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Dashan HUANG

Singapore Management University, DASHANHUANG@smu.edu.sg

WANG LIYAO

Singapore Management University, liyao.wang.2015@phdecons.smu.edu.sg

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Partisan Conflict and Stock Price^{*}

Dashan Huang Liyao Wang
Singapore Management University

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Send correspondence to Dashan Huang, Lee Kong Chian School of Business, Singapore Management University, Singapore 178899. Phone: (65) 6808-5476 and e-mail: dashanhuang@smu.edu.sg.

Partisan Conflict and Stock Price

Abstract

Partisan conflict has been one dominant theme in U.S. politics in recent years. By using the textual index of Azzimonti (2018), this paper shows that partisan conflict positively predicts market returns, controlling for economic predictors and proxies for uncertainty, disagreement, geopolitical risk, and political sentiment. A one standard-deviation increase in partisan conflict is associated with a 0.58% increase in next month market return. The forecasting power concentrates in periods when the president is from the Republican Party or the majority of House is Republicans. Partisan conflict is positively related to downside risk, and makes investors more conservative when its value increases.

JEL Classification: G12, G17, P16

Keywords: Partisan conflict, Political disagreement, Political sentiment, Downside risk

1 Introduction

Partisan conflict has been one dominant theme in U.S. politics in recent years. According to the survey conducted by Pew Research Center in 2017, the gap between the political values of Republicans and Democrats is now larger than any point dating back to 1994. For example, in 1994, 36% of Republicans are more liberal than the median Democrat, while 30% of Democrats are more conservative than the median Republican. By comparison, in 2017, the corresponding two numbers decrease to 5% and 3%, respectively. On the other hand, compared with partisan conflict, other gaps, such as age, education, gender, and race, remain stable over the same sample period. According to another survey conducted by the Business Roundtable in 2013, half of all chief executive officers (CEOs) claim that political conflict within the federal government over the upcoming budget negotiations and the looming debt ceiling crisis is likely to have an adverse effect on their short-term hiring decisions, suggesting that partisan conflict may have a side-effect on the real economy.

This paper investigates the asset pricing implications of partisan conflict, with a focus on its predictability for future U.S. stock market returns. The rise in partisan conflict has been widely discussed by commentators (e.g., [Krugman, 2004](#)) and scholars (e.g., [McCarty, Poole, and Rosenthal, 2006](#)), because partisan conflict has substantive policy consequences, associated with increased levels of political gridlock ([Jones, 2001](#)), implying much reduced rates of policy innovation and a decreased ability to adapt to changes in economic, social, or demographic circumstances ([McCarty, 2007](#)). However, it is an open empirical question whether partisan conflict has a real effect on the stock market.

To answer our research question, we use a recently proposed partisan conflict index, which is constructed by [Azzimonti \(2018\)](#) to track the degree of political disagreement among U.S. politicians at the federal level, by measuring the frequency of newspaper articles reporting disagreement in a given month. Naturally, higher index values indicate greater conflict among political parties, Congress, and the President. By focusing on political disagreement about government policy, both within and between national parties, [Azzimonti \(2018\)](#) shows that the increases in partisan conflict are associated with presidential elections and well-known fiscal policy debates, such as the debt ceiling debate and debates on the Affordable Care Act (both related to its approval and potential repeal in early 2017). [Azzimonti \(2018\)](#) also shows that the partisan conflict index is different from the economic policy uncertainty (EPU) index in [Baker, Bloom, and Davis \(2016\)](#). For

example, the 9/11 attack introduces uncertainty in the economy, but there is very little disagreement about which policies should be implemented. Generally, American politics are very polarized regarding economic policy, but less divided when it comes to national defense issues.

We find that the partisan conflict index significantly and positively predicts future market returns. Over the sample period from January 1981 to December 2017 (444 months), a one-standard deviation increase in partisan conflict is associated with a 0.58% increase in the next one month expected market return. This predictive power remains significant in different subsample periods and slightly changes after controlling for the well-know economic predictors (Welch and Goyal, 2008), uncertainty measures (Bali, Brown, and Caglayan, 2014; Choi, Mueller, and Vedolin, 2017; Jurado, Ludvigson, and Ng, 2015; Baker, Bloom, and Davis, 2016), geopolitical risk (Caldara and Iacoviello, 2018), and disagreement measures (Bali, Brown, and Tang, 2017).

Partisan conflict, as a measure of political disagreement, is different from political sentiment. In the spirit of Addoum and Kumar (2016), we measure political sentiment as the return differential between high and low political-sentiment portfolios and find it negatively correlated with partisan conflict. In predicting market returns, the forecasting sign is positive for partisan conflict and negative for political sentiment, both of which are significant.

In more robustness tests, we find that partisan conflict 1) negatively predicts the following one- to 12-month market returns, in- and out-of-sample, 2) is robust with alternative detrending approaches, and 3) has stronger predictive power for industries such as chemicals, drugs, construction, fabricate, machinery, and finance. In a state-dependent regression, we show that the predictive power of partisan conflict concentrates in periods when the president is affiliated with Republican party or the majority of House is Republicans.

To interpret the results, we show that partisan conflict does not predict future macroeconomic activities, such as industrial production, consumption, and unemployment, etc. By using the decompositions of Campbell, Giglio, Polk, and Turley (2018), we find that partisan conflict can only predict discount rates, rather than cash flows and variance shocks. We attribute the higher risk premium when partisan conflict is high to the higher downside risk. Our interpretation is as follows. The government, through its regulatory institutions and budgetary decisions, implements policies that affect the environment in which firms operate. These policies are typically designed to prevent negative economic outcomes such as recessions and crises.

When parties are polarized and the government is divided, partisan conflict is elevated, and the quality of policies adopted is lower. Thus, partisan conflict exacerbates economic risk by increasing the likelihood of recessions or crises.

To test our interpretation, we measure downside risk with [Kelly and Jiang \(2014\)](#) tail risk and [Giglio, Kelly, and Pruitt \(2016\)](#) partial quantile regression-based systemic risk, where the former is proposed to capture the rare disaster risk in financial markets, and the latter has been proved to be the most robust and powerful measure for the systemic risk of real economic activities. In this paper, we find that partisan conflict is positively related to these two measures. A one-standard deviation increase in partisan conflict is associated with a 0.17 increase in tail risk and a 0.07 increase in systemic risk, both of which are significant at the 5% level.

Do investors pay attention and respond to partisan conflict? To answer this question, we perform two tests. First, we collect the search interest index data for each keyword used in [Azzimonti \(2018\)](#) from Google trends and construct an equally-weighted search interest index on partisan conflict, and find that the search interest index is positively associated with the partisan conflict index, with a correlation of 0.31, suggesting that the public does pay attention to partisan conflict. Second, we collect ETF flows into stocks and bonds and show that when partisan conflict increases, the flows to bonds significantly increase and to stocks significantly decrease, suggesting that investors become more cautionary for investments.

The rest of this paper is organized as follows. Section 2 presents some basic facts about U.S. partisan conflict, which are the motivation of this paper. Section 3 shows that the [Azzimonti \(2018\)](#) partisan conflict index positively predicts market returns and is robust with different controls. Section 4 explores an economic channel by showing that partisan conflict is positively related with downside risk and that investors make more conservative investments when partisan conflict increases, thereby positively predicting market returns. Section 5 concludes.

2 U.S. Partisan Conflict

2.1 Evidence from surveys

The conflicts between Republicans and Democrats on fundamental political values—on government, race, immigration, national security, environmental protection and other areas—reached record levels during Obama’s presidency. Republicans talk about “death taxes”, “illegal aliens”, and “tax reform”, whereas Democrats refer to “estate taxes”, “undocumented workers”, and “tax breaks for the wealthy”.

Based on surveys of more than 5,000 adults conducted over the summer of 2017, Pew Research Center finds widening differences between Republicans and Democrats on a range of measures the Center has been asking about since 1994. Figures 1 and 2 show that the gap between the political values of Republicans and Democrats is now larger than at any point dating back to 1994, a continuation of a steep increases in the ideological divisions between the two parties over more than two decades. For example, in 2017, the median (middle) Republican is now more conservative than 97% of Democrats, and the median Democrat is more liberal than 95% of Republicans. By comparison, in 1994, the two corresponding numbers are only 70% and 64%, respectively. That is, 64% of Republicans are to the right of the median Democrat, while 70% of Democrats are to the left of the median Republican.

Figure 2 also shows that while partisan conflict has been widening in the past two decades, other gaps, such as age, education, gender, and race, relatively remain modest.

2.2 Partisan conflict index

[Azzimonti \(2018\)](#) constructs a partisan conflict index by using a semantic search approach to measure the frequency of newspaper coverage of articles reporting political disagreement about government policy—both within and between national parties—normalized by the total number of news articles to average 100 in 1990. The semantic search for this benchmark index is performed in Factiva (by Dow Jones), a newspaper database containing digitalized copies of all major U.S. newspapers, such as The Washington Post, The New York Times, Los Angeles Times, Chicago Tribune, The Wall Street Journal, Newsday, The Dallas Morning News, The Boston Globe, and Tampa Bay Times. For self-contained, in Appendix we present the newspaper coverage and the set of words used by [Azzimonti \(2018\)](#) in constructing the index.

Specifically, [Azzimonti \(2018\)](#) counts the number of articles that discuss disagreement between political parties, branches of government, or political actors (e.g., candidates not yet in office, legislators, etc.) in a given month. She searches for articles containing at least one keyword in the following two categories, political disagreement and government, and focuses on specific terms related to partisan conflict, such as “divided party”, “partisan divisions”, and “divided Congress”. This search approach captures disagreement not only about economic policy (e.g., related to budgetary decisions, tax rates, deficit levels, welfare programs, etc.), but also about private-sector regulation (e.g., financial and immigration reform), national defense issues (e.g., wars, terrorism), and other dimensions that divide policymakers’ views (e.g., same-sex marriage, gun control, and abortion rights, among others)

Figure 3 plots the monthly partisan conflict index over the period from January 1981 to December 2017. As expected, the rise of this index accelerates with partisan debates, such as Obamacare and debt ceiling, and peaks around the 2013 government shutdown and the 2016 Trump-Clinton president election. The index also dramatically shrinks on some remarkable political and military incidences, such as the 1987 Beirut Bombing, 1990 Gulf War, and 2001 9/11.

