Partisan Conflict and Private Investment *

Marina Azzimonti†

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Abstract

I investigate the hypothesis that news about partisan conflict depress private investment. A reduced-form political economy model illustrates the main channels, emphasizing the effects of new information on agents expectations. I then construct a novel indicator that tracks the behavior of partisan conflict as reported by the media, and use it to test this hypothesis. The benchmark index (PCI), computed monthly between 1981 and 2015, uses a semantic search methodology to measure the frequency of newspaper articles reporting lawmakers' disagreement about policy. I find a negative relationship between innovations in PCI and aggregate investment in the US. This finding is robust to alternative measures of investment, frequency of the data, and to the time-horizon considered (e.g. using an extended series computed annually from 1890). News about partisan conflict are also associated with lower investment rates at the firm level, particularly in firms that rely heavily on government spending and in those who actively engage in campaign contributions through PACs.

JEL Classification: E3, H3.

1 Introduction

American politics have been characterized by a high degree of partisan conflict in recent years. The combination of increasing polarization and divided government has led not only

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†Stony Brook University. Part of this project was developed at the FRB of Philadelphia. The views expressed in this paper are those of the author and do not necessarily reflect those of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

to significant Congressional gridlock (such as the budgetary warfare that eventually triggered the 18th government shutdown in US history in 2013), but also to spells of high fiscal policy uncertainty (such as the 2012 tax-expirations and the fiscal cliff). The unprecedented slow recovery in investment from the Great Recession during the same period suggests the possibility that the two phenomena may be related. Partisan conflict is relevant for the evolution of private investment for two reasons. First, because expected returns on investment become less predictable when the timing, size, and composition of fiscal policy is uncertain. To the extent that investment is irreversible and subject to fixed upfront costs, this induces delays in investment decisions (Baker, Bloom, and Davis, 2015; Canes-Wrone and Park 2011). Second, because the resulting legislative gridlock negatively affects the optimal response to adverse shocks and the quality of policy reforms aimed at preventing them (Alesina and Drazen, 1991). This lowers expected returns, and hence discourages investment. The key channel by which government dysfunction affects private investment in these theories is through investors' expectations. It is therefore important to understand how they are formed. Moreover, to the extent that individuals cannot fully observe the true degree of partisan conflict, it is relevant to determine what shapes their perceptions about political dysfunction.

In this paper, I consider the role of news provided by the media as signals used by investors to learn about the underlying degree of partisan conflict. In a reduced-form political economy model with Bayesian learning, I illustrate how these signals affect investment decisions by changing agents' expectations. Investment returns depend on the state of the economy, and may take extremely low values during low probability events such as a financial crisis, a sovereign debt crisis, or a war (Barro, 2006). I assume that policymakers can reduce the probability of rare events by adopting preventive policies or undertaking reforms, but face political costs to do so. When parties are polarized and the government is divided, partisan conflict is elevated, and the quality of policies adopted is lower. Partisan conflict, thus, exacerbates economic risk by increasing the likelihood of rare events in this simple model.

Agents do not observe the true value of partisan conflict at the time of making investment decisions. This key assumption captures the idea that the profitability of investment is not only risky, but also *uncertain*. Moreover, as the future path of government policy cannot be predicted with certainty, investors also face economic policy uncertainty (EPU). I show that the relationship between partisan conflict and economic policy uncertainty is inverted u-shaped, as increases in the former only introduce policy uncertainty for moderate levels of political discord. When disagreement is extreme, agents know with high certainty that the status-quo will remain unchanged due to government inaction. I assume that investors can obtain imperfectly informative signals about true partisan conflict by reading newspapers. Periods in which they observe a large proportion of articles reporting political discord result in beliefs about partisan conflict being updated upwards. This decreases expected returns on investment—as tail risks are perceived to be more likely—which in turn induces a reduction in the overall level of private investment.

To test the hypothesis that news about partisan conflict depresses investment, I construct a novel indicator of the degree of partisan conflict that is consistent with the theory. The *partisan conflict index* (PCI) is computed using a methodology similar to that of Baker, Bloom, and Davis (2015). In particular, I use 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 within a given period. In order to show that the resulting measure indeed captures a signal about true political discord, I compute the PCI between 1891 and 2013, and show that its behavior is consistent with that of slow-moving variables characterizing the political process. First, I show that the long-run trend in the historical PCI mirrors the evolution of political polarization, as computed by Mc-Carty, Poole, and Rosenthal (2006). Second, I show that changes in (the trend of) the PCI: (i) are more pronounced under a divided government, (ii) are positively related to the number of cloture attempts (a proxy for filibusters), and (iii) decline with the share of seats in Congress controlled by the President's party (a proxy for political power). Third, I find that short-term increases in partisan conflict are associated with presidential elections and well-known fiscal policy debates, such as the approval of Obamacare, the debt ceiling debate, and the fiscal cliff. This is reassuring, suggesting that the indicator captures disagreement about well-known polemic issues. Interestingly, no clear relationship between partisan conflict and recessions (measured by NBER dates or by periods of high unemployment rates) was detected. For example, the index is much lower than average during the Great Depression, but reached significant levels during the panics of 1893 and 1911, and the Great Recession. Taken together, these observations indicate that the index is mainly capturing political factors, rather than the state of the economy. Trends in media coverage are also important determinants of the evolution of the index, as increases in the share of news devoted to politics are associated with larger observations in the PCI. This could simply indicate that newspaper editors respond to demand by expanding the politics section in periods where investors are more eager to learn about political discord. While an interesting topic of study, I will remain agnostic about the direction of causality between these variables (for estimation purposes, I am interested in the signal received by investors).

It is worth noting that while the methodology used to compute the PCI is similar to the one used by Baker, Bloom, and Davis (2015) to measure EPU, the two indexes represent different concepts and are therefore characterized by distinctive features. The main difference lies in the channel by which partisan conflict affects investment decisions. In particular, the PCI represents a *signal about government dysfunction* rather than the degree of economic policy uncertainty. When high levels of the PCI are observed, investors expect policies to be less effective in reducing tail risks, and this depresses investment. While there are cases in which increases in the PCI would be associated with higher economic policy uncertainty (such as during Obamacare debate and the tax-expirations of 2012, when investors could not predict which policies would be undertaken) this need not always be the case. Under extreme values of the PCI (e.g., a shutdown), government inaction is expected. There is very little fiscal uncertainty at that point (at least in the short run), but investment is nonetheless negatively affected due to an increased likelihood of adverse low-probability events. Interestingly, the indexes move in opposite direction when the country is at war or subject to national security threats, such as World War I, Pearl Harbor, and 9/11. The 9/11 attacks, for example, introduced uncertainty in the economy (so EPU was extremely high), but there was very little disagreement about which policies should be implemented (so PCI was extremely low). This suggests that American politics are very polarized regarding economic policy, but less divided when it comes to national defense issues. It also indicates the presence of a partisan 'rally around the flag" effect.

To quantify the effects of innovations in news about partisan conflict on private investment, I first consider a VAR specification using the historical PCI series. Using data from 1929 to 2013, I find that an increase in PCI is associated with a large and persistent reduction in aggregate investment. Even though this approach does not allow me to uncover a causal relationship between the two variables, it illustrates their long-run co-movement. Moreover, it allows me to show that their relationship is not confounding the effects of other slow-moving variables, such as polarization or political power, or that of economic policy uncertainty. The relationship between the PCI and investment is robust to considering high-frequency data, available over a shorter time-horizon (e.g. 1981 to 2015). The advantage of using monthly data is that short-term fluctuations in investment are more likely to be caused by changes in investors expectations (due to learning about the degree of partisan conflict, as suggested by the model), rather than partisan conflict being caused by monthly swings in investment. To better tackle the issue of reverse causality, I implement two-stage least squares (2SLS) using the lagged ratio of newspaper advertisement revenues to employment in the sector as a source of exogenous variation in reported partisan conflict.[1] The argument, which focuses on the 'market for news,' is that advertising revenue declines lead to more sensational reporting, as newspapers tend to highlight conflict between policymakers. Because this approach may still suffer from biases arising from omitted variables, I also study how news about partisan conflict affect the investment rates of publicly traded firms. I use a large panel covering the period 1985:Q1 to 2015:Q1, and exploit the variation on these firms' exposure to government spending, as computed by Belo, Gala, and Li (2013) from input-output tables.[2] Controlling for firm fixed-effects and time fixed-effects, I find a strong negative effect of PCI on investment rates of firms belonging to industries highly exposed to government spending.[3] Firms which are more politically engaged, as proxied by campaign contributions through PACs (obtained from Cooper, Gulen, and Pvthinnikov, 2010), are also found to respond more to increases in the PCI, using a similar estimation model.

The paper is organized as follows. I present and characterize the model in Section 3. A description of how the partisan conflict indicator was constructed is included in Section 4. Section 4.3 describes the evolution of partisan conflict over time. The connections between partisan conflict and economic policy uncertainty are discussed in Section 4.4. Section 5 quantifies the effects of partisan conflict on private investment, and Section 6 concludes.

[1]Because newspaper ad-revenues and employment co-move during the business cycle, common trends are removed when considering their ratio. This guarantees that any relationship between ad-revenue/employment ratios and aggregate investment arises only through the effect of ad-revenues on newspaper reporting behavior.

[2]The exercise is in line with that in Baker, Bloom, and Davis (2015) to tease out the effects of EPU on investment. Their measure of exposure to government spending is obtained from public contracts, covering a smaller number of firms.

[3]This is consistent with the findings in Gulen and Ion (2015).

2 Literature Review

There exists a growing literature studying the effects of economic policy uncertainty on the aggregate economy (see, for example Bloom, 2009; Fernández-Villaverde and Rubio-Ramírez, 2010; Fernández-Villaverde, Guerrón, Kuester, and Rubio-Ramírez, 2012, Stokey, 2013). A common assumption is that fiscal policy follows an exogenous process where its volatility changes over time. In periods of high variability, economic agents delay hiring, investment, or production decisions, and these amplify business cycles.[4] Canes-Wrone and Park (2011) takes this one step further by connecting surges in policy uncertainty with the electoral cycle. They argue that agents have incentives to delay decisions that are subject to large reversibility costs right before elections, particularly when polarization is high and the election is competitive, as these imply high levels of economic policy uncertainty. Their main implication is a pre-election decline in investment. Belo, Gala, and Li (2013) analyze the effects of partisan cycles on stock returns, but focusing on the predictability of election dates, rather than on news about political disagreement. Azzimonti and Talbert (2013) propose an alternative channel by which political disagreement affects economic decisions. Using a standard partisan model of fiscal policy determination (à la Persson and Svensson, 1989) embedded in a neoclassical real business cycle model, they show that polarization increases induce economic policy uncertainty, causing long run investment to decline. The main difference between this paper and the ones mentioned above is that PCI represents a signal about unobservable government dysfunction, rather than the degree of economic policy uncertainty.

The empirical finance literature has tried to identify the effect of news shocks on asset prices, and more recently on business cycle fluctuations, since the work of Beaudry and Portier (2006). As in this paper, the expectation formation process is modeled as a signal extraction problem in which news provide noisy information about the underlying state of the economy (see Beaudry and Portier, 2014). The effects of political disagreement—the main driving force affecting the likelihood of rare events in this paper—are typically abstracted from.[5] Exceptions are Pastor and Veronesi (2013) and Kelly, Pastor, and Veronesi (2013), where political news affect economic outcomes. In Pastor and Veronesi's model, agents are uncertain about the effects of current government policy on stock returns, as well as on the political costs associated from changing the status-quo. The main determinant of investment delays in their model is the 'wait and see' response of agents to policy uncertainty (e.g., the volatility of political costs), a second moment effect. In this paper, on the other hand, partisan conflict depresses investment more directly through a reduction in expected returns. This first moment effect is present even when policy uncertainty is low, in sharp contrast with their results. In addition, I develop a novel index of partisan conflict based on newspaper

[4]These papers are mostly concerned with uncertainty about government policy rather than uncertainty about the state of the economy. This is an important distinction in light of Bachmann, Elstner, and Sims (2013), who find (using US micro-data) that economic uncertainty is inconsistent with a wait-and-see hypothesis.

[5]Because partisan conflict affects tail risks, this paper is tangentially related to studies highlighting the effects of time-varying volatility caused by rare events (Gabaix, 2008; Shen 2005; Kelly and Jiang 2014, among others).

reports about political disagreement, while Pastor and Veronesi's main explanatory variable is economic policy uncertainty.

In terms of the methodology used to construct the index, the closest paper is obviously Baker, Bloom, and Davis (2015). Because the two indexes represent different concepts but are nonetheless related (theoretically and empirically), their similarities and differences are emphasized throughout the paper. A summary of these can be found in the introduction, whereas a more detailed discussion is presented in Section 4.4. This paper shares some features with an increasing number of studies using textual analysis to identify news shocks and stock market behavior, such as Tetlock (2007). Larsen and Thorsrud (2015) construct a news index using the Latent Dirichlet Allocation machine learning algorithm on a Norwegian newspaper database. A main advantage relative to the approach used in this paper is that the set of words searched for does not need to be defined subjectively. Applying this methodology, unfortunately, requires the full database of newspaper articles. This is unfeasible as databases owning US newspapers articles are subject to data mining restrictions.

The PCI is also related to measures of political polarization, such as those computed by McCarty, Poole, and Rosenthal (2006) from roll-call votes or by Jensen, Kaplan, Naidu, and Wilse-Samson (2012) from Congressional Records. This is to be expected: Policymakers' ideological differences, or polarization, are clearly an important determinant of political disagreement. The further apart parties' views over policies are, the higher the level of conflict should be. While the general trend of partisan conflict since the mid sixties is similar to the one observed in these measures, short-term fluctuations are remarkably different. This is due to the fact that polarization measures bundling Congressional behavior typically ignoring filibuster threats and presidential vetoes, which constitute important sources of policy determination. The interaction between the executive and legislative branches, or between the House and the Senate under a divided government, are important factors affecting the determination of partisan conflict (as pointed out by Alesina and Rosenthal, 1995). Moreover, the PCI deviates significantly from the DW-nominate measure constructed by McCarty, Poole, and Rosenthal (2006) in periods where one party controls Congress and the Presidency. Because the PCI is a signal about the outcome of a game (between two parties with different objectives in the political arena), rather than a measure of the distance in their ideal points, the index developed in this paper is conceptually different from polarization, and does not represent an alternative measure of it.

