Investor sentiment and return predictability of economic policy uncertainty

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Abstract

Both economic policy uncertainty (EPU) innovation and investor sentiment affect stock market returns. However, their relative importance is typically examined separately in the finance literature. This study concentrates on examining how different investor sentiment regimes affect the relationship of EPU innovation and future stock market returns. Using the Baker et al. (2016) news-based measure to capture the changes in EPU in the United States and an indirect market-based index (Baker and Wurgler, 2006) as a proxy for different sentiment regimes, we find that EPU innovation is negatively correlated with future stock market returns. The negative predictive ability of changes in EPU on future stock returns is only significant under a high-sentiment regime. After adding the lagged business cycle and market volatility variables, the negative predictive ability of changes in EPU on future stock returns is still better under a high-sentiment regime than the negative predictive ability under a low-sentiment regime.

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1. Introduction

Many scholars have recorded how stock markets are affected by economic policy uncertainty (Sum, 2012a; Antonakakis et al. 2013; Colombo, 2013; Guo et al, 2017 and Christou et al., 2017). For example, Kang and Ratti (2013) conclude that an increase in economic policy uncertainty can Granger-cause reduced market returns in U.S. markets. Antonakakis et al. (2013) and Arouri et al. (2016) find that stock returns decrease if economic policy uncertainty (EPU) increases. This negative effect can be stronger and more persistent when during periods of extreme volatility. From the listed literature, it can be easily found that economic policy uncertainty has negative influence on stock returns.

But why is there a negative relationship between EPU and stock returns? Scholars give possible explanations from different perspectives. From the perspective of the demand side, McDonald and Siegel (1986) believe that firms will tend to decrease investment and also postpone projects if the environment is highly uncertain. Carroll (1996) points out that households will be more likely to reduce consumption of durable goods. Bloom (2009) gives a possible explanation from the supply side, namely that high levels of uncertainty will negatively affect firms' hiring plans.

When investors make investment decisions, they must go beyond simply considering how economic policy uncertainty affects future stock returns. They must also keep in mind that markets are not efficient because investor sentiment also affects the stock market. In fact, there is a large literature showing that stock returns are affected by investor sentiment. For example, Fisher and Statman (2000) conclude that future S&P 500 returns are negatively correlated with both individual sentiment and institutional investor sentiment. On the contrary, a positive relationship between investor sentiment and contemporaneous market returns is documented by Lee at al. (2002). By constructing a market-based indirect sentiment index, Baker and Wurgler (2006) demonstrate that extremely subjective and hard-to-arbitrage securities can be more seriously influenced by a wave of investor sentiment.

An assessment of the literature makes it clear that both economic policy uncertainty and investor sentiment are important factors in determining market returns. However, the relative importance of economic policy uncertainty and investor sentiment is not known. Therefore, this study aims to evaluate the role and effect of changes in economic policy uncertainty (EPU) on future stock market returns by taking different investor sentiment regimes into consideration. We know that EPU is negatively correlated with future excess stock returns and that the effect of short-sale constraints is stronger under a high-sentiment regime than the effect under a low-sentiment regime. Thus, we hypothesize that the predictive power of EPU innovation on future excess stock returns is better under a high-sentiment regime than under a low-sentiment regime.

In this study, we adopt the Baker et al. (2016) EPU index to measure economic policy uncertainty. Since the EPU index is highly auto-correlated, we use an AR(2) model that controls market returns to calculate EPU innovation. Our interest in this study is not the whole investor sentiment but different sentiment regimes, thus we divide the Baker and Wurgler (2006) indirect sentiment index into high- and low-sentiment regimes according to the approach used by Kim et al. (2014). In addition, a variety of business cycle and market volatility variables are used as control variables. We find that EPU innovation is negatively correlated with future stock market returns, which is consistent with Brogaard and Detzel (2015). The negative predictive ability of EPU innovation on future stock market returns is only significant under high-sentiment regime. Even after adding the lagged business cycle and market volatility variables, the negative predictive ability of EPU innovation on future stock market returns is still better under high-sentiment regimes than the negative predictive ability under low-sentiment regimes. In contrast to the research conducted by Brogaard and Detzel (2015), this study distinguishes the influence of EPU innovation on stock returns under both high-sentiment regimes and low-sentiment regimes.

One possible explanation for the difference is the existence of three short-sale constraints. First, the direct cost of selling short—which is a fee the stock lender charges to the short seller—can be expensive. Second, there are other costs and risks associated with shorting. Third, investors are prevented from selling short by legal and institutional constraints. It will not be easy to forecast stock values when investor sentiment is high. Irrational and inexperienced investors will have a substantial impact on markets when investor sentiments are high; therefore, compared with the periods of low-sentiment, the negative predictive power on the future stock returns is most evident during a high-sentiment regime.

There are two main contributions of this study to the literature. First, this study is the only one to our knowledge that directly examines the relationship between changes in economic policy uncertainty and expected stock market returns under both high- and low-sentiment regimes. Second, this study adds a behavioral element (investor sentiment) to financial econometric research. As such, it provides new insights on how EPU innovation affects stock market returns under different sentiment regimes.

