Does the quality of political signals matter for financial markets? Evidence from return predictability

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Abstract

Investor sentiment and the variance risk premium are well-established learning-based predictors of aggregate stock market returns. This study investigates whether the return predictability of investor sentiment and the variance risk premium is impacted by the quality of political signals. Our analysis shows that low-quality political signals substantially weaken return predictability via a prolonged mispricing correction associated with lower market participation. The explanatory power of predictive regression models is significantly improved when a proxy for the quality of political signals is included. Overall, our robust findings provide evidence that low-quality political signals have a negative impact on the functioning of financial markets.

Keywords: Investor sentiment, Variance risk premium, Return predictability, Information quality, Quality of political signals, Qindex, Investors' learning

JEL codes: G11, G14, G18

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1. Introduction

Investors in financial markets nowadays absorb a large amount of news and signals, such as earning announcements, policymakers' statements, and political news, and process the information flow to update their expectations and beliefs and then react in the financial markets (Veronesi, 2000; Epstein and Schneider, 2008). Political news drives the largest portion of stock market movements and jumps (over 36%), more than macroeconomic news (23%) and corporate earnings (11%) combined (Baker, Bloom, Davis, and Sammon, 2021). However, in recent years we have witnessed an unprecedented prolonged period of a deteriorating quality of political signals. The time after the election of Donald J. Trump as the U.S. president was arguably characterized by quasi-truth, alternative facts, and fake news. According to the Washington Post's Fact Checker database, by end of his term, he had made more than 30,570 false or misleading claims.[2] The measure for the quality of political signals – the U.S. Qindex proposed by Białkowski, Dang, and Wei, (2021) – indicates that over the period January 2017 to January 2021, the quality of political signals on average was approximately 43% lower than in the preceding eight years (90.6 versus 129 points).

The key question is whether and to what extent this low quality of signals matters for capital markets. There is scant literature on the topic. Previous theoretical studies have shown that information quality is important. (e.g., Veronesi, 2000; Li, 2005; Epstein and Schneider, 2008; Brevik and Addona, 2010). More recently, Pástor and Veronesi (2013) provide evidence in their theoretical model that expected volatility and correlation are closely associated with investors' learning about potential shocks. Normally, investors revise their expectation on stocks' performance based on a variety of information (e.g., economic news, political signals), and then act on the markets. However, investors' learning

[2] Source: https://www.washingtonpost.com/graphics/politics/trump-claims-database/.

process is subject to the quality of the information and signals received. When political signals are imprecise, investors are less likely to update their beliefs and hesitate to trade in the financial markets, leading to lower political risk premia and market volatility (Pástor and Veronesi, 2017). Białkowski, Dang, and Wei, (2021) show that a low quality of political signals is responsible for weaker correlation between a fear gauge, such as the CBOE VIX, and economic uncertainty, proxied by Baker, Bloom, and Davis' (2016) economic policy uncertainty index.

The aim of this study is to examine if imprecise signals coming from centers of political power affect the aggregate stock market return predictability of learning-based predictors.[3] Out of a battery of scrutinized predictors, we focus on a group of predictors that are largely based on investors' learning process and expectation (forward-looking), namely investor sentiment and the variance risk premium (VRP).

When the quality of political signals is low, we expect the predictive power to be weaker due to the prolonged correction process of mispricing. More specifically, we assume that there are two groups of traders in financial markets: noise traders who have biased beliefs and therefore trade on imprecise signals, and information traders (also known as arbitragers) who are rational and hold unbiased beliefs about stocks' intrinsic value to trade on informative signals (e.g., Black, 1986; DeLong, Shleifer, Summers, and Waldmann, 1990; Kumar and Lee, 2006; Aabo, Pantzalis, and Park, 2017).[4] Investor sentiment reflects the deviation in beliefs about future performance of stocks between noise traders and information traders, which leads to the mispricing of stocks (e.g., DeLong, Shleifer, Summers, and Waldmann, 1990; Barberis, Shleifer and Vishny, 1998; Brown, 1999; Baker

[3] The research on return predictability is motivated by a scrutiny of market inefficiency (e.g., Shiller, Fischer, and Friedman, 1984; Baker and Wurgler, 2000; Shleifer and Vishny, 2003) and time-varying equilibrium expected returns (e.g., Fama and French, 1989; Campbell and Viceira; 1999; Ang, Chen, and Xing, 2006).

[4] In this study, we use information trader and arbitrager interchangeably.

and Wurgler, 2006; Tetlock, 2007; Dumas, Kurshev, and Uppal, 2009; Stambaugh, Yu, and Yuan, 2012; Huang et al., 2015). The predictive power of investor sentiment stems from the price correction led by information traders, who bet against mispricing and are subject to the cost of arbitraging (e.g., Brown and Cliff, 2005; Lemmon and Portniaquina 2006; Stambaugh, Yu, and Yuan, 2012). However, signals can be either information (high-quality) or noises (imprecise or misleading). In an environment of precise political signals, the beliefs (on potential political shocks) of arbitragers are shaped efficiently by flows of newly arriving informative signals. As soon arbitragers learn that the signal quality is low, they will not update their beliefs (Epstein and Schneider, 2008), since they are not sure the signal received is information or noise, and therefore tend to hesitate to trade (Pastor and Veronesi, 2017). On the other hand, trading patterns of noise traders is less affected by the quality of political signals, since they trade on noise and are very likely to treat low-quality signals as part of new information. Consequently, there will be less trading activity and participation in stock markets during the low-quality signal periods, leading to prolonged mispricing and weakening of the predictive power of sentiment stemming from the price correction process. In addition, arbitragers spend resources to better identify a noise and to bet better against mispricing (DeLong, Shleifer, Summers, and Waldmann, 1990). The low quality of political signals could make betting against mispricing more costly, as information traders need to spend more resources to identify the noises traded on by noise traders. Hence, the mispricing of stocks will take even longer to be corrected.

Our argument regarding the quality of political signals and sentiments could also be extended to the VRP, another widely discussed predictor, which is defined as the difference between option-implied and actual realized variance (e.g., Bollerslev, Tauchen, and Zhou, 2009; Drechsler and Yaron, 2011; Gabaix, 2012; Bollerslev, Marrone, Xu, and Zhou, 2014; Kelly and Jiang, 2014; Zhou, 2018; Pyun, 2019). The VRP can be perceived as the compensation required by a risk-averse investor for taking a risk stemming from random changes in the instantaneous variance of asset returns (Todorov, 2010; Bollerslev and Todorov, 2011). The intuition behind the VRP's predictive power is that it captures investors' perceptions of uncertainty about economic fundamentals as well as their expectation on stock prices and variance (Drechsler and Yaron, 2011). When the quality of political signals is low, contents incorporated by both the components the VRP (i.e., option-implied variance and realized variance) tend to be less informative. Particularly, implied variance is based on trading activities in option markets, capturing information and investors' beliefs (e.g., Pan and Poteshman, 2006; Johnson and So, 2012). When the signals are ambiguous, information traders are unable to update their beliefs of directional expectations with valid information and trade less in option markets, while noise traders trade as they used to. Consequently, trading activities in option markets are dominated by noise traders, making the implied volatility less informative. The other component of the VRP, realized variance, is also likely to be fouled by the trading activities dominated by noise traders in the stock market, since arbitragers in stock markets, as discussed earlier, tend to trade less when the signals are of low quality. In this spirit, VRP based on implied volatility and realized volatility could not informatively reflect the unbiased expectation of uncertainty, and therefore has weakened predictive power.[5]

In light of the implications of the above-discussed theoretical studies, we would like to test whether the return predictability of investor sentiment and the VRP, as reported in the past literature, is weakened by the quality of political signals. In this study, we employ 11 widely discussed investor sentiment proxies, including the sentiment index by Baker and Wurgler (2006), the aligned investor sentiment index constructed by Huang et al. (2015),

[5] An alternative explanation for the weaker positive predictive power of VRP could be that investors require a smaller risk premium for taking risks embedded in their portfolios when the quality of information is low (Veronesi, 2000).

the manager sentiment index of Jiang et al. (2019), the short interest index by Rapach et al. (2016), the Financial and Economic Attitudes Revealed by Search (FEARS) sentiment index developed by Da et al. (2015), and others. We also consider the VRP as well as its two components, namely the jump tail variance premium and the normal variance premium (Bollerslev et al. 2015). Our analysis reveals the forecasting power of investor sentiment and the VRP is weaker during times characterized by low-quality political signals. Including the benchmark for the quality of political signals significantly improves the performance of the predictive regression applied in past studies. The results of our test on market participation (channel) provide evidence that market participation decreases with lower-quality political signals.[6] Our results are robust to the selection of multiple measures, forecast horizons, economic predicting variables, and model specifications.

The remainder of this paper is structured as follows. Section 2 describes the data and variables employed. Section 3 discusses the regression analysis on stock market return predictability. Section 4 reports the results of the channel test, and Section 5 concludes.

2. Data

Our sample covers the period January 2001 to December 2020.[7] This time horizon covers the 2007–2008 global financial crisis; the period post the 2016 U.S. presidential election, during which the quality of political signals was arguably low (Pástor and Veronesi, 2017; Białkowski, Dang, and Wei, 2021); and the COVID-19 pandemic period. In the remainder of this section, we discuss the variables considered in our study as well as their sources.

[6] The low quality of political signals can be also considered as a measure of ambiguity. In this sense, our findings on the link between market participation and the quality of political signals are consistent with the findings of Cao et al. (2005), Easley and O’Hara (2009), and Antoniou, Harris, and Zhang (2015).

[7] Our sample starts from January 2001, as the majority of sentiment proxies are available from the beginning of the 21st century.

2.1. Quality of political signals

To measure the quality of political signals in the U.S., we employ the index proposed by Białkowski, Dang, and Wei (2021), namely Qindex. Their benchmark is constructed based on an idea behind the approach applied to generate the EPU index (see Baker, Bloom, and Davis, 2016 for details). The Qindex measures the quality of political signals by reflecting the frequency of articles in leading U.S. nationwide newspapers that contain terms related to policy, signals, and quality. Specifically, the Qindex quantifies the coverage of the quality of political signals in 10 widely circulated newspapers in the U.S.: *USA Today, The Washington Post, The Boston Globe, The New York Times, The Wall Street Journal, Tampa Bay Times, New York Post, New York Daily News, Star Tribune,* and *The Atlanta Journal Constitution*. A monthly count of articles containing the following terms belonging to three categories were obtained: quality (e.g., "false", "misleading", or "ambiguous"), signal (e.g., "signal", "declarations", or "claim"), and policy (e.g., "deficit", "legislation", or "Federal Reserve"). Next, the monthly count of matched articles in each newspaper was divided by the respective monthly total number of articles. The resulting monthly series for each newspaper was standardized and then averaged across newspapers to obtain a monthly multi-paper index. In the last step, the multi-paper index was re-normalized to an average value of 100. Data of the Qindex on a monthly basis are available at https://www.qualityofpoliticalsignals.com.[8]

2.2. Investor sentiment

We employ 11 widely used sentiment measures constructed using data from the equity market, surveys, or textual analysis:

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[8] The study by Białkowski, Dang, and Wei (2021) considers two other proxies of the quality of political signals for the U.S., namely EPU variability (*EPUV*) and the number of false or misleading claims made by former President Donald J. Trump reported by *The Washington Post* (*WPFC*). However, the authors recognize the limitation of those two proxies: *EPUV* is not as accurate as *Qindex*, whereas *WPFC* is only available since January 2017. Additionally, *EPUV* is not exogenous, as it captures opinion dispersion among journalists, which might also be linked with investors' sentiment.

- The investor sentiment index developed by Baker and Wurgler (2006), $SENT^{BW}$. It is based on the first principal component of five standardized stock-market-cased sentiment proxies, including value-weighted dividend premia, first-day returns and volumes of IPOs, closed-end fund discount and equity share in new issues. Baker and Wurgler (2006) report that their sentiment index predicts lower subsequent excess market return. The data are available on Wurgeler's website at https://pages.stern.nyu.edu/~jwurgler/.

- The aligned investor sentiment index constructed by Huang et. al (2015), $SENT^{HJTZ}$. It modifies Baker and Wurgler's (2006) measure by using the partial least square method. Consistent with Baker and Wurgler (2006), Huang et. al (2015) show their sentiment index predicts lower future stock market returns. Data on $SENT^{HJTZ}$ is collected from Huang's website at https://dashanhuang.weebly.com/.

- The manager sentiment index of Jiang et al. (2019), $SENT^{MS}$, which is based on the aggregated textual tone of corporate financial disclosures. The proposed sentiment measure has the ability to predict negative subsequent market returns.

- The short interest index (*SII*) by Rapach et al. (2016), which measures short interest aggregated across securities and is constructed by removing a linear trend from the equal-weighted mean of all asset-level short interest. The short interest index manifests negative return predictability. $SENT^{MS}$ and *SII* measures can be downloaded from Zhou's website at https://apps.olin.wustl.edu/faculty/zhou/.

- The Financial and Economic Attitudes Revealed by Search (FEARS) investor sentiment index developed by Da et al. (2015), $SENT^{FEARS}$. The index reflects the number of Internet searches related to household concerns (e.g., "recession," "unemployment," and "bankruptcy"). The data are available at Da's website, https://www3.nd.edu/~zda/.

- The American Association of Individual Investors (AAII) sentiment index. It is constructed by surveying individual investors about the expected direction of the stock market over the next six months and is widely used in the literature (e.g., Brown, 1999; Jacobs, 2015; Gu, Chen, and Stan, 2021). We use the difference between bullish and bearish AAII sentiments as an alternative sentiment measure, $SENT^{AAII}$. The data for AAII sentiments are collected from Bloomberg.