The partisan conflict remains relatively stable from 1981 to the late 2009, but appears to display an upward trend thereafter, during Obama’s presidency and it has grown even larger in Donald Trump’s first year as president. To ensure it to be stationary in use, Figure 3 also plots the quadratically detrended series, which will be used throughout the paper. In Section 3.6, we show that our results remain the same when alternative detrending methods are used.

3 Partisan Conflict and Return Predictability

3.1 Forecasting market returns

The market return to be predicted is the continuously compounded log return of the S&P 500 index in excess of the risk-free rate. To have an intuitive understanding about the relationship between partisan conflict and market return, Table 1 presents the following one month market returns when the partisan conflict index reaches its top and bottom 10 historical records, respectively. In Panel A, after the index experiences a historical high in month t , the market return in month $t + 1$ is more likely to be positive. For example, after

the index reaches its historical mark in October 2013, the market return is 3.04% in November 2013. In contrast, in Panel B after the index experiences a historical low in month t , the market return in month $t + 1$ is more likely to be negative. For example, in August 2015 the index reaches its 10th historical low, the market realizes a -2.49% return in September 2015.

It appears in Table 1 that partisan conflict is associated with future market returns. To formally test this conjecture, we estimate variants of the following standard predictive regression:

$$R_{t+1} = \alpha + \beta \text{partisan conflict}_t + \psi Z_t + \varepsilon_{t+1}, \quad (1)$$

where Z_t is one of the well-known return predictors in Welch and Goyal (2008), including dividend-price ratio, dividend yield, earnings-price ratio, dividend-payout ratio, book-to-market ratio, net equity expansion, treasury bill rate, long-term bond yield, long-term bond return, term spread, default yield spread, default return spread, inflation rate, and stock sample variance. The sample period runs from January 1981 through December 2017.

Table 2 presents the regression results, in which all independent variables are normalized to have a mean zero and variance one, so that the regression slope measures the variation of next month expected market return in response to one standard deviation increase in the independent variable of interest. As can be seen, partisan conflict has substantial forecasting power for future market returns. In the first row when partisan conflict is the only predictor, a one standard deviation increase in partisan conflict in month t is positively associated with a 0.58% step-up of expected market return in month $t + 1$.

In the second to last row, we include the 14 known return predictors one by one as a control variable to explore whether the partisan conflict index has incremental forecasting power. The results are encouraging and the regression slope on partisan conflict is virtually unchanged from its value in the first row. Consistent with Welch and Goyal (2008), none of the 14 known predictors is significant. Thus, the predictive power of partisan conflict for future market returns appears to be somewhat more robust than known return predictors, at least in our sample period.

Having shown that partisan conflict has significant predictive power on market return, a suspicious reader may wonder how stable the estimator is in regression (1) or to what extent the results in Table 2 are driven

by a subsample period. To address this concern, we estimate the slope of partisan conflict with a rolling 20-year window, and plot the time-varying estimates in Figure 4, where the data point labeled “200501” reflects an estimate based on the 1985:02–2005:01 sample period. As the figure shows, although volatile, nearly 90% of the slopes are statistically significant at 10% level. More importantly, the estimates after 2005 are persistently larger than the full-sample estimate, suggesting that including the early years tend to reduce the economic magnitude of our results.

3.2 Controlling for uncertainty

As argued by [Azzimonti \(2018\)](#), high levels of partisan conflict are interpreted as situations where agreement between the two parties is hard to reach, so policies are expected to be less effective at preventing recessions and tail risks. Moderate levels of partisan conflict should be associated with positive economic policy uncertainty, as investors cannot predict which policies will be undertaken. Examples are the debt ceiling debate (will the government change taxes to avoid a fiscal cliff?), the passage of Obamacare (will Congress modify the health care system effectively, or will this result in an explosion of public debt?), or the uncertainty associated with tax expirations (will tax cuts expire or will the two parties agree on further extensions?) In these situations, partisan conflict should be correlated with macroeconomic risk and uncertainty, such as the EPU in ([Baker, Bloom, and Davis, 2016](#)).

However, [Azzimonti \(2018\)](#) shows in details that an increase in partisan conflict does not necessarily lead to an increase in EPU. Under extreme levels of partisan disagreement (e.g., when Congress is divided and polarization levels are high) the government may enter a gridlock state, or even a shutdown and the relationship between EPU and partisan conflict may break, at least in the short-run. This is consistent with the 2013 shutdown and the first half of 2017. When the partisan conflict index reaches extreme values, investors become very pessimistic about the ability of the government to take the appropriate measures to reduce tail risks or less the effects for recessions, and this may depress investment ([Azzimonti, 2018](#)).

To reduce the concern that the information embedded in partisan conflict largely overlaps with macroeconomic uncertainty, we consider the bivariate regression (1) by replacing Z_t with a proxy for macroeconomic uncertainty. For comprehensive, we consider seven measures, including the economic uncertainty index from [Bali, Brown, and Caglayan \(2014\)](#), treasury implied volatility from [Choi, Mueller,](#)

and Vedolin (2017), economic policy uncertainty and monetary policy uncertainty from Baker, Bloom, and Davis (2016), financial uncertainty from Jurado, Ludvigson, and Ng (2015), VIX, and geopolitical risk measure from Caldara and Iacoviello (2018).

Panel A of Table 3 presents the results. As the table shows, the predictive power of partisan conflict is not affected by any of the uncertainty measures, and its regression slope is similar to, or even larger in some cases than, the univariate case in which partisan conflict is used alone. It is also interesting that five out of 7 macroeconomic uncertainty proxies are not statistically significant in predicting future market returns, and the rest two, financial uncertainty and geopolitical risk, are only marginally significant at the 10% level.

To have a clear understanding of the difference between partisan conflict and uncertainty, Figure 5 plots the time-series of partisan conflict vs. VIX, where the latter is widely used as an uncertainty measure in the literature (Manela and Moreira, 2017). We can make two statements from the figure immediately. First, the two indexes generatively move in opposite directions, with a correlation of -0.30 . For example, in the 1990-1998 sample period, VIX is persistently low, while the partisan conflict index almost always stays above its long-term mean. After the 2008 financial crisis, VIX stays at a low level again, while the partisan conflict index keeps breaking its historical high records. Second, both partisan conflict and VIX reach their high marks in different periods. For example, VIX reaches its historical high in the 2008 financial crisis period, whereas the partisan conflict index breaks its record in the 2013 government shutdown.

Figure 6 plots the time-series of the partisan conflict index vs. geopolitical risk index. Accordingly to Caldara and Iacoviello (2018), geopolitical risk refers to the risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations, and is constructed by counting the frequency of articles related to geopolitical risks in leading international newspapers published in the U.S., the United Kingdom, and Canada. Figure 6 shows that although the partisan conflict index coincides with the geopolitical risk index around the period of U.S. bombs Libya and Gulf war, it reflects the turbulence caused by political debates most of the other times. In contrast, geopolitical risk index mainly captures the influence of wars, terrorism, and events, which break the peaceful international relationships. Indeed, these two indexes generally have a negative -0.14 correlation in our sample period. In sum, it is not possible to simply attribute the predictive power of partisan conflict to that of macroeconomic uncertainty.

3.3 Controlling for disagreement

As argued by [Azzimonti \(2018\)](#), the partisan conflict index is a measure of political disagreement, which raises a concern as to whether its predictive power is subsumed by traditional macroeconomic disagreement measures ([Anderson, Ghysels, and Juergens, 2005](#); [Banerjee, 2011](#); [Atmaz and Basak, 2018](#)).

To differentiate partisan conflict from macroeconomic disagreement, we construct ten measures based on the Blue Chip Economic Indicator surveys, including disagreement on gross domestic product, consumer price index, 3-month treasury bill rate, unemployment rate, industrial production, disposable personal income, non-residential fixed investment, housing starts, 10-year treasury bond rate, and personal consumption expenditure, respectively. Each disagreement measure is computed as the standard deviation of economists forecasts on these macroeconomic variables.

Panel B of Table 3 reports the results from the bivariate regression (1) by replacing Z_t with a macroeconomic disagreement measure. The results show that the predictive ability of partisan conflict remains the same as the standalone case, while none of the macroeconomic disagreement measures has any predictive power.

3.4 Controlling for political sentiment

Recent literature shows that changes in political climate influence stock prices. For instance, [Addoum and Kumar \(2016\)](#) argues that investor demand can be shifted if there is a change of the majority party. They define this shift as political sentiment and argue that cash flows and asset prices of firms or industries with higher political exposures will be more sensitive to this sentiment measure. To offer a clear comparison between political sentiment and partisan conflict, we construct political-sensitivity portfolios following [Addoum and Kumar \(2016\)](#) and construct a political sentiment index as the return differential between high and low political-sensitivity portfolios. We smooth the index with the 6-month moving averages to iron out idiosyncratic noises.

Figure 7 provides a graphical illustration on the difference between partisan conflict and political sentiment. Clearly, these two indexes capture different information, with a correlation of -0.16 . To explore

how they are related to future stock returns, Table 4 presents the results of the following bivariate regressions:

$$R_{t+1} = \alpha + \beta \text{partisan conflict}_t + \psi \text{political sentiment}_t + \varepsilon_{t+1}. \quad (2)$$

When used as a standalone predictor, a one-standard deviation increase in political sentiment suggests a 0.44% decrease in the next one month expected market return. This magnitude is statistically significant and economically sizeable. When partisan conflict is included, the regression slope of political sentiment slightly decrease in magnitude from 0.44% to 0.40%, but remains statistically significant. Similarly, the slope on partisan conflict also slightly decreases from 0.58%, the standalone case, to 0.55% and remains significant as well. As a result, partisan conflict and political sentiment capture different aspects of the U.S. politics.

