals among stocks classified by their *Exposure*. However, the predictability of lagged volatility ($LnVIX_{t-1}$) on short-term reversals has improved and is about the same as that of lagged economic policy uncertainty ($LnEPU_{t-1}$) after controlling for risks. While twenty-three out of twenty-five estimated coefficients on $LnEPU_{t-1}$ are statistically significant at the 10% level, this figure for $LnVIX_{t-1}$ is twenty-two. Controlling for the common risk factors does not affect the predictability of $BWSENT_{t-1}$ on short-term reversals. This evidence reveals that economic policy uncertainty and volatility indexes are the two most significant predictors for short-term reversals among the indexes.

Among the five risk factors, short-term reversals are only related to market, book-to-market, and investment factors. While short-term reversals load positively on market

and book-to-market factors, they load negatively on investment factor. Interestingly, the negative lead-lag effect of short-term reversals becomes more statistically significant after controlling for risks. I find that thirteen out of twenty-five estimated coefficients on the lagged short-term reversal (LMW_{t-1}) are negative and statistically significant at the 10% level.

[Insert Table 5 here]

The last column of Table 5 reports the findings from the regressions using Hi_Lo_t as the dependent variable. Consistent with the results in Table 4, the *EPU* effect on short-term reversals among stocks exposed more to economic policy uncertainty (*EPU*) or volatility (*VIX*) indexes is significantly larger than those exposed less to these indexes after controlling for risks. Furthermore, the *VIX* effect on short-term reversals continues to be more substantial among stocks exposed more to the volatility (*VIX*) and business condition (*ADS*) indexes.

4.5 Do financial crises matter?

Liquidity provisions during financial crises could be abnormally low, exacerbating short-term reversals (Groot, Huij, and Zhou 2012). This section examines if major financial crises influence the *EPU/VIX* effects on the difference between short-term reversals between High- and Low-*Exposure* groups concerning *EPU/VIX/ADS*.[7] A dummy variable *CRISIS* is included in Equation (3). This dummy variable equals one during the following financial crises and is zero otherwise. The crises considered are the Asian Financial crisis (July 1997 to December 1988), the Dotcom bubble (March 2000 to October 2002), the 9/11 incident (September 2001 to October 2001), the Global financial

[7] The author would like to tank a reviewer for bring up this interesting question.

crisis (June 2007 to December 2009), and the Europe debt crisis (January 2009 to December 2010).

Using the difference between short-term reversals between High- and Low-*Exposure* groups (Hi_Lo_t) as the dependent variable, the modified Equation (3) is estimated for the *Exposure (EPU)*, *Exposure (VIX)*, and *Exposure (ADS)* groups.[8] Table 6 reports the finding. The estimated coefficients on *CRISIS* are statistically insignificant, suggesting that financial crises may not affect short-term reversal. This finding is consistent with Groot, Huij, and Zhou (2012). On the contrary, the estimated coefficients on the lagged EPU ($LnEPU_{t-1}$) are positive and statistically significant for the *Exposure (EPU)* and *Exposure (VIX)* groups. This finding indicates that the predictability of *EPU* on short-term reversal for High-*Exposure (EPU/VIX)* stocks is more substantial than Low-*Exposure (EPU/VIX)* stocks after considering the effect of the financial crises. On the other hand, the estimated coefficient on lagged *VIX* ($LnVIX_{t-1}$) is positive and statistically significant for *Exposure (VIX/ADS)* stocks. This result suggests that the financial crises do not affect the stronger predictability of *VIX* on short-term reversal for High-*Exposure (VIX/ADS)* stocks.

[Insert Table 6 here]

4.6 Does size matter?

Prior studies find that tiny and small stocks are affected more by investor sentiment and short-term reversals concentrate on these stocks (e.g. Lemmon and Portniaguina 2006, and Cheng et al., 2017). Therefore, it is interesting to explore how firm size may affect the predictability of *EPU/VIX* on short-term reversal across stocks with various

[8] This study's major findings are the *EPU/VIX* effects on the difference in short-term reversals between *High-Exposure* and *Low-Exposure* stocks concerning *EPU/VIX/ADS*. Therefore, I only report the findings regarding these three indexes for brevity.

exposures to investor sentiment/*EPU*.[9] Since this study's main findings concern a stock's exposure to *EPU*, *VIX*, and ADS, the tests in this section focus on these indexes for brevity.

Following Fama and French (2008) and Cheng et al. (2017), I use size breakpoints computed from the *NYSE* stocks to classify stocks in my sample to three size groups in month *t*: Tiny (stocks with their firm size in month *t-1* that are less than the 20th *NYSE* size percentile), Small (stocks with their firm size in month *t-1* that are between the 20th and 50th *NYSE* size percentiles), and Large (stocks with their firm size in month *t-1* that are larger than the 50th *NYSE* size percentile).

Furthermore, stocks are sorted independently into five groups based on their prior month returns from loser (bottom 20%) to winner (top 20%). In addition, stocks are allocated independently into two groups based on their exposure to *EPU/VIX/ADS* (*Exposure*) in month *t-1*, from low (bottom 50%) to high (top 50%).[10] The intersections of the size-sorted, *Exposure*-sorted, and return-sorted groups generate 30 size-*Exposure (EPU)*-return portfolios, 30 size-*Exposure (VIX)*-return portfolios, and 30 size-*Exposure (ADS)*-return portfolios. Each portfolio has at least nine stocks in each month during the sample period. Short-term reversal (*LMW*) for a given size-*Exposure*-sorted group in month *t* is the difference in returns between the loser and winner portfolios in that group.

Equation (3) is estimated using *LMW* from each size-*Exposure*-sorted group as the dependent variable, and Table 7 displays the results. In each size-sorted group, the estimated coefficients on $LnEPU_{t-1}$ ($\widehat{\beta_2}$) are positive, and all but two are statistically significant at the 10% level. The effect of *EPU* on short-term reversal is not significant

[9] The author thanks a reviewer for bringing up this critical issue.
[10] Since independent sorting is used to form portfolios, stocks are allocated to two *Exposure*-groups such that each size-*Exposur*e-return sorted portfolio has sufficient number of stocks in each month.

for the tiny stocks with Low-*Exposure (EPU/VIX)*. Furthermore, the estimated coefficient on $\widehat{\beta_2}$ for High-*Exposure* stocks is larger than Low-*Exposure* stocks in each size-*Exposure (EPU/VIX)* group. These findings indicate that the predictability of *EPU* on short-term reversal is more substantial for stocks exposed more to *EPU* or *VIX* in each size-sorted group.

[Insert Table 7 here]

On the other hand, Table 7 indicates that all but five of the estimated coefficients on $LnVIX_{t-1}$ ($\widehat{\beta_5}$) are significantly positive. This estimated coefficient is usually statistically insignificant for the Low-*Exposure* small or Low-*Exposure* large stocks. Panels B and C of Table 7 suggest that $\widehat{\beta_5}$ for High-*Exposure (VIX/ADS)* stocks are larger than Low-*Exposure (VIX/ADS)* stocks. In other words, the predictability of *VIX* on short-term reversal is more significant for stocks exposed more to *VIX* or *ADS* in each size-sorted group.

Panel D of Table 7 shows the findings when the difference in *WML* between High- and Low-Exposure stocks (*Hi_Lo*) in each size-sorted group becomes the dependent variable in Equation (3). Though all $\widehat{\beta_2}$ for *Exposure (EPU/VIX)* stocks are positive, it is statistically significant only for the tiny stocks exposed to *EPU*. This finding suggests that the *EPU* effect on the difference in short-term reversal between High-*Exposure (EPU)* and Low-*Exposure (EPU)* stocks is more substantial for tiny stocks. One should be noticed that Table 7 displays that the *EPU* effect on short-term reversal is increasing in firm size. The *EPU* effects for Low-*Exposure* small and Low-*Exposure* large stocks are considerably stronger than Low-*Exposure* tiny stocks. This result may explain the

weaker *EPU* effect on the difference in short-term reversal between High-*Exposure (EPU)* and Low-*Exposure (EPU)* stocks among small and large stocks.