- The Advisor Sentiment index from Investors Intelligence. This is another sentiment measure surveying financial advisors in the U.S. Similarly, we use the bullish advisor sentiment minus the bearish advisor sentiment, $SENT^{advisor}$, as one of our sentiment measures. Lee, Jiang, and Indro (2002) show that higher advisor sentiment leads to higher future excess returns over the period from January 1973 to October 1995. We source the index data from Refinitiv's DataStream.

- U.S. one-year confidence index for individual investors ($SENT^{Indiv}$) proposed by Shiller (2000). It is also a survey-based measure constructed by surveying U.S. individual investors about their expected returns, and has been employed by existing studies (e.g., Bacchetta, Mertens, and Van Wincoop, 2009; Greenwood and Shleifer, 2014). The data are obtained from the website of the International Center for Finance at the Yale School of Management.

- The consumer sentiment index developed by the University of Michigan, $SENT^{MCS}$. It is construed by a telephone survey of a nationally representative sample of households. Data are available at http://www.sca.isr.umich.edu/.

- The Conference Board consumer confidence index, $SENT^{CBC}$, which is developed by mail surveying a random sample of households in the U.S. The data of $SENT^{CBC}$ are obtained from DataStream. Lemmon and Portniaquina (2006) report that consumer sentiment by the University of Michigan and the consumer confidence index by Conference Board negatively predicts future returns over the 1956–2002 period.
- Ipsos Primary Consumer Sentiment index for the U.S., *PCSI*. The index is based on a monthly survey of consumer attitudes on the current and future state of local economies, personal finance situations, savings, and confidence to make large investments. It has been used as a sentiment proxy by previous studies (e.g., Wang and Markellos, 2018; Ferrara and Marsilli, 2019). We collect the data from Refinitiv's DataStream.

2.3. Variance risk premium

Following Bollerslev, Tauchen, and Zhou (2009) and Drechsler and Yaron (2011), we define the *VRP* of the aggregate stock market (proxied by the S&P 500 index) as the difference between the *ex ante* risk-neutral expectation of the future return variation over the $[t, t + 1]$ time interval and the *ex post* realized return variation over the $[t - 1, t]$ time interval:

$$VRP_t \equiv IV_t - RV_t \,, \tag{1}$$

where the risk-neutral expected variance (*IV*) is measured by the square of the CBOE VIX index, and the realized return variation (*RV*) is the realized variance of the high-frequency return of the S&P 500 index over the last month. Specifically, the realized variance is obtained by summing up the squared intraday five-minute log returns of S&P 500 index over a whole month. We obtain the high-frequency data used to calculate realized variance measures from Tick Data.[9]

For our robustness test, we also consider the two components of *VRP* (Bollerslev et al., 2015), namely the left tail jump variance premium (*LJV*) and normal variance premium (defined as *VRP-LJV*). The data for *LJV* are collected from Todorov's website at https://tailindex.com/.

2.4. Market participation

To test the channel via which the return predictability of investor sentiment and the VRP is affected by the quality of political signals, we employ a total of 12 measures for participation in the equity and derivatives markets, including the following:

- Net mutual fund flow to U.S. equities (*Netflow*) from the Investment Company Institute. Accordingly, the net fund low is the dollar value of new sales minus redemptions, combined with net exchanges:

  $$Netflow = (new\ sales - redemptions) + (exchanges\ in - exchanges\ out).$$

  A positive (negative) net flow, or inflow (outflow), indicates new sales plus exchanges into funds are greater (lower) than redemptions and exchanges out of funds.
- The logarithm of share volume (Vol^{SPX}), dollar volume ($DVol^{SPX}$), and value-weighted turnover ratio (TR^{SPX}) of S&P 500 component stocks, where the turnover ratio for each stock is defined as the monthly share volume divided by shares outstanding. The data required to calculate those variables are collected from the CRSP database.
- The logarithm of total share volume (Vol^{all}), dollar volume ($DVol^{all}$), and value-weighted turnover ratio (TR^{all}) of all stocks listed on the NYSE, Amex, and NASDAQ. Data are obtained from the CRSP database.

[9] Source: https://www.tickdata.com/

- The log number of trades for stocks listed on NASDAQ (*Trades*) available in the CRSP database.
- The log volume of call options ($Options^{call}$) and put options ($Options^{put}$) as well as the total option volume ($Options^{SPX}$) whose underlying asset is the S&P 500 index. We obtain the data from Refinitiv's DataStream.
- The log volume of all the options traded on CBOE ($Options^{all}$), with the data collected from the CBOE website.

2.5. Other data

Considering that stock market return predictability of investor sentiment or the VRP may come from the information associated with macroeconomic fundamentals and business cycles (e.g., Bollerslev, Tauchen, and Zhou, 2009; Drechsler and Yaron, 2011; Bollerslev, Marrone, Xu, and Zhou, 2014; Jiang et al., 2019), we use 14 monthly economic variables in the predictive regression model: earnings-price ratio, *EP*, defined as the difference between the log of earnings on the S&P 500 index and the log of prices; dividend-payout ratio, *DE*, defined as the difference between the log of dividends and the log of earnings on the S&P 500 index; dividend-price ratio, *DP*, defined as the difference between the log of a 12-month moving sum of dividends paid on the S&P 500 index and the log of S&P 500 index price; dividend yield, *DY,* defined as the difference between the log of S&P 500 dividends and the log of lagged S&P 500 prices; stock return variance, *SVAR*, calculated as the sum of squared daily returns on the S&P 500 index; book-to-market ratio, *BM*, defined as the ratio of book value to market value for the Dow Jones Industrial Average; net equity expansion, *NTIS*, calculated as the 12-month moving sums of net issues by stocks listed on NYSE divided by the total end-of-year market capitalization of NYSE stocks; Treasury bill rate, *TBL*, defined as the yield of a 3-month T-bill; long-term yield, *LTY*, which is the long-term government bond yield; long-term return, *LTR*, defined as the return on long-term government bonds; term spread, *TMS,* calculated as the long-term yield minus the T-bill rate; default yield spread, *DFY*, defined as the difference between BAA- and AAA-rated bond yields; default return spread, *DFR,* calculated as the difference between the long-term corporate bond return and the long-term government bond return; inflation, *INFL*, calculated based on the Consumer Price Index by Welch and Goyal (2008). The data required for calculation of all 14 economic variables above are available and updated at Goyal's website, http://www.hec.unil.ch/agoyal/.

The data on the S&P 500 index and the VIX index are sourced from Bloomberg, and information about recession periods is collected from the website of the Federal Reserve Bank of St. Louis. For the sake of brevity, we list the description and sources of all the variables mentioned in Sections 2.1-2.5 in Appendix A. The descriptive statistics of the variables employed in our study are summarized in Table 1.

TABLE 1 HERE

The correlation matrix for the key independent variables is presented in Table 2. As part of our analysis, we have tested the variable inflation factors to ensure that our results are not affected by a multicollinearity problem.

TABLE 2 HERE

3. Predictive regression analysis

In this section, we first securitize the effects of the signal quality on the return predictability of investor sentiment, and then we examine the impacts on the predictive effects of the VRP.

3.1. Return predictability of investor sentiment

As a prelude to the regression analysis, Fig. 1 plots the monthly excess stock market return (over the next quarter) against investor sentiment proxied by Baker and Wurgler's (2006) sentiment index ($SENT^{BW}$) by the level of *Qindex*. Baker and Wurgler (2006) document that when investor sentiment is high, the cross-section of stocks earns lower subsequent returns due to the correction of the systematic sentiment-driven mispricing.

Fig. 1 illustrates the extent to which investor sentiment, proxied by $SENT^{BW}$, can predict subsequent stock market returns. Panel A (B) in Fig.1 shows the corresponding plots for the case when *Qindex* is below (above) its sample median. Panel C (Panel D) presents the plots for the *Qindex* measure when it is below (above) its 30th (70th) percentile level over the sample period. The slopes of all the fitted lines are negative (downward-sloping), indicating a negative predictive effect on subsequent market returns. This is consistent with the results reported by Baker and Wurgler (2006). More importantly, it can be seen that the slope of the fitted line in Panel B (Panel D) is flatter when *Qindex* is high, compared with that in Panel A (Panel C). It suggests a weaker predictive power of sentiment when the quality of political signals is low. Moreover, the slope of the fitted line in Panel C (Panel D) is slightly steeper (flatter) than that in Panel A (Panel B), indicating a stronger return predictability of $SENT^{BW}$ during periods when the quality of political signals is high.

FIGURE 1 HERE

Next, we employ the standard predictive regression model widely applied in the literature (e.g., Bollerslev et al., 2009; Jiang et al., 2019):

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \varphi SENT_t^k + \varepsilon_{t+1}, \qquad (2)$$

where the dependent variable is the average of monthly excess returns (in percentage) of the S&P 500 index over the next *h* months. The excess return is defined as a monthly return on the S&P 500 index in excess of the risk-free rate (3-month T-bill rate). *h* could be set as one, three, six or 12 to measure the average monthly future market returns over the next one month, one quarter, six months, or one year, respectively. Taking into account the findings of Bollerslev et al. (2009), we apply the average monthly excess return over next three months (*h=3*) as our primary measure for aggregate stock market returns and the returns over other time horizons for robustness tests. $SENT_t^k$ is a proxy of investor sentiment. It is one of the 11 sentiment measures (i.e., $SENT^{BW}$, $SENT^{HJTZ}$, $SENT^{MS}$, *SII*, $SENT^{FEARS}$, $SENT^{AAII}$, $SENT^{advisor}$, $SENT^{Indiv}$, $SENT^{MCS}$, $SENT^{CBC}$, *PCSI*) employed in this study. To deal with potential heteroscedasticity and autocorrelation, we use the Newey-West standard error with one lag and present the Newey-West t-statistic in the relevant tables.[10] Then, we add the benchmark for the quality of political signals (*Qindex*) as well as its interaction with the sentiment measure to show how the return predictability of investor sentiment is affected:

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \varphi SENT_t^k + \beta Qindex_t + \gamma SENT_t^k \cdot Qindex_t + \varepsilon_{t+1}. \qquad (3)$$

Table 3, Panel A, presents the OLS estimation results for the predictive effects of investors on stock market returns (over the next quarter) without considering the quality of political signals (as in Equation (2)). As shown, when *Qindex* is not included, only four sentiment measures ($SENT^{BW}$, $SENT^{HJTZ}$, $SENT^{MS}$, *SII*) of 11 manifest statistically significant and negative predictive effects. This is in line with past studies (i.e., Baker and Wurgler, 2006; Huang et al., 2015; Rapach et al., 2016; Jiang et al., 2019).[11] The adjusted R-squares range from 6.31% ($SENT^{BW}$) to 10.52% (*SII*). The remaining sentiment measures show a lack of statistically significant power to predict, and the corresponding adjusted R-squares are close to zero.

[10] Tests with an alternative number of lags show consistent results and are available upon request.

[11] It is worth mentioning that previous studies have shown that sentiment measures based on stock markets data (systematic) should negatively predict stock market returns (e.g., Baker and Wurgler, 2006; Huang et al., 2015; Rapach et al., 2016), since higher sentiment indicates overpricing and therefore predicts negative future stock market returns caused by price correction. On the other hand, sentiment measures based on a specific group of investors (surveys) may present positive predictive effects (e.g., Lee, Jiang and Indro, 2002; Gu and Kurov, 2020). Our study focuses on whether the magnitude of return predictability of sentiment measures is weakened rather than the signs of their predictability.

Table 3, Panel B reports the results with consideration of the quality of political signals (*Qindex*) as in Equation (3). After adding *Qindex* and its interaction terms with sentiment measures, the four sentiment measures ($SENT^{BW}$, $SENT^{HJTZ}$, $SENT^{MS}$, *SII*) still present consistently significant predictive effects as in Panel A. In addition, five more sentiment measures ($SENT^{FEARS}$, $SENT^{AAII}$, $SENT^{advisor}$, $SENT^{Indiv}$, $SENT^{MCS}$) show statistically significant predictive effects on aggregate stock market returns. More importantly, apart from $SENT^{CBC}$, all the interaction terms between *Qindex* and sentiment measures manifest statistically significant coefficients with opposite signs, suggesting the return predictability of investor sentiment is weaker during periods when the quality of political signals is low (proxied by high *Qindex*). Using $SENT^{BW}$ as an example, the result in Panel B, Table 3, indicates that a one-standard-deviation increase in *Qindex* will weaken the negatively predictive effect of $SENT^{BW}$ on monthly future excess return by 1.2%. The inclusion of *Qindex* and its interaction terms also improves the explanatory power of the estimation model dramatically, raising the adjusted R-square by 3.1% to 9.3% for sentiment measures that show statistically significant predictive effects. Thus, the explanatory power of the predictive regression models has been improved by at least 49.8% (for $SENT^{MS}$). These findings are consistent with our expectation that the return predictability of investor sentiment is weakened during the periods featuring low-quality political signals proxied by *Qindex*.

TABLE 3 HERE

Given that the stock market return predictability of investor sentiment may come from the information associated with macroeconomic fundamentals and business cycles (e.g., Bollerslev, Tauchen, and Zhou, 2009; Drechsler and Yaron, 2011; Bollerslev, Marrone, Xu, and Zhou, 2014), we follow Jiang et al. (2019) and apply 14 different economic variables as controls. We run the predictive regressions with various permutations of the sentiment measures and economic controlling variables. Specifically, we employ 11 different sentiment measures with 14 different economic variables, and present the coefficient estimation for the sentiment measure and its interaction terms with *Qindex* in Table 4.[12] These results are obtained by running predictive regressions of 154 permutations. The findings in Table 4 indicate that weaker return predictability of investor sentiment during low-quality-signal periods is even more persistent and robust when the economic variables are included. Out of 154 permutations, 122 manifest statistically significant results, with the sentiment and its interaction term showing opposite signs. The other 32 permutations are found to be statistically insignificant, but the coefficient signs of sentiment measures are all opposite to those of their interaction terms with *Qindex*.