3.5 Alternative forecasting horizons

This section explores whether the predictive power of partisan conflict extends to multiple months. As such, we consider the following regression:

$$R_{t,t+h} = \alpha + \beta \text{partisan conflict}_t + \varepsilon_{t,t+h}, \quad (3)$$

where $R_{t,t+h}$ is the h -month market return from month t to month $t+h$ ($h = 1, 3, 6$, and 12). Table 5 reports the results and shows that partisan conflict can predict the market up to a horizon of one year. A one-standard deviation increase in partisan conflict in month t is associated with a 1.08% increase of expected market return in the following one quarter and a 4.80% increase in the following one year.

In addition to in-sample forecasting, Table 5 also reports the out-of-sample performance. We use Campbell and Thompson (2008) out-of-sample R^2 statistic as the out-of-sample performance evaluation criterion, and define it as:

$$R_{OS}^2 = 1 - \frac{\sum_{t=K+1}^T (R_t - \hat{R}_t)^2}{\sum_{t=K+1}^T (R_t - \bar{R}_t)^2}, \quad (4)$$

where K is the size for in-sample parameter training and $T - K$ is the number of out-of-sample observations.

\hat{R}_t and \bar{R}_t are the return forecasts with partisan conflict and historical mean, both of which are estimated using data up to month $t - 1$. If partisan conflict is a viable predictor, the R_{OS}^2 will be positive and its mean-squared forecast error (hereafter MSFE) will be lower than the MSFE with the forecast based on the historical return mean. [Campbell and Thompson \(2008\)](#) show that a monthly R_{OS}^2 of 0.5% can generate significant economic value. The null hypothesis of interest is therefore $R_{OS}^2 \leq 0$ against the alternative hypothesis that $R_{OS}^2 > 0$. We test this hypothesis by using the [Clark and West \(2007\)](#) MSFE-adjusted statistic.

In this paper, we use the first 15-year data as in-sample training and the rest 21-year data as out-of-sample evaluation. Following [Welch and Goyal \(2008\)](#) and [Campbell and Thompson \(2008\)](#), we recursively estimate the expected market returns using the expanding window approach to reduce estimation error. The last column of Table 5 shows that the predictive ability remains significant with this stringent evaluation criterion. The R_{OS}^2 s are 2.48%, 2.02%, and 9.74% at the one-month, one-quarter, and one-year forecasting horizons, respectively.¹

3.6 Alternative detrending methods

To ensure that our results are not driven by the specific quadratic detrending approach, this section explores the predictive ability of partisan conflict with alternative detrending methods. For robustness, we consider four alternatives: 1) raw partisan conflict index, 2) linear detrending, 3) cubic detrending, and 4) stochastic detrending. Following [Campbell \(1991\)](#) and [Rapach, Ringgenberg, and Zhou \(2016\)](#), stochastic detrending is based on a five-year window and the detrended partisan conflict in month t is the difference between the raw partisan conflict in month t minus its average from month $t - 59$ to month t .

Table 6 presents the in- and out-of-sample performance over various forecasting horizons. The results show that the predictive power of partisan conflict is robust to different detrending methods: the regression estimates are economically and statistically significant for all detrending specifications and at all horizons.

3.7 Forecasting industry portfolio returns

[Belo, Gala, and Li \(2013\)](#) show that industry government spending exposure reflects predictable variations in

¹It should be mentioned that, although the out-of-sample R_{OS}^2 can be negative and is usually smaller than the in-sample R^2 , theoretically they do not have a strict relationship ([Welch and Goyal, 2008](#); [Campbell and Thompson, 2008](#)). One reason is that they are based on different sample periods with different econometric criteria.

cash flow and stock returns over political cycles. Firms with higher (lower) government spending exposure experience higher (lower) cash flows and stock returns during Democratic (Republican) presidencies. In addition, [Addoum and Kumar \(2016\)](#) show that shifts in political climate generate predictable patterns in industry returns, which are more pronounced at the aggregate level than at firm level. In this section, we investigate how the predictive power of partisan conflict varies across industry portfolios. Specifically, we consider the following predictive regression:

$$R_{t+1}^i = \alpha + \beta \text{partisan conflict}_t + \varepsilon_{t+1}, \quad (5)$$

where R_{t+1}^i is the excess return of one of the 17 industry portfolios in [Fama and French \(1997\)](#). Results in Table 7 show that partisan conflict significantly predicts nine industries in-sample and eight industries out-of-sample, among which seven industries are significantly predicted both in- and out-of-sample, including Chems (Chemicals), Cnsum (Drugs, Soap, Perfumes, Tobacco), Cnstr (Construction and Construction Materials), FabPr (Fabricated Products), Machn (Machinery and Business Equipment), Finan, and Other. Apparently, most of these sectors are heavily regulated by the government and therefore related to the variations of partisan conflict.

3.8 Forecasting the market over different political regimes

[Santa-Clara and Valkanov \(2003\)](#) and [Pastor and Veronesi \(2018\)](#) show that market returns exhibit a striking pattern: they are much higher under Democratic presidents than under Republican ones. In this section, we examine whether the predictive power of partisan conflict differs over different political regimes. Specifically, we predict the market return with a state-dependent regression as

$$R_{t+1} = \alpha + \beta_1 I_t^{\text{republican}} \text{partisan conflict}_t + \beta_2 I_t^{\text{democratic}} \text{partisan conflict}_t + \varepsilon_{t+1}, \quad (6)$$

where $I_t^{\text{republican}}$ is a dummy variable that equals one if the president is affiliated with republican party or the majority of House/Senate is republican, and zero otherwise. $I_t^{\text{democratic}}$ is a dummy variable that equals one if the president is affiliated with democratic party or the majority of House/Senate is democrats, and zero otherwise. Results in Table 8 show that all the coefficients of republican indicators are positive and

significant at the 5% level. In contrast, the significance of democratic indicators is much weaker with $I_t^{\text{democratic}}$ being only significant at the 10% level when the majority of Senate is democrats. In sum, Table 8 demonstrates a clear pattern that the predictive power of partisan conflict concentrates in the periods when the Republican party is in power.

4 Interpreting the Results

4.1 Forecasting economic activities

One possible explanation as to why partisan conflict predicts market returns is that it is positively associated with future macroeconomic activities. To test this possibility, we forecast economic activities with partisan conflict as

$$y_{t+1} = \alpha + \beta \text{partisan conflict}_t + \sum_{i=1}^{12} \lambda_i y_{t-i+1} + \varepsilon_{t+1} \quad (7)$$

for monthly data, and

$$y_{q+1} = \alpha + \beta \text{partisan conflict}_t + \sum_{i=1}^4 \lambda_i y_{q-i+1} + \varepsilon_{q+1} \quad (8)$$

for quarterly data. We consider eight proxies for economic activities, including the Chicago fed national activity index (CFNAI), industrial production growth, real personal consumption expenditure (consumption), unemployment rate, private gross domestic investment (investment), real GDP growth, business inventory, and capacity utilization (Greenwood, Hercowitz, and Huffman, 1988). In the regressions, these economic variables are adjusted for seasonality and annualized for ease of exposition. Except for the gross private domestic investment and real GDP growth, all of them are measured at monthly frequency.

Panel A of Table 9 shows that partisan conflict cannot predict any of the eight economic activity measures. This result is not necessarily inconsistent with Azzimonti (2018), who shows that, to some extent, partisan conflict represents one type of uncertainty and negatively predicts future firm investments. The main difference is that we focus on the aggregate market level analysis, while Azzimonti (2018) considers the firm level analysis. Since firms' investments are highly heterogenous (Clementi and Palazzo, 2018), the firm level pattern does not necessarily hold at the aggregate level.

According to Campbell, Giglio, Polk, and Turley (2018), if a variable predicts future market returns, it

must predict future cash flows or discount rates or variance shocks or all of the three terms. Based on the results in Panel A, we can exclude the cash flow channel, and thus, partisan conflict must predict discount rates or variance shocks or both. To test this hypothesis, we consider the following regression:

$$y_{q+1} = \alpha + \beta \text{partisan conflict}_q + \psi P/E_q + \varepsilon_{q+1}, \quad (9)$$

where the dependent variable is future discount rates, cash flows, or variance shocks, and P/E is the price-earnings ratio.² We take the average of the partisan conflict index within one quarter as the quarterly partisan conflict measure.

Panel B of Table 9 shows that partisan conflict can only significantly predict discount rates, but not cash flows and variance shocks. A one-standard deviation increase in partisan conflict leads to a 1.40% increase in next quarter discount rates. In contrast, the coefficients on cash flow shock and variance shock are close to zero and not significant, which is consistent with the results in Panel A.

4.2 Relationship with downside risk

The government, through its regulatory institutions and budgetary decisions, implements policies that affect the environment in which firms operate. These policies are typically designed to prevent negative economic outcomes such as recessions and crises. When parties are polarized and the government is divided, partisan conflict is elevated, and the quality of policies adopted is lower. Thus, partisan conflict exacerbates economic risk by increasing the likelihood of recessions or crises.

To test this implication, we consider two downside risk measures, the tail risk in Kelly and Jiang (2014) and the partial quantile regression-based systemic risk in Giglio, Kelly, and Pruitt (2016), and run the following predictive regression:

$$y_{t+1} = \alpha + \beta \text{partisan conflict}_t + \psi y_t + \varepsilon_{t+1}. \quad (10)$$

Table 10 shows that a one-standard deviation increase in partisan conflict is positively associated with a 17% increase in tail risk and a 0.07% increase in systemic risk.

²We thank Christopher Polk for providing these data on his webpage.

4.3 Do investors pay attention to partisan conflict?

[Azzimonti \(2018\)](#) constructs the partisan conflict index by counting the number of articles related to political disagreement published in widely-circulated newspapers. It reflects the opinions from a relatively small group of professionals with sophisticated knowledge. One natural question is whether investors pay attention to partisan conflict. To address this issue, we collect the search interest index data for each keyword used in [Azzimonti \(2018\)](#) from Google trends and construct an equally-weighted search interest index on partisan conflict. Figure 8 shows that the search interest index is positively associated with the partisan conflict index, with a correlation of 0.31. This suggests that the public does pay attention to partisan conflict.

[Gentzkow and Shapiro \(2010\)](#) construct a metric of media slant based on the language used by media outlets, and argue that readers' preferences in the political spectrum are the key drivers of the newspapers content.