Besides, all the estimated coefficients on $LnVIX_{t-1}$ ($\widehat{\beta_5}$) are positive for *Exposure (VIX/ADS)* stocks. Yet, they are statistically significant for *Exposure (VIX)* tiny stocks, *Exposure (VIX)* large stocks, and *Exposure (ADS)* large stocks. These findings indicate that the *VIX* effect on the difference in short-term reversal between High-*Exposure (VIX/ADS)* and Low-*Exposure (VIX/ADS)* stocks is not only concentrated on tiny stocks.

In summary, the *EPU* effect on short-term reversals seems more profound among stocks exposed more to economic policy uncertainty and volatility in each size-sorted group. However, this *EPU* effect is more significant among tiny stocks. Moreover, the *VIX* effect on short-term reversals appears to be more substantial among stocks exposed more to business condition and volatility in each size-sorted group. Nonetheless, this *VIX* effect is more considerable among tiny and large stocks

5. Conclusion

During high sentiment periods, cognitive biases become more significant, and overconfident investors trade aggressively, leading to a larger mispricing and a greater order imbalance. Furthermore, the increases in order imbalance raise the inventory risk of the liquidity providers. Therefore, the market supply of liquidity will decline when investor sentiment increases. It follows that when a stock exposes more to investment sentiment, its price and liquidity provision would be more affected by sentiment. In addition, since economic policy uncertainty influences short-term reversal through overconfidence and liquidity channels, its effect on short-term reversals should be

stronger among stocks exposing more to investor sentiment and economic policy uncertainty.

This study involves four popular investor sentiment indexes besides the economic policy uncertainty index (*EPU*). They are the Bake-Wurgler (2007) sentiment index (*BWSENT*), the Cboe Volatility index (*VIX*), Aruoba-Diebold-Scotti (2009) business conditions index (*ADS*), and the University of Michigan consumer sentiment index (*CSENT*). This study shows that only the *EPU* and *VIX* indexes in the prior month can predict short-term reversals in the current month. In other words, the larger the lagged *EPU*/*VIX* index, the greater the short-term reversals.

This study finds that the *EPU* effect on short-term reversals is positive and is increasing in firm size. Besides, both *EPU* and *VIX* can explain the variation of short-term reversal over time. Furthermore, the *EPU* effect on short-term reversals is more profound among stocks exposed more to the economic policy uncertainty and volatility indexes. Nonetheless, the *EPU* effect on short-term reversals does not depend on stocks' exposure to *BWSENT*, *ADS*, or *CSENT* indexes. This latter finding may be related to the fact that institutional investors are major liquidity providers in the market. Since the *EPU* effect on short-term reversals goes through the liquidity channel, its impact on short-term reversals is expected to be stronger for those stocks with their liquidity provision more relying on institutional investors. Moreover, unlike other sentiment indexes, the volatility index (*VIX*) is more related to institutional investors than individual investors. Hence, the difference in the *EPU* effect on short-term reversals between High-*Exposure* (*VIX*) and Low-*Exposure* (*VIX*) stocks could be more significant than that between High- and Low-*Exposure* stocks of other sentiment indexes. In addition, this study documents that the

VIX effect on short-term reversals is more considerable among stocks exposed more to the volatility and business condition indexes.

The above findings remain after taking into account the Fama-French five risk factors and the effect of the financial crises. Further analyses suggest that the *EPU* and *VIX* effects on short-term reversals are not limited to the tiny stocks.

While the finding that the *EPU* effect on short-term reversals is related to *VIX* and not other investor sentiment indexes is consistent with the liquidity explanation of short-term reversal, it is inconsistent with the overconfidence explanation. Prior literature documents that both institutional and individual investors' sentiments significantly impact stock prices (Baker and Wurgler, 2007; Nagel, 2012). So, what makes the *EPU* effect on short-term reversals only related to the sentiment of institutional investors? This study's finding casts doubt on whether economic policy uncertainty affects short-term reversals through the overconfidence channel. Future research should investigate how the sentiment of individual investors is related to the economic policy uncertainty effect on short-term reversals.

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Table 1 Summary statistics of the indexes

Panel A of this table reports the descriptive statistics of the economic policy uncertainty index (*EPU*), the excess stock market return (*EMKTR*), the Bake-Wurgler (2007) sentiment index (*BWSENT*), the Cboe Volatility index (*VIX*), Aruoba-Diebold-Scotti (2009) business conditions index (*ADS*), and the University of Michigan consumer sentiment index (CSENT). Panel B of this table displays the correlation coefficients among these indexes. Panel C shows the contemporaneous correlation coefficients among the indexes and the short-term reversal factor (*ST_Rev*), and Panel D presents the correlation coefficients between *ST_Rev* in the current month and the indexes in the prior month. The *p*-values of the correlation coefficients are in parentheses.

Panel A Descriptive statistics, January 1986 to December 2018

Index	Mean	Std Dev	Min	Max
EPU	111.89	41.01	44.78	283.67
EMKTR (%)	0.646	4.39	−23.24	12.47
BWSENT	0.121	0.62	−0.94	2.94
VIX	20.05	8.39	8.02	65.45
ADS	−0.11	0.63	−3.65	1.01
CSENT	87.96	11.83	55.30	112.00

Panel B Correlation coefficients of the indexes, January 1986 to December 2018

	$EMKTR_t$	$BWSENT_t$	$LnVIX_t$	ADS_t	$LnCSENT_t$
$LnEPU_t$	−0.122	−0.109	0.336	−0.339	−0.414
	(0.015)	(0.030)	(0.000)	(0.000)	(0.000)
$EMKTR_t$		−0.116	−0.257	0.100	0.039
		(0.021)	(0.000)	(0.047)	(0.44)
$BWSENT_t$			0.117	0.066	0.297
			(0.020)	(0.192)	(0.000)
$LnVIX_t$				−0.329	−0.188
				(0.000)	(0.000)
ADS_t					0.489
					(0.000)

Panel C Contemporaneous correlation coefficients among the indexes and the short-term reversal factor, January 1986 to December 2018

	$LnEPU_t$	$EMKTR_t$	$BWSENT_t$	$LnVIX_t$	ADS_t	$LnCSENT_t$
ST_Rev_t	0.006	0.299	0.083	−0.020	0.077	0.054
	(0.899)	(0.000)	(0.099)	(0.698)	(0.127)	(0.284)

Panel D Correlation coefficients among the indexes in the prior month and the short-term reversal factor in the current month, February 1986 to January 2019

	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$
ST_Rev_t	0.112	0.063	0.069	0.095	0.074	0.030
	(0.026)	(0.214)	(0.168)	(0.059)	(0.141)	(0.551)

Table 2 Descriptive statistics for the beta estimates

The beta estimate of a stock is computed with respect to each sentiment index (or the *EPU* index) and the Fama-French five factors. These sentiment indexes are *BWSENT*, *VIX*, *ADS*, and *CSENT*. The estimation period covers sixty months (with at least twenty-four observations) prior to each month in our testing period, which ranges from February 1988 to January 2019. This table displays the time-series average of selected percentiles of each beta estimate. These time-series averages are calculated from January 1988 to December 2018.

			Percentile		
Index	***20th***	***40th***	***50th***	***60th***	***80th***
BWSENT	−5.127	−1.293	−0.071	1.104	4.486
VIX	−6.811	−1.694	−0.006	1.631	6.295
ADS	−3.736	−1.075	−0.161	0.755	3.330
CSENT	−19.549	−4.208	1.090	6.588	23.212
EPU	−5.569	−1.416	0.044	1.480	5.507

Table 3 Short-term reversals during high and low economic policy uncertainty periods

In each month *t*, stocks are allocated into five groups from low (bottom 20%) to high (top 20%) based on their *Exposure* in month *t-1*. *Exposure* is the absolute value of the beta estimate with respect to each sentiment index (or the *EPU* index). The stocks in each month *t* are further divided independently into five groups from loser (bottom 20%) to winner (top 20%) based on their returns in month *t-1*. The intersections of the five *Exposure*-sorted groups and the five return-sorted groups generate 25 *Exposure*-return sorted portfolios. Equal weighted returns on the reversal portfolio (*LMW, %*) in month *t* is the difference in returns between the loser and winner portfolios in each *Exposure*-sorted group. This table shows the average returns on these reversal portfolios conditional on the economic policy uncertainty index score in month *t-1* from January 1988 to January 2019. The More (Less) uncertainty period is recorded when the economic policy uncertainty index score in month *t-1* is higher than (lower than or equal to) the median score of this index computed from the entire sample period. The *t*-statistics are in parentheses.