TABLE 4 HERE

As a robustness test, we conduct principal components analysis for investor measures by disentangling sentiment measures that predict lower subsequent market return ($SENT^{BW}$, $SENT^{HJTZ}$, $SENT^{MS}$, *SII*, $SENT^{Indiv}$) from those showing positive return predictability ($SENT^{AAII}$, $SENT^{advisor}$, $SENT^{MC}$ $SENT^{CBC}$, *PCSI*). We use the first principal component of each sentiment group as a proxy for investor sentiment and test if their predictive effects are influenced by the quality of political signals (*Qindex*). Appendix B demonstrates the results for the tests with the first principal components for "negative-predicting" sentiment proxies ($PC1^{negtive}$) and "positive-predicting" sentiment measures ($PC1^{positive}$), respectively.[13] These results are statistically significant and persistent across all the specifications, which confirms our previous findings.

[12] For reasons of brevity, we only report a coefficient estimation for the sentiment measure and its interaction terms with *Qindex.* The full set of regression results are available upon request.

[13] For the sake of brevity, we only present the results for $PC1^{negtive}$ by considering $SENT^{BW}$, $SENT^{HJTZ}$, and $SENT^{Indiv}$. We also tested with multiple first principal components based on different combinations of negative-predicting sentiment measures, such as the ones based on $SENT^{BW}$, $SENT^{HJTZ}$, $SENT^{MS}$, *SII,* and $SENT^{Indiv}$. The results are consistent and are available upon request.

As another robustness test, we examine the stock market return predictability over different time horizons. In addition to the primary horizon (three months ahead) applied in our study, we also test with one-month-, six-month-, and 12-month-ahead average monthly excess returns. The results are reported in Table 5.[14] Overall, the results in Table 5 show consistent evidence for the weakening effects of the quality of political signals on sentiments' return predictability. These findings also suggest that such effects could vary with the forecast horizons, which are in line with previous studies (e.g., Bollerslev et al., 2009; Jiang et al., 2019).

TABLE 5 HERE

Overall, we provide evidence that the aggregate stock market return predictability of investor sentiments is statistically and economically weakened by the quality of political signals.

3.2. Return predictability of VRP

As part of our preliminary analysis, we first plot the monthly excess stock market return (over the next quarter) against *VRP* by the level of *Qindex* in Fig. 2. Panel A (B) shows the plots for the case when *Qindex* is below (above) its sample median. Panel C (D) in Fig. 2 presents the plots if *Qindex* is below (above) its 30^{th} (70^{th}) percentile level over the sample period.

Bollerslev et al. (2009) and Drechsler and Yaron (2011) demonstrate that a higher VRP predicts higher subsequent stock market returns, as investors require higher compensation for higher expected economic uncertainty captured by *VRP*. Consistent with Bollerslev et al. (2009) and Drechsler and Yaron (2011), we document that the fitted lines across the panels in Fig. 2 are upward-sloping. Furthermore, as expected, the slope of the fitted line in Panel B (Panel D)

[14] We employ the dividend-price ratio (*DP*) as an example of an economic control variable in our robustness tests (see Tables 5, 7, and 9). We have also considered other economic variables. The results are consistent and available upon request.

is also flatter when *Qindex* is high than that in Panel A (Panel C). This indicates that the predictive magnitude of *VRP* is weakened during periods of low-quality political signals. Again, the slope of the fitted line for *VRP* in Panel C (Panel D) is slightly steeper (flatter) than that in Panel A (Panel B), showing stronger positive return predictability of *VRP* during periods of high-quality political signals.

FIGURE 2 HERE

Before examining how the quality of political signals affects the return predictability of the VRP, we replicate the regression analysis over the period January 1990 to December 2007 as carried out by Bollerslev et al. (2009). The results are shown in Appendix C. As shown in the table, *VRP* manifests statistically significant predictive power over the 1990–2007 period, and the predictability is stronger within a quarterly return horizon as reported by Bollerslev et al. (2009). The magnitudes of the estimated coefficients, t-statistics for *VRP*, and adjusted R-square are also quite close to those reported by Bollerslev et al. (2009). However, *VRP* shows statistically insignificant predictive power with negative adjusted R-squares across different forecast horizons during the January 2001 to December 2020 period.

Next, we examine the return predictability of the VRP by considering the quality of political signals, proxied by *Qindex*, as well as its interaction with *VRP*. Similar to how we tested for investor sentiment previously, we run the following standard predictive regression in Bollerslev et al. (2009) and add the proxy of political signal quality (*Qindex*) together with its interaction term with *VRP*:

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \varphi VRP_t + \beta Qindex_t + \gamma VRP_t \cdot Qindex_t + \theta ECON_t^m + \varepsilon_{t+1}, \quad (4)$$

where *VRP* is the variance risk premium of the S&P 500 index, $ECON_t^m$ is one of the 14 controlling economic variables (i.e., earnings-price ratio, *EP*; dividend-payout ratio, *DE*; dividend-price ratio, *DP*; dividend yield, *DY*; stock return variance, *SVAR*; book-to-market ratio, *BM*; net equity expansion, *NTIS*; Treasury bill rate, *TBL*; long-term yield, *LTY*; long-term return, *LTR*; term spread, *TMS*; default yield spread, *DFY*; default return spread, *DFR*; inflation, *INFL*).

Table 6 presents results for quarterly forecast horizons. In column (1), only *VRP* is included in the predictive regression. Column (2) reports the estimation result with *Qindex* and its interaction terms added, but without considering any economic variables. Columns (3) to (16) show the comprehensive results, controlling for one of the economic variables at a time. As demonstrated in Table 6, after including *Qindex* in the predictive regression model, coefficients estimated of *VRP* are found statistically significant and positive across columns (2) to (16) when economic variables are controlled. Meanwhile, coefficients estimated of the interaction terms between *VRP* and *Qindex* are statistically significant and negative. The estimated result in column (2) suggests that, if *Qindex* increases by one standard deviation, the positive predictive effect of *VRP* on monthly excess return is weakened by 0.23% (2.8% annualized excess return). As expected, these findings indicate that the VRP tends to manifest weaker positive predictive effects on stock market returns in an environment characterized by low-quality political signals.

TABLE 6 HERE

Similarly, we examine the monthly return predictability of *VRP* over different forecast horizons as a robustness test. Additionally, as *VRP* is also available at daily frequency, we test *VRP*'s predictability within regressions on a daily basis, which is subject to more noise, to see if the predictability is still statistically significant. Instead of using the monthly return and *VRP* calculated at the end of each calendar month, we employ rolling windows for all the variables. Specifically, *VRP* on a given day is calculated as the square of the VIX on that day minus the realized return variance of the S&P 500 index in the last 21 trading days; the future one-month return is defined as the compounded return over the next 21 trading days for each trading day, while the "quarterly" future return is the average monthly return over the next 63 trading days. The results of these robustness tests are presented in Table 7 and affirm our findings reported in Table 6.

TABLE 7 HERE

Bollerslev et al. (2015) decompose *VRP* to the jump tail variance premium (*LJV*) and normal variance premium (*VRP-LJV*), and show that much of the return predictability of the VRP may be attributed to its component associated with the compensation required for bearing jump rail risk. We hypothesize that when the quality of political signals is low, derivatives of such options on the main index are mostly traded by noise traders. It will jeopardize the predictability of both components of *VRP* since the implied volatility is driven by noise traders. As another robustness test, we follow the approach of Bollerslev et al. (2015) to decompose *VRP* to *LJV* and *VRP-LJV,* and examine if the quality of political signals influences both components. The results are reported in Table 8, and suggest that low-quality political signals could weaken the positive predictive effects of *LJV* and *VRP-LJV*. In addition, consistent with Bollerslev et al. (2015), we document that the return predictability of *VRP*'s two components is not persistent, particularly when some economic variables (such as *DP* or *DY*) are controlled for (see columns (7) and (8) in Table 8).

TABLE 8 HERE

Overall, we provide evidence that the quality of political signals significantly affects the predictive power of the VRP as a predictor of aggregated stock market returns.

3.3. Portfolio return predictability

Considering that portfolios may respond differently to investor sentiments and the VRP (e.g., Huang et al., 2015; Bollerslev et al., 2015), in the final step of our predictive regression analysis, we investigate the predictive effects of investor sentiment and the VRP on the excess returns of Fama-French portfolios sorted by size, book-to-market ratio, and momentum. To this end, we apply the following regression:

$$\frac{1}{h}\sum_{j=1}^{h} pr_{t+(j-1),t+j}^{i} = \alpha + \varphi X_t^n + \beta Qindex_t + \gamma X_t^n \cdot Qindex_t + \varepsilon_{t+1}, \qquad (5)$$

where the dependent variable is the average monthly excess returns (in excess of the risk-free rate proxied by the 3-month T-bill rate) of univariate sorted portfolio i over the next three months. X_t^n can be either the VRP or one of the sentiment measures. Table 9 reports the estimation results for φ and γ as in Equation (5) for the 1st-, 5th-, and 10th-decile portfolios sorted by size, book-to-market ratio, and momentum over the sample period of January 2001 through December 2020.[15]

TABLE 9 HERE

As presented in Table 9, the VRP and the key measures of investor sentiment manifest statistically significant predictive effects on the monthly excess returns of univariate sorted portfolios. Specifically, 84 out of 108 regressions demonstrate consistently statistically significant results, and all of the interaction terms present opposite signs against that of predictors' coefficients. Consistent with our results reported previously, all the interaction terms between the predictor (VRP or investor sentiment) and *Qindex* show opposite signs against that of the predictors, suggesting the weakened return predictability of the VRP and investor sentiment on portfolio returns during the time when the political signals are imprecise.

4. Channel test

In this section, we examine a channel though which the quality of political signals affects aggregate stock market return predictability. As discussed in the introduction, when the quality of political signals is low, market participation is expected to decrease. This is due to

[15] Results for other portfolio deciles by factor are available upon request.

the fact that rational arbitragers do not update their unbiased beliefs using imprecise information, and are confronted with a higher cost of identifying the noise to bet against the corresponding mispricing. Hence, arbitragers trade less during periods of imprecise political signals. On the other hand, for noise traders, who do not distinguish between reliable information and noise, the quality of political signals does not affect their trading. Consequently, the trading activities on equity and derivative markets are dominated by noise traders, which results in weakening return predictability by lengthening the price correction process (for sentiment) and fouling the information contained in implied/realized market variance (for the VRP). Thus, we expect market participation in stock and equity option markets to be lower when the quality of political signals is low (equivalent to a high value of the Qindex).

Fig. 3 shows the monthly time series of the Qindex and market participation measures.[16] The figure indicates that market participation, proxied by net mutual fund flow, stock turnover ratio, and volume in option markets, tends to decrease with higher values of the Qindex. This suggests that there is less trading activity during periods characterized by low-quality political signals.

FIGURE 3 HERE

Considering that some of the participation measures are not stationary and tend to increase over time (e.g., dollar volume of stocks traded), we de-trend all the participation variables in later regression analysis to address the issue caused by an omitted trending variable. The relationship between the quality of political signals and market participation is tested using the following contemporaneous regression model:

$$Participation_t = \alpha + \beta Qindex_t + \theta Trend_t + \mu \boldsymbol{C_t} + \varepsilon_t, \qquad (6)$$

[16] For reasons of brevity, we do not present the figures for all participation measures. They are available upon request.

where the dependent variable is one of the 12 participation measures (*Netflow*, Vol^{SPX}, TR^{SPX}, $DVol^{SPX}$, Vol^{all}, TR^{all}, $DVol^{all}$, *Trades*, $Options^{SPX}$, $Options^{all}$, $Options^{call}$, $Options^{put}$); *Trend* is a time variable to control for omitted trending in market participation; ***C*** is a vector of control variables, including the realized market volatility (*RVOL*), monthly return of the S&P 500 index (R_m), and a recession dummy variable (*Recession*).

Table 10 reports the regression results for our channel test. Panel A presents the baseline specifications by including only *Qindex* and *Trend* given that some measures are non-stationary. Panel B shows the regression results with all the control variables. *Qindex* manifests a statistically significant and negative correlation with all 12 participation measures across all the specifications in Table 10. These findings provide evidence supporting our argument regarding the channel via which return predictability is weakened by the low quality of political signals.

5. Conclusion

In this study, we investigate if the low quality of political signals coming from centers of governmental power has an impact on stock market return predictability. Our analysis of 14 well-established predictors (11 sentiment proxies and three VRP proxies) over a period of 20 years shows that low-quality political signals substantially weaken the ability to foresee aggregate stock market returns. We present empirical evidence that the inclusion of a proxy for the quality of political signals, such as the U.S. Qindex, in predictive models preserves the properties of the well-known sentiment proxies and the VRP. In addition, guided by theoretical literature on noise and information traders (e.g., Black, 1986; DeLong, Shleifer, Summers, and Waldmann, 1990; Kumar and Lee, 2006; Dumas, Kurshev and Uppal, 2009; Stambaugh, Yu, and Yuan, 2012), we identify a channel though which the quality of political signals affects the stock market return predictability of investor sentiment and the VRP.

The contribution of our paper is two-fold. First, our study fills the gap in the vast literature on stock market predictability by identifying the quality of political signals as a crucial element for the attributes of known learning-based predictors. It is worth highlighting the fact that messages coming from political leaders are one of many sources of information for investors. Nevertheless, their quality alone already plays a decisive role for the success or failure of examined measures as stock market return predictors. Second, our study shows the impact on financial markets of prolonged periods characterized by a deteriorating quality of political signals (such as January 2017 to January 2021). Taking into account the importance of national politics for capital markets, further research on the topic is needed, in particular in the area of corporate finance.