4.4 Do investors respond to partisan conflict?

If investors pay attention to partisan conflict, do they adjust their investments accordingly? To answer this question, we offer some evidences from observational data. We compute the weight of investment flows into bonds (stocks) as quarterly ETF flows into bonds (stocks) at quarter q normalized by the sum of total net asset in bonds and stocks at quarter $q-1$. We use quadratic detrending method to remove the time trend in flows. Following [Lian, Ma, and Wang \(2018\)](#), we control the Campbell-Shiller price-earnings ratio (P/E10), the past 12-month excess stock return, VIX^2 (the square of VIX, which measures the expected variance of S&P500 index), real GDP growth, and the credit spread ([Gilchrist and Zakrajsek, 2012](#)). We consider two sets of political dummy variables including presidential affiliation and House majority. The dummy variable equals to one if the president is affiliated with Republican (House majority is Republican), and zero otherwise. We take the average of partisan conflict index within one quarter as the quarterly partisan conflict measure and run the following regression:

$$\Delta W_q = \alpha + \beta \text{partisan conflict}_q * \text{dummy}_q + \gamma \text{partisan conflict}_q + \rho \text{dummy}_q + X'_{q-1} \psi + \sum_{i=1}^4 \lambda_i \Delta W_{q-i} + \varepsilon_q, \quad (11)$$

where ΔW denotes the change in weight of ETF flows into bonds or stocks, and $\text{partisan conflict} \times \text{dummy}$ refers to the interaction term between partisan conflict and political dummy. X includes all the control variables which are lagged by one period. All regressions include four lags of ΔW in case that ETF flows are persistent over time.

5 Conclusion

By using the textual index of [Azzimonti \(2018\)](#), this paper shows that partisan conflict positively predicts market returns, controlling for economic predictors and proxies for uncertainty and disagreement. A one standard-deviation increase in partisan conflict is associated with a 0.58% increase in next month market return. The forecasting power concentrates in periods when the president is from the Republican Party or the majority of House is Republicans. Economically, partisan conflict is positively related to downside risk, and makes investors more conservative when its value increases.

There are a number of subjects that are of interest for future research. First, while we focus on the stock market, it is interesting to examine the predictability of partisan conflict in other markets. Second, while it is beyond the scope of this paper, it would be interesting to explore the effect of partisan conflict in a general equilibrium model. Finally, what drives the movements of partisan conflict deserves further research.

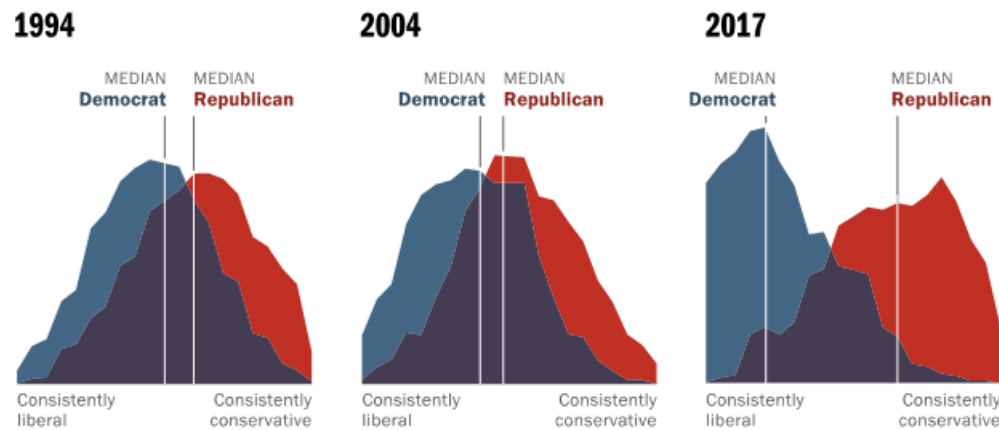
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Democrats and Republicans more ideologically divided than in the past

Distribution of Democrats and Republicans on a 10-item scale of political values



Notes: Ideological consistency based on a scale of 10 political values questions (see methodology). The blue area in this chart represents the ideological distribution of Democrats and Democratic-leaning independents; the red area of Republicans and Republican-leaning independents. The overlap of these two distributions is shaded purple.

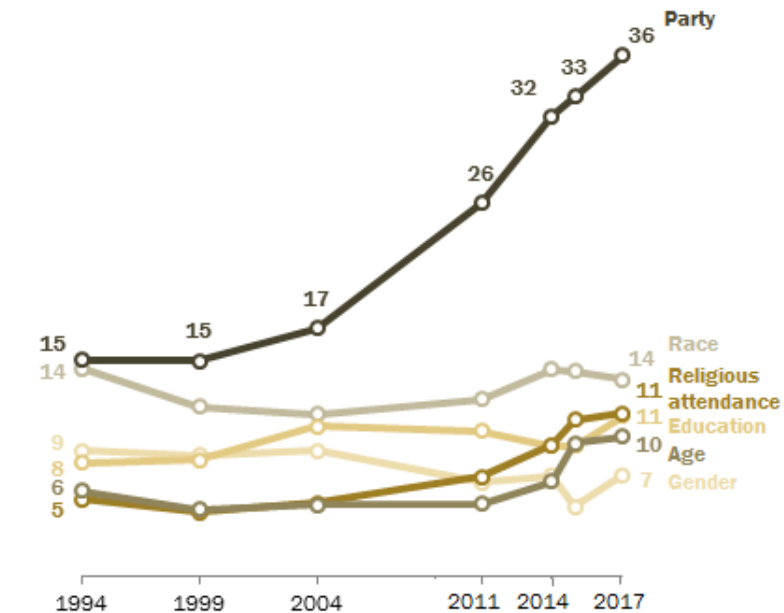
Source: Survey conducted June 8-18, 2017.

PEW RESEARCH CENTER

Figure 1 Political polarization in the American public (2017, Pew Research Center)

As partisan divides over political values widen, other gaps remain more modest

Average gap in the share taking a conservative position across 10 political values, by key demographics



Notes: Indicates average gap between the share of two groups taking the conservative position across 10 values items. Party= difference between Rep/Lean Rep and Dem/Lean Dem. Race=white non-Hispanic/black non-Hispanic. Education=college grad/non-college grad. Age=18-49/50+. Religion=weekly+ religious service attenders/less often. Source: Survey conducted June 8-18 and June 27-July 9, 2017.

PEW RESEARCH CENTER

Figure 2 Political polarization vs. other gaps in the American public (2017, Pew Research Center)

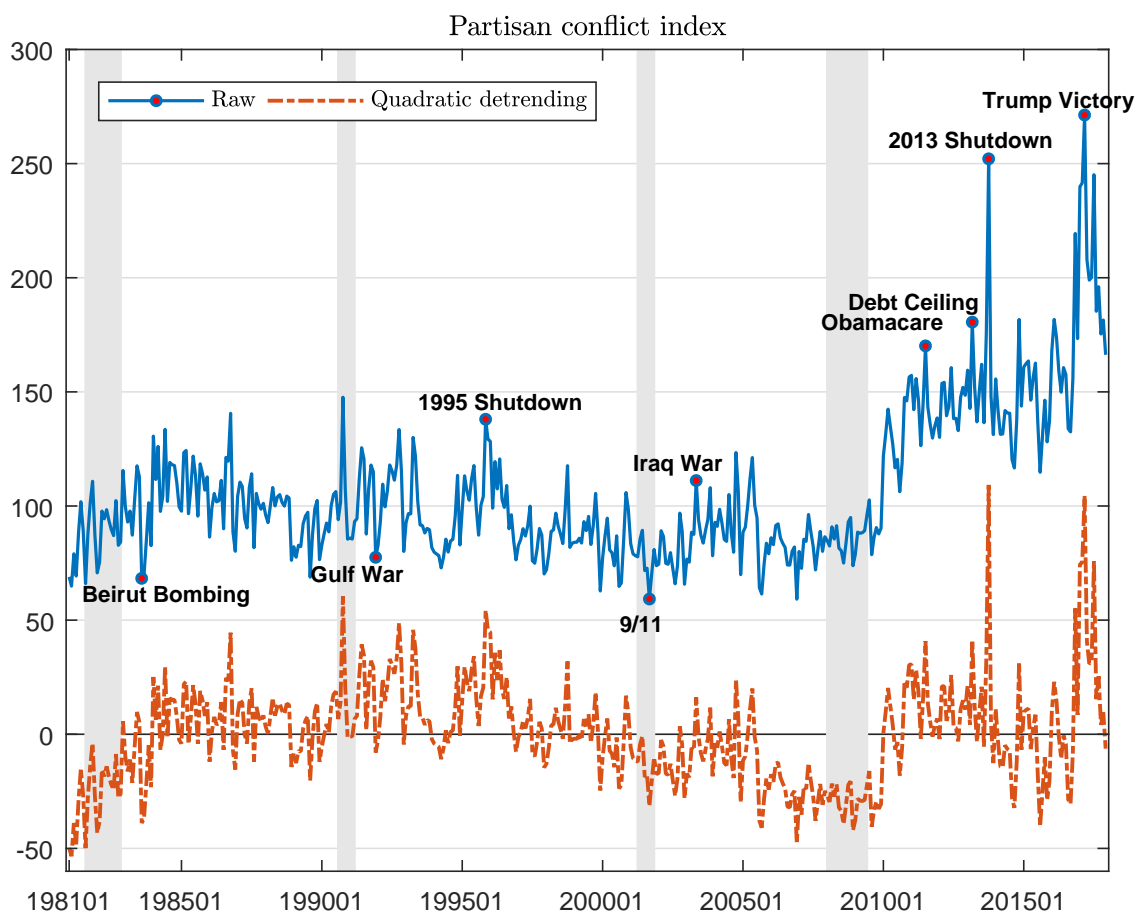


Figure 3 Partisan conflict index

This figure plots the partisan conflict index in [Azzimonti \(2018\)](#). The sample period is 1981:01–2017:12