Panel A: Exposure to the Bake-Wurgler sentiment index (*BWSENT*)

			Exposure		
Uncertainty	**Low**	**2**	**3**	**4**	**High**
More (Mo)	1.269 (4.09)	1.174 (3.91)	1.270 (4.26)	1.323 (4.73)	1.421 (4.29)
Less (Le)	0.201 (0.72)	0.288 (1.09)	0.356 (1.28)	0.107 (0.39)	0.100 (0.38)
Mo minus Le	1.068 (2.55)	0.886 (2.22)	0.914 (2.24)	1.216 (3.10)	1.321 (3.11)

Panel B: Exposure to the Volatility index (*VIX*)

			Exposure		
Uncertainty	**Low**	**2**	**3**	**4**	**High**
More (Mo)	1.177 (3.74)	1.233 (3.97)	1.179 (3.99)	1.186 (3.82)	1.664 (5.18)
Less (Le)	0.339 (1.29)	0.471 (1.86)	0.235 (0.77)	0.132 (0.51)	−0.035 (−0.11)
Mo minus Le	0.808 (2.00)	0.762 (1.90)	0.944 (2.23)	1.054 (2.61)	1.699 (3.84)

Panel C: Exposure to the Business conditions index (*ADS*)

			Exposure		
Uncertainty	**Low**	**2**	**3**	**4**	**High**
More (Mo)	1.266 (4.07)	1.341 (4.65)	1.226 (4.04)	1.324 (4.42)	1.340 (4.03)
Less (Le)	0.570 (2.04)	0.179 (0.72)	0.234 (0.84)	0.063 (0.24)	0.027 (0.09)
Mo minus Le	0.696 (1.66)	1.162 (3.05)	0.992 (2.40)	1.261 (3.20)	1.313 (2.94)

Table 3 continued

Panel D: Exposure to the Consumer sentiment index (*CSENT*)

			Exposure		
Uncertainty	**Low**	**2**	**3**	**4**	**High**
More (Mo)	1.239 (3.75)	1.266 (4.41)	1.354 (4.72)	1.190 (4.14)	1.462 (4.44)
Less (Le)	0.352 (1.36)	0.353 (1.12)	0.215 (0.86)	0.212 (0.78)	−0.029 (−0.10)
Mo minus Le	0.887 (2.11)	0.913 (2.14)	1.139 (2.99)	0.978 (2.47)	1.491 (3.39)

Panel E: Exposure to the Economic policy uncertainty index (*EPU*)

			Exposure		
Uncertainty	**Low**	**2**	**3**	**4**	**High**
More (Mo)	1.356 (4.27)	1.235 (4.00)	1.105 (4.10)	1.461 (4.98)	1.351 (4.02)
Less (Le)	0.243 (0.83)	0.406 (1.50)	0.122 (0.48)	0.304 (1.09)	−0.101 (−0.36)
Mo minus Le	1.113 (2.57)	0.829 (2.02)	0.983 (2.66)	1.157 (2.86)	1.452 (3.31)

Table 4 Economic policy uncertainty and short-term reversals conditional on stocks' exposure to investor sentiment

This table reports the results from the estimation of the following regression model:

$$LMW_{jt}^{i}\left(or\ H\_L_{t}^{i}\right) = \alpha + \beta_1 LMW_{jt-1}^{i}(or\ H\_L_{t-1}^{i}) + \beta_2 LnEPU_{t-1} + \beta_3 EMKTR_{t-1} + \beta_4 BWSENT_{t-1} + \beta_5 LnVIX_{t-1} + \beta_6 ADS_{t-1} + \beta_7 LnCSENT_{t-1} + \varepsilon_{jt}^{i},$$

where LMW_{jt}^{i} is the return on the *j*th reversal portfolio (*j* = Low to High) classified by *Exposure* of the *i*th index (*i* = *BWSENT*, *VIX*, *ADS*, *CSENT*, or *EPU*) in month *t*. $Hi - Lo_{t}^{i}$ is the difference in returns on the reversal portfolios between the High-*Exposure* group and the Low-*Exposure* group of the *i*th index in month *t*. $LnEPU_{t-1}$, $EMKTR_{t-1}$, $BWSENT_{t-1}$, $LnVIX_{t-1}$, ADS_{t-1}, and $LnCSENT_{t-1}$ are the natural logarithm of the economic policy uncertainty index, the excess market return, the Bake-Wurgler sentiment index, the natural logarithm of the volatility index, the business conditions index, and the natural logarithm of the consumer sentiment index in month *t-1*, respectively. The variable ε_{jt}^{i} is the error term. The estimation period is from February 1988 to January 2019, and the *t*-statistics are in parentheses.

Panel A Exposure to the Bake-Wurgler sentiment index (*BWSENT*)

Exposure	**Intercept**	LMW_{t-1}	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$	$Adj\ R^2$
Low (Lo)	−14.981	−0.126	1.723	0.042	0.778	0.956	0.495	1.113	0.03
	(−1.35)	(−1.62)	(2.46)	(0.56)	(1.78)	(1.44)	(1.11)	(0.54)	
2	−6.094	−0.117	1.184	0.064	0.901	1.478	0.463	−0.666	0.03
	(−0.58)	(−1.55)	(1.81)	(0.88)	(2.42)	(2.25)	(1.07)	(−0.35)	
3	−13.149	−0.102	1.532	−0.017	0.789	0.924	0.532	0.948	0.03
	(−1.20)	(−1.15)	(2.56)	(−0.22)	(2.11)	(1.49)	(1.18)	(0.45)	
4	−14.179	−0.182	1.856	0.068	0.780	1.773	0.346	0.255	0.07
	(−1.32)	(−1.86)	(2.95)	(0.93)	(1.85)	(2.66)	(0.92)	(0.13)	
High (Hi)	−16.168	−0.124	1.808	0.086	0.707	1.799	0.057	0.724	0.05
	(−1.42)	(−1.27)	(2.80)	(0.99)	(1.76)	(2.65)	(0.13)	(0.34)	
	Intercept	H_L_{t-1}	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$	$Adj\ R^2$
Hi − Lo	−0.467	0.036	0.084	0.036	−0.046	0.703	−0.349	−0.455	0.01
	(−0.06)	(0.64)	(0.17)	(0.67)	(−0.17)	(1.50)	(−1.17)	(−0.33)	

Table 4 continued

Panel B: Exposure to the Volatility index (*VIX*)

Exposure	**Intercept**	LMW_{t-1}	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$	$Adj\ R^2$
Low (Lo)	−9.603	−0.169	1.241	0.021	0.678	0.689	0.466	0.598	0.03
	(−0.92)	(−2.19)	(2.02)	(0.27)	(1.84)	(1.05)	(1.04)	(0.30)	
2	−8.377	−0.086	1.132	−0.019	0.963	0.984	0.444	0.256	0.03
	(−0.82)	(−1.09)	(1.94)	(−0.26)	(2.63)	(1.56)	(0.99)	(0.13)	
3	−8.384	−0.169	1.455	0.034	0.686	1.029	0.695	−0.126	0.03
	(−0.73)	(−2.27)	(2.33)	(0.48)	(1.56)	(1.69)	(1.75)	(−0.06)	
4	−17.135	−0.150	1.597	0.079	1.023	1.717	0.196	1.195	0.06
	(−1.56)	(−1.34)	(2.33)	(0.99)	(2.15)	(2.69)	(0.45)	(0.59)	
High (Hi)	−19.942	−0.120	2.528	0.097	0.626	2.096	0.162	0.641	0.07
	(−1.69)	(−1.10)	(3.78)	(1.03)	(1.46)	(2.75)	(0.32)	(0.30)	
	Intercept	H_L_{t-1}	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$	$Adj\ R^2$
Hi − Lo	−10.207	−0.059	1.308	0.081	0.002	1.355	−0.265	0.032	0.05
	(−1.60)	(−1.02)	(2.74)	(1.11)	(0.01)	(2.13)	(−0.57)	(0.03)	