This paper is also related to the literature trying to determine the causal effects of political disagreement and fiscal uncertainty on economic outcomes. Baker and Bloom (2013) use natural disasters, terrorist attacks, and political shocks in a panel of countries to instrument their stock market proxies for first and second moment shocks. They find that both first and second moment shocks are highly significant factors driving business cycles. The instrument used in this paper is different, as I focus on the incentives of newspaper editors to exaggerate disagreement rather than focusing on a natural experiment. Given this particular choice of instrument, the paper is related to the literature on the market for news (Gentzkow and Shapiro, 2010), in which newspaper owners and editors act as rational agents wishing to maximize profits. While I do not explicitly model their incentives, using ad-revenues as an instrument implicitly assumes such maximizing behavior.

Finally, the paper is connected to the media literature in political economy (see Prat and Stromberg, 2012 for a discussion). This literature has mostly concentrated on studying the influence of the media on voting behavior (Della Vigna and Kaplan, 2007; Bernhardt, Krasa, and Polborn, 2008; or more recently, Prat, 2015) and on the degree of polarization between political parties (Layman, Carsey, and Horowitz, 2006; Campante and Hojman, 2013) or political gridlock (Stone, 2013). I abstract from the strategic behavior of policymakers and newspaper owners, focusing instead on news as exogenous signals received by investors. Moreover, rather than analyzing the effects of the media on voting behavior, I concentrate on its effect on private investment. It would be interesting to extend the model by considering strategic factors, but that is currently outside the scope of this paper.

3 Model

Consider an infinite horizon economy populated by one-period lived firms in the interval $[0, 1]$. Each period, firms have access to an investment opportunity with uncertain returns r_t. To produce, a firm must pay a fixed cost f, drawn from a uniform distribution in the interval $[0, \phi]$ at the beginning of the period. Upon investment, they receive the payoff r_t. Firms have preferences exhibiting constant absolute risk-aversion,

$$u(r_t) = \frac{1}{a}\left(1 - e^{-ar_tI}\right),$$

where a is the coefficient of absolute risk aversion, and $I \in \{0, 1\}$ denotes the decision to invest.

Following Barro (2006, 2009), returns depend on the state of the economy

$$r_t = z_t + \nu_t,$$

where z_t reflects standard economic fluctuations and is normally distributed with mean μ and variance σ^2. The random term ν_t captures low-probability events where production jumps down sharply, such as wars, great recessions (or depressions), sudden stops, sovereign debt crises, banking crises, or financial crises. Rare events happen with probability p_t and contract production by $\log(1 - \kappa)$, with $\kappa < 1$. The distribution of ν_t satisfies

$$\text{with probability } p_t: \qquad \nu_t = \log(1 - \kappa)$$

$$\text{with probability } 1 - p_t: \qquad \nu_t = 0.$$

The government can implement policies or undertake reforms in order to prevent rare events, thus reducing tail-risk by lowering p_t. Examples are banking regulation (e.g. reserve requirements or deposit insurance), financial reforms (e.g. Dodd-Frank), budget rules (e.g. a balanced budget amendment to prevent excessive debt creation and hence the likelihood of defaults), enhancing homeland security (e.g. the Intelligence Reform and Terrorism Prevention Act of 2004), or simply managing the federal budget to reduce the risk of 'fiscal cliffs' and default episodes.[6] The degree of sophistication, or quality of the reform, enhances

[6]The channel presented in this model was inspired by insightful conversations with Pierre Yared.

the probability of preventing such events. To capture this, I assume that p_t is a decreasing function of quality, denoted by x_t:

$$p(x_t) = \frac{1}{m} e^{-x_t}, \tag{1}$$

where m is a large positive number. Notice that even if no preventing efforts are undertaken (that is, when $x_t = 0$), the event has a low probability of happening. At each period, the objective of the government is to maximize the benefit of a preventive policy or reform, $1 - p(x_t)$ (e.g. reduce the probability of a rare event), minus the cost associated with implementing it, denoted by $TC(x_t)$

$$\max_{x_t} [1 - p(x_t)] - TC(x_t). \tag{2}$$

Implementing policies targeted at preventing rare events involves effort and political costs. Because these events are infrequent, policymakers need to devote a large amount of effort to data gathering, intelligence, policy design, etc. Therefore, we would expect the costs of preventive policies or reforms to increase with x_t, the degree of policy sophistication. In addition, when policymakers are divided, it is more costly to implement a reform of a given quality. This could be due to the fact that legislators have different views about the costs and benefits of such reform, or because it affects their constituency asymmetrically. Polarization and divided government make reforms more politically costly and, therefore, less likely. To capture this, I assume that the total cost of implementing a reform of quality x_t also depends on political disagreement,

$$TC(x_t) = \frac{1}{m} \left(\epsilon + \theta e^{-\frac{1}{c_t}} \right) x_t,$$

where ϵ and θ are constants that satisfy $\epsilon + \theta < 1$, and $c_t \geq 0$ denotes the degree of 'partisan conflict'. High levels of partisan conflict make policy implementation more costly, $\partial TC / \partial c > 0$.

What is partisan conflict? Partisan conflict results from the interaction between two parties with different objectives in the political arena. Policymakers' ideological differences (polarization) are clearly important determinants of political disagreement. The further apart parties' views over policies are, the higher the level of conflict should be, and hence the more difficult it would be to reach consensus. How political power is divided between the two parties must also affect the degree of conflict (as suggested by Alesina and Rosenthal, 1995). Consider the extreme case of one particular party controlling both chambers of Congress and the presidency. Then partisan conflict should be low, regardless of how polarized these parties are. There are other factors affecting the political environment, such as the influence of interest groups, the political affiliation of the President and his relationship with both chambers of Congress, the composition of Congress committees, etc. Rather than modeling the determinants of a complex political process, I focus on this reduced form in order to concentrate on the implications of partisan conflict on investment decisions. It would be interesting, in future work, to model these interactions explicitly.

Partisan conflict is assumed to be constant for T periods, when an election is held and a new value of c is drawn from a distribution $F(c)$ with positive support. The rationale behind this specification is that elections change the pool of policymakers, affecting the views and the balance of power of different political players. The effects of partisan conflict on government policy are summarized in Lemma 3.1.

Lemma 3.1 *In this economy:*

i. The government's optimal policy x satisfies

$$x_t(c) = -\ln\left(\epsilon + \theta e^{-\frac{1}{c}}\right),$$

with $x(0) = -\ln\epsilon$ and $\lim_{c\to\infty} x_t(c) = -\ln(\epsilon+\theta)$.

ii. The likelihood of a rare-event is characterized by

$$p_t(c) = \frac{1}{m}\left(\epsilon + \theta e^{-\frac{1}{c}}\right),$$

where $p(0) = \frac{\epsilon}{m}$ and $\lim_{c\to\infty} p_t(c) = \frac{\epsilon+\theta}{m}$.

iii. Partisan conflict reduces the quality of reforms and increases the probability of a crisis:

$$\frac{\partial x_t(c)}{\partial c} < 0 \qquad \textit{and} \qquad \frac{\partial p_t(c)}{\partial c} > 0.$$

Proof 3.1 *Optimal policy x results from solving problem 2. The probability of a rare event is obtained by replacing $x_t(c)$ into eq. 1.*

Figure 1 depicts government's policy x as a function of partisan conflict (left panel), together with the probability of a crisis (right panel).

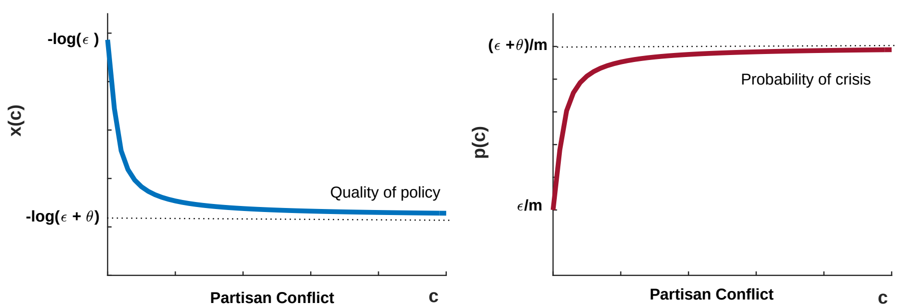

Figure 1: Government policy and probability of a rare-event as a function of partisan conflict.

We can see that when c increases, the quality of preventive measures and reforms goes down. That political dysfunction is associated with lower quality policies is consistent with the observation that legislative productivity declines when gridlock intensifies (Binder, 1999). This increases the probability of extremely low outcomes, $p(c)$, making investment riskier, as highlighted in the following corollary.

Corollary 3.1 *Partisan conflict reduces the profitability of investment*

$$\frac{\partial E(r_t)}{\partial c} < 0,$$

and exacerbates economic risk by increasing the volatility of returns

$$\frac{\partial Var(r_t)}{\partial c} > 0.$$

Proof 3.2 *From the definition of* r_t, $E(r_t) = \mu + E(\nu_t)$, *so* $\partial E(r_t)/\partial c = \partial p/\partial c\,[ln(1-\kappa)] < 0$ *as* $ln(1-\kappa) < 0$. *For the second result, note that* $Var(r_t) = \sigma^2 + Var(\nu_t)$, *with* $Var(\nu_t) = [ln(1-\kappa)]^2(p(c) - p(c)^2)$. *So* $\partial Var(r_t)/\partial c = [ln(1-\kappa)]^2(1-2p)\partial p/\partial c$. *The result follows from the fact that* $p < 0.5$.

3.1 Information structure

Agents do not know the true value of partisan conflict c at the time of making investment decisions. This key assumption captures the idea that the profitability of investment is not only risky, but also *uncertain.* Since the probability of rare-events p depends on partisan conflict c—which is unobservable—the distribution of returns is unknown: The model features Knightian uncertainty. Moreover, as x depends on c, the future path of government policy is also uncertain. Thus, investors face economic policy uncertainty in the sense of Baker, Bloom, and Davis (2015). The relationship between partisan conflict, economic policy uncertainty, and investment will be characterized in more detail below, but it is useful at this point to properly define these concepts in the context of the model.

Definition 3.1 *'Political uncertainty' refers to the variance of partisan conflict* $Var(c_t)$. *'Economic policy uncertainty' refers to the variance of government policy,* $Var(x_t)$.

The prior distribution of c at time 0 is assumed to be inverse-gamma with parameters α_0 and β_0,

$$c \sim \mathrm{IG}(\alpha_0, \beta_0). \tag{3}$$

Investors observe n unbiased signals s^i, with $i \in \{1, ..., n\}$, between the outset of period t and the time of investment. It is assumed that signals s^i are drawn from an exponential distribution centered around the true value of partisan conflict c,

$$s^i \sim \exp(c). \tag{4}$$

Since this distribution has positive support, s^i always takes non-negative values.[7] Intuitively, these signals capture period t's flow of political news associated with future policies or a potential reform. Investors observe political speeches, debates, and negotiations through news outlets on a daily basis. These events provide information about the degree of political

[7] Recall that the pdf of an exponential distribution is $f(s) = \frac{1}{c}e^{-\frac{s}{c}}$, for $s \geq 0$ and 0 otherwise.

disagreement allowing them to revise their beliefs about the likelihood of effective policies being implemented.

After observing the signals, agents update their beliefs using Bayes' rule. The posterior distribution of c at the time of making an investment decision, at any period $t < T$, is given by

$$c_t \sim \mathrm{IG}(\hat{\alpha}_t, \hat{\beta}_t),$$

where the posterior parameters evolve according to

$$\hat{\alpha}_t = \hat{\alpha}_{t-1} + n, \qquad \text{and} \qquad \hat{\beta}_t = \hat{\beta}_{t-1} + n\bar{s}_t.$$

In the expression above, $\bar{s}_t$ denotes the sample mean $\bar{s}_t = \sum_{i=1}^{n} s_t^i/n$ of the political signals observed in period t (see Appendix 7.1 the derivation of the posterior distribution and its moments). The posterior mean of partisan conflict, $\hat{c}_t$, is equal to

$$\hat{c}_t(\bar{s}_t) \equiv E(c_t|\bar{s}_t, \hat{\alpha}_{t-1}, \hat{\beta}_{t-1}) = \frac{\hat{\beta}_t}{\hat{\alpha}_t - 1}.$$

The posterior variance, or political uncertainty, equals

$$Var(c_t) = \frac{\hat{c}_t^2}{(\alpha_0 + tn - 2)} \tag{5}$$

indicating that greater expected partisan conflict is—keeping everything else constant—associated with more political uncertainty, $\partial Var(c_t)|\partial \hat{c}_t > 0$. Hence, periods of intense disagreement between policymakers not only reduce the expectations about the effectiveness of policies, but may also introduce higher uncertainty to investors.

Political uncertainty also induces economic policy uncertainty in this model, as $Var(x_t) \neq 0$ when partisan conflict c is unknown. Notice that if c were observable, $x_t(c)$ would be constant between elections, so $Var(x_t) = 0$, $t \in \{k, k+T\}$, $\forall k \geq 0$. Because c is unobservable, agents must form expectations about the path of government policy at every point in time. The relationship between EPU and partisan conflict described in the following Lemma.

Lemma 3.2 *The relationship between expected partisan conflict, $\hat{c}_t$, and economic policy uncertainty, $Var(x_t)$, is non-monotonic*

$$\frac{\partial Var(x(c_t))}{\partial \hat{c}_t} \begin{cases} \geq 0 & \textit{if} \quad \hat{c}_t \leq \varsigma \\ < 0 & \textit{if} \quad \hat{c}_t > \varsigma \end{cases},$$

where ς solves

$$\epsilon = \varsigma(\epsilon + \theta e^{-\frac{1}{\varsigma}}).$$

Proof 3.3 *See Appendix 7.2.*

This follows from the negative relationship between x and c, and the fact that political uncertainty is increasing in partisan conflict. When $c = 0$, policymakers choose the optimal effort level $x^* = -\ln(\epsilon)$, and political uncertainty is negligible. As c rises, so does $Var(\hat{c})$, which in turn causes EPU to increase. Because effort decreases with partisan conflict, the effect of political uncertainty on EPU weakens as c goes up. Eventually, $c > \varsigma$, so even though political uncertainty is very large, agents can predict with relative certainty that the government will make no effort to prevent adverse events, $x \sim 0$, so EPU is small. The relationship between EPU and partisan conflict is illustrated in Figure 2.

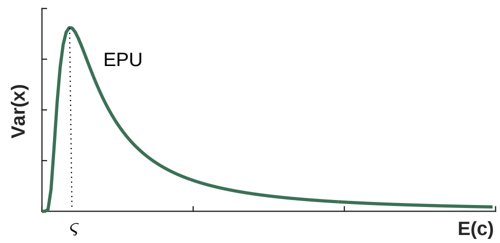

Figure 2: Economic Policy Uncertainty, $Var(x(c))$, as a function of partisan conflict.