The paper is organized as follows: We first review the relevant literature in section 2. We then describe our data and methodology (section 3). We then present our empirical analysis (section 4), and report our robustness checks (section 5). Our conclusions are presented in section 6.

2. Relevant literature

Researchers agree that both economic policy uncertainty and investor sentiment can affect stock market returns, but their influence on stock markets is typically examined separately. This research tries to investigate how innovation in economic policy uncertainty affects stock market returns under the influence of different sentiment regimes.

2.1. Economic policy uncertainty

How does future policy uncertainty affect market prices? Pastor and Veronesi (2010) document that the declarations of policy changes on average causes a decrease in stock prices and that this decrease can be more serious with a larger government policy uncertainty. They argue that uncertainty about future government actions can have a positive effect if the government responds properly to unanticipated shocks, but that political uncertainty can also have a negative effect because political uncertainty is not fully diversifiable. In line with their statement, Arouri et al. (2016) find that stock returns will be reduced significantly if economic policy uncertainty increases.

Baker et al (2016) developed an EPU index for measuring the influence of policy uncertainty. The index is based on data from developed countries such as United States, Canada, and Germany, as well as from developing countries such as South Korea and China. Since the development of the index, a series of studies have begun to emphasize the importance of EPU on stock markets ((Sum, 2012a; Sum, 2012b; Jones and Olson, 2013; Mensi et al., 2016; Wu et al., 2016; Guo et al., 2017).

Antonakakis et al. (2013) find a negative relationship between policy uncertainty and stock market returns after employing S&P500 returns, the VIX index and the policy uncertainty index. Specifically, stock market returns decline with increased stock market volatility and increased policy uncertainty.

Using a structural VARs method, Colombo (2013) found that shocks of economic policy uncertainty in the United States caused a significant decrease in industrial production and a decline in prices in the European Union. Applying an in-sample and out-of-sample analysis, the work of Karnizova and Li (2014) indicates that recessions can be predicted by policy uncertainty. The interest of Klößner and Sekkel (2014) is the spillover of policy uncertainty and they find that the dynamics of policy uncertainty can be explained by spillovers.

Sum (2012b) focuses on EPU innovation and finds that there is a negative relation between stock returns and economic policy uncertainty shocks. He also finds that when changes in economic policy uncertainty are higher, the expected stock returns are lower. This finding is consistent with Brogaard and Detzel (2015), who state that innovation in EPU negatively forecasts expected stock returns.

In the study we present here, we use the Baker et al. (2016) EPU index to measure economic policy uncertainty. Since the EPU index is highly auto-correlated, an AR(2) model which controls lagged market returns is used to calculate EPU innovation.

2.2. Investor sentiment

According to the efficient market hypothesis (EMH), the prices of stocks in the market exactly match their fundamental value. However, Keynes (1936) first argued that prices can fluctuate and their values can no longer reflect the fundamentals because of the effect of investors' "animal spirits." Since that time, numerous scholars have in fact demonstrated that markets are not efficient, and that stock returns can be influenced by investor sentiment. For example, De long et al. (1990) found that prices may not reflect fundamental values and that rational investors can earn a lower expected return than noise traders. By constructing a search-based sentiment measure to reveal the U.S. retail investor sentiment, Da et al. (2015) report the predictive ability of the FEARS index on short-term return reversals. Ben-Rephael et al. (2017) construct a direct measure of abnormal institution investor attention (AIA) and they show that institutional attention leads retail attention and reacts to major news events more quickly. Utilizing a number of sentiment proxies, Smales (2017) illustrates that different firms respond differently to changes in investor sentiment.

All the above listed empirical results indicate that markets are not efficient market because investor sentiment affects stock prices and thus stock market returns. As Baker and Wurgler (2007) point out, whether investor sentiment can affect stock prices is no longer a question; the real question is how to measure investor sentiment and quantify its effect. After examining the existing literature, we find that sentiment can be measured using either direct or indirect methods. However, using direct sentiment measures leads to different findings that using indirect methods (De Bondt, 1993; Brown and Cliff, 2005). Another problem is the possibility that investors may not act in the market consistent with what they report in surveys. In this study, we adopt the Baker and Wurgler (2006) indirect sentiment index. Since our interest in this study is the impact of different sentiment regimes we also follow the method of Kim et al. (2014) and divide the indirect sentiment index into high-sentiment and low-sentiment regimes.

3. Data and methodology

This section introduces measurement definition and the data that were used in this study. Section 3.1 describes the Baker et al. (2016) EPU index and the Baker and Wurgler

(2006) indirect sentiment index. Section 3.2 presents data used.

3.1. Measurement definition

3.1.1. Economy policy uncertainty

Previous studies have used the “event studies” approach to assess how economic policy uncertainty influences asset prices. For example, Belo et al. (2012) find that the relationship between cash flows and stock returns is positive during periods of Democratic presidencies, while this relationship becomes negative during periods of Republican presidencies. Boutchkova et al. (2012) examine the impact of local and global political risk on industry return volatility and find that domestic political uncertainty affects systematic volatility and that greater idiosyncratic volatility is translated by global political risks.