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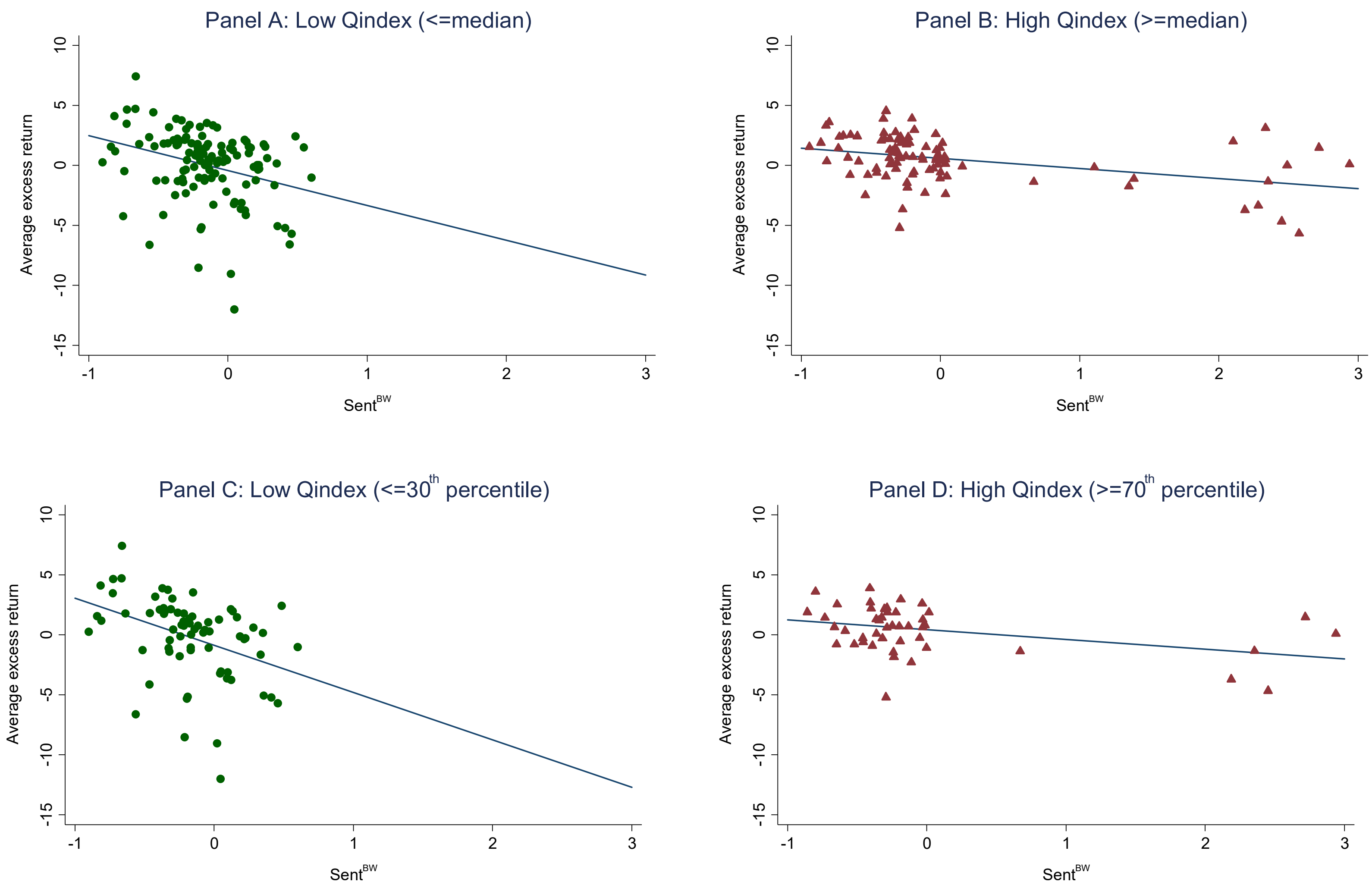
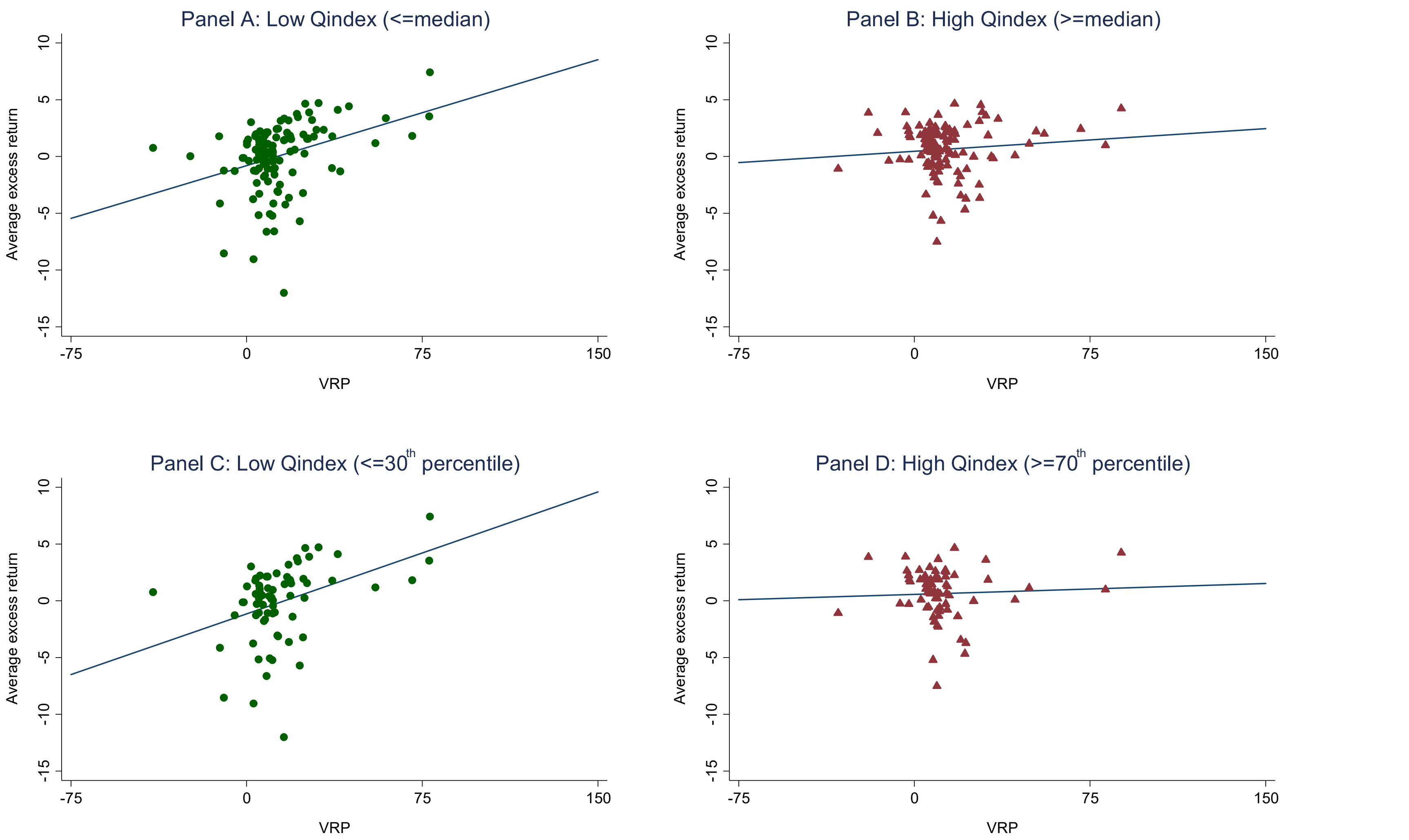
Fig. 1 Plots of excess market return and investor sentiment by Qindex levels



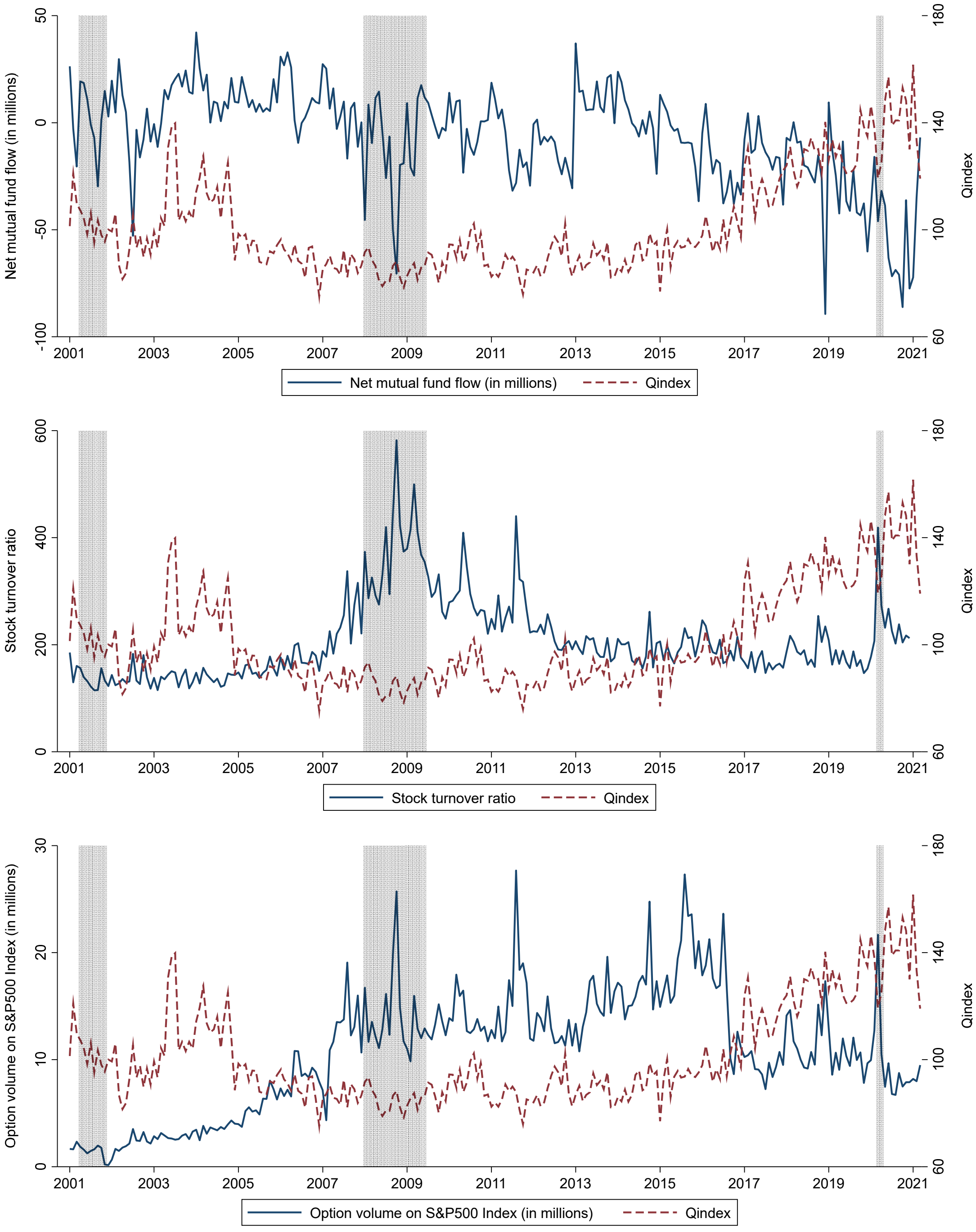
This figure presents the monthly excess stock market return (over the next quarter) against investor sentiment proxied by Baker and Wurgler's (2006) sentiment index ($SENT^{BW}$) by the level of *Qindex*. Panel A (B) exhibits the plot for *Qindex* is below (above) its sample median over the full sample period January 2001 to December 2020. Panel C (D) exhibits the plot for *Qindex* is below (above) its 30th (70th) percentile level over the sample period. The samples used to prepare the above graphs were trimmed. Outliers with a value of five standard deviations away from the mean were excluded.

Fig. 2 Plots of excess market return and the variance risk premium (VRP) by different Qindex levels



This figure shows the monthly excess stock market return (over the next quarter) against the VRP by the different levels of *Qindex*. Panel A (B) presents the plot for *Qindex* is below (above) its sample median over the full sample period January 2001 to December 2020. Panel C (D) presents the plot for *Qindex* is below (above) its 30th (70th) percentile level over the sample period. The samples used to prepare the above graphs were trimmed. Outliers with a value of five standard deviations away from the mean were excluded.

Fig 3. Market participation and quality of political signals



This figure presents the time series of three participation measures (net mutual fund flow, stock turnover ratio, and volume in the option market) and Qindex with vertical bars illustrating NBER-dated recessions.