Result: *We should expect partisan conflict to induce economic policy uncertainty for moderate levels of government dysfunction, as investors cannot predict with certainty which policy will be undertaken. Under extreme levels of partisan conflict, on the other hand, we should expect partisan conflict and EPU to move in opposite direction, as a government gridlock becomes more likely.*

In this model, expected partisan conflict $\hat{c}_t$ changes for two reasons: (i) because there is an election every T periods, where true partisan conflict c changes and priors are re-set according to eq. (3); and (ii) because between elections (when c is unchanged), agents receive signals $\bar{s}_t > 0$ about the true value of partisan conflict. We are mostly interested in understanding the effects of the latter.

3.2 The Partisan Conflict Index

The posterior mean of partisan conflict, $\hat{c}_t$, can be written as a weighted sum between the prior mean and the sample mean as follows

$$\hat{c}_t(\bar{s}_t) = \omega_t \bar{s}_t + (1 - \omega_t)\hat{c}_{t-1} \quad \text{with} \quad \omega_t = \frac{n}{\hat{\alpha}_{t-1} + n - 1}. \tag{6}$$

Positive values of the political signal $s_t^i > 0$ indicate disagreement between policymakers. When investors observe an increase in the number of articles reporting partisan conflict in their sample, beliefs about c—and hence the total cost of adopting the policy—are updated upwards. This, in turn, lowers investors' expectations about the quality of government policy. In what follows, we will refer to $\bar{s}_t$ as the *partisan conflict index*, a news-generated indicator that summarizes investors' information about political disagreement. From the discussion above, we can conclude that

Result: *Higher values of the PCI, keeping everything else constant, result in beliefs about partisan conflict being updated upwards and hence are associated with*

i. Higher tails risks $\frac{\partial p(\bar{s}_t)}{\partial \bar{s}_t} > 0$.

ii. More political uncertainty $\frac{Var(\hat{c}_t)}{\partial \bar{s}_t} > 0$.

iii. Higher EPU only for moderate values of the PCI (e.g., as long as $\hat{c}_t < \varsigma$*).*

This is illustrated in the following graph, which depicts the evolution of signals and beliefs for a simulated economy that lasts $T = 9$ periods (and assuming $c = 10$).

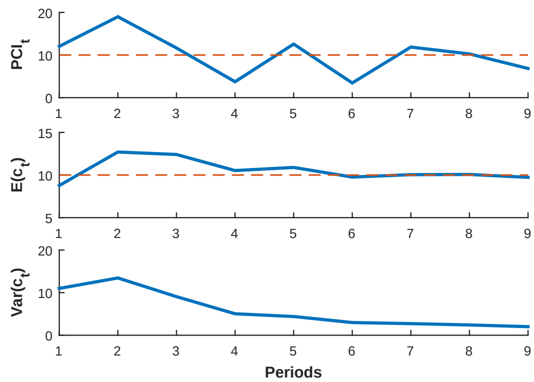

Figure 3: Evolution of signals $\bar{s}_t$, or PCI (first plot), posterior beliefs about partisan conflict, $E(c_t) = \hat{c}_t$ (second plot), and political uncertainty $Var(\hat{c}_t)$ (third plot).

Note: Parameter values $c = 10$, $\alpha_0 = 4$, $\beta_0 = 10$, $n = 5$, $T = 9$.

The first plot in Figure 3 shows the evolution of the partisan conflict index $\bar{s}_t$ over time (solid line) together with the true value of partisan conflict c (dotted line). As agents observe increases in the number of newspaper articles reporting political disagreement $\bar{s}_t$, their beliefs about true partisan conflict $\hat{c}_t$ rise, as seen in the second plot. The effect of these signals is larger in the first few periods (that is, right after an election), as investors have little information about c. As time goes by, signals are given relatively lower weight. The last plot, which depicts the evolution of $Var(c_t)$, illustrates that uncertainty about partisan conflict c decreases over time. However, the decline is non-monotonic, as extremely high realizations of the PCI (as seen in period 2) may introduce significant political uncertainty. Notice that higher partisan conflict is not always associated with greater political uncertainty. While higher realizations of $\bar{s}_t$ increase $Var(c_t)$, its effect is tamed by the fact that as agents learn about the true value of partisan conflict, they give a smaller weight to $\bar{s}_t$.[8] This implies that political uncertainty may increase under extremely large realizations of PCI, but that would not necessarily be the case for moderate increases.

[8]This could also be seen from eq. (5), as a new value of $\bar{s}_t$ increases both the numerator through $\hat{c}_t$ and the denominator through t.

Recall that after T periods there is an election in which the value of c changes. Because agents reset their priors about c according to eq. (3), political uncertainty increases significantly in election periods.

Result: *We should expect partisan conflict to be more volatile around midterm and presidential elections.*

The effects of elections on expected partisan conflict are ambiguous in our model, as $\hat{c}_t$ may increase or decrease depending on the distance between the prior $c_0 = \frac{\beta_0}{\alpha_0 - 1}$ and the true value of partisan conflict c. If agents underestimate true partisan conflict $c_0 < c$, the sequence $\hat{c}_t$ would be increasing. If they were to overestimate it $c_0 > c$, the sequence $\hat{c}_t$ would be decreasing instead. Finally, note that because x_t is unobservable and beliefs are reset every T periods, investors never learn the true value of partisan conflict, so signals are always informative in this model.

3.3 Partisan conflict and private investment

In this section, I analyze the effects of PCI in the economy. The timing of events can be summarized as follows

- At the outset of period t, each firm learns their fixed cost f.
- Signals $\{s_1, ..., s_n\}$ are observed and beliefs are updated.
- Investment decisions take place.
- The government chooses x_t given c (both unobservable).
- The shocks to stock returns z_t and ν_t are realized, and production and consumption take place.
- After T periods there is an election, where beliefs are reset according to eq. (3).

Notice that the only dynamic link between periods is the evolution of beliefs. Because firms are one-period lived, their maximization problem is static. Government decisions also involve intra-period trade-offs, an assumption made to simplify the analysis. We will solve period t's problem by backwards induction.

At the last stage of period t, the government chooses the quality of a reform x_t in order to maximize its objective (2), as described in Lemma 3.1.

Given policy, an agent decides whether to invest or not in order to maximize expected utility

$$\max\left\{E\left[\frac{1}{a}\left(1 - e^{-ar_t}\right)\right] - f, 0\right\}$$

They invest as long as the expected benefit of doing so exceeds the (known at this stage) fixed cost f. This implies that agents decisions follow a cut-off rule, where $I = 1$ if and only if $f \leq f_c$, with

$$f_c = E\left[\frac{1}{a}\left(1 - e^{-ar_t}\right)\right]. \tag{7}$$

The expectation is taken not only over possible realizations of r_t, but also over the probability of rare-events $p(c)$, as agents do not observe c, the true value of partisan conflict at the time of investment. The following proposition characterizes the cutoff rule $f_c(\bar{s}_t)$ as a function of PCI.

Proposition 3.1 *Let $\hat{p}(\bar{s}_t)$ denote the expected probability of a rare event as a function of the partisan conflict index $\bar{s}_t$, then*

$$f_c(\bar{s}_t) = \frac{1}{a}\left(1 - e^{-a\frac{2\mu - a\sigma^2}{2}}\left[\hat{p}_t(\bar{s}_t)e^{-a\ln(1-\kappa)} + 1 - \hat{p}_t(\bar{s}_t)\right]\right)$$

with

$$\begin{aligned}\hat{p}_t(\bar{s}_t) &= E\left(\frac{1}{m}\left(\epsilon + \theta e^{-\frac{1}{c}}\right)|\bar{s}_t, \hat{\alpha}_{t-1}, \hat{\beta}_{t-1}\right) \\ &= \frac{1}{m}\left(\epsilon + \theta\frac{\left[\hat{\beta}_t(\bar{s}_t)\right]^{\hat{\alpha}_t}}{\left[1 + \hat{\beta}_t(\bar{s}_t)\right]^{\hat{\alpha}_t}}\right),\end{aligned}$$

where

$$\hat{\alpha}_t = \hat{\alpha}_{t-1} + n, \qquad \textit{and} \qquad \hat{\beta}_t(\bar{s}_t) = \hat{\beta}_{t-1} + n\bar{s}_t.$$

Proof 3.4 *See Appendix 7.3.*

At the investment stage, agents do not know the true value of c but have observed a series of political signals from the news and updated their beliefs. The expression for $\hat{p}_t(\bar{s}_t)$ follows from the fact that the posterior is inverse-gamma with parameters $\hat{\alpha}_t$ and $\hat{\beta}_t$. I have made explicit the dependence on $\bar{s}_t$ to emphasize the role of signals about partisan conflict on agents' expectations.

Given the cutoff rules, aggregate investment Υ is given by the share of investors who choose $I = 1$,

$$\Upsilon(\bar{s}_t) = \int_0^{f_c(\bar{s}_t)} \frac{1}{\phi} df = \frac{1}{\phi} f_c(\bar{s}_t). \tag{8}$$

Firms whose realization of f_i falls below the threshold f_c choose to invest. Given that the distribution of fixed costs is uniform, aggregate investment $\Upsilon(\bar{s}_t)$ simply corresponds to the shaded area of Figure 4 (top panel).

We can show how aggregate investment depends on PCI.

Corollary 3.2 *Aggregate investment is decreasing in the partisan conflict index $\bar{s}_t$,*

$$\frac{\partial \Upsilon(\bar{s}_t)}{\partial \bar{s}_t} < 0.$$

Proof 3.5 *Differentiate eq. (8) using the closed form expression for f_c obtained in Proposition 3.1.*

This Corollary establishes our main result, namely, that aggregate investment declines when the partisan conflict indicator rises. Intuitively, as investors observe a large proportion of news articles reporting political disagreement, they expect effective measures aimed at preventing rare-events not to be undertaken. This lowers expected returns, shifting down the threshold value f_c. As the bottom panel of Figure 4 shows, this results in a smaller number of firms choosing $I = 1$. The dotted area in the plot corresponds to the decline in investment induced by the negative PCI shock.

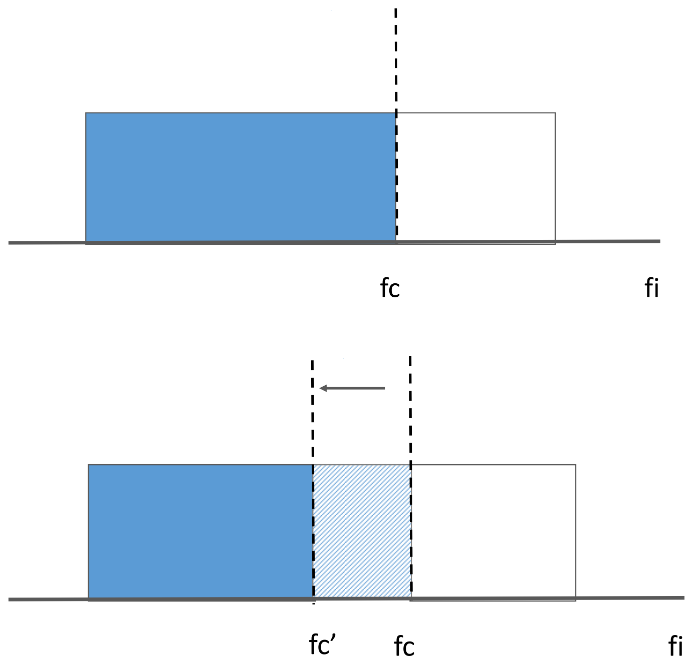

Figure 4: News shock and aggregate investment.

Notice that real investment may be affected even if there is no actual change in fundamentals, that is, even if partisan conflict c remains the same. This suggests that perceptions about political dysfunction, and hence decisions depending on these perceptions, may also be affected by the dynamics characterizing the media market.

Limitations and Generalizations This model is clearly very stylized, but it points to a link between the flow of political news and investors' expectations. It suggests that news about partisan conflict discourage private investment by rising tail risks.

The distributional assumptions determining the stochastic behavior of priors (inverse-gamma) and news-shocks (exponential) were made primarily for tractability. The main result is robust to more standard distributional assumptions, such as a normally distributed prior c and signals s. However, the normality assumption could result in negative realizations of partisan conflict or posterior probability of rare events outside of the $[0, 1]$ interval. The IG-exponential assumption, on the other hand, ensures that $\hat{p}_t(\bar{s}_t) \in [0, 1]$ and $\hat{c}_t > 0$, $\forall t$.

I assumed that the only shock to true partisan conflict is the outcome of elections. It would be interesting, however, to extend the model to allow for other shocks to partisan conflict arising at random times through a Poisson process. The rationale is that policymakers must react to unexpected shocks such as a terrorist attack, a natural disaster, or sovereign default by a trade partner, among others. The degree of conflict at that point in time may change significantly, depending on how controversial the specific issue that needs immediate resolution is. Investors would react by re-setting their priors, which would cause a spike in political uncertainty. These shocks would emphasize the importance of the partisan conflict index, as news signals would be very informative right after the shock.

I also assumed that there is no uncertainty about the state of the economy outside of that caused by political uncertainty. We could consider an environment in which the distribution of returns was subject to shocks to σ, or even to the size of the crisis κ, caused by external factors (such as a war, a financial crisis/recession suffered by a trade partner, a monetary policy shocks, etc.). Agents would react to this additional source of uncertainty by changing their investment decisions, even if $\bar{s}_t$ were constant. Moreover, we would expect policies to react to these shocks in order to stabilize the economy. It would be interesting to analyze such environment, and the implications of this for the relationship between partisan conflict, news, and economic policy uncertainty.

Finally, I assumed that partisan conflict is always detrimental for the economy. Clearly, the U.S. constitutional system of checks and balances was designed to prevent extreme and/or dictatorial policies, which may well negatively affect the economy as well. Those considerations could be included in an extended version of the model in which policymakers had different views about the size of the government and the role of redistributive policies. We would expect that news about partisan conflict may have asymmetric effects on investment, as a gridlock could be beneficial for investors under a left-wing government. The analysis of this environment, while of great interest, is left for future research.

4 Measuring partisan conflict

The main objective of this section is to construct an indicator of the degree of partisan conflict consistent with the theory presented above, to later assess how it affects private investment. Recall that in the model, investors observe n signals s_i and use them to construct a sample mean $\bar{s}_t$ that is applied to update their beliefs about the distribution of c. To simplify the analysis, suppose that agents give a score of 1 to articles that suggest the presence of political disagreement or gridlock, and 0 otherwise. Then, $\bar{s}_t$ represents the fraction of news articles reporting partisan conflict over the total number of articles read in a given period t. The data counterpart of $\bar{s}_t$, the partisan conflict index, will be precisely this measure:

$$\bar{s}_t = \frac{\#\,\text{of articles about partisan conflict in } t}{\text{total } \#\text{ articles in } t}.$$

Notice that this measure is intended to capture a signal that investors use to update their beliefs about the unobservable degree of partisan conflict, and hence *shapes* their perceptions about the true value of c. The following section describes the details regarding the identification of newspaper articles, and the construction of a time series for $\bar{s}_t$.