We use the Baker et al. (2016) EPU index rather than the event study method to proxy economic policy uncertainty. The reason is that the event study method is a discrete approach and it assumes that new regimes will resolve uncertainty. However, the EPU index is available on an ongoing basis and it can also quantify uncertainty resolution.

However, the EPU index is highly auto-correlated. Thus, we use the auto-regression by including lagged values of excess market returns to calculate EPU innovation. Based on the Bayesian information criterion, we adopt 2 lags for EPU and 1 lag for excess market returns.

3.1.2. Investor sentiment

Since investor sentiment affects stock prices, it is important to accurately measure sentiment and to quantify its effects (Baker and Wurgler, 2007; Da et al. 2015). Investor sentiment can be measured by either direct or indirect methods. Unfortunately, different results have been found by using direct measures (De Bondt, 1993; Brown and Cliff, 2005). This means that the impact of investor sentiment on returns is sensitive to direct measures. The possibility also exists that investors may not act in the market in ways that are not consistent with how they respond in surveys. However, the indirect measure does not have this issue. Given these concerns, in this study we adopt the Baker and Wurgler (2006) indirect sentiment index, which is based on six components: initial public offerings(IPO) (Stigler, 1964; Ritter, 1991), closed-end fund discount (Zweig, 1973; Lee et al. 1991), returns on initial public offerings (Ritter, 1991), equity share in new issues (Baker and Wurgler, 2000), NYSE share turnover (Baker and Stein, 2004), and dividend premium (Baker and Wurgler, 2004).

3.2. Data

The EPU index is obtained from http://www.policyuncertainty.com; the monthly EPU index is used. The monthly sentiment index and excess stock market returns come from the website of Professor Jeffery Wurgler. VXO is the Chicago Board Options Exchange monthly index of implied volatility on Standard and Poor's 100 (S&P 100) index. Following Brogaard and Detzel (2015), we calculate the created variance index (VAR).

It is the square of VOL, which is constructed by computing the standard deviation of daily stock returns within a month. Both VXO and daily stock returns are downloaded from Wharton Research Data Services. A variety of business cycle variables used in this study are available from the Federal Reserve and Wharton Research Data Services. The reason why we add business cycle variables and uncertainty variables as controls is that (1) business cycle variables are economic determinants of the EPU index, and (2) VAR and VXO represent realized uncertainty and implied uncertainty, which command risk premiums. These control variables are constructed according to Brogaard and Detzel (2015). We also estimate AR(p) processes for EPU because the EPU index is highly auto-correlated. Due to data availability limitations, the time period of this study runs from January 1986 to September 2015. There are 357 monthly observations.

****Table 1 here****

Table 1 shows the summary statistics of monthly excess returns, investor sentiment, EPU innovation, and the control variables used in this study. The standard deviation of SENT (0.5936), ΔRREL (0.1672), ΔTERM (0.2693), ΔDEFAULT (0.1060), and ΔLOD(D/P) (0.0075) are less than 1, while the standard deviation of excess market return (4.4851), EPU innovation (17.6135), changes of VXO (4.0570), and changes of VAR are larger (2.6026).

****Table 2 here****

Table 2 reports correlation coefficients of monthly excess returns, investor sentiment, EPU innovation, and the control variables. The correlation coefficient of EPU innovation and expected excess stock market returns is -0.1061, which indicates a negative relationship between EPU innovation and future excess stock returns. The correlation coefficients of ΔTERM and expected excess stock market returns is -0.1147 and correlation coefficients of ΔDEFAULT and expected excess stock market returns is -0.3382, which means the expected returns are lower when ΔTERM and ΔDEFAULT are higher, and higher when ΔTERM and ΔDEFAULT are lower. The correlation coefficients of ΔVXO and ΔVAR on expected excess market returns are -0.2189 and -0.415, respectively. This indicates that both the implied volatility and the realized volatility command a negative risk premium.

Following Campbell and Yogo (2006) and Brogaard and Detzel (2015), the Bayesian information criterion (BIC; with up to 12 lags) is used to estimate the lag length. Kang and Ratti (2013) find that an increase in EPU Granger-causes the market returns to drop in the United Sates. Therefore, we include excess market return in equation (1) to calculate EPU innovation.

$$EPU_t = a + \sum_i^m b_i \, EPU_{t-m} + \sum_j^n b_j \, MKT_{t-n} + \varepsilon_t^{EPU}, (1)$$

where m and n represent the lagged month of the EPU index and market excess returns.

****Table 3 here****

Table 3 represents AR(P) models of EPU as well as with lagged market excess returns. Column (1) shows the result of AR(P) models without market excess returns, while column (2) shows the result of AR(P) models with market excess returns. We also use a Dickey-Fuller generalized least squares (DF-GLS) test to test the unit root. Based on our analysis, we find that there are 2 lags in EPU and 1 lag in market excess returns. Similar to Brogaard and Detzel (2015), adding the lagged one month of market excess returns contributes to isolate the unanticipated component of the EPU index. However, EPU has a unit root is rejected at the 5%.