Panel C: Exposure to the Business conditions index (*ADS*)

Exposure	**Intercept**	LMW_{t-1}	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$	$Adj\ R^2$
Low (Lo)	−11.793	−0.123	1.613	0.040	1.104	0.577	0.552	0.803	0.03
	(−1.08)	(−1.45)	(2.57)	(0.54)	(2.86)	(0.83)	(1.14)	(0.39)	
2	−17.183	−0.134	1.859	0.046	0.755	1.028	0.690	1.428	0.04
	(−1.70)	(−1.44)	(3.26)	(0.66)	(2.19)	(1.80)	(1.51)	(0.75)	
3	−13.950	−0.198	1.512	0.037	0.616	1.592	0.685	0.704	0.05
	(−1.39)	(−1.87)	(2.60)	(0.45)	(1.53)	(2.56)	(1.54)	(0.37)	
4	−12.166	−0.160	1.425	0.096	0.652	1.962	−0.027	0.108	0.06
	(−1.15)	(−1.85)	(2.12)	(1.25)	(1.44)	(3.51)	(−0.07)	(0.06)	
High (Hi)	−14.477	−0.096	1.894	0.067	0.957	1.907	0.171	0.167	0.05
	(−1.12)	(−1.09)	(2.68)	(0.72)	(2.02)	(2.47)	(0.39)	(0.07)	
	Intercept	H_L_{t-1}	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$	$Adj\ R^2$
Hi − Lo	−2.007	−0.006	0.308	0.024	−0.096	1.239	−0.287	−0.744	0.02
	(−0.25)	(−0.09)	(0.54)	(0.34)	(−0.40)	(2.05)	(−0.68)	(−0.49)	

Table 4 continued

Panel D: Exposure to the Consumer sentiment index (*CSENT*)

Exposure	**Intercept**	LMW_{t-1}	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$	***Adj R^2***
Low (Lo)	−18.815	−0.093	1.675	0.013	1.310	1.327	0.542	1.786	0.06
	(−1.73)	(−1.25)	(2.52)	(0.18)	(2.85)	(2.06)	(1.04)	(0.88)	
2	−2.748	−0.138	1.205	0.011	1.013	0.728	0.595	−0.916	0.03
	(−0.25)	(−2.14)	(2.11)	(0.15)	(2.50)	(1.09)	(1.33)	(−0.43)	
3	−14.236	−0.096	1.784	0.045	0.762	1.544	0.597	0.506	0.05
	(−1.34)	(−1.26)	(2.91)	(0.67)	(1.97)	(2.58)	(1.49)	(0.26)	
4	−14.077	−0.193	1.628	0.076	0.702	1.398	0.289	0.712	0.05
	(−1.25)	(−1.52)	(2.71)	(0.96)	(1.87)	(2.31)	(0.69)	(0.34)	
High (Hi)	−19.558	−0.140	1.991	0.088	0.519	1.913	−0.103	1.210	0.05
	(−1.73)	(−1.31)	(2.84)	(0.94)	(1.28)	(2.63)	(−0.24)	(0.58)	
	Intercept	H_L_{t-1}	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$	***Adj R^2***
Hi − Lo	0.924	0.038	0.164	0.043	−0.723	0.448	−0.543	−0.700	0.04
	(0.13)	(0.65)	(0.34)	(0.66)	(−2.81)	(0.85)	(−1.35)	(−0.50)	

Panel E: Exposure to the Economic policy uncertainty index (*EPU*)

Exposure	**Intercept**	LMW_{t-1}	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$	***Adj R^2***
Low (Lo)	−14.237	−0.179	1.504	0.098	0.560	1.550	0.404	0.804	0.04
	(−1.19)	(−2.05)	(2.15)	(1.18)	(1.63)	(2.35)	(0.91)	(0.35)	
2	−14.668	−0.166	0.988	0.012	0.880	1.583	0.222	1.423	0.05
	(−1.36)	(−1.84)	(1.72)	(0.16)	(2.01)	(2.73)	(0.58)	(0.72)	
3	−10.550	−0.118	1.545	0.006	0.712	0.800	0.501	0.380	0.03
	(−1.02)	(−1.32)	(2.73)	(0.10)	(2.11)	(1.40)	(1.34)	(0.19)	
4	−6.593	−0.153	1.241	0.051	0.862	1.468	0.123	−0.572	0.04
	(−0.61)	(−1.83)	(1.94)	(0.67)	(2.02)	(2.38)	(0.29)	(−0.28)	
High (Hi)	−20.337	−0.123	2.724	0.103	0.934	1.631	0.410	0.786	0.06
	(−1.73)	(−1.27)	(3.88)	(1.21)	(1.88)	(2.16)	(0.85)	(0.37)	
	Intercept	H_L_{t-1}	$LnEPU_{t-1}$	$EMKTR_{t-1}$	$BWSENT_{t-1}$	$LnVIX_{t-1}$	ADS_{t-1}	$LnCSENT_{t-1}$	***Adj R^2***
Hi − Lo	−5.375	0.016	1.191	−0.001	0.381	0.063	0.070	−0.121	0.00
	(−0.71)	(0.26)	(2.27)	(−0.01)	(1.11)	(0.12)	(0.21)	(−0.09)	

Table 5 Economic policy uncertainty and short-term reversals conditional on stocks' exposure to investor sentiment and the Fama-French five risk factors

This table reports the results from the estimation of the following regression model:

$$LMW_{jt}^{i}\left(or\ Hi\_Lo_{t}^{i}\right) = \alpha + \beta_1 LMW_{jt-1}^{i}\left(or\ Hi\_Lo_{t-1}^{i}\right) + \beta_2 LnEPU_{t-1} + \beta_3 EMKTR_{t-1} + \beta_4 BWSENT_{t-1} + \beta_5 LnVIX_{t-1} + \beta_6 ADS_{t-1} + \beta_7 LnCSENT_{t-1} + \gamma_1 EMKTR_t + \gamma_2 SMB_t + \gamma_3 HML_t + \gamma_4 RMW_t + \gamma_5 CMA_t + \varepsilon_{jt}^{i},$$

where LMW_{jt}^{i} is the return on the *j*th reversal portfolio (*j* = Low to High) classified by *Exposure* of the *i*th index (*i* = *BWSENT*, *VIX*, *ADS*, *CSENT*, or *EPU*) in month *t*. $Hi\_Lo_{t}^{i}$ is the difference in returns on the reversal portfolios between the High-*Exposure* group and the Low-*Exposure* group of the *i*th index in month *t*. $LnEPU_{t-1}$, $EMKTR_{t-1}$, $BWSENT_{t-1}$, $LnVIX_{t-1}$, ADS_{t-1}, and $LnCSENT_{t-1}$ are the natural logarithm of the economic policy uncertainty index, the excess market return, the Bake-Wurgler sentiment index, the natural logarithm of the volatility index, the business conditions index, and the natural logarithm of the consumer sentiment index in month *t-1*, respectively. $EMKTR_t$, SMB_t, HML_t, RMW_t, and CMA_t are the market, size, book-to-market, profitability, and investment factors in month t. ε_{jt}^{i} is the error term. The estimation period is from February 1988 to January 2019, and the *t*-statistics are in parentheses.