4.1 Index construction

To construct the partisan conflict index I use a search-based approach that measures the frequency of newspaper articles reporting political disagreement about government policy. The assumption underlying the index is that greater media coverage of ideologically divisive issues, legislative gridlock, presidential vetoes, or filibuster threats indicates intense disagreement between policymakers (either across party lines or within a party).

I will compute two indexes: *Historical Partisan Conflict*(HPC), covering the period 1891-2013, and a benchmark measure, *Partisan Conflict Index* (PCI), covering the interval 1981-present. The latter is updated monthly by the Federal Reserve Bank of Philadelphia, and available free of charge in their website.[9]

Historical Partisan Conflict is computed annually using news articles from five major newspapers that have been digitalized since 1891 for the whole sample period: The Wall Street Journal, The New York Times, Chicago Tribune, Los Angeles Times, and The Washington Post. I abstract from other newspapers that have been digitalized only for a sub-period, because with a small number of newspapers, the addition or elimination of a newspaper significantly changes the trend of the estimated index.[10] The advantage of this measure is that it allows us to characterize the long-run trend in partisan conflict and compare it with other slow-moving variables such as polarization and the composition of Congress. The main disadvantage is that the search cannot be refined to the same degree as the benchmark case is. While we can restrict the search over actual articles (excluding, for example, advertisements or obituaries), we cannot restrict it to domestic news or distinguish opinions and commentaries from regular news.

The search used in the construction of the *Partisan Conflict Index* is performed monthly in Factiva (by Dow Jones), covering the interval 1981-2015. An advantage of using Factiva's search engine versus the ones provided by each particular newspaper is that the search outcome is homogeneous and an identical set of predefined filters can be applied. In particular, I restrict the comprehensive Boolean search to major US newspapers (see Table 7 in Appendix 7.4 for a full list of sources included) with news written exclusively in English and restricted to events occurring in, or related to, the US.[11] The top news sources resulting from the search are 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 (see Figure 18 in Appendix 7.4 for a decomposition of sources). Routine general news, reviews, interviews, etc. are also excluded in order to reduce the incidence of false positives. A comprehensive list of filters applied can be found in Appendix 7.5. Articles with less than 200 words and republished news are excluded (this is standard in the semantics

[9] The PCI is available free of charge at https://www.philadelphiafed.org/research-and-data/real-time-center/partisan-conflict-index.

[10] The benchmark series is constructed from the whole sample of newspapers for which digitalized versions exist. Because the number of newspapers included is much larger, jumps in the series do not appear as newspapers are included or excluded at particular points in time.

[11] Factiva indexes articles according to the region they are most related to through a semantic algorithm. To filter out news that are not related to the US, I exclude articles which have been indexed to countries/regions *other* than the US. This will include articles which are indexed to the US, as well as articles which have not been coded.

literature). Note that the search is performed on full articles, not just titles or abstracts.

The index is computed as follows. First, I count 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. This is the data counterpart of $\sum_{i=1}^{n} s_i$ in the model. In particular, I search for articles containing at least one keyword in the following two categories: (i) political disagreement and (ii) government. Figure 5 summarizes the resulting terms used in each category. I focus on articles including keywords at the intersection of those two categories. In addition, I also search for specific terms related to partisan conflict, such as "divided party," "partisan divisions," and "divided Congress." Note that the search involves terms related to the political debate (e.g., "fail to compromise"), as well as the outcome of the partisan warfare (e.g. "gridlock" and "filibuster"). The exact Boolean search query is replicated in Appendix 7.6.

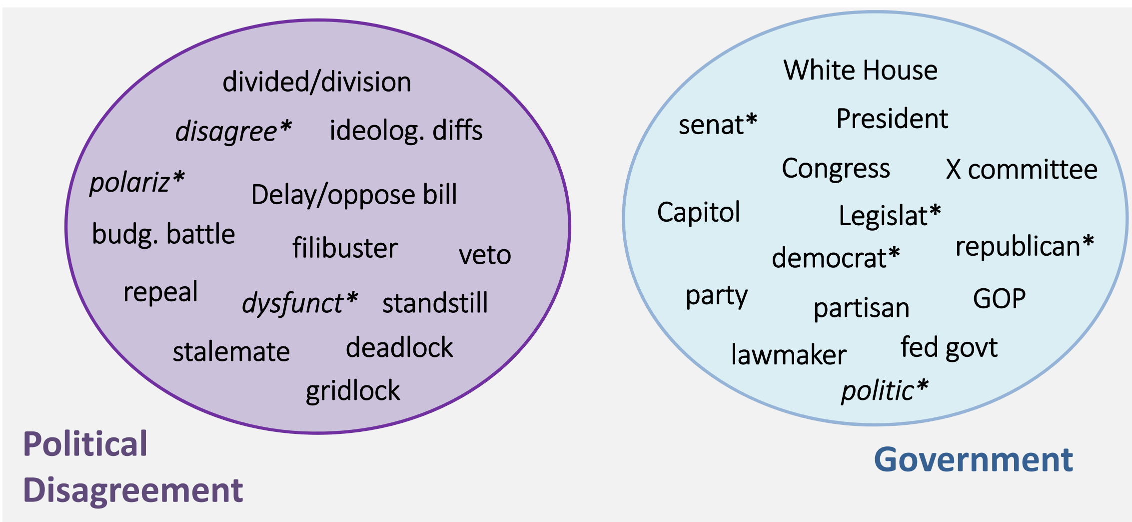

Figure 5: Sample keywords used in the search.

Note: The term "X committee" stands for Appropriations Committee, Finance Committee, or Ways and Means Committee.

The search 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, abortion rights, among others). A representative article that the search picks up can be seen in Appendix 7.7.

For the PCI benchmark series, the particular words included in each category were chosen using a two-stage procedure. In the first stage, I selected words normally used in the political economy and political science literatures that refer to political disagreement. From the outcome of this first-stage search, three articles per month over the period 1981-2012 were selected at random from The New York Times and thoroughly read by the author. Additional words used by the media that were identified during this human audit were incorporated into the initial search in the second stage. The objective of this refinement was to reduce the incidence of false negatives. Some of the original keywords were eliminated in order to reduce false positives. Articles were identified as false positives or false negatives by analyzing whether the article was indeed describing disagreement between policymakers. There is, clearly, some subjectivity in this selection as, due to lack of resources, the author was the sole auditor in the process. Words were eliminated when the incidence of false-positives (or negatives) was higher than 30 % of the articles selected. In addition, the words "polarization" and "dysfunctional" were excluded from the historical search used to construct HPC because these words entered the media language only in the 1980s. The remaining words were observed with a relatively constant frequency in the historical newspapers (using 10-year intervals). In addition "political" and "disagreement" have also been excluded from the historical search because they retrieved a disproportionate amount of foreign news (notably during WWI and WWII). This shortcoming does not arise in the benchmark search used to construct PCI where we can restrict it to domestic articles.[12]

Because the volume of digitalized news varies over time, I scale the raw partisan conflict count by the total number of articles in the same newspapers over the same time interval. To do this in the benchmark PCI, I perform a search every month from January 1981 until the present containing the word "today."[13] By doing this, the resulting measure of partisan conflict is consistent with the definition of $\bar{s}_t$ presented at the outset of this section. For the historical series, HPC, I divide the raw partisan conflict count by the number of articles every year that contain the word "the," rather than "today," due to the fact that, early in the sample, there was usually a delay between the date on which an event happened and the date on which it was reported. Finally, I normalize both the PCI and HPC scores to average 100 in the year 1990. This normalization is without loss of generality.

4.2 The historical evolution of partisan conflict

In this section, I study the behavior of the PCI over a long period of time (1891-2013). By comparing its evolution to other indicators of political discord, I attempt to validate the index as an informative signal of true partisan conflict.

The HPC index declined between 1891 and the early 1920s, remained relatively stable until 1965, and exhibited an increasing trend thereafter, as seen from Figure 6. The rise in partisan conflict accelerated during the Great Recession, peaking with the 2013 government shutdown. This behavior, as shown in the next subsections, is consistent with that of other slow-moving variables characterizing political disagreement, such as political polarization and the distribution of political power (e.g. whether the government is divided or not, the degree of presidential influence in Congress, the number of filibusters, etc.) and media trends.

Because these variables are related with the PCI at different frequencies than other shocks (such as elections and wars), the analysis will be divided in two parts: (i) the long-run trend and (ii) short-term fluctuations. To isolate long-run trends from short-term fluctuations, I

[12] Robustness to the set of words is discussed in Appendix 7.8

[13] Using the word "the" to count the total number of articles instead causes no noticeable difference in the index. As we will see in Section 5.3 the estimation results are robust to using this alternative normalization.

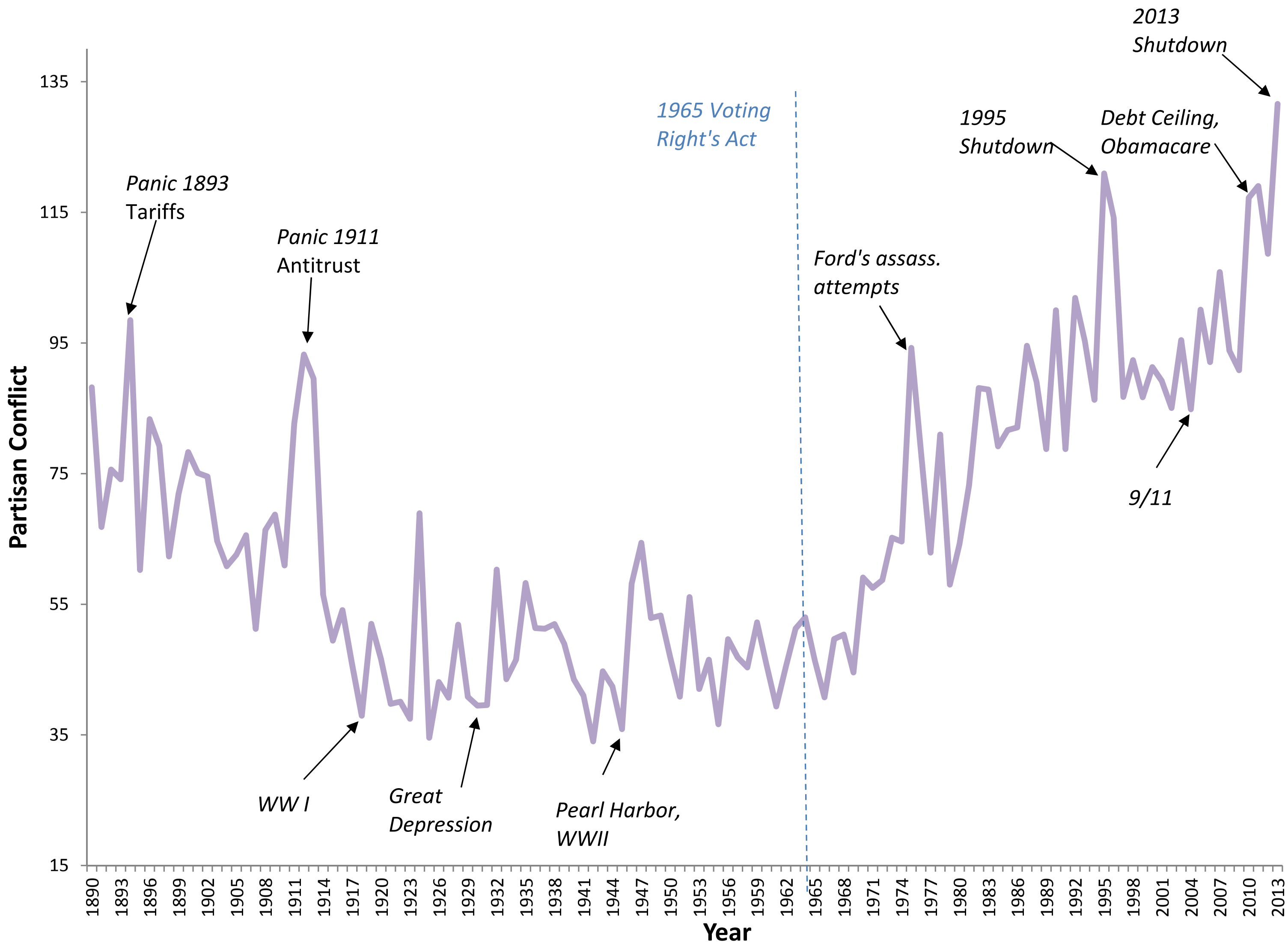

Figure 6: Historical partisan conflict, 1891-2013.

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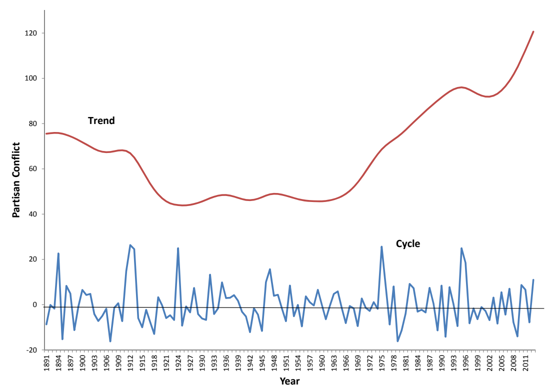

Figure 7: Historical partisan conflict, HP-filtered ($w = 6.25$).

apply an HP-filter to the series. Since HPC is computed annually, it is filtered using a weight of $w = 6.25$ (see in Ravn and Uhlig, 2002).[14] Figure 7 shows the evolution of the resulting two components of partisan conflict for the HPC series.

4.2.1 Long-run trend of HPC

I first focus on the relationship between the long-run trend of the HPC series and variables which, according to the political economy literature, reflect political discord. I also discuss the relationship between the PCI and trends in media coverage. A discussion of the relationship between PCI and income inequality can be found in Appendix 7.9.

Political determinants Polarization is possibly one of the most important factors (although not the only one) determining partisan conflict. We should expect partisan conflict to intensify when political polarization rises. Intuitively, it is more difficult for parties to agree on the course of social and economic policy when their ideological differences are large. Interestingly, McCarty, Poole, and Rosenthal (2006) document that polarization between political parties has risen significantly in the postwar era. This pattern is consistent with the sustained increase in the PCI over the same period, as shown in Figure 8.