4. Empirical analysis

This section introduces models and results. An in-sample predictability analysis is presented in section 4.1. Because the in-sample analysis cannot guarantee the same result as the out-of-sample analysis, an out-of-sample predictability analysis is also used and the result is shown in section 4.2.

4.1. In-sample predictability analysis

We first test whether innovation in EPU negatively forecasts excess market returns. To test this question, the following model is used in the analysis:

$$r_{t+1} = \alpha_1 + \beta' \Delta EPU_t + \gamma' \Delta X_t + \varepsilon_{t+1}, \qquad (2)$$

where r_{t+1} is the monthly market excess return in month $t+1$; ΔEPU_t is the error term ε_t^{EPU} from model (1). X_t represents the business cycle and uncertainty control variables.

****Table 4 here****

Table 4 shows how EPU innovation and the control variables affect future excess market returns. In Panel A, we run the regression of future excess market returns on EPU innovation and controls. The coefficient of EPU innovation and future excess market return is -0.270 (as shown in Column 1) and the t-statistic is -2.00. This means EPU innovation negatively forecasts expected excess market returns. The coefficients of ΔTERM and ΔDEFAULT on future excess market return are -1.9132 and -14.3291, respectively. This is in consistent with the result in Table 1. The coefficients of changes in VXO and changes in VAR on excess stock market returns are all negative and significant, which means when changes of VXO and changes of VAR are higher, next month excess stock market returns will be lower. In contrast, the positive and significant coefficients of changes in RREL and changes in LOG(D/P) indicate that when changes in RREL and changes in LOG(D/P) are higher in this month, the expected excess stock market returns will also be higher in the next month.

In panel B, we investigate the influence of EPU innovation on expected excess returns by controlling one variable at each time, and then controlling all variables at the same time. The results of controlling one variable each time are shown in columns (1) to (6). The coefficients of EPU innovation on expected excess market returns are all negative and significant. Column (7) reports the result of adding all the control variables at the same time. The coefficient of EPU innovation on expected excess market returns is -0.0448 and the t-statistic is -3.65, which means that the relation between EPU innovation and future excess stock returns is still negative and still significant. The adjusted R^2 is 26.46 after adding all the control variables.

To address the issue of how different sentiment regimes affect the relationship between EPU innovation and expected excess market returns, we add a dummy variable and use model (3) in the analysis.

$$r_{t+1} = \alpha_1 + \alpha_2' D_t + \beta_1' \Delta EPU_t + \beta_2' \Delta EPU_t \times D_t + \gamma' \Delta X_t + \varepsilon_{t+1}, \qquad (3)$$

D_t is the sentiment dummy variable, when the value in month t is below the median of the sentiment index, D_t equals 0; otherwise D_t equals 1. Following Kim at al. (2014), we define a high-sentiment month when D_t equals 1 and a low-sentiment month when D_t equals 0.

Table 5 reports regression results for EPU innovation and excess market returns after adding the dummy variable and controlling variables.

****Table 5 here****

Similar to the previous analysis in table 4, we first add one control variable each time. The results are shown in columns (1) to (6). After that, we add all the control variables at the same time; column (7) shows the result. The difference is that we add the sentiment dummy variable when we run the regressions. The coefficients of EPU innovation and excess stock market returns represent the relationship of EPU innovation and future excess stock returns under a low-sentiment regime, while the coefficients on the interaction term (ΔEPU$\times$D) reflect the relationship between EPU innovation and excess stock market returns under a high-sentiment regime. Except for column (5), the coefficients of changes in EPU and future excess stock market returns under a low-sentiment regime are all negative (but not significant). Even though the negative predictive ability of EPU innovation on future excess stock returns is significant after adding changes of VXO control, this significance is only at 10%. On the other hand, the relation between EPU innovation and excess stock market returns under a high-sentiment regime are all negative and highly significant, because the absolute values of the t-statistic of the interaction term are no less than 2.70. In summary, the results shown in table 5 indicate that there is a negative relationship between EPU innovation and future excess stock returns and that the negative predictability ability of EPU innovation on future excess stock returns is better during a high-sentiment regime that it is during a low-sentiment regime. This finding is consistent with our hypothesis.

4.2. Out-of-sample predictability analysis

The previous analysis has shown that EPU innovation is negatively correlated with future stock market returns and that the negative predictive ability of changes in EPU on future stock market returns is only significant under a high-sentiment regime. However, this analysis is an in-sample analysis and it is subject to outliers and data mining. Thus, we will test whether the hypothesis still holds by using an out-of-sample predictability analysis.