Table 5 continued

Panel A Exposure to the Bake-Wurgler sentiment index (*BWSENT*)

Exposure	**Low (Lo)**	**2**	**3**	**4**	**High (Hi)**	**Hi_Lo**
Intercept	−19.149	−9.800	−16.294	−19.440	−19.318	0.136
	(−1.96)	(−1.09)	(−1.68)	(−2.01)	(−1.85)	(0.02)
LMW_{t-1}	−0.130	−0.103	−0.077	−0.172	−0.105	
	(−1.83)	(−1.86)	(−1.18)	(−2.32)	(−1.23)	
H_L_{t-1}						0.044
						(0.74)
$LnEPU_{t-1}$	1.673	1.075	1.441	1.935	1.677	0.025
	(2.30)	(1.59)	(2.18)	(2.79)	(2.55)	(0.05)
$EMKTR_{t-1}$	0.037	0.053	−0.023	0.059	0.073	0.035
	(0.47)	(0.76)	(−0.30)	(0.77)	(0.82)	(0.68)
$BWSENT_{t-1}$	0.774	0.885	0.803	0.579	0.728	0.039
	(1.54)	(2.17)	(2.03)	(1.27)	(1.78)	(0.15)
$LnVIX_{t-1}$	1.060	1.576	1.079	1.909	1.918	0.749
	(1.68)	(2.62)	(1.78)	(3.12)	(3.17)	(1.64)
ADS_{t-1}	0.183	0.123	0.222	0.131	−0.262	−0.354
	(0.44)	(0.28)	(0.48)	(0.32)	(−0.70)	(−1.12)
$LnCSENT_{t-1}$	1.977	0.160	1.603	1.213	1.445	−0.547
	(1.08)	(0.10)	(0.84)	(0.67)	(0.75)	(−0.40)
$EMKTR_t$	0.269	0.278	0.240	0.214	0.252	−0.018
	(3.29)	(3.69)	(2.97)	(2.91)	(3.64)	(−0.37)
SMB_t	−0.034	−0.039	−0.080	−0.030	−0.039	0.004
	(−0.27)	(−0.32)	(−0.60)	(−0.24)	(−0.31)	(0.07)
HML_t	0.254	0.264	0.281	0.291	0.285	0.035
	(1.82)	(1.87)	(2.09)	(2.40)	(2.26)	(0.43)
RMW_t	0.191	0.153	0.106	0.261	0.099	−0.079
	(0.79)	(0.73)	(0.45)	(1.14)	(0.48)	(−0.95)
CMA_t	−0.344	−0.382	−0.441	−0.344	−0.450	−0.133
	(−1.97)	(−2.49)	(−2.81)	(−2.07)	(−2.53)	(−1.19)
Adj R^2	0.13	0.17	0.13	0.17	0.15	0.00

Table 5 continued

Panel B: Exposure to the Volatility index (*VIX*)

Exposure	**Low (Lo)**	**2**	**3**	**4**	**High (Hi)**	**Hi_Lo**
Intercept	−12.711	−12.683	−13.791	−21.512	−22.382	−9.759
	(−1.29)	(−1.38)	(−1.46)	(−2.16)	(−2.18)	(−1.58)
LMW_{t-1}	−0.155	−0.095	−0.137	−0.148	−0.105	
	(−2.14)	(−1.56)	(−2.76)	(−1.47)	(−1.28)	
H_L_{t-1}						−0.059
						(−1.04)
$LnEPU_{t-1}$	1.165	1.115	1.461	1.544	2.383	1.260
	(1.80)	(1.82)	(2.16)	(2.15)	(3.37)	(2.62)
$EMKTR_{t-1}$	0.015	−0.024	0.022	0.058	0.100	0.091
	(1.18)	(−0.33)	(0.29)	(0.71)	(1.10)	(1.32)
$BWSENT_{t-1}$	0.650	0.919	0.513	0.931	0.737	0.124
	(1.55)	(2.32)	(1.03)	(1.97)	(1.64)	(0.36
$LnVIX_{t-1}$	1.762	1.157	1.161	1.891	2.196	1.400
	(1.15)	(1.99)	(2.01)	(3.14)	(3.35)	(2.33)
ADS_{t-1}	0.204	0.156	0.454	−0.078	−0.238	−0.406
	(0.40)	(0.37)	(1.06)	(−0.21)	(−0.57)	(−0.89)
$LnCSENT_{t-1}$	1.279	1.083	0.939	2.084	1.215	−0.060
	(0.69)	(0.62)	(0.50)	(1.14)	(0.63)	(−0.05)
$EMKTR_t$	0.223	0.238	0.234	0.209	0.314	0.088
	(2.68)	(3.20)	(2.84)	(2.83)	(4.04)	(1.62)
SMB_t	−0.031	−0.045	−0.002	0.025	−0.149	−0.118
	(−0.24)	(−0.38)	(−0.01)	(0.22)	(−1.10)	(−1.79)
HML_t	0.185	0.316	0.261	0.381	0.235	0.055
	(1.31)	(2.25)	(1.99)	(3.12)	(1.60)	(0.53)
RMW_t	0.159	0.151	0.299	0.103	0.094	−0.061
	(0.74)	(0.74)	(1.09)	(0.55)	(0.38)	(−0.71)
CMA_t	−0.283	−0.430	−0.437	−0.508	−0.327	−0.035
	(−1.66)	(−2.72)	(−2.65)	(−3.01)	(−1.79)	(−0.29)
Adj R^2	0.10	0.14	0.14	0.17	0.18	0.06

Table 5 continued

Panel C: Exposure to the Business conditions index (*ADS*)

Exposure	**Low (Lo)**	**2**	**3**	**4**	**High (Hi)**	**Hi_Lo**
Intercept	−15.933	−21.087	−17.910	−16.302	−17.523	−0.992
	(−1.61)	(−2.34)	(−2.00)	(−1.77)	(−1.51)	(−0.13)
LMW_{t-1}	−0.105	−0.134	−0.170	−0.153	−0.082	
	(−1.52)	(−1.93)	(−2.23)	(−2.03)	(−1.08)	
H_L_{t-1}						0.001
						(0.01)
$LnEPU_{t-1}$	1.620	1.803	1.456	1.320	1.779	0.182
	(2.37)	(2.99)	(2.34)	(1.90)	(2.43)	(0.32)
$EMKTR_{t-1}$	0.044	0.036	0.030	0.078	0.054	0.006
	(0.58)	(0.51)	(0.36)	(1.04)	(0.56)	(0.08)
$BWSENT_{t-1}$	1.048	0.693	0.571	0.586	0.978	−0.036
	(2.53)	(1.83)	(1.26)	(1.24)	(2.11)	(−0.13)
$LnVIX_{t-1}$	1.775	1.104	1.715	2.044	2.061	1.225
	(1.13)	(1.95)	(2.86)	(3.86)	(3.06)	(2.05)
ADS_{t-1}	0.313	0.381	0.340	−0.346	−0.126	−0.351
	(0.61)	(0.94)	(0.79)	(−0.98)	(−0.30)	(−0.77)
$LnCSENT_{t-1}$	1.567	2.258	1.511	1.039	0.834	−0.821
	(0.84)	(1.32)	(0.90)	(0.61)	(0.38)	(−0.57)
$EMKTR_t$	0.216	0.263	0.286	0.267	0.221	0.003
	(2.38)	(3.47)	(3.55)	(3.84)	(3.13)	(0.04)
SMB_t	−0.081	−0.027	−0.099	0.020	−0.037	0.051
	(−0.56)	(−0.22)	(−0.73)	(0.18)	(−0.29)	(0.73)
HML_t	0.220	0.247	0.284	0.281	0.317	0.097
	(1.52)	(2.21)	(2.33)	(2.56)	(1.86)	(0.78)
RMW_t	0.217	0.175	0.185	0.172	0.056	−0.160
	(1.91)	(0.83)	(0.79)	(0.80)	(0.25)	(−1.47)
CMA_t	−0.398	−0.291	−0.384	−0.391	−0.481	−0.076
	(−2.42)	(−2.09)	(−2.31)	(−2.33)	(−2.61)	(−0.62)
Adj R^2	0.12	0.15	0.18	0.18	0.13	0.03

Table 5 continued

Panel D: Exposure to the Consumer sentiment index (*CSENT*)