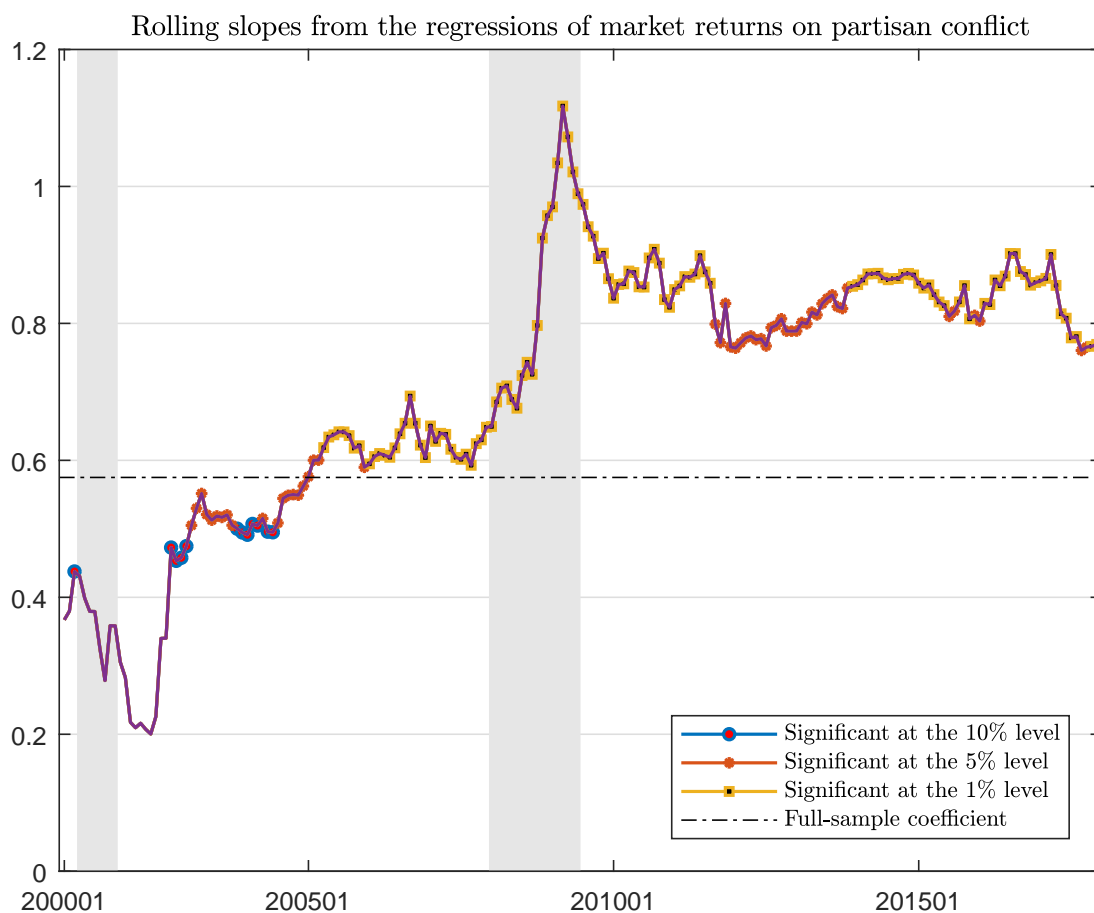


Figure 4 Rolling slopes from the regressions of market returns on partisan conflict index

This figure plots the slopes from the regressions of market returns on partisan conflict index with a rolling window of 20 years, where the dashed line indicates the full sample estimate. The political conflict index is from [Azzimonti \(2018\)](#), and the sample period is 1981:01–2017:12.

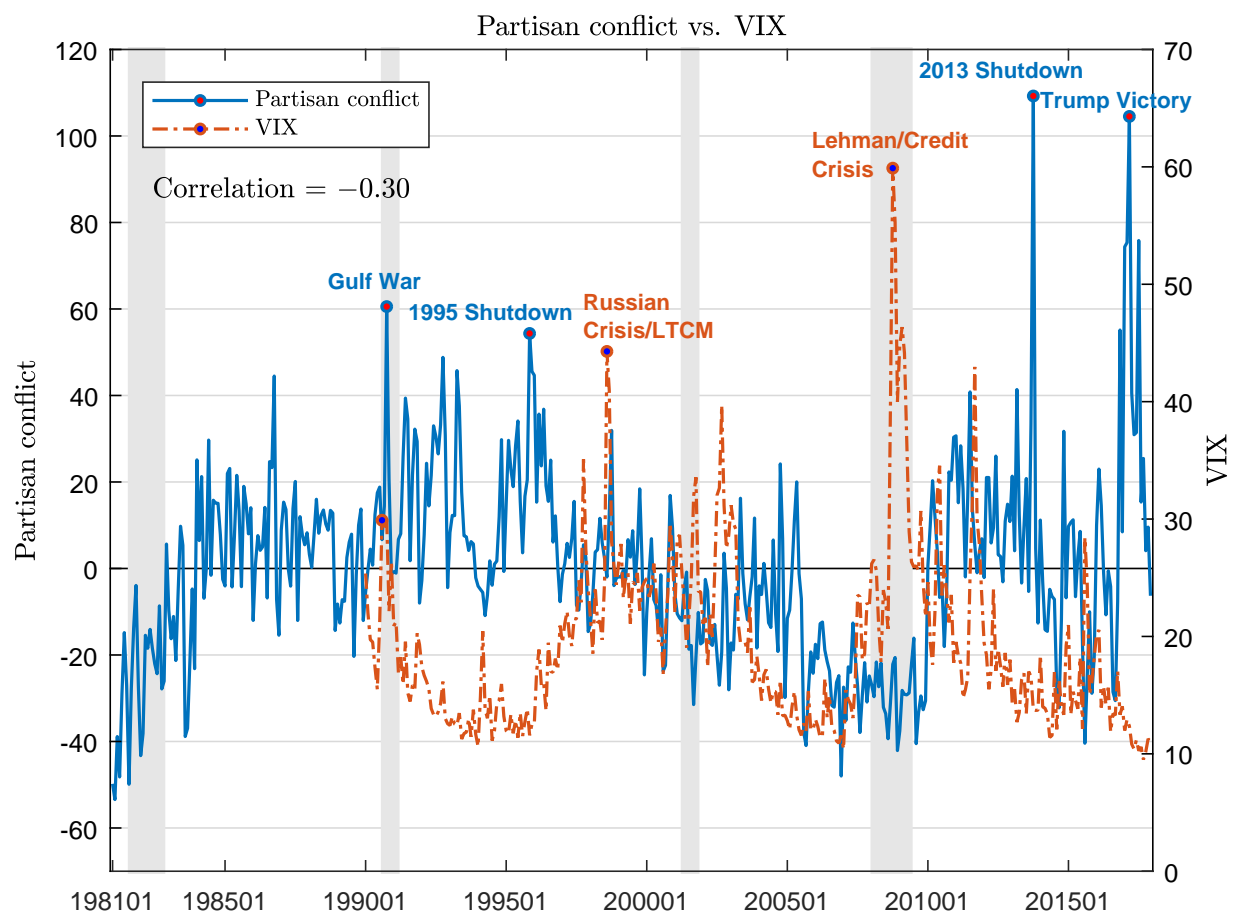


Figure 5 Partisan conflict vs. VIX

This figure plots the partisan conflict index and VIX, where the former is from [Azzimonti \(2018\)](#) and the latter is from CBOE. The sample period is 1981:01–2017:12 for partisan conflict index and 1990:01–2017:12 for VIX.

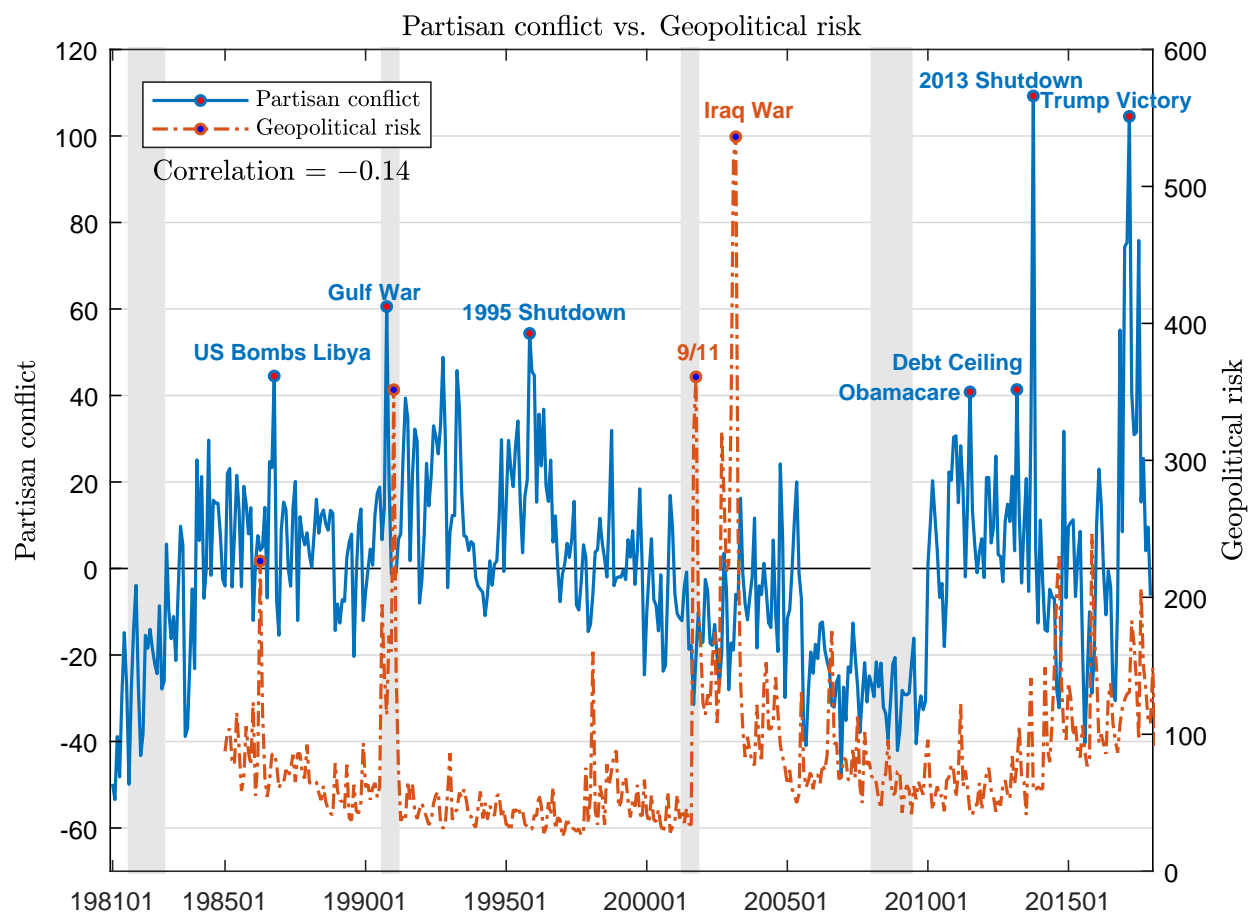


Figure 6 Partisan conflict vs. geopolitical risk

This figure plots the partisan conflict and geopolitical risk indexes, where the former is from [Azzimonti \(2018\)](#) and the latter is from [Caldara and Iacoviello \(2018\)](#). The sample period is 1981:01–2017:12 for partisan conflict index and 1985:01–2017:12 for geopolitical risk index.