Table 1 Summary statistics

	Description	No.	Mean	Std. dev	5^{th} pctl	95^{th} pctl	Sample period
Qindex	Index of quality of political signals	240	100.7	17.68	81.80	138.5	Jan. 01 - Dec. 20
$SENT^{BW}$	Sentiment index by Baker & Wurgler	216	-0.065	0.653	-0.746	1.389	Jan. 01 - Dec. 18
$SENT^{HJTZ}$	Aligned investment sentiment index	216	-0.359	0.741	-0.997	1.774	Jan. 01 - Dec. 18
$SENT^{MS}$	Manager sentiment index	180	0.000	1.003	-1.561	1.102	Jan. 03 - Dec.17
SII	Short interest index	168	0.501	1.119	-0.641	3.216	Jan. 01 - Dec. 14
$SENT^{FEARS}$	FEARS sentiment index	89	0.013	0.409	-0.559	0.410	Jul. 04 - Dec.11
$SENT^{AAII}$	AAII individual sentiment	240	5.820	14.40	-16.76	33.07	Jan. 01 - Dec. 20
$SENT^{advisor}$	Advisor sentiment index	240	23.96	14.17	-3.857	41.29	Jan. 01 - Dec. 20
$SENT^{Indiv}$	Shiller's individual confidence index	240	76.77	8.648	62.99	90.58	Jan. 01 - Dec. 20
$SENT^{MCS}$	Univ. of Michigan consumer sentiment	240	84.48	11.39	61.90	98.50	Jan. 01 - Dec. 20
$SENT^{CBC}$	Conference board consumer confidence	240	90.35	25.30	48.00	129.0	Jan. 01 - Dec. 20
PCSI	US consumer sentiment index	228	52.47	6.272	41.20	62.57	Jan. 02 - Dec. 20
VRP	Variance risk premium	240	10.92	34.91	-7.899	43.37	Jan. 01 - Dec. 20
LJV	Jump tail variance	228	58.41	59.39	13.02	143.6	Jan. 01 - Dec. 19
VRP-LJV	Difference between VRP and LJV	228	-46.53	69.05	-140.9	0.489	Jan. 01 - Dec. 19
Netflow	Net mutual fund flow to equity market	240	-5.955	22.60	-45.73	24.07	Jan. 01 - Dec. 20
Vol^{SPX}	Log share volume of SPX stocks	240	24.64	0.307	24.25	25.26	Jan. 01 - Dec. 20
TR^{SPX}	Log turnover ratio of SPX stocks	240	5.002	0.279	4.648	5.564	Jan. 01 - Dec. 20
$DVol^{SPX}$	Log dollar volume of SPX stocks	240	28.33	0.435	27.59	28.94	Jan. 01 - Dec. 20
Vol^{all}	Log share volume of all stocks	240	25.55	0.350	24.96	26.12	Jan. 01 - Dec. 20
TR^{all}	Log turnover ratio of all stocks	240	5.282	0.319	4.844	5.923	Jan. 01 - Dec. 20
$DVol^{all}$	Log dollar volume of all stocks	240	29.05	0.520	28.09	29.71	Jan. 01 - Dec. 20
Trades	Log number of trades on Nasdaq stocks	240	18.81	0.587	17.72	19.60	Jan. 01 - Dec. 20
$Options^{SPX}$	Log volume of options on SPX	240	15.96	0.810	14.39	16.80	Jan. 01 - Dec. 20
$Options^{all}$	Log volume of all options traded on CBOE	206	18.18	0.384	17.27	18.63	Nov. 03 - Dec. 20
$Options^{call}$	Log volume of call options on SPX	240	14.99	0.788	13.51	15.80	Jan. 01 - Dec. 20
$Options^{put}$	Log volume of put options on SPX	240	15.49	0.830	13.83	16.34	Jan. 01 - Dec. 20

Table 2 Correlation matrix

	Qindex	$SENT^{BW}$	$SENT^{HJTZ}$	$SENT^{MS}$	SII	$SENT^{FEARS}$	$SENT^{AAII}$	$SENT^{advisor}$	$SENT^{Indiv}$	$SENT^{MCS}$	$SENT^{CBC}$	PCSI
$SENT^{BW}$	0.013											
$SENT^{HJTZ}$	-0.041	0.760										
$SENT^{MS}$	-0.255	0.474	-0.005									
SII	-0.248	0.461	0.082	0.430								
$SENT^{FEARS}$	0.122	-0.074	-0.182	-0.171	-0.141							
$SENT^{AAII}$	0.218	0.059	-0.014	-0.136	-0.389	-0.043						
$SENT^{advisor}$	0.342	-0.083	-0.271	-0.120	-0.474	0.137	0.518					
$SENT^{Indiv}$	-0.069	0.314	0.249	-0.239	-0.048	0.114	0.318	-0.180				
$SENT^{MCS}$	0.602	0.202	-0.113	-0.079	-0.228	0.037	0.348	0.532	-0.025			
$SENT^{CBC}$	0.558	0.352	-0.063	0.109	0.063	0.003	0.160	0.467	-0.176	0.888		
PCSI	0.537	0.305	-0.420	-0.016	-0.107	-0.009	0.223	0.500	-0.235	0.916	0.944	
VRP	-0.037	0.030	0.078	-0.171	-0.130	0.067	0.122	0.146	0.102	-0.067	-0.131	-0.164

This table shows the pairwise correlation for the main independent variables. For reasons of brevity, we only present the correltion matrix for key independent variables.

Table 3 Return predictability of investor sentiment and the quality of political signals

	Panel A: Univariate regressions $\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \varphi SENT_t^k + \varepsilon_{t+1}$			Panel B: Bivariate regressions $\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \varphi SENT_t^k + \beta Qindex_t + \gamma SENT_t^k \cdot Qindex_t + \varepsilon_{t+1}$					
	φ	t-stat	Adj. R^2 (%)	φ	t-stat	γ	t-stat	Adj. R^2 (%)	ΔR^2
$SENT^{BW}$	-1.030***	-2.74	6.31	-8.043***	-2.61	6.799**	2.42	9.71	3.40
$SENT^{HJTZ}$	-0.980***	-2.83	7.43	-8.469**	-2.51	7.454**	2.30	12.20	4.77
$SENT^{MS}$	-0.722***	-3.35	8.17	-4.325**	-2.53	3.615**	2.31	12.24	4.07
SII	-0.827**	-2.43	10.52	-10.28***	-3.60	10.87***	3.46	18.10	7.58
$SENT^{FEARS}$	1.467	1.52	2.58	21.81**	2.44	-23.30**	-2.35	7.40	4.82
$SENT^{AAII}$	-0.013	-0.80	0.10	0.183*	1.91	-0.193**	-2.27	4.95	4.85
$SENT^{advisor}$	0.013	0.51	0.04	0.361**	2.50	-0.380***	-2.77	9.37	9.33
$SENT^{Indiv}$	-0.034	-1.50	0.81	-0.372**	-2.26	0.325**	2.20	3.87	3.06
$SENT^{MCS}$	-0.007	-0.25	-0.32	0.242*	1.67	-0.283**	-2.12	6.29	6.61
$SENT^{CBC}$	-0.009	-0.79	0.31	0.064	0.98	-0.093	-1.52	7.00	6.69
PCSI	-0.019	-0.42	-0.22	0.309	1.21	-0.386*	-1.69	6.11	6.33

This table reports the estimation results for predictive regression of the future excess market return on investor sentiment without (with) considering the quality of political signals in Panel A (B). The dependent variable is the average monthly excess returns over the next quarter (h=3). $SENT_t^k$ is a proxy of investor sentiment. It is one of the 11 sentiment measures (i.e., $SENT^{BW}$, $SENT^{HJTZ}$, $SENT^{MS}$, *SII*, $SENT^{FEARS}$, $SENT^{AAII}$, $SENT^{advisor}$, $SENT^{Indiv}$, $SENT^{MCS}$, $SENT^{CBC}$, *PCSI*) given in the first column. *Qindex* in Panel B is the proxy for the quality of political signals divided by 100. The descriptions of the investor sentiment measures are available in Appendix A. Newey-West standard errors with one lag are estimated and t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 Return predictability of investor sentiment with economic variables

Economic Var.		SENT^{BW}	SENT^{HJTZ}	SENT^{MS}	SII	SENT^{FEARS}	SENT^{AAII}	SENT^{advisor}	SENT^{Indiv}	SENT^{MCS}	SENT^{CBC}	PCSI
EP	SENT	-8.345***	-10.727***	-4.243**	-10.376***	24.317**	0.182*	0.375**	-0.371**	0.240*	0.060	0.290
		(-2.65)	(-2.96)	(-2.34)	(-3.44)	(2.30)	(1.93)	(2.52)	(-2.25)	(1.66)	(0.92)	(1.13)
	SENT×Qindex	7.104**	9.420***	3.559**	10.982***	-26.164**	-0.192**	-0.392***	0.325**	-0.284**	-0.090	-0.374
		(2.47)	(2.74)	(2.19)	(3.31)	(-2.22)	(-2.29)	(-2.78)	(2.19)	(-2.13)	(-1.48)	(-1.64)
DE	SENT	-8.166**	-12.295***	-4.201**	-10.787***	24.548**	0.202**	0.436***	-0.365**	0.257*	0.071	0.355
		(-2.57)	(-3.28)	(-2.28)	(-3.68)	(2.26)	(2.17)	(2.91)	(-2.20)	(1.77)	(1.09)	(1.37)
	SENT×Qindex	6.910**	11.013***	3.522**	11.446***	-26.389**	-0.206**	-0.445***	0.320**	-0.292**	-0.098	-0.419*
		(2.39)	(3.05)	(2.13)	(3.55)	(-2.18)	(-2.49)	(-3.13)	(2.14)	(-2.18)	(-1.61)	(-1.82)
DP	SENT	-6.414*	-12.689***	-4.155**	-8.991***	24.296**	0.248***	0.531***	-0.202	0.449***	0.201***	0.755***
		(-1.96)	(-3.31)	(-2.23)	(-2.94)	(2.19)	(2.94)	(3.67)	(-1.33)	(3.18)	(3.15)	(3.11)
	SENT×Qindex	5.543*	12.013***	3.446**	9.236***	-26.006**	-0.225***	-0.526***	0.224	-0.447***	-0.210***	-0.754***
		(1.95)	(3.23)	(2.03)	(2.76)	(-2.11)	(-2.92)	(-3.81)	(1.63)	(-3.37)	(-3.51)	(-3.38)
DY	SENT	-6.029*	-12.571***	-4.080**	-8.470***	23.942**	0.228***	0.534***	-0.193	0.417***	0.190***	0.747***
		(-1.97)	(-3.43)	(-2.20)	(-2.64)	(2.09)	(2.63)	(3.77)	(-1.29)	(2.94)	(2.98)	(3.12)
	SENT×Qindex	5.291**	11.993***	3.388**	8.659**	-25.639**	-0.212***	-0.538***	0.221	-0.415***	-0.199***	-0.738***
		(1.98)	(3.39)	(2.01)	(2.47)	(-2.02)	(-2.68)	(-3.97)	(1.61)	(-3.12)	(-3.32)	(-3.35)
SVAR	SENT	-9.385***	-7.718**	-3.794**	-9.717***	18.299**	0.177*	0.357**	-0.379**	0.230	0.056	0.285
		(-2.95)	(-2.35)	(-2.42)	(-3.31)	(2.33)	(1.85)	(2.46)	(-2.35)	(1.59)	(0.86)	(1.11)
	SENT×Qindex	8.087***	6.774**	3.122**	10.278***	-19.653**	-0.189**	-0.381***	0.332**	-0.276**	-0.086	-0.368
		(2.77)	(2.17)	(2.18)	(3.19)	(-2.25)	(-2.22)	(-2.75)	(2.27)	(-2.06)	(-1.42)	(-1.61)
BM	SENT	-6.822**	-9.133**	-4.138**	-7.705**	21.638**	0.171*	0.382***	-0.221	0.266*	0.087	0.310
		(-2.15)	(-2.53)	(-2.57)	(-2.40)	(2.34)	(1.96)	(2.87)	(-1.33)	(1.95)	(1.34)	(1.24)
	SENT×Qindex	6.197**	8.674**	3.389**	8.003**	-22.979**	-0.169**	-0.400***	0.219	-0.288**	-0.104*	-0.362
		(2.13)	(2.47)	(2.34)	(2.30)	(-2.24)	(-2.20)	(-3.18)	(1.46)	(-2.29)	(-1.74)	(-1.65)
NTIS	SENT	-8.116**	-7.891***	-3.538***	-10.816***	20.768***	0.143*	0.331**	-0.452***	0.192	0.042	0.221
		(-2.57)	(-2.64)	(-2.63)	(-3.64)	(3.01)	(1.69)	(2.49)	(-2.73)	(1.56)	(0.74)	(0.99)
	SENT×Qindex	6.835**	6.844**	3.006**	11.329***	-22.606***	-0.165**	-0.352***	0.361**	-0.237**	-0.069	-0.298
		(2.37)	(2.41)	(2.40)	(3.53)	(-2.93)	(-2.17)	(-2.79)	(2.37)	(-2.05)	(-1.29)	(-1.49)
TBL	SENT	-7.727**	-12.673***	-4.201**	-10.053***	22.906**	0.173*	0.387***	-0.222	0.261*	0.084	0.353
		(-2.39)	(-3.36)	(-2.29)	(-3.35)	(2.38)	(1.82)	(2.79)	(-1.12)	(1.81)	(1.17)	(1.34)
	SENT×Qindex	6.552**	11.695***	3.511**	10.679***	-24.609**	-0.181**	-0.409***	0.203	-0.284**	-0.102	-0.401*
		(2.27)	(3.20)	(2.11)	(3.28)	(-2.29)	(-2.15)	(-3.13)	(1.16)	(-2.16)	(-1.61)	(-1.74)
LTY	SENT	-6.807**	-8.895***	-3.891**	-8.897***	21.258*	0.131	0.395***	-0.207	0.231	0.114*	0.330
		(-2.25)	(-2.67)	(-2.39)	(-2.95)	(1.91)	(1.35)	(2.90)	(-1.30)	(1.59)	(1.68)	(1.27)
	SENT×Qindex	5.867**	8.133**	3.185**	9.539***	-22.860*	-0.128	-0.422***	0.270*	-0.259*	-0.138**	-0.400*
		(2.14)	(2.52)	(2.16)	(2.93)	(-1.85)	(-1.46)	(-3.29)	(1.94)	(-1.89)	(-2.19)	(-1.70)