Exposure	**Low (Lo)**	**2**	**3**	**4**	**High (Hi)**	**Hi_Lo**
Intercept	−22.418	9.363	−18.243	−18.044	−22.217	1.355
	(−2.16)	(−1.08)	(−1.93)	(−1.77)	(−2.23)	(0.19)
LMW_{t-1}	−0.089	−0.111	−0.101	−0.180	−0.120	
	(−1.37)	(−2.60)	(−1.55)	(−1.72)	(−1.40)	
H_L_{t-1}						0.039
						(0.72)
$LnEPU_{t-1}$	1.633	1.336	1.731	1.568	1.823	0.073
	(2.34)	(2.06)	(2.68)	(2.46)	(2.53)	(0.15)
$EMKTR_{t-1}$	0.015	0.005	0.029	0.064	0.077	0.035
	(0.20)	(0.07)	(0.44)	(0.78)	(0.83)	(0.58)
$BWSENT_{t-1}$	1.315	0.740	0.667	0.629	0.602	−0.650
	(2.77)	(1.61)	(1.58)	(1.66)	(1.43)	(−2.67)
$LnVIX_{t-1}$	1.488	0.913	1.611	1.488	2.053	0.457
	(2.41)	(1.53)	(2.99)	(2.58)	(3.12)	(0.91)
ADS_{t-1}	0.300	0.379	0.299	−0.008	−0.487	−0.696
	(0.59)	(0.78)	(0.89)	(−0.02)	(−1.16)	(−1.74)
$LnCSENT_{t-1}$	2.495	2.251	1.365	1.553	1.842	−0.717
	(1.30)	(1.14)	(0.80)	(0.82)	(1.00)	(−0.52)
$EMKTR_t$	0.208	0.233	0.250	0.255	0.286	0.081
	(2.46)	(2.65)	(3.48)	(3.45)	(3.95)	(1.49)
SMB_t	−0.046	−0.049	0.006	−0.026	−0.092	−0.045
	(−0.38)	(−0.34)	(0.05)	(−0.21)	(−0.69)	(−0.60)
HML_t	0.227	0.309	0.268	0.258	0.327	0.111
	(1.59)	(2.24)	(2.14)	(2.12)	(2.30)	(1.54)
RMW_t	0.162	0.364	0.160	0.181	0.043	−0.108
	(0.85)	(0.36)	(0.74)	(0.81)	(0.18)	(−1.01)
CMA_t	−0.439	−0.419	−0.280	−0.339	−0.464	−0.036
	(−2.84)	(−2.49)	(−1.66)	(−2.34)	(−2.44)	(−0.30)
Adj R^2	0.14	0.15	0.15	0.16	0.17	0.05

Table 5 continued

Panel E: Exposure to the Economic policy uncertainty index (*EPU*)

Exposure	**Low (Lo)**	**2**	**3**	**4**	**High (Hi)**	**Hi_Lo**
Intercept	−19.770	−18.329	−14.805	−11.450	−22.594	−1.956
	(−1.90)	(−1.85)	(−1.52)	(−1.26)	(−2.22)	(−0.27)
LMW_{t-1}	−0.151	−0.161	−0.113	−0.148	−0.105	
	(−2.70)	(−2.07)	(−1.52)	(−2.32)	(−1.27)	
H_L_{t-1}						0.036
						(0.57)
$LnEPU_{t-1}$	1.576	0.938	1.545	1.194	2.510	0.885
	(2.10)	(1.54)	(2.54)	(1.73)	(3.48)	(1.70)
$EMKTR_{t-1}$	0.095	0.005	0.002	0.030	0.090	−0.018
	(1.13)	(0.07)	(0.03)	(0.40)	(1.06)	(−0.37)
$BWSENT_{t-1}$	0.386	0.832	0.618	0.718	1.048	0.643
	(0.97)	(1.75)	(1.77)	(1.55)	(2.12)	(1.65)
$LnVIX_{t-1}$	1.724	1.669	0.902	1.543	1.777	0.013
	(2.85)	(2.93)	(1.67)	(2.85)	(2.62)	(0.02)
ADS_{t-1}	0.196	−0.076	0.245	−0.202	0.042	−0.078
	(0.42)	(−0.19)	(0.62)	(−0.51)	(0.10)	(−0.23)
$LnCSENT_{t-1}$	1.803	2.187	1.217	0.457	1.381	−0.521
	(0.90)	(1.20)	(0.66)	(0.26)	(0.74)	(−0.39)
$EMKTR_t$	0.223	0.252	0.236	0.281	0.261	0.028
	(2.55)	(3.14)	(3.17)	(3.86)	(3.44)	(0.49)
SMB_t	−0.049	−0.046	−0.038	0.011	−0.055	0.019
	(−0.35)	(−0.36)	(−0.34)	(0.09)	(−0.41)	(0.25)
HML_t	0.265	0.238	0.225	0.310	0.309	0.048
	(1.85)	(1.77)	(1.79)	(2.41)	(2.28)	(0.57)
RMW_t	0.316	0.165	0.222	0.208	0.013	−0.312
	(1.24)	(0.73)	(1.14)	(0.90)	(0.06)	(−2.86)
CMA_t	−0.438	−0.297	−0.306	−0.332	−0.510	−0.064
	(−2.96)	(−1.81)	(−2.24)	(−1.99)	(−2.65)	(−0.50)
Adj R^2	0.14	0.14	0.14	0.16	0.18	0.06

Table 6 Do financial crises matter?

This table reports the results from the estimation of the following regression model:

$$Hi\_Lo_{t-1}^{i} = \alpha + \theta CRISIS_t + \beta_1 Hi\_Lo_{t-1}^{i} + \beta_2 LnEPU_{t-1} + \beta_3 EMKTR_{t-1} + \beta_4 BWSENT_{t-1} + \beta_5 LnVIX_{t-1} + \beta_6 ADS_{t-1} + \beta_7 LnCSENT_{t-1} + \gamma_1 EMKTR_t + \gamma_2 SMB_t + \gamma_3 HML_t + \gamma_4 RMW_t + \gamma_5 CMA_t + \varepsilon_{jt}^{i},$$

where $Hi\_Lo_t^i$ is the difference in returns on the reversal portfolios between the High-*Exposure* group and the Low-*Exposure* group of the *i*th index (*i* = *EPU*, *VIX*, or *ADS*) in month *t*. The dummy variable equals one during financial crises, and it is zero otherwise. Other variables are described in Table 5. The estimation period is from February 1988 to January 2019, and the *t*-statistics are in parentheses.

Exposure	**EPU**	**VIX**	**ADS**
Intercept	−1.872	−9.800	−1.013
	(−0.27)	(−1.57)	(−0.13)
$CRISIS_t$	0.499	−0.111	−0.104
	(1.00)	(−0.27)	(−0.21)
H_L_{t-1}	0.036	−0.059	0.000
	(0.57)	(−1.04)	(0.01)
$LnEPU_{t-1}$	0.924	1.251	0.174
	(1.79)	(2.58)	(0.31)
$EMKTR_{t-1}$	−0.019	0.091	0.006
	(−0.40)	(1.32)	(0.09)
$BWSENT_{t-1}$	0.549	0.145	−0.017
	(1.41)	(0.42)	(−0.06)
$LnVIX_{t-1}$	−0.284	1.466	1.288
	(−0.47)	(2.38)	(1.99)
ADS_{t-1}	−0.043	−0.414	−0.358
	(−0.13)	(−0.91)	(−0.79)
$LnCSENT_{t-1}$	−0.411	−0.085	−0.843
	(−0.32)	(−0.07)	(−0.59)
$EMKTR_t$	0.030	0.088	0.002
	(0.52)	(1.60)	(0.04)
SMB_t	0.020	−0.118	0.051
	(0.26)	(−1.79)	(0.73)
HML_t	0.046	0.056	0.098
	(0.53)	(0.53)	(0.78)
RMW_t	−0.320	−0.059	−0.158
	(−2.89)	(−0.67)	(−1.46)
CMA_t	−0.063	−0.035	−0.076
	(−0.50)	(−0.29)	(−0.62)
Adj R^2	0.06	0.06	0.07

Table 7 Does firm size matter

In each month *t*, stocks are allocated into three groups of tiny, small, and large stocks based on their market capitalization in month *t-1*, using the *NYSE* 20th and 50th percentiles as breakpoints. Then, stocks are independently sorted into two groups based on their *Exposure* to *EPU*, *VIX*, or *ADS* in month *t-1* from low (bottom 50%) to high (top 50%). Finally, stocks are independently sorted into quintiles according to their returns in month *t-1* from loser (bottom 20%) to winner (top 20%). The intersections of the three size-sorted groups, the two *Exposure*-sorted groups, and the five return-sorted groups generate thirty size-Exposure-return portfolios associated with each index. Equal weighted returns (%) on the reversal portfolio in month *t* is the difference in returns between the loser and winner portfolios in each size-*Exposure* sorted group.