While both series exhibit a decline early in the sample, partisan conflict decreases at a much faster rate and lies below polarization until the 72nd Congress. As the PCI identifies political outcomes rather than policymakers' preferences, the divergence in the two series could be explained by changes in the composition of the government, affecting the political power of the Democratic and Republican parties. For example, between the 63rd and the 71st Congresses both chambers had a Democratic majority. Therefore, even if parties were very polarized, de facto disagreement—as proxied by the PCI—, was not.

To test the conjecture that polarization is associated with higher PCI whereas control of the government by one party is associated with lower PCI, I estimate the following model

[14]HP filtering has been chosen rather than first differences because the trend is not completely removed from the series when using differences. Using a smoothing parameter of $w = 100$ also resulted in slow-moving trends observed in the residual. More details are available from the author upon request.

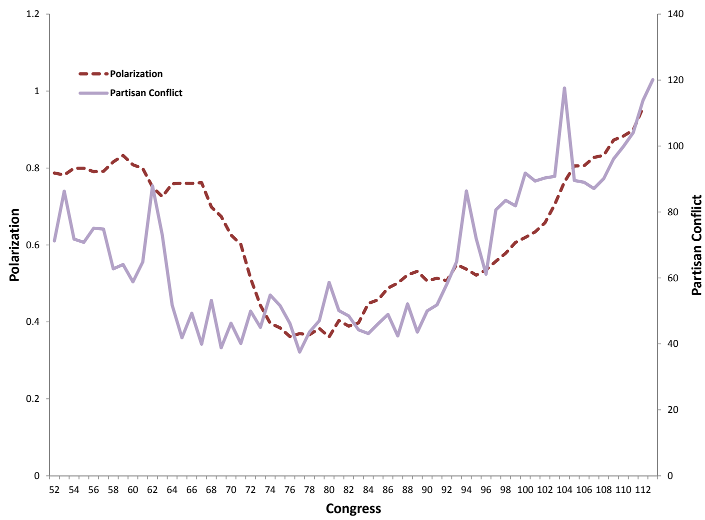

Figure 8: Historical partisan conflict and political polarization.

Notes: Polarization obtained from McCarty, Poole, and Rosenthal (2006), who use information on roll-call votes in Congress to compute legislators' ideal points in each Congress. Measure normalized to 100 in 1990. Data are from *http://voteview.com/downloads.asp.*

over the period 1891-2012 (from the 62nd to the 112th Congresses):

$$\Delta HPC_c = \alpha_0 + \alpha_1 \Delta Polar_c + \alpha_2 I_{div,c} + \epsilon_c, \tag{9}$$

where $c =$ denotes a particular Congress. The dependent variable is the first difference in the trend of partisan conflict, ΔHPC_c.[15] The variable $\Delta Polar_c$ represents changes in the trend of political polarization (also de-trended using the HP filter), obtained from McCarty, Poole, and Rosenthal (2006; see note in Figure 8 for more details). The dichotomic variable $I_{div,c}$ equals 1 under a divided government (that is, when a party has a majority in the House and the other party a majority in the Senate) and 0 otherwise. Finally, ϵ_c represents the error term.

The estimated coefficients are reported in the first column of Table 1. Both are positive and statistically significant, indicating that polarization and partisan conflict are indeed positively related, and that the PCI is typically higher under a divided Congress.

I consider an alternative measure of partisan control, $Pres\ Seats\ H_c$, representing the share of seats held by the President's party in the House. Including changes in its trend as an additional explanatory variable does not change the results from the benchmark case, as shown in the second column of Table 1. A negative and statistically significant coefficient associated with $\Delta Pres\ Seats\ H_c$ indicates that when the Presidency and the House are controlled by the same party, political disagreement—as reported by the media—declines.[16]

Interestingly, the share of seats controlled by the President's party in the Senate $Pres\ Seats\ S_c$

[15] First differences are used to ensure stationarity.

[16] Notice that the trend is calculated by HP-filtering $Pres\ Seats\ H_c$.

Table 1: The long-run behavior of HPC

Dep var: ΔHPC_c	(1)	(2)	(3)	(5)	(6)
$\Delta Polar_c$	0.195**	0.189**	0.144**	-0.077	0.113*
	(0.0732)	(0.0735)	(0.0634)	(0.060)	(0.062)
$I_{div,c}$	2.502***	2.307***	2.008***	1.86***	1.93***
	(0.681)	(0.743)	(0.664)	(0.46)	(0.47)
$\Delta Pres\, Seats\, H_c$		-41.45**		-16.72	
		(16.07)		(10.75)	
$\Delta Pres\, Seats\, S_c$			-4.289		
			(10.61)		
$\Delta Cloture_{\ c}$				0.51***	
				(0.13)	
$\Delta MediaCov_{\ c}$					0.61***
					(0.09)
Observations	60	52	52	46	60
R-squared	0.145	0.181	0.093	0.55	0.59

Notes: The dependent variable is the first difference in the trend of partisan conflict. The independent variables in specification (1) are $I_{div,c}$ and the first difference of the polarization trend. Specification (2) includes the first difference in the trend component of the share of seats controlled by the President's party in the House, $\Delta Pres\, Seats\, H_c$, while specification (3) includes the equivalent measure in the Senate, $\Delta Pres\, Seats\, S_c$. Sample period is 1891-2012. Specification (4) augments specification (2) by a lagged value of the first difference in the trend component of inequality, $\Delta Top1\,\%_{\ c}$, measured as the income share held by the to 1%. Specification (5) augments Specification (2) by adding changes in the trend to cloture motions filed. Each observation corresponds to a Congress. Specification (6) extends Specification (1) to account for trends media coverage, $\Delta MediaCov_{\ c}$. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

has no significant impact on the partisan conflict index, as shown in column (3) of this table. This is reasonable given super-majority rules and filibusters in the Senate. For much of US history, filibusters were rare and only used in matters of great importance. Nowadays, they have become a major tool by which a large part of the majority party's Senate agenda is blocked by an organized minority party filibuster. The threat of a filibuster is typically proxied by the number of cloture motions filed, as they are filed not only to interrupt filibusters in progress, but also to preempt anticipated filibusters. The evolution of the PCI is remarkably similar to that of cloture motions filed, as seen in Figure 9. Their correlation, computed between the 66th and 112th Congress, is 89%.[17]

[17] The number of motions filed prior to 1975 was close to zero, exhibited a large spike in early 1975 (beginning of the 94th Congress). This is due to a procedural reform by which the number of Senators needed to invoke cloture is reduced from two-thirds to three-fifths (about 60 out of 100). While this reform would explain an increase in the average number of motions filed, it does not explain the rising trend. Barber and McCarthy (2013) conjecture that the increasing portion arises as a result of rising polarization.

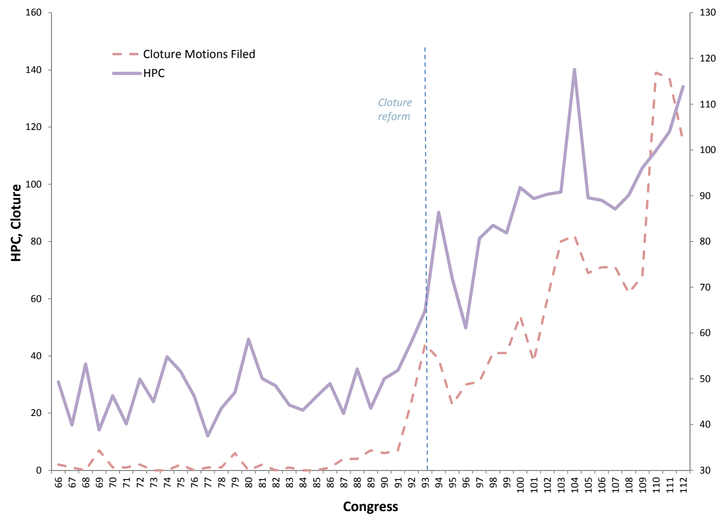

Figure 9: Historical partisan conflict and filibuster threats (cloture motions filed), 66th to 112th Congresses.

The strong positive relationship between PCI and cloture holds even after controlling for polarization and the distribution of political power, as seen from the highly significant coefficient of $\Delta Cloture_c$ in column (4) of Table 1. The model estimated is identical to the one in Specification (2), but augmented to incorporate changes in the trend of cloture motions files. The model fit is better than in previous specifications, as indicated by an R2 of 0.59. Interestingly, polarization becomes insignificant once cloture is considered. This could be due to the fact that partisan conflict captures filibuster threats (recall that 'filibuster' is a word used in the search), whereas polarization is based only on actual votes. Notice, however, that since I only have observations from the 66th Congress and onwards, the sample over which Specifications (2) and (5) are computed is different.

Media coverage Because the partisan conflict index is based on news reports, changes in media coverage are also likely to impact the measure. Figure 10 shows the evolution of HPC (solid line) alongside a measure of media coverage of government news (broken line). The latter corresponds to the share $\frac{G}{T}$, where the number of government-related news articles G are identified using the set of words in the "Government" ball of Figure 5, and T, the total number of articles in a year, is proxied by articles including the word "the."

The two variables exhibit a very similar trend. Extending the benchmark regression in eq. (9) to include changes in the trend of media coverage reinforces this observation: the correlation between changes in the trend of media coverage and those in HPC is about 0.6, and statistically significant. Moreover, the resulting R2 is increased from 0.145 in the benchmark case (Specification 1) to 0.59 in Specification (6), as seen in Table 1. This result is robust to including other control variables such as the share of seats controlled by the President in the House or Senate, or the trends in cloture. Results are omitted due to space constraints, but

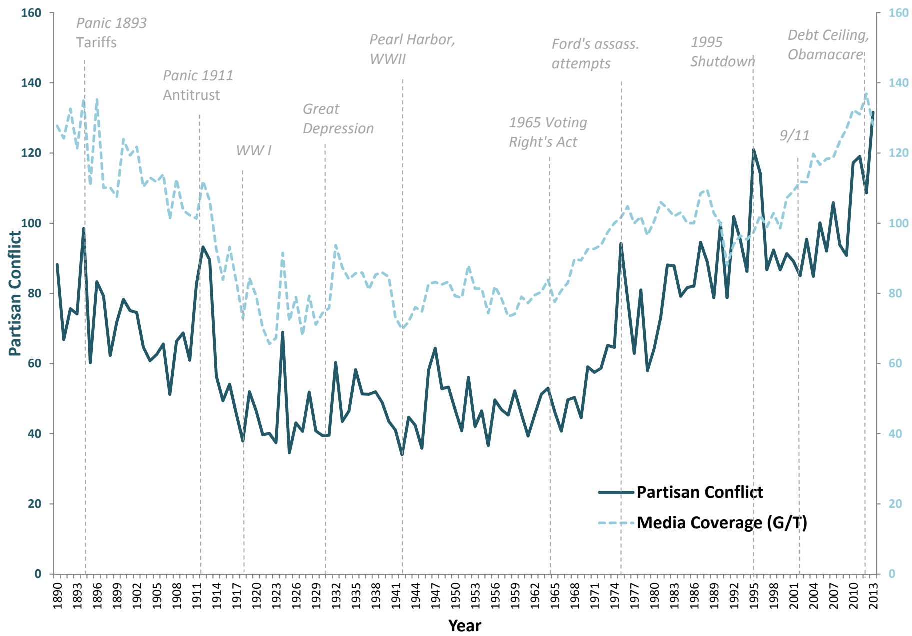

Figure 10: Historical partisan conflict (solid line) and media coverage (broken line).

are available upon request from the author.

That the HPC index is highly correlated with the share of news devoted to politics over time could be due to the fact that newspapers devote a larger share of news to politics in periods of high disagreement, precisely when investors are most interested in obtaining a signal about true partisan conflict. On the other hand, it could well be the case that trends in media coverage respond to other factors, such as competition from alternative news sources (i.e. TV, radio, or the internet) that emphasize political disagreement. The HPC index would be a more accurate reflection of true partisan conflict in the former case than in the latter case. I am mostly interested in the effect of news about partisan conflict on investors' decisions, regardless of whether these news are reporting true changes in political discord or are simply an artifact of media manipulation. The analysis in Section 5.3 sheds some light on this issue, by emphasizing the reaction of investors to changes in PCI triggered by the media (rather than fundamentals of partisan conflict) given the choice of news ads as an instrument. It would be interesting, in future work, to try to disentangle the effects of these two forces more systematically.

4.2.2 Short-run fluctuations of HPC

In this section, I focus on the relationship between the PCI and determinants of (true) partisan conflict at shorter frequencies. More specifically, I consider how changes in the cyclical component of HPC are related to: (i) elections, (ii) recessions, and (iii) wars. The benchmark model follows.

$$\hat{H}PC_t = \beta_0 + \beta_1 PresElec_t + \beta_2 War_t + \beta_3 Recess_t + \epsilon_t,$$

where $\hat{H}PC_t$ denotes the cycle component of HP-filtered partisan conflict data in year t, $PresElec_t$ denotes a dummy variable that takes a value of 1 in years where a presidential election is held. The dichotomic variable War_t takes a value of 1 if there is more than 1 military death per 100,000 people in the population in a given year and 0 otherwise.[18] This variable captures, for example, the Spanish-American War, WWI, WWII, the Korean War, and the most violent years of the Vietnam war. The variable $Recess_t$, which follows the NBER definition of a recession, is obtained from the Federal Reserve Bank of St. Louis FRED dataset. The results for the benchmark specification are summarized in the first column of Table 2, and will be discussed below.

(i) Elections The most natural source of short-run fluctuations in the PC indicator is the arrival of election dates, an anticipated shock. We should expect the index to be higher than average during elections purely for mechanical reasons: Newspapers increase the proportion of articles covering political debates and emphasize differences between candidates during those periods. In addition, partisan conflict may also intensify endogenously, as legislators try to pursue a particular agenda or block specific legislation to tilt election results in their party's favor (see Groseclose and McCarty, 2001 on strategic disagreement). Political agents (incumbent legislators, the opposition, the President, etc.) have incentives to exaggerate their positions to signal a particular type in an attempt to attract votes, also referred to as 'posturing' in the political economy literature (see Ash, Morelli, and Van Weelden, 2014). An estimated coefficient of $\beta_1 = 3.32$ indicates that the index does indeed spike in years in which Presidential elections take place. This is not the case when midterm elections are considered (see Specification 2). This result should be taken with caution, however, since there is a midterm election every other year in the historical sample. When shorter intervals are analyzed (e.g., at a monthly frequency), periods surrounding a midterm election are indeed characterized by higher observations of the index.