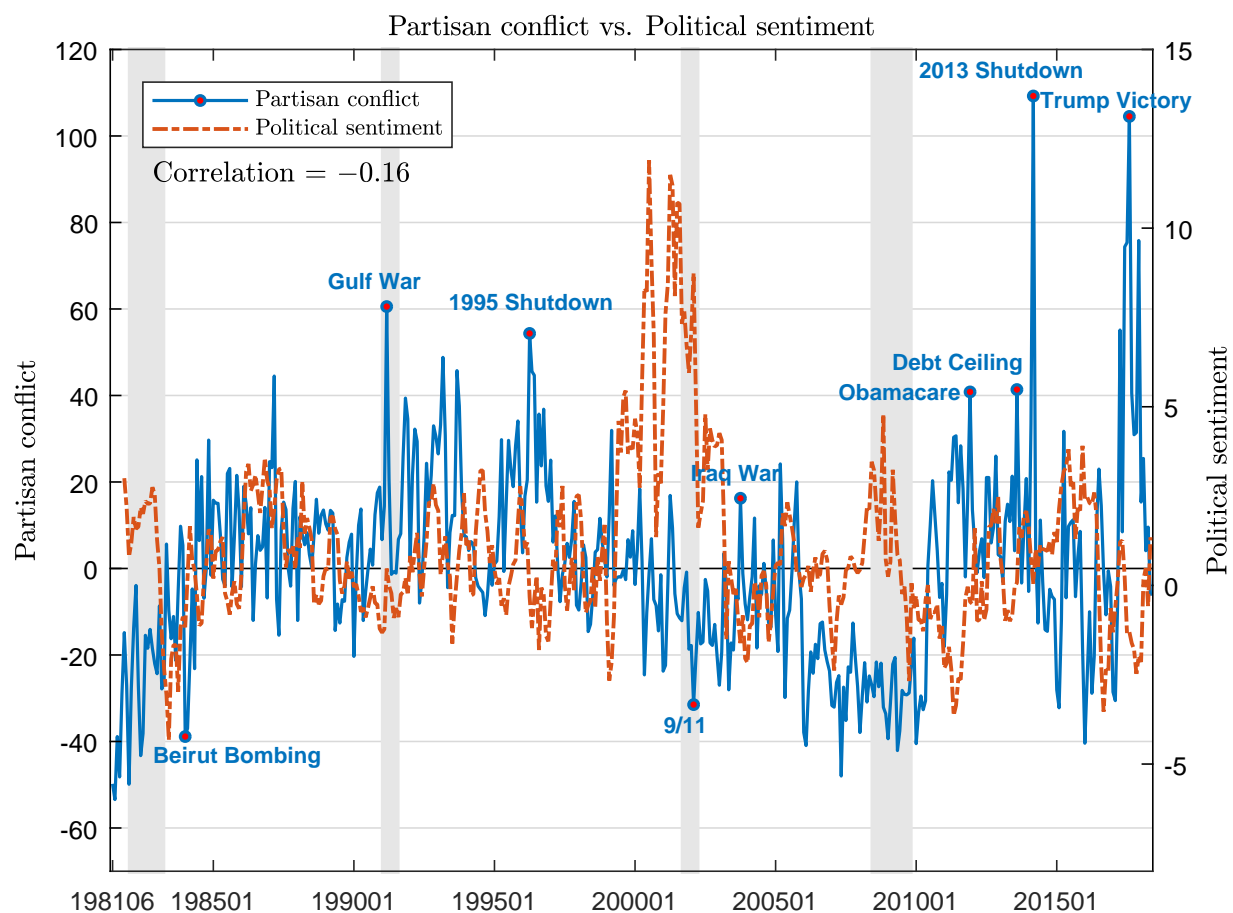


Figure 7 Partisan conflict vs. political sentiment

This figure plots the partisan conflict and political sentiment indexes, where the former is from [Azzimonti \(2018\)](#), and the latter is measured as the return differential between high and low political-sentiment portfolios following [Addoum and Kumar \(2016\)](#), which is smoothed by the 6-month moving averages to iron out idiosyncratic noises. The sample period is 1981:01–2017:12.

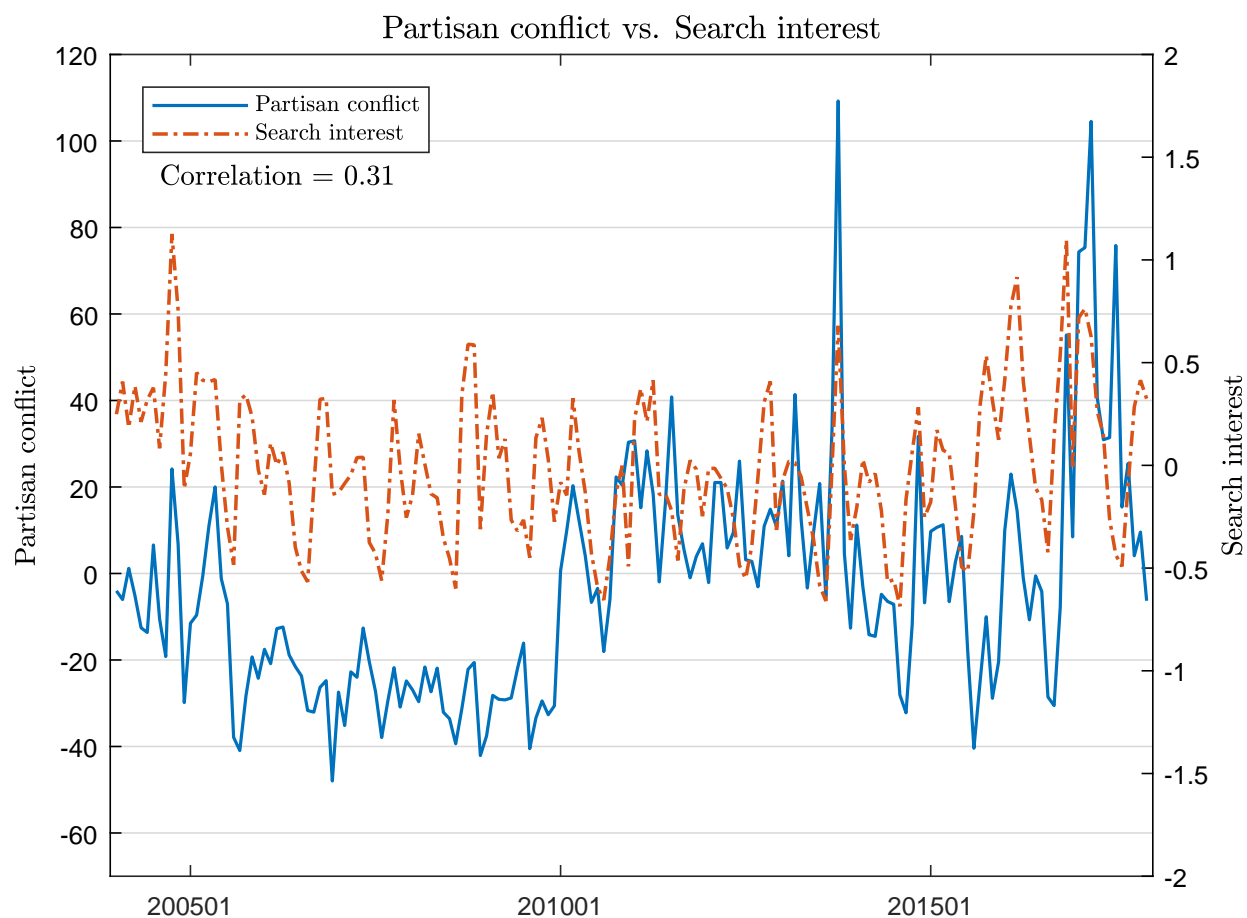


Figure 8 Partisan conflict vs. its attention index

This figure plots the [Azzimonti \(2018\)](#) partisan conflict index and its attention index (i.e., Google search interest), where the attention index is constructed by equally weighting the Google search volumes of the partisan conflict key words used in [Azzimonti \(2018\)](#). The sample period is 2004:01–2017:12.

Table 1 Market returns following historical records of the partisan conflict index

This table reports the next one month market returns following the top and bottom 10 historical records of the [Azzimonti \(2018\)](#) partisan conflict index. The sample period is 1981:01–2017:12.