Following Campbell and Thompson (2008) and Kim et al. (2014), we use a one month rolling window to redefine the high-sentiment regime. The redefined sentiment regime at time t is then used to predict excess stock returns in the next month. A total of 200 observations (based on data available from January 1986 to August 2002) is used to estimate the initial parameter. The excess stock return in September 2002 is predicted after we obtain the initial parameter. According to this process, we have 157 forecasts of expected excess stock returns. Model (3) is still used in the out-of-sample analysis. Similar to the previous analysis, we do not add any control variables at first. Then we add one control variable at each time. Finally, we add all the control variables at the same time. We also calculate $\widehat{R_{\tau+1}}$ and $\overline{R_{\tau+1}}$ by using model (2). $\widehat{R_{\tau+1}}$(unrestricted model) is the forecasted expected excess stock market returns, while $\overline{R_{\tau+1}}$(benchmark model) is the historical average excess stock market returns. After obtaining $\widehat{R_{\tau+1}}$ and $\overline{R_{\tau+1}}$, the out-of-sample R^2 statistic can be computed, which is $1 - \frac{\sum_{\tau=0}^{T-1}(R_{\tau+1}-\widehat{R_{\tau+1}})^2}{\sum_{\tau=0}^{T-1}(R_{\tau+1}-\overline{R_{\tau+1}})^2}$. If the value of the out-of-sample R^2 statistic is positive, this means that the unrestricted model is better than the benchmark model due to the reduced forecast errors.

****Table 6 here****

Table 6 reports the results of the out-of-sample predictability analysis. Rows 1 and 2 report results of the out-of-sample analysis without adding any control variables; one control variable is added each time and the results are shown in rows 3 to 14. The last two rows represent the results of out-of-sample analysis after adding all control variables. We do not add sentiment dummy variables and the results are shown in rows 1, 3, 5, 7, 9, 11, 13 and 15, while rows 2, 4, 6, 8, 10, 12, 14 and 16 report the results of adding the interaction of EPU innovation and high sentiment. From row 1 in table 6, we can see that the average value of EPU innovation without the investor sentiment regimes dummy variable has an OOS R^2 value of 0.9435%, which is higher than zero. All of the OOS R^2 statistics in table 5 are positive. After adding the interaction term between EPU innovation and sentiment dummy variable, the OOS R^2 statistic in row 1 increases to 1.1752%. This means that the performance of EPU innovation on future excess stock returns with the definition of the high sentiment regime is better than that without the definition of high sentiment regime. From rows 3 to 14, we find a similar pattern, namely, the OOS R^2 statistic becomes bigger with the interaction term than without the interaction term, when we add one control variable. After adding all the control variables, the OOS R^2 statistic still increases when the interaction term is added.

In summary, the OOS R^2 statistics confirms that the definition of a high sentiment regime improves the predictive ability of EPU innovation on future excess stock market returns, which is consistent with the previous analysis.

5. Robustness check

In section 5.1, the whole sample is divided into two subsamples. The impact of EPU innovation on future excess stock returns with different sentiment regimes is examined in these two subsamples. In section 5.2, the higher sentiment regime is defined, which is the top 25% value of the sentiment index. Then we re-examine whether the predictive ability of EPU innovation on future excess stock returns is still better under the higher sentiment regime.

5.1. Different time periods

We have demonstrated that EPU innovation is negatively correlated with future stock market returns, and that the negative predictive ability of EPU innovation on future stock market returns is only significant under a high-sentiment regime. After adding the lagged business cycle and market volatility variables, the negative predictive ability of EPU innovation on future stock market returns is still better under a high-sentiment regime than under a low-sentiment regime. To check the robustness of the findings, the whole sample is divided into two subsamples. The period of the first subsample is from January 1986 to November 2000, and the period of the second subsample is from

December 2000 to September 2015. The results are presented in table 7.

****Table 7 here****

Panel A shows the results from January 1986 to November 2000. In columns (1) to (7), we see that the predictive ability of EPU innovation on expected market returns is negative and significant only during high-sentiment regimes. During low-sentiment regimes, the predictive ability of innovation EPU on expected market returns is negative and statistically insignificant. A similar pattern can be found in Panel B. Therefore, the results in both Panel A and Panel B indicate that the hypothesis still holds under different time periods.

5.2. Higher investor sentiment periods

In the previous analysis we defined the high-sentiment regime and found that the negative predictive ability of EPU innovation on future stock market returns was better under a high-sentiment regime than under a low-sentiment regime, regardless of whether we do or do not add control variables. To check the robustness of this finding, we define a higher sentiment regime as the top 25% value of the sentiment index. The lower sentiment regime is re-defined as the bottom 25% value of the sentiment index. We then re-examine whether the predictive ability of EPU innovation on future excess stock returns under this higher sentiment regime still holds. Table 8 reports the results.

****Table 8 here****

The coefficients of EPU innovation on excess stock market returns are still negative but not significant during the low-sentiment regime. In contrast, the coefficients of EPU innovation on excess stock market returns under the high-sentiment regime are negative and highly significant. After comparing the coefficients and t-statistics of EPU innovation and excess stock market returns under the high and low sentiment regimes, it is clear that the predictive ability of EPU innovation is better during high-sentiment regimes than the predictive ability of EPU innovation under low-sentiment regimes. This is in consistent with our hypothesis.

6. Conclusion

In this thesis, we investigate whether the predictive ability of EPU innovation on future excess market returns is affected by different sentiment regimes. We find that EPU innovation is negatively correlated with future stock market returns. The negative predictive ability of changes in EPU on future stock returns is only significant under a high-sentiment regime. After adding the lagged business cycle and market volatility variables, the negative predictive ability of changes in EPU on future stock returns is still better under a high-sentiment regime than the negative predictive ability under a low-sentiment regime.