This table reports the results from the estimation of the following regression model:

$$LMW_{jkt}^{i}\left(or\ Hi\_Lo_{kt}^{i}\right) = \alpha + \beta_1 LMW_{jkt-1}^{i}\left(or\ Hi\_Lo_{kt-1}^{i}\right) + \beta_2 LnEPU_{t-1} + \beta_3 EMKTR_{t-1} + \beta_4 BWSENT_{t-1} + \beta_5 LnVIX_{t-1} + \beta_6 ADS_{t-1} + \beta_7 LnCSENT_{t-1} + \gamma_1 EMKTR_t + \gamma_2 SMB_t + \gamma_3 HML_t + \gamma_4 RMW_t + \gamma_5 CMA_t + \varepsilon_{jt}^{i},$$

where LMW_{jkt}^{i} is the return on the *j*th reversal portfolio (*j* = Low or High) in the *k*th size-sorted group (*k* = Tiny, Small, or Large) and the *i*th *Exposure*-sorted group (*i* = *EPU*, *VIX*, or *ADS*) in month *t*. $Hi\_Lo_{kt}^{i}$ is the difference in returns on the reversal portfolios between the High-*Exposure* group and the Low-*Exposure* group of the *i*th index in each size-sorted group in month *t*. Other variables are described in Table 5. The estimation period is from February 1988 to January 2019, and the *t*-statistics are in parentheses.

Table 7 continued

Panel A: Exposure to the Economic policy uncertainty index (*EPU*)

Size	**Tiny**		**Small**		**Large**	
Exposure	**Low**	**High**	**Low**	**High**	**Low**	**High**
Intercept	−6.609	−13.296	−20.220	−11.807	−33.264	−35.482
	(−0.68)	(−1.53)	(−2.07)	(−1.14)	(−2.87)	(−2.79)
LMW_{t-1}	−0.085	−0.100	0.002	−0.028	−0.161	−0.098
	(−1.78)	(−1.85)	(0.03)	(−0.32)	(−1.79)	(−1.00)
$LnEPU_{t-1}$	0.646	1.715	1.635	1.979	1.560	2.135
	(1.05)	(2.92)	(2.33)	(2.43)	(2.21)	(2.49)
$EMKTR_{t-1}$	−0.070	−0.043	0.068	0.079	0.134	0.101
	(−0.94)	(−0.64)	(0.93)	(1.00)	(1.46)	(1.05)
$BWSENT_{t-1}$	0.325	0.884	0.772	0.662	0.532	0.666
	(0.94)	(2.39)	(1.56)	(1.22)	(1.17)	(0.94)
$LnVIX_{t-1}$	2.215	1.337	0.983	1.275	1.451	1.783
	(4.19)	(2.38)	(1.41)	(1.80)	(1.88)	(2.39)
ADS_{t-1}	−0.035	−0.013	0.157	−0.070	0.438	−0.092
	(−0.10)	(−0.04)	(0.30)	(−0.15)	(0.74)	(−0.19)
$LnCSENT_{t-1}$	−0.424	0.478	2.241	−0.221	4.879	4.510
	(−0.23)	(0.28)	(1.25)	(−0.11)	(2.31)	(1.94)
$EMKTR_t$	0.224	0.217	0.205	0.316	0.308	0.398
	(3.34)	(3.66)	(2.22)	(3.38)	(3.22)	(3.88)
SMB_t	−0.072	−0.036	−0.081	−0.089	−0.040	−0.032
	(−0.64)	(−0.34)	(−0.58)	(−0.54)	(−0.28)	(−0.19)
HML_t	0.242	0.253	0.120	0.324	0.258	0.418
	(2.17)	(2.27)	(0.69)	(1.91)	(1.48)	(2.50)
RMW_t	0.148	0.110	0.260	0.187	0.313	0.269
	(0.70)	(0.58)	(1.14)	(0.65)	(1.35)	(0.87)
CMA_t	−0.292	−0.325	−0.315	−0.464	−0.271	−0.572
	(−2.11)	(−2.34)	(−1.55)	(−2.22)	(−1.45)	(−2.18)
Adj R^2	0.14	0.15	0.08	0.14	0.15	0.16

Table 7 continued

Panel B: Exposure to the Volatility index (*VIX*)

Size	**Tiny**		**Small**		**Large**	
Exposure	**Low**	**High**	**Low**	**High**	**Low**	**High**
Intercept	−4.378	−15.215	−15.049	−14.675	−28.425	−42.389
	(−0.50)	(−1.64)	(−1.55)	(−1.35)	(−2.66)	(−3.17)
LMW_{t-1}	−0.017	−0.132	0.016	−0.064	−0.180	−0.112
	(−0.30)	(−2.04)	(0.21)	(−0.74)	(−2.35)	(−1.06)
$LnEPU_{t-1}$	0.862	1.684	1.431	2.081	1.750	2.039
	(1.55)	(2.65)	(1.93)	(2.63)	(2.34)	(2.51)
$EMKTR_{t-1}$	−0.131	−0.010	0.040	0.102	0.122	0.133
	(−1.96)	(−0.14)	(0.54)	(1.32)	(1.41)	(1.37)
$BWSENT_{t-1}$	0.705	0.565	0.488	0.963	0.739	0.515
	(1.94)	(1.31)	(1.02)	(1.71)	(1.37)	(0.80)
$LnVIX_{t-1}$	0.997	2.041	0.926	1.351	1.008	2.273
	(1.79)	(3.56)	(1.31)	(1.98)	(1.40)	(3.00)
ADS_{t-1}	0.156	−0.128	0.137	−0.021	0.310	−0.025
	(0.41)	(−0.36)	(0.24)	(−0.04)	(0.74)	(−0.05)
$LnCSENT_{t-1}$	−0.337	0.475	1.339	0.270	3.878	5.841
	(−0.19)	(0.28)	(0.73)	(0.13)	(1.97)	(2.39)
$EMKTR_t$	0.213	0.225	0.208	0.296	0.315	0.392
	(3.21)	(3.63)	(2.24)	(3.22)	(3.42)	(3.93)
SMB_t	−0.053	−0.063	−0.069	−0.101	−0.023	−0.055
	(−0.47)	(−0.58)	(−0.47)	(−0.67)	(−0.17)	(−0.32)
HML_t	0.249	0.249	0.115	0.289	0.313	0.357
	(2.10)	(2.17)	(0.69)	(1.73)	(1.92)	(2.14)
RMW_t	0.132	0.113	0.261	0.127	0.261	0.339
	(0.64)	(0.59)	(1.05)	(0.48	(1.11)	(1.10)
CMA_t	−0.385	−0.288	−0.318	−0.419	−0.323	−0.531
	(−2.70)	(−2.04)	(−1.77)	(−1.91)	(−1.57)	(−2.30)
Adj R^2	0.14	0.16	0.07	0.13	0.15	0.17

Table 7 continued

Panel C: Exposure to the Business condition index (*ADS*)