	Partisan conflict	Next one month return
Panel A: Returns following top 10 historical records		
Oct-2013	109.24	3.04
Mar-2017	104.52	1.01
Jul-2017	75.82	0.13
Feb-2017	75.35	0.14
Jan-2017	74.36	3.83
Oct-1990	60.55	5.69
Nov-2016	55.13	1.87
Nov-1995	54.34	1.26
Oct-1992	48.81	3.09
Apr-1993	45.74	2.37
Panel B: Returns following bottom 10 historical records		
Aug-2015	−40.41	−2.49
Aug-2009	−40.50	3.58
Sep-2005	−40.94	−1.85
Dec-2008	−42.10	−8.62
Jan-1982	−43.27	−6.09
Dec-2006	−47.98	1.08
Apr-1984	−48.20	−0.49
Jan-1981	−49.80	1.04
Aug-1981	−49.89	−6.41
Feb-1981	−53.43	2.55

Table 2 Forecasting market returns with partisan conflict index

This table reports the results of predicting market returns with [Azzimonti \(2018\)](#) partisan conflict index as

$$R_{t+1} = \alpha + \beta \text{partisan conflict}_t + \psi Z_t + \varepsilon_{t+1},$$

where Z_t is one of the economic predictors in [Welch and Goyal \(2008\)](#). Reported are the regression slope, t -value, and R^2 . ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 1981:01–2017:12.

	β	t -value	ψ	t -value	R^2
	0.58***	3.01			1.81
Dividend-price ratio	0.57***	2.98	0.24	1.15	2.12
Dividend yield	0.57***	2.96	0.26	1.24	2.17
Earning-price ratio	0.56***	3.02	0.14	0.50	1.90
Dividend payout ratio	0.59***	3.20	0.10	0.36	1.86
Book-to-market ratio	0.59***	3.03	0.15	0.67	1.92
Net equity expansion	0.59***	3.26	−0.10	−0.42	1.86
Treasury bill rate	0.56***	2.77	−0.12	−0.57	1.88
Long-term bond yield	0.57***	2.89	−0.13	−0.64	1.90
Long-term bond return	0.57***	2.96	0.24	1.17	2.11
Term spread	0.57***	2.79	0.01	0.06	1.80
Default yield spread	0.61***	3.44	0.10	0.32	1.85
Default return spread	0.57***	3.01	0.38	1.17	2.59
Inflation rate	0.57***	3.02	0.16	0.64	1.94
Stock sample variance	0.62***	3.27	0.26	1.37	2.17

Table 3 Controlling for uncertainty and disagreement

This table reports the results of predicting market returns with [Azzimonti \(2018\)](#) partisan conflict index as

$$R_{t+1} = \alpha + \beta \text{partisan conflict}_t + \psi Z_t + \varepsilon_{t+1},$$

where Z_t is one of the economic uncertainty or disagreement measures. Economic uncertainty measures include the economic uncertainty index from [Bali, Brown, and Caglayan \(2014\)](#), treasury implied volatility from [Choi, Mueller, and Vedolin \(2017\)](#), economic policy uncertainty, financial uncertainty from [Jurado, Ludvigson, and Ng \(2015\)](#), monetary policy uncertainty from [Baker, Bloom, and Davis \(2016\)](#), CBOE VIX, and geopolitical risk measure from [Caldara and Iacoviello \(2018\)](#), and economic disagreement measures are calculated as the standard deviations of economists' forecasts from the Blue Chip Economic Indicator survey, including gross domestic product, consumer price index, 3-month treasury bill rate, unemployment rate, industrial production, disposable personal income, non-residential fixed investment, housing starts, 10-year treasury bond rate, and personal consumption expenditure. Reported are regression slopes, t -values, and R^2 s. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 1981:01–2017:12.

	β	t -value	ψ	t -value	R^2
Panel A: Controlling for uncertainty					
Economic uncertainty index	0.81***	3.66	0.06	0.16	3.62
Treasury implied volatility	0.70***	2.84	−0.22	−0.54	3.12
Economic policy uncertainty	0.57**	2.34	0.11	0.34	1.91
Financial uncertainty	0.43**	2.10	−0.59*	−1.67	3.36
VIX	0.79***	3.91	0.22	0.59	3.40
Monetary policy uncertainty	0.58**	2.65	0.16	0.55	1.99
Geopolitical risk	0.65***	2.97	0.40	1.86	2.73
Panel B: Controlling for disagreement					
Disagreement on gross domestic product	0.58***	2.73	0.09	0.35	1.85
Disagreement on consumer price index	0.59***	2.89	0.08	0.28	1.84
Disagreement on 3-month treasury bill	0.58***	2.73	0.04	0.24	1.81
Disagreement on unemployment rate	0.56***	2.65	0.29	1.28	2.26
Disagreement on industrial production	0.59***	2.83	0.23	1.03	2.09
Disagreement on disposable personal income	0.57***	2.76	−0.06	−0.21	1.83
Disagreement on non-residential fixed investment	0.59***	2.84	0.15	0.64	1.93
Disagreement on housing starts	0.58***	2.78	0.01	0.07	1.81
Disagreement on 10-year treasury bond	0.84***	3.22	0.27	0.82	3.77
Disagreement on personal consumption expenditure	0.73***	3.50	−0.17	−0.60	3.70

Table 4 Controlling for political sentiment

This table reports the results of predicting market returns with [Azzimonti \(2018\)](#) partisan conflict index as

$$R_{t+1} = \alpha + \beta \text{partisan conflict}_t + \psi \text{political sentiment}_t + \varepsilon_{t+1},$$

where political sentiment is defined as the return differential between high and low political-sensitivity portfolios in [Addoum and Kumar \(2016\)](#). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 1981:01–2017:12.

β	t -value	ψ	t -value	R^2
		−0.44**	−2.07	1.05
0.55***	2.84	−0.40*	−1.91	2.67

Table 5 Forecasting market returns with different horizons

This table presents the results of predicting market returns with partisan conflict index as:

$$R_{t,t+h} = \alpha + \beta \text{partisan conflict}_t + \varepsilon_{t,t+h},$$

where $R_{t,t+h} = \sum_{j=1}^h R_{t+j}/h$ is the average market return between months t and $t+h$ ($h = 1, 3, 6, 12$). Reported are regression slope, t -value, in-sample R^2 , and out-of-sample R_{OS}^2 . Statistical significance for R_{OS}^2 is based on the p -value of the [Clark and West \(2007\)](#) MSFE-adjusted statistic for testing: $H_0 : R_{OS}^2 \leq 0$ against $H_A : R_{OS}^2 > 0$. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The in-sample period is 1981:01–2017:12 and the out-of-sample period is 1996:01–2017:12.

Horizon	β	t -value	R^2	R_{OS}^2
$h = 1$	0.58***	3.01	1.80	2.48***
$h = 3$	1.08**	2.22	2.03	2.02*
$h = 6$	2.58***	2.60	5.15	4.18**
$h = 12$	4.80***	2.63	7.96	9.74***

Table 6 Forecasting market returns using alternative detrended partisan conflict indexes

This table presents the results of predicting market returns as:

$$R_{t,t+h} = \alpha + \beta \text{partisan conflict}_t + \varepsilon_{t,t+h},$$

$R_{t,t+h} = \sum_{j=1}^h R_{t+j}/h$ is the average market return between months t and $t+h$ ($h = 1, 3, 6, 12$). We consider the raw partisan conflict index without detrending and with alternative detrended methods, including linear, cubic, and stochastic detrending approaches, respectively. Reported are regression slope, t -value, in-sample R^2 , and out-of-sample R_{OS}^2 . Statistical significance for R_{OS}^2 is based on the p -value of the [Clark and West \(2007\)](#) MSFE-adjusted statistic for testing: $H_0 : R_{OS}^2 \leq 0$ against $H_A : R_{OS}^2 > 0$. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The in-sample period is 1981:01–2017:12 and the out-of-sample period is 1996:01–2017:12.

Horizon	β	t -value	R^2	R_{OS}^2
Panel A: No detrending				
$h = 1$	0.48***	3.10	1.27	1.44***
$h = 3$	0.96***	2.63	1.63	1.59***
$h = 6$	2.16***	2.93	3.97	2.23***
$h = 12$	4.44***	2.81	7.08	7.79***
Panel B: Linear detrending				
$h = 1$	0.52***	2.75	1.46	1.71***
$h = 3$	1.02**	2.14	1.81	2.12**
$h = 6$	2.40***	2.47	4.53	4.27**
$h = 12$	4.92***	2.57	8.70	10.50***
Panel C: Cubic detrending				
$h = 1$	0.46***	2.61	1.14	1.53**
$h = 3$	0.63*	1.67	0.69	0.51
$h = 6$	1.86***	2.62	2.65	1.19**
$h = 12$	3.48***	2.92	4.28	4.31***
Panel D: Stochastic detrending				
$h = 1$	0.48**	2.55	1.20	1.50**
$h = 3$	0.72*	1.74	0.88	0.74*
$h = 6$	1.74**	2.47	2.62	2.61***
$h = 12$	3.60***	2.65	4.87	5.87***

Table 7 Forecasting industry portfolio returns

This table presents the results of predicting industry portfolio returns as:

$$R_{t+1}^i = \alpha + \beta \text{partisan conflict}_t + \varepsilon_{t+1},$$

where R_{t+1}^i is industry i 's return from Ken French's website. Reported are the regression coefficient, t -value, in-sample R^2 , and out-of-sample R_{OS}^2 . Statistical significance for R_{OS}^2 is based on the p -value of the Clark and West (2007) MSFE-adjusted statistic for testing: $H_0 : R_{OS}^2 \leq 0$ against $H_A : R_{OS}^2 > 0$. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The in-sample period is 1981:01–2017:12 and the out-of-sample period is 1996:01–2017:12.

Industry	β	t -value	R^2	R_{OS}^2
Food	0.25	1.58	0.37	0.39*
Mines	0.01	0.01	0.01	−0.52
Oil	0.42	1.55	0.61	−0.31
Clths	0.30	1.03	0.24	−0.01
Durbl	0.52*	1.85	0.88	0.91
Chems	0.56**	2.01	0.92	0.71*
Cnsum	0.42**	2.36	0.95	1.48***
Cnstr	0.71***	2.70	1.43	1.95***
Steel	0.36	0.89	0.21	−0.12
FabPr	0.48**	2.01	0.79	0.81*
Machn	0.59**	2.10	0.76	0.65*
Cars	0.42	1.42	0.42	0.17
Trans	0.38	1.60	0.54	0.55
Utils	0.32*	1.85	0.70	0.38
Rtail	0.32	1.44	0.39	−0.06
Finan	0.66**	2.42	1.47	1.84**
Other	0.52***	2.53	1.13	1.42**

Table 8 Forecasting market returns with partisan conflict index over different political regimes

This table presents the results of forecasting market return with a state-dependent regression as:

$$R_{t+1} = \alpha + \beta_1 I_t^{\text{republican}} \text{partisan conflict}_t + \beta_2 I_t^{\text{democratic}} \text{partisan conflict}_t + \varepsilon_{t+1},$$

where $I_t^{\text{republican}}$ is a dummy variable that equals one if the president is affiliated with republican party or the majority of House/Senate is republican, and zero otherwise. $I_t^{\text{democratic}}$ is a dummy variable that equals one if the president is affiliated with democratic party or the majority of House/Senate is democrats, and zero otherwise. Reported are the regression slopes, t -values, and R^2 . ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 1981:01–2017:12.