The possible explanation of our fining is that there exist short-sale constraints. Firstly, the direct cost of selling short, which is a fee the stock lender charged to the short seller, can be expensive. Secondly, there are other costs and risks associated with shorting. Finally, investors are prevented from selling short by legal and institutional constraints. It will not be easy to forecast stock values when investor sentiments are high. The irrational and inexperienced sentiment investors have a governing role in the markets; thus, compared with the periods of low-sentiment, the negative predictive power on the future stock returns is more strongly applied during the regime of high-sentiment.

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Table 1: Summary statistics

	Obs	1%	25%	50%	Median	Std. Dev.	75%	99%
MKTRF	357	-10.7200	-1.9600	1.1700	1.1700	4.4851	3.5000	10.1900
SENT	357	-.7930	-.0957	.1422	0.1422	0.5936	.5166	2.4053
ΔEPU	356	-33.7057	-10.1792	-2.7302	-2.7302	17.6135	7.3605	60.7743
ΔRREL	356	-.5587	-.0582	.0113	.0113	.1672	.0831	.3675
ΔTERM	356	-.6900	-.1800	-.0250	-.0250	.2693	0.1650	.6400
ΔDEFAULT	356	-.2900	-.0400	-.0100	-.0100	.1060	.0400	.2900
ΔLOD(D/P)	356	-.7892	-.3373	-.1278	-.1278	.0075	.3974	.8711
ΔVXO	356	-6.2805	-2.0150	-.6384	-.6384	4.0570	.9929	14.9799
ΔVAR	356	-2.3248	-.9736	-.5287	-.5287	2.6026	.2070	10.5609

This table reports summary statistics for variables used in this study. The sample period is from January 1986 through September 2015. SENT is the Baker and Wurgler sentiment index. EPU is the Baker, Bloom, and Davis EPU index. RREL is the yield on the three-month U.S. Treasury bill minus the 12-month rolling average. TERM is the spread between three-month and 10-year U.S. Treasury bond yields. DEFAULT is the spread between AAA and BAA bond yields. LOG(D/P) is the smoothed log-dividend-price ratio on the CRSP value-weighted return series, where D represents the 12-month rolling sum of dividends. VXO is the implied volatility series on the S&P 100 index. VAR is the monthly variance of daily returns on the CRSP value-weighted return index.

Table 2: Correlation matrix

	MKTRF	ΔEPU	ΔRREL	ΔTERM	ΔDEFAULT	ΔLOD(D/P)	ΔVXO	ΔVAR
MKTRF	1.0000							
ΔEPU	-0.1061	1.0000						
ΔRREL	0.1355	-0.0892	1.0000					
ΔTERM	-0.1147	-0.0355	-0.4221	1.0000				
ΔDEFAULT	-0.3382	0.1723	-0.1888	0.0621	1.0000			
ΔLOD(D/P)	0.0305	0.0165	-0.0807	0.0442	0.0959	1.0000		
ΔVXO	-0.2189	-0.0500	-0.2423	0.2214	0.3357	-0.0292	1.0000	
ΔVAR	-0.415	0.1007	-0.1146	0.0801	0.2643	0.0903	0.0732	1.0000

This table reports correlation coefficients of predictors. EPU is the Baker, Bloom, and Davis EPU index. RREL is the yield on the three-month U.S. Treasury bill minus the 12-month rolling average. TERM is the spread between three-month and 10-year U.S. Treasury bond yields. DEFAULT is the spread between AAA and BAA bond yields. LOG(D/P) is the smoothed log-dividend-price ratio on the CRSP value-weighted return series, where D represents the 12-month rolling sum of dividends. VXO is the implied volatility series on the S&P 100 index. VAR is the monthly variance of daily returns on the CRSP value-weighted return index. The sample period is from January 1986 through September 2015.

Table 3: AR(p) coefficients and DF-GLS statistics

	EPU	
	(1)	(2)
AR(1)	**0.7756*** **	**0.7209*** **
	(14.59)	**(13.28)**
AR(2)	**0.0744** **	**0.1281** **
	(2.40)	**(2.37)**
MKT_{t-1}		**-0.7891*** **
		(-3.69)
DF-GLS	**-3.07** **	
N	355	355
Adj.-R^2	0.71	0.72

This table represents the AR(p) model of EPU as well as with lagged market excess returns. The Dickey-Fuller generalized least square (DF-GLS) statistics is used to estimate coefficients. Estimation with EPU uses 355 monthly observations. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Table 4: Forecasting of excess stock return

Panel A: Regressions of Excess Stock Returns on EPU Innovation and Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔEPU	**-.0270** **						
	(-2.00)						
ΔRREL		**3.6387*****					
		(2.57)					
ΔTERM			**-1.9132****				
			(-2.17)				
ΔDEFAULT				**-14.3291*****			
				(-6.76)			
ΔLOG(D/P)					**1.0966***		
					(1.87)		
ΔVXO						**-.2423*****	
						(-4.22)	
ΔVAR							**-.7150*****
							(-8.57)
Adj.-R^2 (%)	0.84	1.56	1.04	11.19	0.70	4.52	16.99

Table 4: Forecasting of Excess Stock Return (Continued)