(ii) Recessions The state of the economy can potentially affect partisan conflict, and hence the PCI, in the short run. Recessions are periods when automatic stabilizers (such as unemployment benefits) kick in. Several of these stabilizers are highly redistributive in nature, and thus potentially conflictive. We should expect partisan conflict to intensify in "bad times," when revenues tend to be low and spending needs tend to be large. An example is the 2007 recession, when the subsequent conflict over tax-cut expirations led to gridlock and hence extreme values in HPC. Surprisingly, the HPC index is not statistically different during booms and recessions, as seen by the high standard error on the coefficient ot $Recess$. Inspection of Figure 6 reveals that while HPC is significantly higher during the 1893 and 1911 panics, it takes one of it lowest values of the century during the Great Depression. To test the robustness of this result, I include alternative proxies for recessions in specifications (3) and (4). In (3), a lagged value of the unemployment rate (obtained from FRED) is introduced. In

[18]Data are obtained from http://violentdeathproject.com/countries/united-states.

(4), a lagged value of the HP-filtered unemployment rate is used instead. The coefficients are statistically insignificant, reinforcing the observations that the state of the economy is not an important determinant of the cyclical behavior of the PCI, at least at the annual frequency.[19]

Table 2: The cyclical behavior of HPC

Dep var: $\hat{H}PC_t$	(1)	(2)	(3)	(4)
$PresElec_t$	3.32**		3.12*	3.10*
	(1.53)		(1.63)	(1.63)
$MidtermElec_t$		1.91		
		(1.35)		
War_t	-2.95**	-3.28**	-2.37*	-2.39*
	(1.45)	(1.52)	(1.42)	(1.40)
$Recess_t$	-0.35	-0.28		
	(1.66)	(1.65)		
U_{t-1}			-0.024	-0.25
			(0.118)	(0.38)
Observations	123	123	112	112
R-squared	0.0580	0.038	0.049	0.05

Notes: The dependent variable is HP-filtered (using weight $w = 6.25$) historical partisan conflict. The independent variables in specification (1) are the dichotomic variables which take a value of 1 if there is a Presidential election ($PresElec_t$), a war (War_t) or a recession ($Recess_t$) . Specification (2) considers a midterm election instead ($MidtermElec_t$). Specification (3) includes considers the lagged unemployment rate (U_{t-1}) as an alternative proxy for a recession, while specification (4) considers HP-filtered values of the unemployment rate (lagged one period). Sample period is 1891-2013 for specifications 1-3, and 1901-2013 for specifications (3) and (4). Each observation corresponds to a calendar year. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

(iii) Wars Finally, I analyze how wars affect news about partisan conflict. Following Mueller (1973), a large strand of the political science literature has analyzed the effects of dramatic and sharply focused international crises (or wars) on the popular support of the President of the United States. The unprecedented increase in George W. Bush's public approval ratings, from 51% to 86% following the September 11th terrorist attacks, is a typical example of the 'rally around the flag" effect. Mathews (1919) argues that *one effect of war upon the party system (...) is to bring about, at least for a time, a relatively greater stability of party control, if not complete quiescence of partisanship, either through coalition or through cessation of party opposition, or both.* This would suggest that a rally around the flag should

[19]Lagged values of GDP growth can also be used as alternative proxies for a recession (ommitted due to space constraints). Their coefficients are also statistically insignificant.

be observed at the party level. Interestingly, lower-than-average HPC scores are recorded during episodes of war and national security threats in the historical series. The clearest examples are given by the First War World and the Second War World in Figure 6. As the third row of Table 2 indicates, HPC is significantly lower during wars even after other sources of short-term fluctuations are considered. One may argue that lower PC scores are observed during wars because newspapers devote a larger percentage of coverage to documenting events related to the war itself, rather than to government policy. Inspection of the evolution of the EPU suggests that this is not the case, as this series increases significantly during these events. An example is given by the large spike in EPU observed during 9/11, a period where partisan conflict reached record lows (relative to trend).[20]. This will be discussed in more detail in the next section, where I contrast the evolution of partisan conflict to that of EPU.

Taken together, the results of this section indicate that: (i) HPC is higher during Presidential elections, (ii) there exists a *partisan* rally-around-the flag, (iii) there is no evidence that HPC is higher during recessions than it is in booms.

4.3 The (more recent) evolution of partisan conflict

In this section I describe the more recent evolution of partisan conflict. Figure 11 depicts the benchmark PCI measure. Recall that this measure is more precise, due to the greater availability of digitalized newspapers and the possibility of filtering out foreign news, among others. Additionally, it is computed at a monthly frequency, which allows us to better analyze the behavior of partisan conflict at shorter frequencies.

The first observation is that the index has fluctuated around a constant mean for most of the sample, but exhibited an increasing trend starting at the outset of the Great Recession (e.g., around 2007). The index reached its highest level of our 30-year sample period during the shutdown of 2013. Interestingly, these trends are consistent with the behavior of disapproval ratings as measured by Gallup, discussed in more detail in Appendix 7.10.

The circles in Figure 11 indicate months associated with presidential elections, while the vertical bars represent those in which Congress held midterm elections. Consistently with fact (i), the index spikes when elections are held. The rally-around-the flag effect (fact ii. above) is even more evident when analyzing the monthly PCI, as the series is clearly below average during both Gulf Wars, the Beirut and Oklahoma City bombings and, particularly, 9/11 when it decreased dramatically from the spike associated with the Bush vs Gore election. This reinforces the previous observation that partisan conflict subsides significantly not only when the country is at war, but also when it is subject to national security threats.

The figure also displays other historical events (with diamonds) that resulted in deviations from the trend. Most noticeable are the government shutdown of 2013, the passage of "Obamacare," the debt ceiling debate, and the period surrounding the fiscal cliff. This is reassuring, suggesting that the indicator captures disagreement about well-known polemic issues. True partisan conflict is also expected to increase at short frequencies when polemic issues over which a decision must be taken arise in the legislative agenda. As Lowell (1902)

[20]Recall that both EPU and PCI share the same denominator, namely, the number of newspaper articles during a period

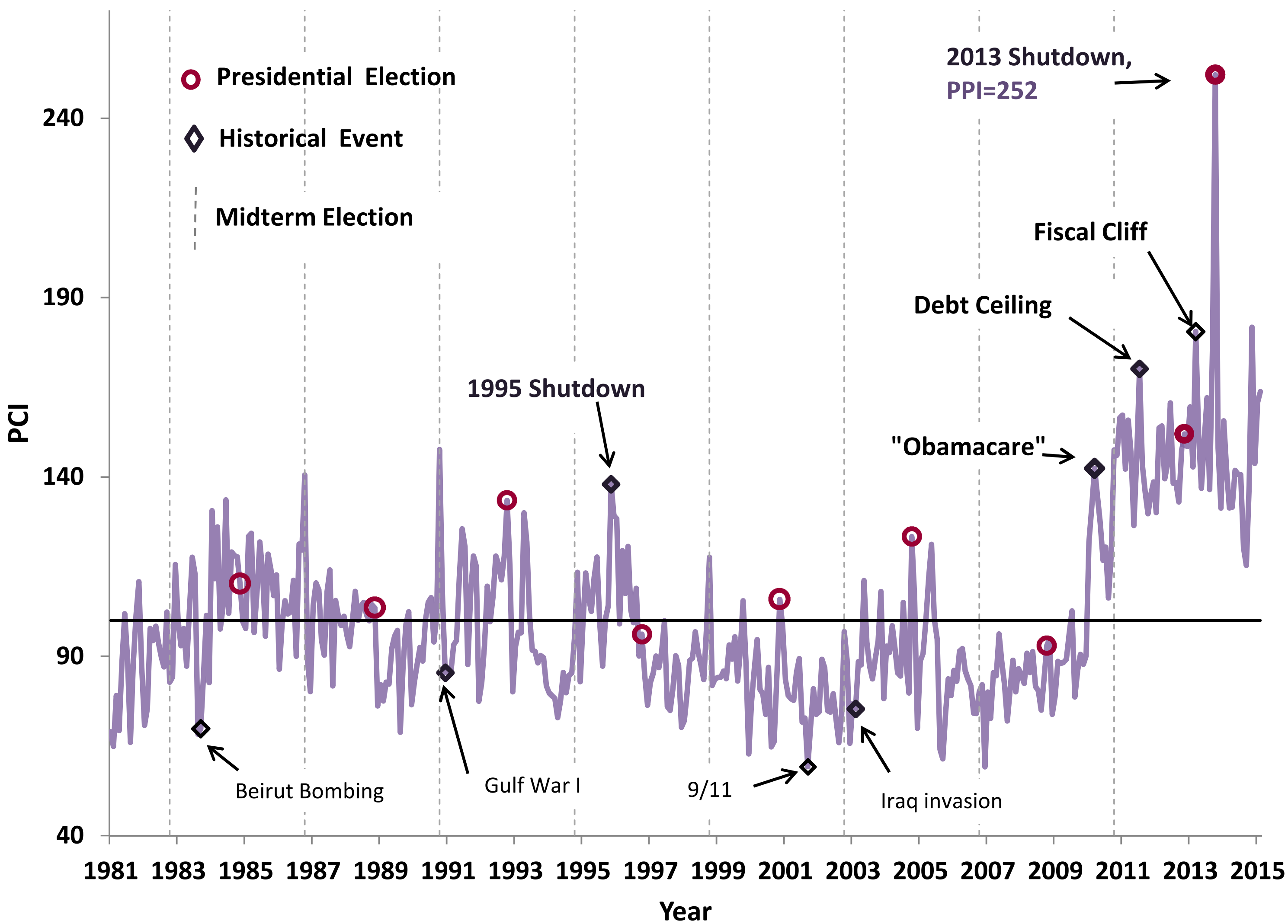

Figure 11: Partisan conflict index (PCI=$\bar{s}_t$), 1981-2015. PCI normalized to 100 in 1990. Circles represent presidential elections (month of election or the month before); diamonds are historical events, and vertical lines are midterm elections.

noted *...the amount of party voting depends largely upon the accident of some question in which the parties are sharply divided happening to come up for decision...in England, parties frame the issues. In America the issues do not, indeed, make the parties, but determine the extent of their opposition to each other in matters of legislation.* Figure 12, which depicts the benchmark PC scores together with a series of tax expirations, illustrates that reported partisan conflict intensifies when Congress is forced to make a dated decision affecting the federal budget (triggered by one of these expirations). The monthly correlation between the two series is 0.7. A higher-than-normal sequence of tax expirations since 2007 could have explained the increase in PCI over the same period. [21]

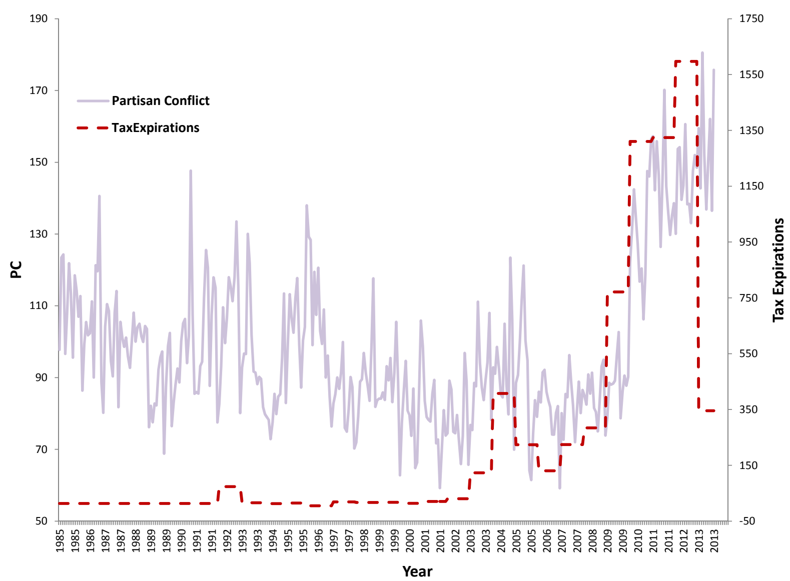

Figure 12: Partisan conflict and tax expirations.

4.4 Partisan conflict and economic policy uncertainty

The methodology used to compute the PCI is similar to the one Baker, Bloom, and Davis (2015) followed to construct EPU. While we both use a semantic search approach to identify relevant newspaper articles, the set of words used in the searches is dramatically different. While these authors include the words 'economic/economy,' 'uncertainty' and an proxies for 'policy,' I search for words that indicate disagreement between policymakers.

In addition, as EPU and PCI represent different concepts (see Section 3.1), they are characterized by distinctive features. The PCI represents a signal about the degree of government dysfunction, which, in our model, is used by investors to infer the quality of fiscal

[21] At a particular point in time, it is impossible, unfortunately, to disentangle whether partisan conflict is high because parties are ideologically far apart on a particular issue from the relevance of the issue per se. Polarization levels cannot, therefore, be inferred from PCI at very short frequencies. The index can be a better proxy for polarization over longer time spans where specific issues are "averaged out."

policy and regulation. High levels of partisan conflict are interpreted as situations where agreement between two parties that share decision-making power is hard to reach, so policies are expected to be less effective at preventing 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 situations like these, we would expect government dysfunction to induce economic policy uncertainty and the two indexes to move in tandem. Figure 13, which depicts the PCI (solid line) together with the news-based EPU index (dashed line), shows that the indexes share a similar trend.

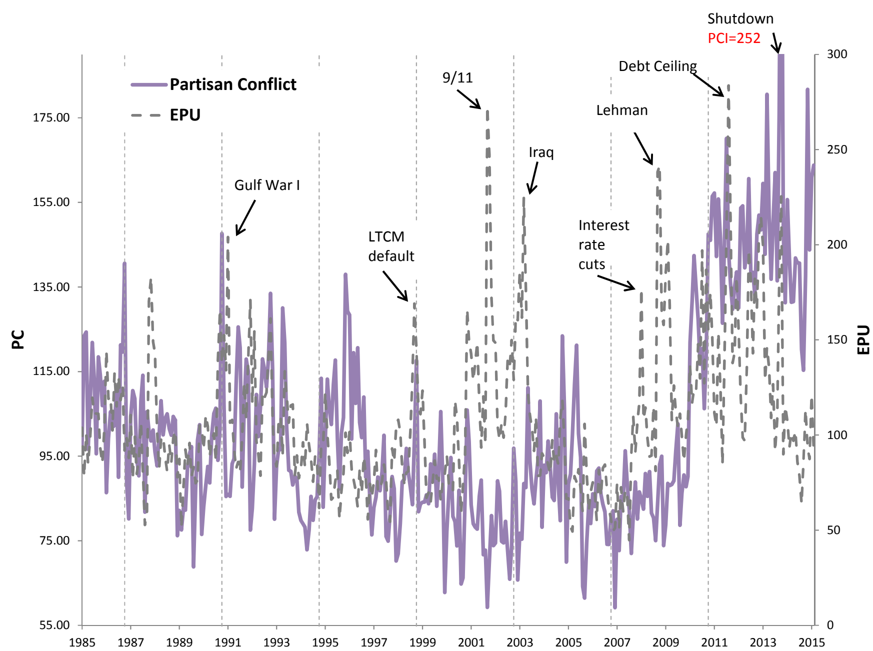

Figure 13: Partisan conflict (solid) and news-based economic policy uncertainty (dashed). Shutdown spike truncated for readability.