LTR	SENT	-8.040***	-8.497**	-4.283**	-10.223***	20.112**	0.185*	0.361**	-0.373**	0.245*	0.066	0.314
		(-2.61)	(-2.49)	(-2.53)	(-3.59)	(2.29)	(1.91)	(2.49)	(-2.26)	(1.68)	(1.00)	(1.22)
	SENT×Qindex	6.796**	7.479**	3.571**	10.805***	-21.404**	-0.193**	-0.379***	0.326**	-0.286**	-0.094	-0.391*
		(2.42)	(2.29)	(2.31)	(3.45)	(-2.20)	(-2.27)	(-2.76)	(2.20)	(-2.14)	(-1.55)	(-1.71)
TMS	SENT	-8.866***	-11.348***	-4.559**	-10.470***	22.129**	0.191**	0.361**	-0.417**	0.238	0.064	0.278
		(-2.71)	(-2.92)	(-2.50)	(-3.77)	(2.39)	(1.99)	(2.49)	(-2.28)	(1.58)	(0.98)	(1.03)
	SENT×Qindex	7.462**	10.168***	3.774**	10.973***	-23.676**	-0.202**	-0.380***	0.372**	-0.281**	-0.109*	-0.378
		(2.52)	(2.75)	(2.31)	(3.59)	(-2.30)	(-2.37)	(-2.76)	(2.20)	(-2.05)	(-1.84)	(-1.61)
DFY	SENT	-9.167***	-10.096***	-4.469***	-10.573***	24.680**	0.187**	0.452***	-0.372**	0.234*	0.046	0.239
		(-2.89)	(-2.84)	(-2.73)	(-3.59)	(2.19)	(2.09)	(2.91)	(-2.31)	(1.66)	(0.72)	(0.95)
	SENT×Qindex	7.780***	9.003***	3.756**	11.178***	-26.362**	-0.195**	-0.451***	0.325**	-0.278**	-0.079	-0.338
		(2.69)	(2.64)	(2.51)	(3.46)	(-2.11)	(-2.44)	(-3.14)	(2.23)	(-2.13)	(-1.35)	(-1.51)
DFR	SENT	-7.875**	-8.432**	-4.125**	-10.234***	22.318**	0.181*	0.367**	-0.374**	0.243*	0.064	0.309
		(-2.59)	(-2.57)	(-2.56)	(-3.57)	(2.45)	(1.93)	(2.48)	(-2.29)	(1.70)	(0.98)	(1.21)
	SENT×Qindex	6.640**	7.415**	3.441**	10.849***	-23.865**	-0.191**	-0.388***	0.327**	-0.284**	-0.093	-0.385*
		(2.40)	(2.35)	(2.32)	(3.43)	(-2.34)	(-2.29)	(-2.73)	(2.22)	(-2.15)	(-1.53)	(-1.69)
INFL	SENT	-8.147***	-8.515**	-4.264**	-10.360***	18.522**	0.187*	0.359**	-0.382**	0.242*	0.062	0.305
		(-2.65)	(-2.49)	(-2.55)	(-3.77)	(2.12)	(1.89)	(2.50)	(-2.33)	(1.67)	(0.97)	(1.21)
	SENT×Qindex	6.882**	7.498**	3.544**	10.917***	-19.745**	-0.195**	-0.379***	0.333**	-0.284**	-0.091	-0.383*
		(2.46)	(2.29)	(2.31)	(3.62)	(-2.02)	(-2.23)	(-2.77)	(2.25)	(-2.12)	(-1.52)	(-1.70)

This table reports the estimation results for the predicative regressions with economic variables as controls:

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \varphi SENT_t^k + \beta Qindex_t + \gamma SENT_t^k \cdot Qindex_t + \theta ECON_t^m + \varepsilon_{t+1}$$

For the sake of brevity, only φ and γ are reported. The dependent variable is the average monthly excess returns over the next quarter (*h*=3). *Qindex* is the proxy for the quality of political signals divided by 100. $SENT_t^k$ is one of the 11 sentiment measures (i.e., $SENT^{BW}$, $SENT^{HJTZ}$, $SENT^{MS}$, *SII*, $SENT^{FEARS}$, $SENT^{AAII}$, $SENT^{advisor}$, $SENT^{Indiv}$, $SENT^{MCS}$, $SENT^{CBC}$, *PCSI*) given in the first row. $ECON_t^m$ is one of the 14 controlling economic variables (i.e., earnings-price ratio, *EP*; dividend-payout ratio, *DE*; dividend-price ratio, *DP*; dividend yield, *DY*; stock return variance, *SVAR*; book-to-market ratio, *BM*; net equity expansion, *NTIS*; treasury bill rate, *TBL*; long-term yield, *LTY*; long-term return, *LTR*; term spread, *TMS*; default yield spread, *DFY*; default return spread, *DFR*; inflation, *INFL*) presented in the first column. These results reported above are obtained by running 154 predicative regressions. The detailed description for investor sentiment measures and economic variables is available in Appendix A. Newey-West standard errors with one lag are estimated and t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5 Return predictability of investor sentiment over alternative forecast horizons

		$SENT^{BW}$	$SENT^{HJTZ}$	$SENT^{MS}$	SII	$SENT^{FEARS}$	$SENT^{AAII}$	$SENT^{advisor}$	$SENT^{Indiv}$	$SENT^{MCS}$	$SENT^{CBC}$	PCSI
One month	SENT	-3.270	-12.407*	-4.285*	-7.433*	18.440**	0.262**	0.458***	-0.167	0.484**	0.225**	0.710*
		(-0.63)	(-1.96)	(-1.91)	(-1.89)	(2.15)	(2.24)	(2.69)	(-0.74)	(2.51)	(2.32)	(1.92)
	SENT *Qindex	2.291	11.440*	3.553*	7.759*	-19.010**	-0.236**	-0.476***	0.204	-0.495**	-0.239**	-0.733**
		(0.48)	(1.79)	(1.75)	(1.76)	(-1.99)	(-2.15)	(-2.90)	(1.05)	(-2.56)	(-2.53)	(-2.05)
	Adj. R2 (%)	3.22	8.58	4.38	6.42	0.54	4.49	6.82	3.46	6.43	6.52	4.08
Six months	SENT	-4.150	-6.557**	-3.265**	-8.794***	4.817	0.121*	0.299**	-0.034	0.351***	0.145***	0.576***
		(-1.51)	(-2.26)	(-2.16)	(-4.81)	(0.69)	(1.82)	(2.56)	(-0.34)	(2.92)	(2.79)	(2.97)
	SENT *Qindex	3.310	6.008**	2.687*	8.853***	-4.989	-0.103*	-0.284**	0.077	-0.339***	-0.152***	-0.563***
		(1.36)	(2.10)	(1.94)	(4.51)	(-0.63)	(-1.77)	(-2.57)	(0.86)	(-3.22)	(-3.22)	(-3.28)
	Adj. R2 (%)	16.66	12.68	14.45	34.2	5.93	4.05	4.36	4.3	6.35	9.56	6.75
12 months	SENT	-6.611***	-2.675***	-1.885***	-2.422*	-1.895	0.111**	0.179***	0.081	0.146**	0.041	-0.103
		(-3.72)	(-2.70)	(-2.70)	(-1.89)	(-0.65)	(2.51)	(3.62)	(1.17)	(2.41)	(1.55)	(-1.03)
	SENT *Qindex	5.428***	2.241**	1.469**	1.760	2.438	-0.093**	-0.173***	-0.040	-0.130**	-0.047*	0.059
		(3.38)	(2.37)	(2.34)	(1.13)	(0.77)	(-2.57)	(-3.71)	(-0.72)	(-2.42)	(-1.92)	(0.65)
	Adj. R2 (%)	40.32	29.81	22.63	60.99	10.53	29.93	32.5	28.98	29.32	27.59	4.49

This table reports the estimation results for the predicative regressions within different forecast horizons:

$$\frac{1}{h}\sum_{j=1}^{h} r_{t+(j-1),t+j} = \alpha + \varphi SENT_t^k + \beta Qindex_t + \gamma SENT_t^k \cdot Qindex_t + \theta ECON_t^m + \varepsilon_{t+1}$$

To conserve space, only φ and γ are reported. The dependent variable is the average monthly excess returns over next one month (h=1), six months (h=6), or 12 months (h=12). *Qindex* is the proxy for the quality of political signals divided by 100. $SENT_t^k$ is one of the 11 sentiment measures (i.e., $SENT^{BW}$, $SENT^{HJTZ}$, $SENT^{MS}$, *SII*, $SENT^{FEARS}$, $SENT^{AAII}$, $SENT^{advisor}$, $SENT^{Indiv}$, $SENT^{MCS}$, $SENT^{CBC}$, *PCSI*) given in the first row. $ECON_t^m$ is an economic controlling variable proxied by dividend-price ratio (*DP*) in the table. The descriptions of investor sentiment measures and economic variables are available in Appendix A. Newey-West standard errors with one lag are estimated and t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6 Return predictability of the VRP and the quality of political signals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
VRP	0.005	0.137***	0.142***	0.134***	0.130***	0.128***	0.140***	0.140***	0.129***	0.130***	0.136***	0.137***	0.139***	0.137***	0.137***	0.136***
	(0.40)	(3.84)	(3.76)	(3.96)	(4.37)	(4.15)	(3.95)	(4.40)	(3.35)	(4.04)	(3.89)	(3.83)	(3.81)	(3.90)	(3.82)	(3.76)
Qindex		3.939***	4.082***	3.908***	4.853***	4.765***	3.994***	6.092***	3.974***	3.843***	2.153*	3.939***	3.741***	3.973***	3.937***	3.929***
		(2.97)	(2.91)	(2.90)	(3.67)	(3.58)	(3.07)	(4.33)	(3.05)	(2.95)	(1.67)	(2.97)	(2.94)	(3.06)	(3.00)	(2.96)
VRP*Qindex		-0.120***	-0.123***	-0.118***	-0.112***	-0.110***	-0.120***	-0.121***	-0.114***	-0.114***	-0.117***	-0.120***	-0.121***	-0.120***	-0.120***	-0.119***
		(-3.57)	(-3.49)	(-3.65)	(-3.81)	(-3.65)	(-3.79)	(-3.98)	(-3.24)	(-3.74)	(-3.66)	(-3.56)	(-3.54)	(-3.61)	(-3.56)	(-3.51)
$ECON^m$			0.421	0.227	4.502***	4.539***	18.018	15.681***	15.987	-31.740***	-58.463***	0.636	-7.173	6.550	0.385	8.776
			(0.57)	(0.41)	(2.80)	(3.03)	(0.30)	(4.43)	(0.92)	(-2.67)	(-4.15)	(0.11)	(-0.57)	(0.10)	(0.03)	(0.14)
_cons	0.303	-3.815***	-2.648	-3.592**	13.106**	13.336**	-3.959***	-10.496***	-3.751***	-3.278**	0.115	-3.819***	-3.455**	-3.920**	-3.813***	-3.818***
	(1.09)	(-2.76)	(-1.20)	(-2.23)	(1.97)	(2.16)	(-2.90)	(-4.90)	(-2.82)	(-2.39)	(0.08)	(-2.77)	(-2.58)	(-2.57)	(-2.79)	(-2.75)
Controlling $ECON^m$	None	None	EP	DE	DP	DY	SVAR	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL
Adj. R^2 (%)	-0.01	8.31	8.31	8.08	15.11	15.3	8.03	18.6	9.07	11.31	15.12	7.93	8.04	7.93	7.92	7.94

This table reports the estimation results for predictive regression of the future excess market return on the VRP. The dependent variable is the average monthly excess returns over the next quarter. *Qindex* is the proxy for the quality of political signals divided by 100. $ECON_t^m$ is one of the 14 controlling economic variables (i.e., earnings-price ratio, *EP*; dividend-payout ratio, *DE*; dividend-price ratio, *DP*; dividend yield, *DY*; stock return variance, *SVAR*; book-to-market ratio, *BM*; net equity expansion, *NTIS*; treasury bill rate, *TBL*; long-term yield, *LTY*; long-term return, *LTR*; term spread, *TMS*; default yield spread, *DFY*; default return spread, *DFR*; inflation, *INFL*) presented in the first column. The detailed description for economic measures is available in Appendix A. Newey-West standard errors with one lag are estimated and t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7 Robustness test for the return predictability of the VRP

	Monthly regression				Daily regressions			
	Three months	One months	Six months	12 months	Three months	One months	Six months	12 months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VRP	0.130***	0.222***	0.067***	0.032***	0.015**	0.025	0.018***	0.007***
	(4.37)	(2.62)	(3.66)	(3.61)	(2.20)	(1.61)	(3.65)	(3.39)
Qindex	4.853***	6.212***	3.991***	2.471***	3.425***	2.926***	3.044***	2.409***
	(3.67)	(3.76)	(4.37)	(4.58)	(9.99)	(4.40)	(13.95)	(18.57)
VRP*Qindex	-0.112***	-0.203**	-0.056***	-0.029***	-0.014**	-0.023	-0.016***	-0.007***
	(-3.81)	(-2.53)	(-3.16)	(-3.82)	(-2.29)	(-1.54)	(-3.74)	(-3.70)
DP	4.502***	4.606	4.830***	4.381***	4.059***	1.990**	4.259***	4.225***
	(2.80)	(1.62)	(5.33)	(9.13)	(8.93)	(2.02)	(15.73)	(34.07)
cons	13.106**	12.070	15.382***	15.224***	12.998***	5.255	14.150***	14.693***
	(1.97)	(1.08)	(3.92)	(7.50)	(7.10)	(1.36)	(12.52)	(28.44)
Adj. R2 (%)	15.11	9.48	20.72	26.93	7.86	1.15	15.4	25.77
N	240	240	240	240	5032	5032	5032	4923