Panel B: Regressions of Excess Stock Returns on EPU Innovation with Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔEPU	**-.0237***	**-.0280****	**-.0216***	**-.0275****	**-.0299****	**-.0306*****	**-.0448*****
	(-1.77)	**(-2.09)**	**(-1.75)**	**(-2.04)**	**(-2.27)**	**(-2.62)**	**(-3.65)**
ΔRREL	**3.8983*****						.1115
	(2.73)						(0.08)
ΔTERM		**-1.9236****					-1.0360
		(-2.19)					(-1.21)
ΔDEFAULT			**-13.7758*****				**-8.4558*****
			(-6.43)				**(-3.95)**
ΔLOG(D/P)				**1.0127***			18.6298
				(1.72)			(0.67)
ΔVXO					**-.2519*****		**-.1014***
					(-4.41)		**(-1.82)**
ΔVAR						**-.7041*****	**-.5332*****
						(-8.50)	**(-6.33)**
Adj.-R^2 (%)	2.63	1.90	11.94	1.39	5.79	18.34	26.46

Panel A reports estimates from the OLS regression of the monthly excess stock market returns on the lagged one month ΔEPU, lagged one month ΔRREL, lagged one month ΔTERM, lagged one month ΔDEFAULT, lagged one month ΔLOG(D/P), lagged one month ΔVXO and lagged one month ΔVAR. Panel B reports estimates of regression of the monthly excess stock market returns with lagged one month ΔEPU and control variables. Robust t-statistics following Newey–West (1987) corrected t-statistics with 12 lags are reported in parentheses. The sample period is from January 1986 through September 2015. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Table 5: Forecasting of excess stock return with EPU innovation and sentiment dummy variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D	-.7444	-.7362	-.5578	-.7401	-.6411	-0.7102	-.7387
	(-1.64)	(-1.62)	(-1.47)	(-1.63)	(-1.42)	(-1.53)	(-1.58)
ΔEPU	-.0231	-.0270	-.0116	-.0258	**-.0286***	-.0169	-.0116
	(-1.38)	(-1.64)	(-1.00)	(-1.51)	**(-1.72)**	(-1.60)	(-1.23)
ΔEPU×D	**-.0869*****	**-.0936*****	**-.0879*****	**-.0907*****	**-.0872*****	**-.0555*****	**-.0599*****
	(-3.36)	**(-3.40)**	**(-2.99)**	**(-3.12)**	**(-2.75)**	**(-3.00)**	**(-3.06)**
ΔRREL	**3.3403****						.2421
	(2.09)						(0.16)
ΔTERM		**-2.1700***					-.9938
		(-1.89)					(-0.92)
ΔDEFAULT			**-13.6334*****				**-8.4538*****
			(-7.50)				**(-2.97)**
ΔLOG(D/P)				**1.0492****			.5862
				(2.28)			(1.24)
ΔVXO					**-.2368*****		-.1120
					(-2.85)		(-1.30)
ΔVAR						**-.6639*****	**-.5386*****
						(-8.48)	**(-7.94)**
Adj.-R^2 (%)	7.73	7.92	16.36	6.21	10.83	20.01	26.21

This table reports estimates from the OLS regression of the monthly excess stock market returns with lagged one month ΔEPU and sentiment dummy variables. D is sentiment dummy variable, the value of it equals to 1 in the high-sentiment regime; otherwise is 0. Robust t-statistics following Newey–West (1987) corrected t-statistics with 12 lags are reported in parentheses. The sample period is from January 1986 through September 2015. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Table 6: Out-of-sample predictive power

Row	Comparison	OOS R^2(%)
1	ΔEPU vs. const	0.9435
2	(ΔEPU×D) vs. const	1.1752
3	(ΔEPU, ΔRREL) vs. const	0.0252
4	(ΔEPU×D, ΔRREL) vs. const	0.0300
5	(ΔEPU, ΔTERM) vs. const	0.2875
6	(ΔEPU×D, ΔTERM) vs. const	0.3144
7	(ΔEPU, ΔDEFAULT) vs. const	0.2364
8	(ΔEPU×D, ΔDEFAULT) vs. const	0.2365
9	(ΔEPU, ΔLOG(D/P)) vs. const	0.0019
10	(ΔEPU×D, ΔLOG(D/P)) vs. const	0.0064
11	(ΔEPU, ΔVXO) vs. const	0.0902
12	(ΔEPU×D, ΔVXO) vs. const	0.1007
13	(ΔEPU, ΔVAR) vs. const	0.1704
14	(ΔEPU×D, ΔVAR) vs. const	0.1780
15	(ΔEPU, all control variables) vs. const	0.1986
16	(ΔEPU×D, all control variables) vs. const	0.8461

This table reports results from one-month-ahead out-of-sample forecast comparisons of stock market excess returns. All variable definitions are identical to those in Table 3. Each row reports forecast comparisons of unrestricted models, which include predictor variables for stock market excess returns, with the constant expected stock market excess returns benchmark (const). OOS R2 suggested by Welch and Goyal (2008) and Campbell and Thompson (2008).