Partisan conflict need not, however, always cause economic policy uncertainty to increase. Recall that their relationship is expected to be non-monotonic, as shown in Lemma 3.2. 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. Such periods are characterized by high *political uncertainty* (that is, where the precision of signals is low), but potentially full *policy certainty* in the short run. The reason being that, when c_t is extremely large $Var(c_t)$ is high, but the status quo remains unchanged due to government inaction (that is, $x \simeq 0$). Hence, even though investors may not be able to infer the true value of c_t accurately, the expected value of conflict is so large that preventive policies will not be undertaken. As a result, we should expect the two indexes to move in opposite directions when partisan conflict reaches extreme values. This is consistent with the behavior of the series in Figure 13 around the 2013 shutdown. Notice, however, that shutdowns are still detrimental for the economy according to our theory. When the PCI reaches extreme values, investors become very pessimistic about the ability of the government to take the appropriate measures to reduce tail risks, and this depresses investment.

The data counterpart of Figure 2 is presented in Figure 14, which shows the relationship between PCI and EPU during 1985 and 2014 (quarterly data), together with the fitted line from a 4th order polynomial approximation. As we can see from the graph, higher levels of partisan conflict are associated with greater economic policy uncertainty for the most part. The apparent non-monotonicity is driven by the 2013 shutdown. I conclude that there is not enough empirical evidence for the non-monotonicity predicted by the theory. Moreover, a scatterplot of historical PC and EPU series for the period 1900-2013, reveals an almost linear relationship between the two variables. This is due to the fact that both series exhibit a very similar long-run trend.

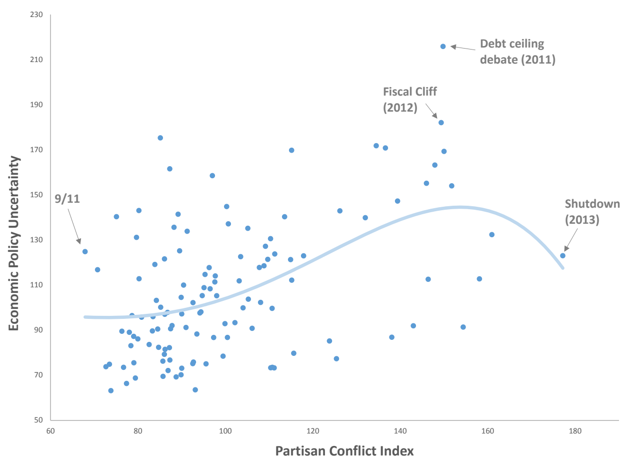

Figure 14: Economic policy uncertainty (News-based) as a function of partisan conflict (dots) for Q1:1985-Q4:2014. The solid line represents the fitted values of a 4th order polynomial.

There is no clear relationship, however, between cyclical PCI and EPU (that is, between deviations from trend of these two variables). This happens because measured EPU may fluctuate as a consequence of factors unrelated to policy and regulation determined by the executive and legislative powers, and thus to partisan conflict. Inspecting Figure 13, we can see that EPU is affected by monetary policy (such as interest rate cuts by the Federal Reserve) but the PCI is completely unresponsive to it. This is reasonable, as monetary policy is chosen by an independent authority, but may cause (monetary) policy uncertainty. Finally, there are important differences in the behavior of the two variables in the presence of military conflict: While the EPU increases during wars or under national security threats (for example, 9/11 or the Gulf Wars), partisan conflict tends to remain relatively low or even decrease. The fact that the EPU increases sharply during these events indicates the existence of a substantial proportion of newspaper articles discussing government policy. These articles are not, however, reporting high levels of conflict between parties. This suggests that lower-than-average values of the PCI during national threats do indeed reflect rallies around the flag, rather than just being a by-product of changes in media coverage toward war-related news. Because of all these factors, the correlation between partisan conflict and the news-based index of economic policy uncertainty developed by Baker, Bloom, and Davis (2015) is only 0.34 in the recent period (1985-2015).[22]

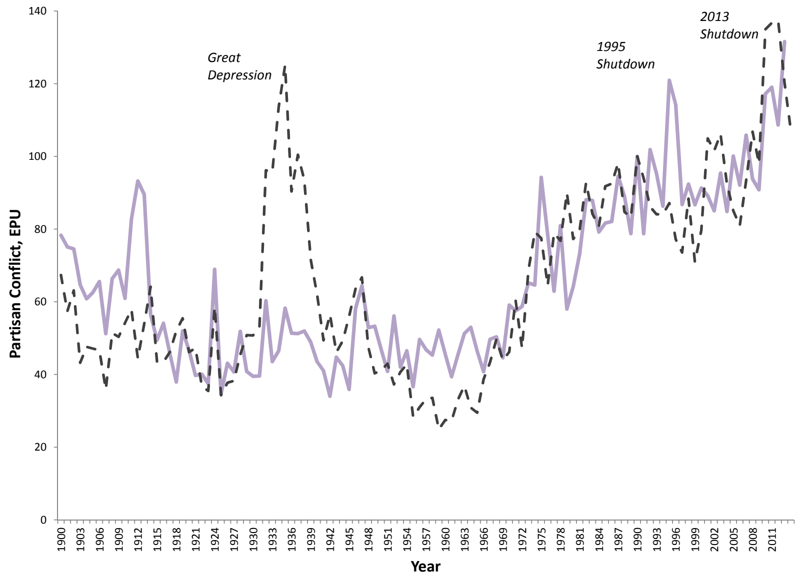

Figure 15: Partisan conflict (solid) and news-based economic policy uncertainty (dashed). Both series are normalized to 100 in 1990.

The last important difference between the two series lies on the fact that there exist two types of EPU. The first one, which has been explored in the theoretical section, relates to *which* policies would be chosen at each point in time, or more specifically, whether preventives policies would be implemented at all. The second one is associated with the uncertain *consequences* of policies that have already been chosen by the government (see Pastor and Veronesi, 2013 for a theoretical discussion). Partisan conflict only causes the first type of uncertainty. Discussions surrounding the approval of a stimulus package or whether the debt-ceiling would be lifted to avert default are clear examples. The policies implemented in response to the Great Depression, 9/11, or the Iraq wars, on the other hand, faced little or no opposition, in a period of low PC. For example, the New Deal was easily approved with a Democratic supermajority in both houses. The response to the terrorist attacks in 2001 was clearly a bipartisan effort. The large spikes observed in the EPU series result from uncertainty about whether the implemented policies would be effective (to end the Great Depression, to dis-

[22]This correlation is computed using only the news-based index of economic policy uncertainty and not the final EPU. The reason is that tax expirations account for about one-third of the EPU index, which I wanted to exclude to make the comparison. If I use the benchmark EPU measure, which includes tax expirations, the correlation between the two indexes is about 0.47.

courage further attacks, or to avoid a war with other Middle-Eastern countries), rather than about whether they would be implemented or not. The disconnect between the two series in these episodes is evident by looking a the historical partisan conflict and economic policy uncertainty series, in Figure 15.

5 Partisan Conflict and Private Investment

In this section, I explore empirically the effects of news about partisan conflict on private investment.[23] In particular, I want to test whether innovations to the PCI depress private investment, as implied by the model presented in Section 3.

To do so, I take four complementary approaches. In the first one, I consider a VAR specification using yearly data from 1929 to 2013. Although this approach does not allow me to robustly identify a causal relationship between HPC and investment, it illustrates their long-run co-movement. Moreover, I can show that their relationship is not confounding the effects of other slow-moving variables such as polarization or the share of seats held by the President in Congress, neither it is capturing the effects of economic policy uncertainty. The second approach uses high-frequency (e.g., monthly) PCI data instead. The rationale is that short-term fluctuations in investment are more likely to be caused to changes in investors expectations (due to learning about the degree of partisan conflict), rather than partisan conflict being caused by monthly swings in investment.

The third approach tries to deal with the issue of causality more directly by using instrumental variables. To distinguish the causal effect of partisan conflict on private investment, I implement two-stage least squares (2SLS) using the lagged ratio of newspaper advertisement revenues to employment in the sector as a source of exogenous variation in partisan conflict. The argument, which focuses on the 'market for news,' is that advertising revenue declines lead to more sensational reporting as newspapers tend to highlight conflict between policymakers (Jamieson and Cappella, 2008).

In the last approach, I use panel data of publicly traded firms to identify the effects of partisan conflict on private investment. Using firm-level regressions that control for firm fixed-effects and year fixed-effects, I find that there is a significant negative correlation between partisan conflict and investment rates, particularly in firms belonging to sectors highly exposed to government spending and those actively engaged in campaign contributions through PACs.

5.1 VAR Approach

To test the impact of partisan conflict on aggregate investment, I estimate a vector auto regression (VAR) model and recover orthogonal shocks by using a Cholesky decomposition of the following: War, Recession, Divided Congress, Historical Partisan Conflict, Log-Investment, and Log-GDP. War is proxied with the number of military deaths per 100,000 people in the population in a given year, while the recession indicator is obtained from the NBER. Investment and output are obtained from the Bureau of Economic Analysis (BEA),

[23] The effects of partisan conflict on agents' expectations are briefly discussed on Appendix 7.11

and correspond to seasonally adjusted 'Gross Private Domestic Investment' and 'Gross Domestic Product,' respectively. Real variables are constructed using the GDP deflator, and expressed in billions of 2005 dollars. The sample is restricted to the period 1929-2013 due to lack of investment data prior to the start date.

In the baseline specification, I use yearly data with three-year lags. The VAR is stable, so impulse-response functions can be constructed. Figure 16 shows that an increase of a one-standard deviation of the—orthogonalized—shock to the historical partisan conflict index causes a significant and persistent reduction of log-investment. Moreover, I can show that partisan conflict indeed Granger-causes (log) investment in this model. A standard deviation of the HPC corresponds to a 22.5 point increase in the index, implying a 13% reduction (on average) in aggregate real investment upon impact. The largest impact is seen after one year, in which investment declines 16%. Interestingly, HPC increased by about 26 points (slightly above a one-standard deviation) between 2010 and 2011, suggesting that part of the slow recovery in investment could have resulted from investors' reaction to news about political turmoil.

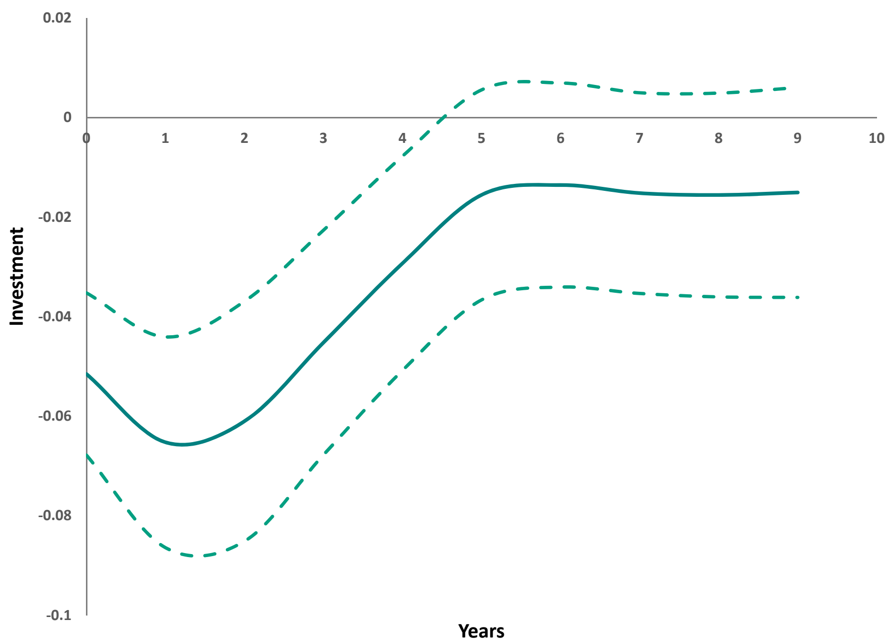

Figure 16: Impulse-response function of a one-standard deviation increase in HPC. Solid line: mean estimate; dashed outer lines: one-standard-error bands. Estimated using a yearly Cholesky VAR model with War, Recession, Divided Congress, Historical Partisan Conflict, Log-Investment, and Log-GDP (in that order).

Figure 17 shows the response of log-investment under alternative specifications. The solid line replicates the response obtained under the benchmark model. The line denoted 'Last' (solid with x-markers) considers an alternative ordering of the Cholesky decomposition: War, Recession, Divided Congress, Log-Investment, Log-GDP, and HPC. That is, we allow for the possibility of log-investment and log-output to cause HPC. Even though the response is smaller from period 1 and onwards (there is no response on impact by construction), the qualitative result holds: increases in HPC are associated with declines in private investment. The dashed-line includes polarization and the share of seats held by the President in the House (PPH), two variables which were shown to be significant determinants in the trend of HPC (see Section 4.2.1 for a description of these variables and their impact on HPC). The model considers War, Recession, Divided Congress, PPH, Polarization, HPC, Log-Investment, and Log-GDP (in that order). Finally, the dotted line incorporates EPU to the model.[24] We can see that the main result, namely that the relationship between HPC and log-investment is negative, is robust to several modifications of the benchmark model.

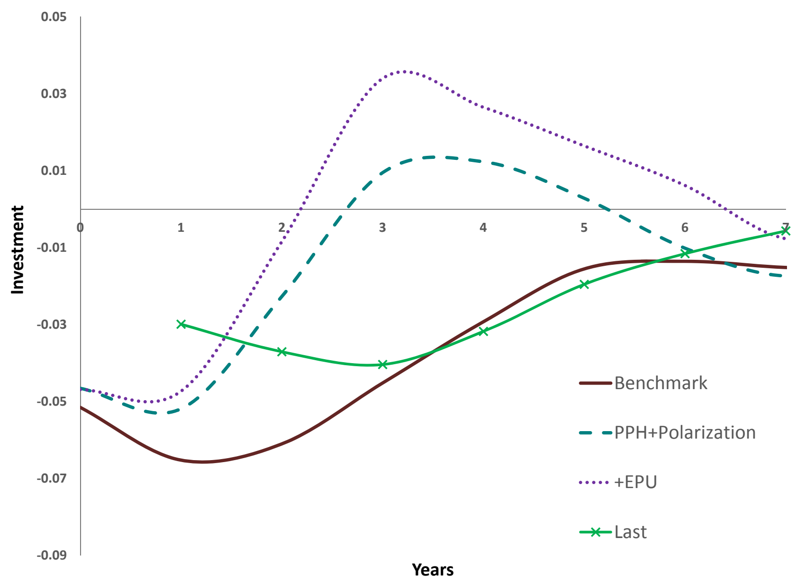

Figure 17: Impulse-response function of a one-standard deviation increase in HPC. 'Benchmark' (solid line) estimated using a VAR with War, Recession, Divided Congress, HPC, Log-Investment, and Log-GDP (in that order); 'Last' (x-marker) uses War, Recession, Divided Congress, Log-Investment, Log-GDP, HPC; 'PPH+Polarization' (dashed line) includes: War, Recession, Divided Congress, PPH, Polarization, HPC, Log-Investment, and Log-GDP (in that order); Finally, '+EPU' (dotted line) considers: War, Recession, Divided Congress, PPH, Polarization, HPC, EPU, Log-Investment, and Log-GDP (in that order).