State determination	β_1	t -value	β_2	t -value	R^2
Presidential affiliation	0.52**	2.45	0.26	1.63	1.88
House majority	0.53***	3.63	0.28	1.17	1.92
Senate majority	0.36***	2.56	0.46*	1.91	1.86

Table 9 Forecasting economic activities

Panel A presents the results of predicting economic and corporate activities with partisan conflict index as:

$$y_{t+1} = \alpha + \beta \text{partisan conflict}_t + \sum_{i=1}^{12} \lambda_i y_{t-i+1} + \varepsilon_{t+1}$$

for monthly data, and

$$y_{q+1} = \alpha + \beta \text{partisan conflict}_q + \sum_{i=1}^4 \lambda_i y_{q-i+1} + \varepsilon_{q+1}$$

for quarterly data. The economic activity measures include Chicago fed national activity index (CFNAI), industrial production growth, real personal consumption expenditure (consumption), unemployment rate, private gross domestic investment (investment), Real GDP growth, business inventory, and capacity utilization (Greenwood, Hercowitz, and Huffman, 1988). Panel B reports the results of predicting discount rate shock, cash flow shock, and variance shock of the market return with partisan conflict index and price earning ratio as

$$y_{q+1} = \alpha + \beta \text{partisan conflict}_q + \psi P/E_q + \varepsilon_{q+1},$$

where the shocks and quarterly P/E data are from Campbell, Giglio, Polk, and Turley (2018). We take the average of the index within one quarter as the quarterly partisan conflict measure. Reported are the slope of disagreement, its Newey-West t -value, and R^2 . ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

y	β	t -value	R^2
Panel A: Forecasting economic activities			
CFNAI	-0.08	-0.21	40.82
Industrial production	0.61	1.60	21.44
Consumption	0.07	0.25	19.06
Unemployment	-0.12	-1.30	20.59
Investment (quarterly)	1.48	1.42	20.84
Real GDP (quarterly)	0.20	1.03	28.44
Business inventory	0.13	0.48	58.66
Capacity utilization	0.36	1.21	20.24
Panel B: Forecasting market return component shocks			
Discount rate shock	1.40**	1.98	3.02
Cash flow shock	0.05	0.16	0.02
Variance shock	0.01	0.01	0.58

Table 10 Relationship with downside risk

This table reports the relationship between partisan conflict index and tail risk as:

$$y_{t+1} = \alpha + \beta \text{partisan conflict}_t + \psi y_t + \varepsilon_t,$$

where y_t is the tail risk in Kelly and Jiang (2014) tail risk or partial quantile regression-based systemic risk in Giglio, Kelly, and Pruitt (2016). Reported are the regression slope, t -value, and R^2 . ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	β	t -value	ψ	t -value	R^2
Tail risk	0.17**	1.96	0.83***	27.08	72.73
Systemic risk	0.07**	2.29	0.73***	15.73	60.17

Table 11 Predicting ETF flows

This table reports the results of predicting ETF flows as:

$$\Delta W_q = \alpha + \beta \text{partisan conflict}_q * \text{dummy}_q + \gamma \text{partisan conflict}_q + \rho \text{dummy}_q + X'_{q-1} \psi + \sum_{i=1}^4 \lambda_i \Delta W_{q-i} + \varepsilon_q$$

where W_q refers to quarterly ETF flows into bonds (stocks) at quarter q normalized by the sum of total net asset in bonds and stocks at quarter $q - 1$, and ΔW_q is the change in weight of ETF flows into bonds (stocks). X includes control variables following [Lian, Ma, and Wang \(2018\)](#): the Campbell-Shiller price-earnings ratio (P/E10), the past 12-month excess stock return, VIX^2 (the square of VIX , which measures the expected variance of the S&P500 index), real GDP growth, and the credit spread ([Gilchrist and Zakrajsek, 2012](#)). We lag all the control variables by one period. All regressions include four lags of ΔW . We consider two sets of political dummy variables including presidential affiliation (panel A) and House majority (panel B). The dummy variable equals to one if the president is affiliated with Republican (House majority is Republican), and zero otherwise. Partisan conflict measure is from [Azzimonti \(2018\)](#), we take the average of the index within one quarter as the quarterly partisan conflict measure. Reported are the regression slope, t -value, and R^2 . ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample period is 1997Q1–2017Q4.

ETF flows	Panel A: Presidential affiliation				Panel B: House majority			
	Bond		Stock		Bond		Stock	
Partisan conflict*dummy	0.20*	0.24**	−0.22	−0.28**	0.21***	0.11**	−0.77**	−0.93***
	(1.67)	(2.13)	(−0.91)	(−2.11)	(5.14)	(2.05)	(−2.24)	(−4.41)
Partisan conflict	−0.22*	−0.17***	0.34	0.26***	−0.26***	−0.14**	1.01**	1.04***
	(−1.71)	(−2.59)	(1.14)	(3.01)	(−6.16)	(−2.40)	(2.46)	(4.70)
Dummy	−0.03	−0.08	−0.03	−0.31**	0.10***	0.17***	−0.37***	−0.45***
	(−0.70)	(−1.51)	(−0.44)	(−2.01)	(2.87)	(2.54)	(−2.58)	(−3.58)
P/E10		−0.12		0.32		−0.06		0.38
		(−1.38)		(1.04)		(−0.76)		(1.12)
12-month MKT return		−0.09***		−0.28**		0.04		−0.04
		(−3.15)		(−2.25)		(0.58)		(−0.26)
VIX^2		−0.01		0.43**		0.07		0.36**
		(−0.29)		(2.19)		(1.08)		(2.01)
T-bill		0.18*		−0.63		0.13		−0.60
		(1.67)		(−1.29)		(1.08)		(−1.19)
Real GDP growth		−0.01		−0.55		−0.11*		−0.57
		(−0.32)		(−1.58)		(−1.83)		(−1.63)
Credit spread		0.05		−1.58***		0.10		−1.31**
		(0.92)		(−2.58)		(1.33)		(−2.23)
Constant	0.01	0.02	−0.01	0.01	0.01	0.01	−0.02	0.01
	(0.12)	(0.15)	(−0.28)	(0.11)	(0.14)	(0.09)	(−0.41)	(0.15)
R^2	42.29	49.26	35.01	52.98	40.43	47.37	37.05	54.11

Appendix

The newspapers used in constructing the [Azzimonti \(2018\)](#) partisan conflict index are as follows.

News source	Start date	News source	Start date
The Arizona Republic	Jan-1999	The New York Times	Jun-1980
The Arkansas Democrat Gazette	Oct-1994	Newsday	Jul-1985
The Atlanta Journal Constitution	Jan-1986	The News-Gazette	Mar-2000
The Baltimore Sun	Sept-1990	The Oklahoman	Nov-1981
Boston Herald	Jul-1991	Omaha World-Herald	Aug-1983
Buffalo News	Feb-1992	The Orange County Register	Nov-1986
Charlotte Observer	Jan-1994	The Oregonian	Jul-1989
Chicago Sun-Times	Jul-1985	Orlando Sentinel	Oct-1987
Chicago Tribune	Jan-1985	The Philadelphia Inquirer	Oct-1994
The Christian Science Monitor	Sept-1988	Pittsburgh Post-Gazette	Jul-1990
The Cincinnati Enquirer	Jan-2002	The Plain Dealer	Mar-1989
The Columbus Dispatch	Dec-1991	The Sacramento Bee	Jan-2003
The Boston Globe	Jan-1987	San Antonio Express-News	Feb-1994
The Courier Journal	Jan-2002	The San Francisco Chronicle	Apr-2012
The Dallas Morning News	Aug-1984	San Jose Mercury News	Jan-1994
The Denver Post	Aug-1988	The Seattle Times	Dec-2008
Detroit Free Press	Jan-1994	South Florida Sun-Sentinel	Jan-1990
The Detroit News	Jan-2002	St. Louis Post-Dispatch	Jan-1992
The Fort Worth Star-Telegram	Jun-2001	St. Paul Pioneer Press	Jan-1994
The Hartford Courant	May-1991	The Star-Ledger	Jan-1991
Houston Chronicle	Apr-2012	Star-Tribune	Jan-1986
Indianapolis Star	Jan-2002	Tampa Bay Times	Nov-1986
Investor's Business Daily	Jan-2002	Tampa Tribune	Jul-2011
The Kansas City Star	Jan-1991	The Times-Picayune	Apr-1992
Los Angeles Times	Jan-1985	USA Today	Apr-1987
The Miami Herald	Oct-1994	U-T San Diego	Jan-2000
The Milwaukee Journal Sentinel	Jan-2000	The Wall Street Journal	Jun-1979
New York Daily News	Dec-1992	The Washington Post	Jan-1984
New York Post	Sept-1997	Washington Post.com	Oct-2007

The set of words in the Factiva query follow:

Political disagreement: standstill, stalemate, gridlock, disagreement, fail to compromise, polarization, polarized, dysfunctional, ideological difference(s), deadlock, budget battle/fight, filibuster, standoff, veto, vetoes, vetoing, delay/oppose bill.

Government: White House, senate, senator, Capitol, Congress, congressman(woman), party, partisan, Republican, GOP, Democrat, political, politician, legislator, lawmaker, “the President”, Appropriation Committee, Finance Committee, Ways and Means Committee, federal government.