This table reports the estimation results for the predicative regressions within different forecast horizons. The dependent variable is the average monthly excess returns over the next three months, one month, six months, or 12 months. Columns (1) to (3) present the results based on monthly regression. Columns (5) to (8) present the estimated results with regression on a daily basis, where the future monthly excess market return is estimated with a rolling window over the next 63, 21, 126, or 252 trading days. *Qindex* is the proxy for the quality of political signals divided by 100. *DP* is the dividend-price ratio used as a representative control economic variable. Newey-West standard errors with one lag are estimated and t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8 Return predictability of VRP components and the quality of political signals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
LJV	0.038***	0.212***	0.222***	0.222***	0.065	0.066	0.199**	0.111	0.228***	0.181**	0.137*	0.215***	0.211***	0.239***	0.211***	0.210***
	(3.80)	(2.81)	(2.84)	(2.91)	(0.76)	(0.78)	(2.36)	(1.38)	(2.94)	(2.27)	(1.72)	(2.71)	(2.79)	(3.11)	(2.73)	(2.77)
VRP- LJV	0.035***	0.186***	0.189***	0.193***	0.060	0.059	0.152*	0.103	0.205***	0.164**	0.103	0.188***	0.179***	0.201***	0.186***	0.182***
	(5.03)	(2.79)	(2.74)	(2.93)	(0.81)	(0.79)	(1.81)	(1.47)	(2.98)	(2.34)	(1.39)	(2.77)	(2.67)	(2.93)	(2.74)	(2.67)
Qindex		4.807**	5.304**	4.971**	3.866	3.779	4.993**	5.226**	4.929**	4.291*	3.622*	4.864**	4.803**	5.099**	4.763**	4.898**
		(2.15)	(2.27)	(2.09)	(1.61)	(1.60)	(2.29)	(2.32)	(2.24)	(1.89)	(1.68)	(2.10)	(2.15)	(2.24)	(2.19)	(2.22)
LJV *Qindex		-0.193**	-0.194**	-0.200**	-0.040	-0.039	-0.182**	-0.079	-0.213**	-0.164*	-0.110	-0.195**	-0.189**	-0.217***	-0.192**	-0.190**
		(-2.35)	(-2.29)	(-2.44)	(-0.44)	(-0.42)	(-1.99)	(-0.89)	(-2.52)	(-1.91)	(-1.27)	(-2.28)	(-2.32)	(-2.61)	(-2.29)	(-2.30)
(VRP- LJV) *Qindex		-0.167**	-0.163**	-0.172**	-0.030	-0.029	-0.139	-0.072	-0.191**	-0.146*	-0.074	-0.169**	-0.157**	-0.180**	-0.166**	-0.162**
		(-2.26)	(-2.13)	(-2.36)	(-0.37)	(-0.35)	(-1.57)	(-0.93)	(-2.49)	(-1.89)	(-0.90)	(-2.25)	(-2.11)	(-2.38)	(-2.22)	(-2.16)
$ECON^m$			1.002	-0.241	5.178***	4.909***	-115.63	15.07***	16.023	-25.04**	-56.65***	1.774	-12.724	-73.159	1.689	39.314
			(1.17)	(-0.35)	(2.69)	(2.90)	(-1.31)	(4.26)	(0.88)	(-2.05)	(-3.41)	(0.26)	(-0.81)	(-0.88)	(0.12)	(0.59)
_cons	-0.317	-4.832**	-2.397	-5.256*	16.874*	15.768**	-4.906**	-9.692***	-4.871**	-3.861	-1.465	-4.890**	-4.569**	-4.486**	-4.793**	-5.021**
	(-0.93)	(-2.08)	(-0.85)	(-1.85)	(1.91)	(2.05)	(-2.20)	(-3.50)	(-2.17)	(-1.61)	(-0.68)	(-2.04)	(-2.10)	(-2.00)	(-2.12)	(-2.20)
$ECON^m$	None	None	EP	DE	DP	DY	SVAR	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL
Adj. R2 (%)	7.13	8.32	9.81	8.04	14.90	14.95	9.90	17.89	9.07	9.84	13.79	7.95	8.24	8.79	7.92	8.20
N	228	228	228	228	228	228	228	228	228	228	228	228	228	228	228	228

This table reports the estimation results for the return predictability of two components of the VRP (Bollerslev, Todorov, and Xu, 2015), namely jump tail variance (*LJV*) and normal variance (*VRP-LJV*). The dependent variable is the average monthly excess returns over the next quarter. *Qindex* is the proxy for the quality of political signals divided by 100. $ECON_t^m$ is one of the 14 controlling economic variables (i.e., earnings-price ratio, *EP*; dividend-payout ratio, *DE*; dividend-price ratio, *DP*; dividend yield, *DY*; stock return variance, *SVAR*; book-to-market ratio, *BM*; net equity expansion, *NTIS*; treasury bill rate, *TBL*; long-term yield, *LTY*; long-term return, *LTR*; term spread, *TMS*; default yield spread, *DFY*; default return spread, *DFR*; inflation, *INFL*) presented in the first column. The detailed description for these economic measures is available in Appendix A. Newey-West standard errors with one lag are estimated and t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9 Portfolio return predictability and the quality of political signals

Panel A Size portfolios		VRP	$SENT^{BW}$	$SENT^{HJTZ}$	$SENT^{MS}$	SII	$SENT^{FEARS}$	$SENT^{AAII}$	$SENT^{advisor}$	$SENT^{Indiv}$	$SENT^{MCS}$	$SENT^{CBC}$	PCSI
Small	X^n	0.013**	-0.909**	-1.185***	-0.245	-0.327	2.614**	0.018	0.034*	-0.017	0.055***	0.023***	0.084**
		(2.07)	(-2.30)	(-2.90)	(-1.24)	(-0.90)	(2.56)	(1.52)	(1.75)	(-0.90)	(2.89)	(3.24)	(2.51)
	X^n *Qindex	-0.011*	0.847**	1.181***	0.135	0.249	-2.751**	-0.015	-0.036*	0.027	-0.062***	-0.028***	-0.098***
		(-1.73)	(2.38)	(2.96)	(0.76)	(0.63)	(-2.39)	(-1.32)	(-1.89)	(1.56)	(-3.10)	(-4.01)	(-2.88)
Middle	X^n	0.013***	-0.642*	-1.266***	-0.256	-0.607*	2.150**	0.019*	0.044***	-0.021	0.049***	0.022***	0.080***
		(2.90)	(-1.80)	(-3.16)	(-1.37)	(-1.69)	(2.14)	(1.94)	(2.74)	(-1.15)	(3.04)	(3.21)	(2.70)
	X^n *Qindex	-0.011**	0.603*	1.242***	0.181	0.608	-2.256*	-0.019*	-0.046***	0.026	-0.054***	-0.025***	-0.087***
		(-2.44)	(1.93)	(3.16)	(1.07)	(1.54)	(-1.99)	(-1.95)	(-2.93)	(1.60)	(-3.28)	(-3.78)	(-2.99)
Big	X^n	0.010***	-0.412	-1.006***	-0.296**	-0.641***	1.963**	0.020***	0.040***	-0.009	0.034***	0.015***	0.060***
		(4.00)	(-1.64)	(-3.48)	(-2.16)	(-2.88)	(2.32)	(3.12)	(3.76)	(-0.76)	(3.27)	(3.14)	(3.35)
	X^n *Qindex	-0.008***	0.356	0.951***	0.244*	0.660***	-2.120**	-0.019***	-0.040***	0.011	-0.034***	-0.016***	-0.058***
		(-3.51)	(1.63)	(3.38)	(1.97)	(2.69)	(-2.26)	(-3.19)	(-3.93)	(1.04)	(-3.48)	(-3.41)	(-3.61)

Panel A Book-to-market portfolios													
Low	X^n	0.011***	-0.380	-0.995***	-0.278*	-0.704**	1.610**	0.023***	0.044***	0.002	0.033***	0.014**	0.054**
		(4.00)	(-1.32)	(-3.21)	(-1.79)	(-2.45)	(2.48)	(3.21)	(3.72)	(0.19)	(2.79)	(2.42)	(2.58)
	X^n *Qindex	-0.009***	0.346	0.954***	0.240*	0.726**	-1.726**	-0.022***	-0.044***	0.001	-0.033***	-0.014**	-0.052***
		(-3.58)	(1.39)	(3.16)	(1.70)	(2.32)	(-2.39)	(-3.31)	(-3.92)	(0.08)	(-2.93)	(-2.55)	(-2.77)
Middle	X^n	0.011***	-0.598**	-0.899***	-0.301**	-0.476**	1.879*	0.017**	0.035***	-0.015	0.034***	0.015***	0.060***
		(4.01)	(-2.49)	(-3.22)	(-2.20)	(-2.18)	(1.85)	(2.54)	(3.13)	(-1.10)	(2.80)	(2.62)	(2.66)
	X^n *Qindex	-0.009***	0.544**	0.876***	0.241*	0.463*	-1.970*	-0.016**	-0.036***	0.019	-0.035***	-0.016***	-0.062***
		(-3.52)	(2.59)	(3.26)	(1.93)	(1.89)	(-1.75)	(-2.47)	(-3.34)	(1.48)	(-3.00)	(-3.03)	(-2.91)
High	X^n	0.018***	-0.817*	-1.591***	-0.303	-0.540	3.857**	0.018	0.053***	-0.041*	0.072***	0.035***	0.127***
		(2.95)	(-1.97)	(-3.23)	(-1.22)	(-1.35)	(2.35)	(1.45)	(2.66)	(-1.73)	(3.35)	(3.83)	(3.13)
	X^n *Qindex	-0.015**	0.756**	1.550***	0.205	0.503	-4.106**	-0.016	-0.054***	0.048**	-0.075***	-0.038***	-0.132***
		(-2.54)	(2.07)	(3.25)	(0.91)	(1.14)	(-2.25)	(-1.34)	(-2.75)	(2.22)	(-3.42)	(-4.32)	(-3.30)

Panel C Momentum portfolios													
Loser	X^n	0.025**	-0.949	-1.696**	-0.379	-1.069**	3.866*	0.017	0.068**	0.019	0.076***	0.034***	0.108**
		(2.56)	(-1.47)	(-2.57)	(-1.04)	(-2.12)	(1.79)	(0.91)	(2.31)	(0.74)	(2.60)	(3.08)	(2.12)
	X^n *Qindex	-0.021**	0.874	1.644**	0.260	1.005*	-4.107*	-0.015	-0.073**	0.002	-0.078***	-0.037***	-0.116**
		(-2.32)	(1.59)	(2.57)	(0.79)	(1.82)	(-1.72)	(-0.87)	(-2.57)	(0.08)	(-2.66)	(-3.49)	(-2.32)
Middle	X^n	0.013***	-0.527**	-1.201***	-0.292*	-0.412	2.805**	0.017**	0.033***	-0.010	0.031***	0.012**	0.053**
		(3.79)	(-2.07)	(-3.45)	(-1.74)	(-1.56)	(2.38)	(2.26)	(2.63)	(-0.70)	(2.64)	(2.30)	(2.49)
	X^n *Qindex	-0.011***	0.517**	1.184***	0.243	0.386	-3.048**	-0.016**	-0.033***	0.013	-0.033***	-0.013***	-0.055***
		(-3.28)	(2.33)	(3.51)	(1.58)	(1.32)	(-2.33)	(-2.28)	(-2.79)	(1.00)	(-2.85)	(-2.62)	(-2.71)
Winner	X^n	0.011***	-0.561*	-1.130***	-0.373*	-1.090***	0.975	0.026***	0.060***	-0.011	0.047***	0.021***	0.074***
		(3.21)	(-1.69)	(-3.17)	(-1.92)	(-3.06)	(1.09)	(2.82)	(4.41)	(-0.81)	(3.21)	(2.97)	(2.87)
	X^n *Qindex	-0.010***	0.499*	1.081***	0.321*	1.174***	-0.966	-0.025***	-0.060***	0.013	-0.047***	-0.021***	-0.073***
		(-2.99)	(1.70)	(3.09)	(1.77)	(2.95)	(-0.94)	(-2.93)	(-4.63)	(1.02)	(-3.31)	(-3.21)	(-3.08)

This table reports the estimation results of predictive regressions for Fama-French value-weighted portfolios univariate sorted by size (in Panel A), book-to-market ratio (in Panel B), and momentum (in Panel C). The dependent variable is the average monthly excess returns over the next quarter. *Qindex* is the proxy for the quality of political signals divided by 100. Dividend-price ratio, *DP*, is used as a representative economic control variable. Newey-West standard errors with one lag are estimated and t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10 Trading activities and the quality of political signals

Panel A	(1) Netflow	(2) Vol^{SPX}	(3) TR^{SPX}	(4) $DVol^{SPX}$	(5) Vol^{all}	(6) TR^{all}	(7) $DVol^{all}$	(8) Trades	(9) $Options^{SPX}$	(10) $Options^{all}$	(11) $Options^{call}$	(12) $Options^{put}$
Qindex	-31.303***	-0.820***	-0.771***	-0.261***	-0.559***	-0.866***	-0.532***	-0.368***	-2.619***	-1.042***	-2.596***	-2.635***
	(-3.05)	(-5.84)	(-6.40)	(-2.80)	(-4.28)	(-6.32)	(-4.74)	(-2.74)	(-12.86)	(-7.52)	(-12.56)	(-12.81)
Trend	-0.149***	0.002***	0.001***	0.006***	0.004***	0.002***	0.007***	0.008***	0.011***	0.006***	0.010***	0.011***
	(-6.42)	(5.77)	(5.22)	(24.18)	(16.86)	(7.67)	(25.42)	(27.31)	(13.09)	(12.86)	(12.64)	(13.23)
_cons	45.287***	25.261***	5.601***	27.822***	25.579***	5.872***	28.637***	18.112***	17.202***	18.288***	16.262***	16.703***
	(4.77)	(175.78)	(45.24)	(296.40)	(188.87)	(40.97)	(243.34)	(130.69)	(104.76)	(168.97)	(97.86)	(100.31)
Adj. R2 (%)	36.02	19.9	20.42	78.84	51.86	24.81	78.75	82.98	69.84	62.37	68.7	69.79
N	240	240	240	240	240	240	240	240	240	206	240	240