Size	**Tiny**		**Small**		**Large**	
Exposure	**Low**	**High**	**Low**	**High**	**Low**	**High**
Intercept	−11.563	−10.494	−9.256	−17.929	−37.232	−36.298
	(−1.25)	(−1.19)	(−1.12)	(−1.54)	(−3.40)	(−2.72)
LMW_{t-1}	−0.059	−0.102	−0.030	−0.015	−0.155	−0.115
	(−1.28)	(−1.75)	(−0.34)	(−0.16)	(−1.47)	(−1.32)
$LnEPU_{t-1}$	1.732	1.102	1.435	2.098	1.988	1.963
	(3.08)	(1.80)	(2.19)	(2.49)	(2.71)	(2.30)
$EMKTR_{t-1}$	−0.067	−0.040	0.096	0.063	0.118	0.136
	(−1.05)	(−0.55)	(0.47)	(0.75)	(1.35)	(1.41)
$BWSENT_{t-1}$	0.803	0.614	0.734	0.750	0.537	0.744
	(2.41)	(1.55)	(1.52)	(1.37)	(1.06)	(1.10)
$LnVIX_{t-1}$	1.386	1.810	0.619	1.482	1.109	2.317
	(2.59)	(3.27)	(0.96)	(2.01)	(1.44)	(3.22)
ADS_{t-1}	0.453	−0.280	0.326	−0.080	0.523	−0.168
	(1.31)	(−0.76)	(0.59)	(−0.18)	(0.96)	(−0.36)
$LnCSENT_{t-1}$	0.098	0.180	0.252	0.878	5.560	4.508
	(0.06)	(0.11)	(0.15)	(0.41)	(2.72)	(1.85)
$EMKTR_t$	0.265	0.192	0.221	0.290	0.293	0.416
	(3.73)	(3.27)	(2.34)	(3.16)	(2.86)	(4.60)
SMB_t	−0.077	−0.044	−0.145	−0.052	−0.062	−0.022
	(−0.60)	(−0.44)	(−0.99)	(−0.33)	(−0.43)	(−0.14)
HML_t	0.241	0.248	0.123	0.308	0.249	0.409
	(2.25)	(2.19)	(0.77)	(1.69)	(1.59)	(2.25)
RMW_t	0.224	0.060	0.272	0.139	0.263	0.357
	(0.99)	(0.33)	(1.05)	(0.52)	(1.04)	(1.23)
CMA_t	−0.299	−0.332	−0.328	−0.461	−0.312	−0.539
	(−2.32)	(−2.23)	(−1.77)	(−2.09)	(−1.55)	(−2.32)
Adj R^2	0.18	0.13	0.10	0.13	0.14	0.19

Table 7 continued

Panel D Differences in short-term reversal between High- and Low-*Exposure* stocks (*Hi_Lo*)

Exposure		**EPU**			**VIX**			**ADS**	
Size	**Tiny**	**Small**	**Large**	**Tiny**	**Small**	**Large**	**Tiny**	**Small**	**Large**
Intercept	−5.713	7.920	−3.356	−9.288	1.001	−13.982	2.030	−8.005	0.648
	(−1.04)	(1.13)	(−0.46)	(−1.60)	(0.11)	(−1.57)	(0.40)	(−0.94)	(0.08)
Hi_Lo_{t-1}	−0.002	0.049	0.055	−0.008	−0.092	−0.026	−0.003	0.038	0.006
	(−0.03)	(1.13)	(1.15)	(−0.15)	(−1.70)	(−0.39)	(−0.04)	(0.67)	(0.10)
$LnEPU_{t-1}$	0.954	0.323	0.562	0.667	0.546	0.347	−0.656	0.638	0.003
	(2.35)	(0.63)	(1.01)	(1.59)	(0.88)	(0.69)	(−1.73)	(1.13)	(0.00)
$EMKTR_{t-1}$	0.022	−0.006	−0.040	0.091	0.051	0.021	0.018	−0.037	0.006
	(0.62)	(−0.12)	(−0.69)	(2.21)	(0.87)	(0.42)	(0.46)	(−0.78)	(0.09)
$BWSENT_{t-1}$	0.518	−0.132	0.156	−0.206	0.443	−0.166	−0.189	0.034	0.180
	(2.46)	(−0.49)	(0.36)	(−0.55)	(1.22)	(−0.55)	(−0.66)	(0.12)	(0.44)
$LnVIX_{t-1}$	−0.821	0.252	0.249	0.885	0.407	1.193	0.354	0.795	1.104
	(−2.30)	(0.47)	(0.40)	(1.85)	(0.68)	(1.97)	(0.87)	(1.45)	(1.83)
ADS_{t-1}	0.028	−0.212	−0.437	−0.234	−0.201	−0.267	−0.662	−0.381	−0.550
	(0.10)	(−0.72)	(−0.95)	(−0.75)	(−0.50)	(−0.68)	(−1.99)	(−1.21)	(−1.40)
$LnCSENT_{t-1}$	0.769	−2.301	−0.032	0.720	−1.097	1.957	−0.058	0.553	−0.939
	(0.74)	(−1.71)	(−0.02)	(0.65)	(−0.68)	(1.20)	(−0.06)	(0.34)	(−0.56)
$EMKTR_t$	−0.004	0.110	0.073	0.009	0.088	0.072	−0.077	0.070	0.124
	(−0.12)	(2.02)	(1.13)	(0.24)	(1.52)	(1.35)	(−1.71)	(1.34)	(2.27)
SMB_t	0.035	−0.006	0.035	−0.015	−0.036	−0.020	0.031	0.096	0.057
	(0.75)	(−0.07)	(0.45)	(−0.27)	(−0.50)	(−0.25)	(0.59)	(1.30)	(0.79)
HML_t	0.007	0.214	0.150	0.001	0.177	0.054	0.007	0.176	0.164
	(0.11)	(2.30)	(1.27)	(0.02)	(2.03)	(0.57)	(0.10)	(1.51)	(1.29)
RMW_t	−0.046	−0.077	−0.040	−0.035	−0.149	0.092	−0.183	−0.135	0.103
	(−0.67)	(−0.77)	(−0.32)	(−0.53)	(−1.57)	(0.92)	(−1.94)	(−1.44)	(0.86)
CMA_t	−0.024	−0.167	−0.315	0.073	−0.124	−0.202	−0.037	−0.130	−0.209
	(−0.26)	(−1.34)	(−1.76)	(0.65)	(−0.91)	(−1.96)	(−0.34)	(−1.04)	(−1.58)
Adj R^2	0.02	0.05	0.03	0.02	0.03	0.02	0.04	0.05	0.05

APPENDIX: Variable definitions and sources

Aruoba-Diebold-Scotti (2009) business conditions index (ADS_t): The business conditions index in month *t* is collected from the Federal Reserve Bank of Philadelphia (https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads).

Bake-Wurgler (2007) sentiment index ($BWSENT_t$): The investor sentiment index in month *t* is collected from the webpage of Jeffrey Wurgler (https://pages.stern.nyu.edu/~jwurgler/).

Cboe Volatility index (VIX_t): The Chicago Board Options Exchange (Cboe) volatility index is the average daily Cboe volatility index in month *t*. The variable $LnVIX_t$ is the natural logarithm of *VIX* in month *t*. The daily index is collected from Cboe (https://www.cboe.com/tradable_products/vix/vix_historical_data).

Consumer sentiment index ($CSENT_t$): University of Michigan seasonally unadjusted consumer sentiment index in month *t*. The variable $LnCSENT_t$ is the natural logarithm of *CSENT* in month *t*. The monthly index is collected from the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org).

Economic policy uncertainty index (EPU_t): Economic policy uncertainty index in month t. This index is constructed by Baker, Bloom, and Davis (2016) and is available on the Economic Policy Uncertainty website (*policyuncertainty.com*). The variable $LnEPU_t$ is the natural logarithm of *EPU* in month *t*.

Excess market return ($EMKTR_t$): Value-weighted market return minus the risk-free rate in month *t*, and it is the market factor of the five Fama-French factors. The five Fama-French factors are collected from the webpage of Ken French (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Exposure to the EPU/sentiment index ($Exposure_t$): a stock's exposure to *EPU*/sentiment index in month *t* is the absolute value of its *EPU*-beta/sentiment-beta estimates. These betas are estimated from the sixty-month period prior to and including month *t*.

Financial crisis (*CRISIS*): This variable takes the value of one in the following crises and it is zero otherwise. These crises are the Asian Financial crisis (July 1997 to December 1988), the Dotcom bubble (March 2000 to October 2002), the 9/11 incident (September 2001 to October 2001), the Global financial crisis (June 2007 to December 2009), and the Europe debt crisis (January 2009 to December 2010).

Investment factor (CMA_t): This factor in month *t* is one of the five Fama-French factors.

Profitability factor (RMW_t): This factor in month *t* is one of the five Fama-French factors.

Short-term reversal factor (ST_Rev_t): This factor in month *t* is collected from the webpage of Ken French.

Size factor (SMB_t): This factor in month *t* is one of the five Fama-French factors.

Stock return (R_t): stock return (%) in month *t*.

Reversal portfolio return (LMW_t): Return on the reversal portfolio (%) in month *t* is the difference in returns between the loser and winner portfolios in that month.

Value factor (HML_t): This factor in month *t* is one of the five Fama-French factors.