Table 7: Forecasting of excess stock return with EPU innovation and sentiment dummy variable in different subsamples

Panel A: from January 1986 to November 2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D	-.8850	-.8280	-.7065	-.6681	-.7717	-.7998	-.4698
	(-1.29)	(-1.26)	(-1.06)	(-0.95)	(-1.13)	(-1.17)	(-0.70)
ΔEPU	-.0154	-.0295	-.0121	-.0178	-.0194	-.0093	-.0222
	(-0.63)	(-1.22)	(-0.50)	(-0.72)	(-0.77)	(-0.36)	(-0.89)
ΔEPU×D	**-.1225****	-.1247***	**-.1275****	**-.1299*****	**-.1283*****	**-.1249*****	**-.1217*****
	(-3.91)	**(-4.18)**	**(-4.24)**	**(-4.21)**	**(-4.17)**	**(-3.99)**	**(-4.05)**
ΔRREL	2.068						-1.9778
	(1.07)						(-0.96)
ΔTERM		**-4.1015*****					**-4.7796*****
		(-3.50)					**(-3.76)**
ΔDEFAULT			**-16.0459*****				**-16.8886*****
			(-3.07)				**(-3.27)**
ΔLOG(D/P)				.6219			.6810
				(0.83)			(0.95)
ΔVXO					-.0830		-.0246
					(-0.92)		(-0.28)
ΔVAR						-.1006	-.1937
						(-0.75)	(-1.52)
Adj.-R^2 (%)	8.46	14.01	12.66	8.22	8.29	8.15	18.25

Table 7: Forecasting of excess stock return with EPU innovation and sentiment dummy variable in different subsamples (Continued)

Panel B: from December 2000 to September 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D	-.7636	-1.0509	-.6286	-.8011	-.7381		-.5481
	(-1.11)	(-1.55)	(-1.01)	(-1.13)	(-1.16)		(-1.28)
ΔEPU	-.0232	-.0281	-.0104	-.0271	-.0262	-.0120	-.0013
	(-1.48)	(-1.23)	(-0.71)	(-1.17)	(-1.25)	(-0.82)	(-0.12)
ΔEPU×D	**-.0653*** **	**-.0639** **	**-.0607*** **	**-.0633** **	**-.0576** **	**-.0483** **	**-.0372***
	(-2.58)	**(-2.48)**	**(-2.59)**	**(-2.48)**	**(-2.40)**	**(-2.05)**	**(-1.84)**
ΔRREL	**4.2758** **						3.2914
	(2.00)						(1.50)
ΔTERM		.2555					2.5051
		(0.20)					(1.45)
ΔDEFAULT			**-13.3953*** **				**-7.3035** **
			(-7.24)				**(-2.26)**
ΔLOG(D/P)				1.2483			**1.8991*** **
				(1.14)			**(2.46)**
ΔVXO					**-.3430*** **		-.1741
					(-4.90)		(-1.36)
ΔVAR						**-.6979*** **	**-.5396*** **
						(-5.79)	**(-6.48)**
Adj.-R^2	6.35	4.20	20.00	4.89	15.86	19.74	31.96

This table reports estimates from the OLS regression of the monthly excess stock market returns with lagged one month ΔEPU and sentiment dummy variables. Panel A is from January 1986 through November 2000 and panel B is from December 2000 through September 2015. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

Table 8: Forecasting of excess stock return with EPU innovation under top 25% sentiment dummy variable.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D^H	-.6598	-.7056	-.4771	-.5672	-.5574	-.5574	-.5673
	(-1.48)	(-1.60)	(-1.27)	(-1.24)	(-1.41)	(-1.21)	(-1.19)
ΔEPU	-.0257	-.0125	-.0140	-.0291	-.0140	-.0183	-.0132
	(-1.51)	(-1.29)	(-1.21)	(-1.64)	(-1.09)	(-1.49)	(-1.35)
$\Delta EPU \times D^H$	**-.0697*****	**-.0759*****	**-.0848*****	**-.0768*****	**-.0811*****	**-.0664****	**-.0756*****
	(-3.30)	**(-3.69)**	**(-3.40)**	**(-3.40)**	**(-3.47)**	**(-2.48)**	**(-3.35)**
ΔRREL	**3.5524****						.2841
	(2.50)						(0.19)
ΔTERM		-1.9286					-.7337
		(-1.62)					(-0.67)
ΔDEFAULT			**-14.1694****				**-8.3474*****
			(-7.10)				**(-2.83)**
ΔLOG(D/P)				1.7202			.5703
				(0.06)			(1.16)
ΔVXO					**-.2539*****		-.1267
					(-3.06)		(-1.44)
ΔVAR						**-.7164*****	**-.5959*****
						(-8.62)	**(-8.11)**
Adj.-R^2 (%)	4.08	3.72	13.31	3.04	7.67	19.50	25.72

This table reports estimates the monthly excess stock market returns with lagged one month ΔEPU and sentiment dummy variables. D^H is the dummy variable for the top 25% high-sentiment periods. Robust t-statistics following Newey–West (1987) corrected t-statistics with 12 lags are reported in parentheses. The sample period is from January 1986 through September 2015. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.