Panel B	(1) Netflow	(2) Vol^{SPX}	(3) TR^{SPX}	(4) $DVol^{SPX}$	(5) Vol^{all}	(6) TR^{all}	(7) $DVol^{all}$	(8) Trades	(9) $Options^{SPX}$	(10) $Options^{all}$	(11) $Options^{call}$	(12) $Options^{put}$
Qindex	-32.905***	-0.771***	-0.722***	-0.220***	-0.510***	-0.807***	-0.482***	-0.330***	-2.634***	-0.947***	-2.603***	-2.655***
	(-3.70)	(-7.45)	(-8.46)	(-3.04)	(-5.31)	(-8.43)	(-5.41)	(-2.88)	(-13.07)	(-8.19)	(-12.77)	(-13.03)
RVOL	-0.584***	0.015***	0.014***	0.007***	0.013***	0.015***	0.008***	0.010***	0.012***	0.008***	0.013***	0.010***
	(-3.45)	(6.04)	(6.15)	(4.64)	(6.14)	(5.67)	(3.75)	(4.33)	(3.34)	(2.88)	(3.88)	(2.94)
R_m	80.976***	0.943**	0.653*	0.289	0.797**	0.534	0.168	0.469	-0.547	-0.191	0.039	-0.917
	(2.72)	(2.29)	(1.87)	(1.00)	(2.20)	(1.34)	(0.46)	(1.13)	(-0.75)	(-0.48)	(0.05)	(-1.20)
Trend	-0.167***	0.002***	0.002***	0.006***	0.004***	0.002***	0.007***	0.008***	0.011***	0.006***	0.010***	0.011***
	(-8.19)	(7.22)	(6.87)	(27.34)	(18.49)	(9.05)	(26.72)	(27.30)	(13.08)	(14.51)	(12.67)	(13.19)
Recession	-2.230	0.101	0.109	0.140**	0.118	0.153*	0.181**	0.102	-0.211	0.133*	-0.184	-0.228
	(-0.55)	(1.20)	(1.42)	(2.00)	(1.61)	(1.76)	(2.03)	(1.11)	(-1.26)	(1.68)	(-1.17)	(-1.29)
_cons	58.598***	24.918***	5.274***	27.617***	25.271***	5.505***	28.403***	17.881***	17.051***	18.062***	16.071***	16.579***
	(6.23)	(225.50)	(57.12)	(360.96)	(249.39)	(52.64)	(290.47)	(150.88)	(102.08)	(175.06)	(94.07)	(98.81)
Adj. R2 (%)	0.5138	0.5233	0.5694	0.8481	0.7198	0.6043	0.8440	0.8698	0.7178	0.7266	0.7093	0.7159
N	240	240	240	240	240	240	240	240	240	206	240	240

This table reports the estimation results for the following contemporaneous regressions:

$$Participation_t = \alpha + \beta Qindex_t \ + \theta Trend_t + \mu \boldsymbol{C}_t + \varepsilon_t,$$

where the dependent variable is one of 12 participation measures, including the net mutual fund flow (in million USD) to U.S. equities (*Netflow*); log of share volume (Vol^{SPX}), dollar volume ($DVol^{SPX}$) and value-weighted turnover ratio (TR^{SPX}) of S&P 500 component stocks; log of total share volume (Vol^{all}), dollar volume ($DVol^{all}$) and value-weighted turnover ratio (TR^{all}) of all stocks listed on NYSE, Amex, and NASDAQ; log number of trades for stocked listed on NASDAQ (*Trades*); log volume of call options ($Options^{call}$) and put options ($Options^{put}$) as well as the total option volume ($Options^{SPX}$) whose underlying asset is the S&P 500 index, and log volume of all the options traded on CBOE ($Options^{all}$). *Qindex* is the proxy for the quality of political signals divided by 100; *Trend* is a time variable to control for omitted trending in market participation; ***C*** is a vector of control variables including the realized volatility of S&P 500 index (*RVOL*), monthly return of S&P 500 index (R_m) and a recession dummy variable (*Recession*). Panel A reports the estimation for baseline regressions, and Panel B presents the results with control variables. Newey-West standard errors with one lag are estimated and t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A: Variable description

Variable	Description
Qindex	Index of quality of political signals constructed by Białkowski, Dang, and Wei (2021)
$SENT^{BW}$	Investor sentiment index constructed by Baker & Wurgler (2006) based on the first principal component of five standardized stock-market-cased sentiment proxies
$SENT^{HJTZ}$	Aligned investment sentiment index constructed by Huang et. al (2015), which modifies Baker and Wurgler's (2006) sentiment index by using the partial least square method
$SENT^{MS}$	Manager sentiment index developed by Jiang et al. (2019), which is based on the aggregated textual tone of corporate financial disclosures
SII	Short Interest Index by Rapach et al. (2016), which measures short interest aggregated across securities
$SENT^{FEARS}$	The Financial and Economic Attitudes Revealed by Search (FEARS) investor sentiment index developed by Da et al. (2015), which reflects the number of Internet searches related to household concerns (e.g., "recession," "unemployment," and "bankruptcy")
$SENT^{AAII}$	Difference between American Association of Individual Investors (AAII) bullish sentiment and AAII bearish sentiment
$SENT^{advisor}$	Difference between bullish and bearish Advisor Sentiments from Investors Intelligence
$SENT^{Indiv}$	U.S. One-Year Confidence Index for individual investors proposed by Shiller (2000)
$SENT^{MCS}$	The consumer sentiment index developed by the University of Michigan, which is constructed by telephone surveying a nationally representative sample of households
$SENT^{CBC}$	Conference Board consumer confidence index, which is developed by mail-surveying a random sample of households in the U.S.
PCSI	Refinitiv-Ipsos Primary Consumer Sentiment Index for the U.S., based on a monthly survey of consumer attitudes on economies, finance situations, savings, and investment confidence
VRP	Variance risk premium defined as the difference between the risk-neutral expected variance (VIX^2) and the realized return variation
LJV	Jump tail variance constructed by Bollerselv, Todorov, and Xu (2015)
VRP-LJV	Normal variance defined as *VRP- LJV*
Netflow	Net mutual fund flow (in million USD) to U.S. equities from the Investment Company Institute
Vol^{SPX}	Log of the share volume of S&P 500 component stocks
TR^{SPX}	Log of weighted-average turnover ratio of S&P 500 component stocks, where turnover ratio of each stock is defined as the monthly share volume dividend by shares outstanding
$DVol^{SPX}$	Log of the dollar volume of S&P 500 component stocks
Vol^{all}	Log of the share volume of all stocks all stocks listed on NYSE, Amex, and NASDAQ
TR^{all}	Log of weighted-average turnover ratio of all stocks listed on NYSE, Amex, and NASDAQ
$DVol^{all}$	Log of the dollar volume of all stocks all stocks listed on NYSE, Amex, and NASDAQ
Trades	Log number of trades of stocked listed on NASDAQ
$Options^{SPX}$	Log volume of options on S&P 500 index
$Options^{all}$	Log volume of all option contracts traded on CBOE
$Options^{call}$	Log volume of call options on S&P 500 index
$Options^{put}$	Log volume of put options on S&P 500 index
EP	Earnings-price ratio defined as the difference between the log of earnings on the S&P 500 index and the log of prices
DE	Dividend-payout ratio, defined as the difference between the log of dividends and the log of earnings on the S&P 500 index
DP	Dividend-price ratio, defined as the difference between the log of a 12-month moving sum of dividends paid on the S&P 500 index and the log of the S&P 500 index price
DY	Dividend yield, defined as the difference between the log of S&P 500 dividends and the log of lagged S&P 500 prices
SVAR	Stock return variance, calculated as the sum of squared daily returns on the S&P 500 index

BM	Book-to-market ratio, defined as the ratio of book value to market value for the Dow Jones Industrial Average
NTIS	Net equity expansion, calculated as the 12-month moving sums of net issues by stocks listed on NYSE divided by the total end-of-year market capitalization of NYSE stocks
TBL	Treasury bill rate, defined as the yield of a 3-month U.S. T-bill
LTY	Long-term yield, which is the long-term government bond yield.
LTR	Long-term return, defined as the return on long-term U.S. government bonds
TMS	Term spread, calculated as the long-term yield minus the U.S T-bill rate
DFY	Default yield spread, defined as the difference between BAA- and AAA-rated bond yields
DFR	Default return spread, calculated as the difference between the long-term corporate bond return and the long-term government bond return
INFL	Inflation, calculated based on the U.S. Consumer Price Index
RVOL	Realized volatility of daily returns on the S&P 500 index
Recession	NBER-based recession indicators for the U.S.

Appendix B: Test with first principal component of sentiment measures

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$PC1^{negative}$	-6.215***	-6.606***	-6.647***	-6.315***	-6.214***	-5.918***	-5.844***	-6.187***	-6.534***	-5.972***	-6.223***	-6.675***	-6.272***	-6.165***	-6.169***
	(-3.17)	(-3.28)	(-3.28)	(-2.95)	(-2.97)	(-3.11)	(-2.84)	(-3.52)	(-3.25)	(-3.02)	(-3.16)	(-3.24)	(-3.17)	(-3.23)	(-3.19)
Qindex *$PC1^{negative}$	5.539***	5.864***	5.941***	5.795***	5.727***	5.275***	5.355***	5.452***	5.919***	5.404***	5.545***	5.963***	5.594***	5.492***	5.495***
	(2.97)	(3.06)	(3.07)	(2.87)	(2.92)	(2.92)	(2.74)	(3.30)	(3.09)	(2.88)	(2.95)	(3.06)	(2.98)	(3.02)	(2.99)
Qindex	4.116**	4.167**	4.524**	5.566***	5.656***	3.779**	5.482***	4.075**	4.505**	3.983**	4.141**	4.547**	4.297**	4.099**	4.096**
	(2.22)	(2.24)	(2.42)	(3.09)	(3.23)	(2.10)	(2.65)	(2.49)	(2.44)	(2.14)	(2.24)	(2.46)	(2.37)	(2.25)	(2.22)
$ECON^m$	None	EP	DE	DP	DY	SVAR	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL
Adj. R2 (%)	20.61	21.56	22.36	23.26	23.35	20.89	22.18	24.86	22.96	21.53	20.27	21.48	20.3	20.38	20.27

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$PC1^{positive}$	2.159**	2.147**	2.370**	3.929***	3.725***	2.050**	2.066**	1.802**	2.226**	2.149**	2.171**	2.119**	1.994*	2.148**	2.145**
	(2.11)	(2.08)	(2.24)	(3.70)	(3.52)	(1.98)	(2.17)	(2.05)	(2.19)	(2.10)	(2.11)	(2.02)	(1.87)	(2.12)	(2.13)
Qindex * $PC1^{positive}$	-2.479***	-2.472***	-2.629***	-3.867***	-3.679***	-2.418**	-2.257***	-2.141***	-2.456***	-2.417**	-2.490***	-2.475**	-2.373**	-2.468***	-2.473***
	(-2.65)	(-2.62)	(-2.73)	(-3.94)	(-3.75)	(-2.55)	(-2.61)	(-2.62)	(-2.68)	(-2.53)	(-2.64)	(-2.59)	(-2.49)	(-2.65)	(-2.66)
Qindex	5.266***	5.297***	5.013***	5.733***	5.545***	5.442***	6.536***	5.334***	4.720***	3.439***	5.270***	5.074***	5.336***	5.242***	5.310***
	(4.18)	(3.79)	(3.69)	(4.22)	(4.00)	(4.17)	(4.94)	(4.44)	(3.83)	(2.61)	(4.18)	(3.96)	(4.18)	(4.12)	(4.06)
$ECON^m$	None	EP	DE	DP	DY	SVAR	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL
Adj. R2 (%)	10.03	9.63	10.24	21.05	21.33	10.09	16.33	10.9	11.1	14	9.68	9.99	9.81	9.73	9.98

This table presents the tests with the first principal component of investor sentiment that predict lower (higher) subsequent market returns in Panel A (Panel B). In Panel A the first principal component ($PC1^{negative}$) is estimated based on a group of sentiment measures, including $SENT^{BW}$, $SENT^{HJTZ}$ and $SENT^{Indiv}$ over the period from January 2001 to December 2018. The first principal component tested in Panel B ($PC1^{positive}$) is based on $SENT^{AAII}$, $SENT^{advisor}$, $SENT^{MC}$ $SENT^{CBC}$, *PCS* over the period from January 2002 to December 2020. $ECON_t^m$ is one of the 14 controlling economic variables (i.e., earnings-price ratio, *EP*; dividend-payout ratio, *DE*; dividend-price ratio, *DP*; dividend yield, *DY*; stock return variance, *SVAR*; book-to-market ratio, *BM*; net equity expansion, *NTIS*; treasury bill rate, *TBL*; long-term yield, *LTY*; long-term return, *LTR*; term spread, *TMS*; default yield spread, *DFY*; default return spread, *DFR*; inflation, *INFL*). The descriptions of economic measures are available in Appendix A. Newey-West standard errors with one lag are estimated and t-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix C: Replication of Bollerslev, Tauchen, and Zhou (2009)

	Bollerslev et al. (2009)				Replication results				Sample period			
	1990–2007				1990–2007				2001–2020			
Monthly return horizon	1	3	6	12	1	3	6	12	1	3	6	12
VRP	0.39*	0.47***	0.30**	0.12	0.41**	0.53***	0.35***	0.21*	-0.034	0.058	0.025	-0.031
	(1.76)	(2.86)	(2.15)	(1.00)	(1.97)	(3.32)	(2.64)	(1.70)	(-0.14)	(0.40)	(0.29)	(-0.74)
_cons	-0.55	-2.08	1.12	4.62	0.63	-1.71	1.36	3.45	4.031	3.636	4.125*	4.795***
	(-0.13)	(-0.56)	(0.33)	(1.50)	(0.13)	(-0.41)	(0.37)	(1.02)	(0.89)	(1.09)	(1.78)	(3.10)
Adj. R^2 (%)	1.07	6.82	5.42	1.23	1.27	8.3	7.49	3.38	-0.37	-0.01	-0.28	-0.01

This table presents the results of the replication of the analysis reported by Bollerslev, Tauchen, and Zhou (2009). We verify if the variance risk premium (VRP) predicts the aggregate stock market return in the U.S. The dependent variable is the annualized monthly excess return (in percentage) of the S&P 500 index over the next one-. three-, six-, or 12-month period. The excess return is defined as the monthly return on the S&P 500 index in excess of the risk-free rate (3-month T-bill rate). For replicating reasons, Hodrick's (1992) *t*-statistics are reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.