I cannot, unfortunately, show Granger-causality in all the specifications. The results should therefore be interpreted as "informed correlations" between these variables.

[24] The ordering is War, Recession, Divided Congress, PPH, Polarization, HPC, EPU, Log-Investment, and Log-GDP in that case.

5.2 High-frequency Approach

In this subsection, I quantify the impact of news about partisan conflict on aggregate investment at shorter frequencies. Using the monthly PCI series, I estimate an OLS regression of the following specification

$$\hat{I}_t = \alpha_0 + \alpha_1 Z_t + \alpha_2 \hat{r}_{t-1} + \beta \hat{PCI}_t + \epsilon_t, \tag{10}$$

where $\hat{I}$ denotes de-trended real private investment, $\hat{r}$ the de-trended interest rate, Z indicates the state of the economic cycle, $\hat{PCI}$ the de-trended partisan conflict index, and ϵ represents the error term.

While measures of private investment are only available at the quarterly level, the Department of Commerce's durable goods report (published monthly) includes a measure of manufacturers' new orders that is considered a good proxy for U.S. business investment spending plans. In particular, I use the variable 'Manufacturers New Orders: Nondefense Capital Goods Excluding Aircraft' (seasonally adjusted) over the sample period January 1992-December 2014 (the longest time-span available for the series). Investment is deflated using the 'Producer Price Index' provided by the Bureau of Labor Statistics (series id PCUOMFG-OMFG). Interest rates r are proxied by the 'Effective Federal Funds Rate,' a series obtained from the FRED Economic Data (provided by the Federal Reserve Bank of Saint Louis). The variable Z takes a value of 1 if the economy is in a recession (as defined by the NBER recession dates) and 0 otherwise. This recession indicator is also obtained from FRED. Investment, interest rates, and the PCI have been de-trended using a Hodrick-Prescott filter (HP-filter), with the standard weight $w = 14400$ for monthly data. HP-filtering has been chosen over first differences because the trend was not completely removed from the series when using first differences. In addition, I am interested in the effect of political dysfunction at real business cycle frequencies, which are best isolated with an HP-filter.

The regression results are presented in Table 1. Specification (1) corresponds to the model presented in eq. (10), where errors have been corrected for heteroskedasticity. Because residuals exhibited serial autocorrelation in that specification, the standard errors in specification (2) have been corrected with an AR process with three lags.[25]

The coefficient on $\hat{PCI}_t$ is statistically significant, suggesting that news about partisan conflict are associated with lower investment even at shorter frequencies. As mentioned before, the issue of reverse causality is less likely to arise in this specification, as investment decisions are probably affected by news shocks rather than partisan conflict being determined by low investment at the monthly frequency.

Specification (3) considers the possibility of non-linear effects of PCI on investment. It is reasonable to expect that very large deviations from trend in partisan conflict, where government inaction is almost certain, may depress private investment to a greater extent than small deviations. To test this hypothesis, I construct the variable $\hat{PCI}_t^H$ which equals $\hat{PCI}$ when deviations from trend (on either direction) are larger than one standard deviation,

[25] The choice of lags was based on observation of the partial autocorrelation graph of the errors from Specification (1).

Table 3: OLS regression results

Dependent variable: $\hat{I}_t$	(1)	(2)	(3)	(4)	(5)
$\hat{P}CI_t$	−0.076*	−0.0726*		−0.073*	
	(0.05)	(0.038)		(0.039)	
Z_t	−7.20*	−8.59	−8.58		
	(4.30)	(6.18)	(6.17)		
$\hat{r}_{t-1}$	12.79***	9.71***	9.67***	9.69***	9.7***
	(1.36)	(3.17)	(3.18)	(2.94)	(2.94)
$\hat{P}CI_t^H$			−0.088**		−0.72*
			(0.038)		(0.039)
$\hat{P}CI_t^L$			−0.049		−0.92
			(0.07)		(0.23)
U_{t-1}				−1.73	−1.73
				(1.32)	(1.33)
Observations	275	275	275	275	275
R-squared	0.32	n.a.	n.a.	n.a.	n.a.

Notes: Variables detrended using an HP filter (w = 14400 for monthly data). Robust standard errors controlling for heteroskedasticity are reported in parenthesis. Standard errors corrected for autocorrelation (AR process with three lags) in specifications (2) and (3). *** p<0.01, ** p<0.05, * p<0.1

denoted by $\sigma(\hat{P}CI)$, and it is zero otherwise.[26]. That is,

$$\hat{P}CI_t^H = \begin{cases} \hat{P}CI & \text{if} \quad |\hat{P}CI| > \sigma(\hat{P}CI) \\ 0 & \text{otherwise.} \end{cases}$$

The complement of this, $\hat{P}CI_t^L$ equals zero when the index's deviations are low, while $\hat{P}CI_t^L = \hat{P}CI$ when $|\hat{P}CI| \leq \sigma(\hat{P}CI)$. About 60% of the observations lie within one standard deviation from the mean.

The results, which are summarized in the third column of Table 1, indicate that the detrimental effects of negative political signals are significant when increases in partisan conflict are large. Moreover, the size of the coefficient on $\hat{P}CI_t^H$ is larger in magnitude than the one computed in specifications (1) and (2), being statistically significant at the 2% level in this case. On the other hand, $\hat{P}CI_t^L$ is statistically insignificant. In other words, investors seem to discard signals that involve marginal changes in partisan conflict when making investment decisions. These results also hold if we were to use a 0.5-standard deviation threshold to define $\hat{P}CI_t^H$ and $\hat{P}CI_t^L$, in which case about half of the observations would lie within one-half standard deviation from the mean.

Finally, the results are robust to using the lagged unemployment rate (obtained from the BLS) instead of the dichotomic NBER recession indicator, as seen in columns (4) and (5) of

[26]I would like to than Dario Caldara for suggesting this specification.

the table. Summarizing, I find that news about partisan conflict are associated with lower investment even at the monthly level, and using the more refined measure of PCI.

5.3 Instrumental Variables Approach

In this section I try to deal more directly with the potential issue of reverse causality by using instrumental variables. In particular, the (lagged) ratio of newspaper advertisement revenues to employment in the sector will be used as a source of exogenous variation in partisan conflict. The rationale of this approach is that declines in advertising revenue driven by competition from alternative news outlets (such as cable TV and the internet) lead to more sensational reporting.

Gentzkow and Shapiro (2010) showed that news content is mostly demand driven; that is, the ideological slant of newspapers is driven by the ideology of the audience they are trying to capture, rather than that of the owners or the editors. In other words, editors and newspaper owners behave as profit maximizing agents. Mainstrem newspapers have been facing increased competition from cable TV (e.g. Fox News) and internet outlets (e.g., Huffinton Post, politico.com, etc). These new outlets are characterized by being more 'partisan,' in an attempt to identify with readers in a particular niche. For example, Fox News is significantly to the right of all the other mainstream television networks according to Groseclose and Milyo (2005). Moreover, their news reports emphasize disagreement (see Jamieson and Cappella, 2008). The resulting decline of ad revenues and newspaper circulation has forced traditional newspapers to change their reporting style in order to attract a lost audience. The following excerpt from an innovation report for The New York Times that leaked on April 2014 suggests the editors and the management pressuring the reporters to make their articles more attractive: *At our competitors, Audience Development is seen as the responsibility of every editor and reporter...these efforts can be compared to using an engaging lede, compelling headline, or gripping photo to draw readers to the story. NYT Innovation Report 2014.* We should expect that as ad revenues decline, the frequency of news emphasizing disagreement goes up.

Because advertisement revenue may be correlated to the state of the economy, the instrument used will be the ratio of advertisement revenues to employment in the newspaper publishing sector. To the extent that both—advertisement revenues and employment in the sector—respond similarly to business cycle fluctuations, the ratio should not co-move with the cycle, and hence with investment. Finally, because implementing changes in the editorial staff and reporting style takes time, the instrument is lagged four periods; in other words, the variable corresponds to ad revenue shares in the same quarter of the previous year. This should ensure that the instrument is exogenous from today's perspective and uncorrelated with medium term business cycles.

Estimation The estimation strategy for the 2SLS is as follows. The second stage estimation is analogous to the one presented in the previous section,

$$\log \hat{I}_t = \beta_0 + \beta_0 \log \hat{P}CI_t + \beta_2 X_t + \epsilon_t, \tag{11}$$

where $\log \hat{I}_t$ denotes natural logarithm of de-trended real private investment, $\log \hat{PCI}$ is the natural logarithm of de-trended partisan conflict index (resulting from the first stage estimation described below), and X_t represents a set of control variables. In particular, $X_t = \{Z_{t-1}, \hat{r}_{t-1}\}$, where Z captures the state of the economy and r denotes de-trended interest rates. Natural logarithms are used because this specification improves the model's fit, but the main conclusions are robust to using raw measures instead.

Investment is obtained at the quarterly level for the sample period Q1:1981 to Q2:2013 from the Bureau of Economic Analysis (BEA), and corresponds to seasonally adjusted 'Gross Private Domestic Investment.' Real investment I_t is constructed using the GDP deflator, and is expressed in billions of 2005 dollars. Interest rates (r_t) are proxied by quarterly averages of the 'Effective Federal Funds Rate,' obtained from FRED. Partisan conflict (PCI_t) is constructed from the seasonally adjusted monthly series by taking quarterly averages.[27] Finally, the state of the economy Z is proxied with a measure of total factor productivity (TFP) based on the Solow residual (see details in Appendix 7.12). This variable is preferable to the NBER-based recession indicator because it allows us to take into account the intensity of a recession.[28] Investment, interest rates, and partisan conflict have been de-trended using an HP filter (and denoted with hats), with the standard weight $w = 1600$ for quarterly data. Notice that the lagged value Z_{t-1} is used, to ensure that the variable is exogenous to current investment levels (this variable is also de-trended using the HP filter, as explained in Appendix 7.12).

The first stage estimation equation follows

$$\log \hat{PCI}_t = \alpha_0 + \alpha_1 \log \hat{Ads}_{t-4} + \alpha_2 X_t + \eta_t, \tag{12}$$

where $X_t = \{Z_{t-1}, \hat{r}_{t-1}\}$ as above, and $\log \hat{Ads}_{t-4}$ represents the de-trended natural logarithm of ad-revenue shares, lagged four quarters (that is, during same quarter of the previous year). Ad revenue shares are computed as

$$Ads_t = \frac{AR_t}{N_t},$$

where AR_t denotes newspaper advertisement revenues and N_t is employment in the newspaper sector. The variable AR_t is obtained from the Newspaper Association of America, and spans the interval Q1:1983 to Q4:2012. It has been seasonally adjusted using the US Census X-12 ARIMA procedure. Employment in the newspaper sector (N_t) is obtained from the Current Employment Statistics survey (National) of the Bureau of Labor Statistics, and corresponds to the total number of employees in the Newspaper Publishing sector (NAICS Code 51111). The variable $\hat{Ads}_t$ used in eq. (12) corresponds to HP-filtered Ads_t (using $w = 1600$).

Results from the 2SLS are presented in Table 2, along the coefficients from a simple OLS estimation of eq. (11), that is, where $\log \hat{PCI}_t$ represents actual rather than fitted values of de-trended partisan conflict.

[27] Partisan conflict has been seasonally adjusted using the US Census X-12 ARIMA procedure, so that the adjustment in this variable is consistent with the one used for advertisement revenues (which exhibited a noticeable seasonality, as explained next).

[28] Data constraints (in particular the lack of a series for output and investment at the monthly level) prevented me from using TFP in Section 5.2.

Table 4: 2SLS regression results

Dependent variable	*OLS* $\log \hat{I}_t$	First Stage $\log(\hat{PCI})_t$	Second Stage $\log \hat{I}_t$
Instrument: $\log \hat{A}ds_{t-4}$		−1.08***	
		(0.24)	
$\log(\hat{PCI})_t$	−0.08***		−0.33***
	(0.03)		(0.10)
Observations	118	118	118
R-squared	0.755	0.13	0.593
2SLS Tests:			
Endogeneity test			6.8928
Chi-sq(1) P-val			0.0087
Weak Identification statistic			20.474
Stock-Yogo weak ID test critical val (10%)			16.38
Underidentification statistic			9.756
Chi-sq(1) P-val			0.0018

Notes: The first column displays the regression results for the OLS specification, the second one for the first-stage of the 2SLS and the last column for the second-stage. Variables are detrended using an HP filter (w = 1600 for quarterly data). Underidentification test corresponds to Kleibergen-Paap rk LM and weak identification test to Kleibergen-Paap rk Wald F statistic. Robust standard errors (controlling for heteroskedasticity and autocorrelation) are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

The results from the first stage indicate that a decline of 1% in the share of advertisement revenues increases the partisan conflict index by the same amount. The Kleibergen-Paap rk Wald F statistic is 20.474, above the Stock-Yogo weak ID test critical value of 16.38, indicates that this is not a weak instrument. The p-value for the Kleibergen-Paap rk LM statistic is 0.0018, allowing us to reject the null hypothesis of underidentification. The endogeneity test result confirms that OLS estimates suffered from endogeneity bias.

The 2SLS estimate of the effect on private investment induced by partisan conflict is −0.34, and statistically significant. A 10 percent increase in the PCI results in a 3.4% decline in investment. The standard errors have been corrected for heteroskedasticiy and autocorrelation. Notice that the IV estimate of the effects of partisan conflict on investment is much larger than the OLS estimator. This suggests that endogeneity may be significantly biasing the OLS estimation.

Robustness The results are robust to alternative specifications of partisan conflict, such as non-seasonally adjusted PCI and an alternative measure where newspaper counts are normalized by the total number of articles in a given period. The results are summarized in Table 3, which only displays second stage estimation results for readability. The first column replicates the findings of Table 2 for our benchmark case (see eq. 11), where I use the seasonally adjusted and de-trended PCI (in logs) as the main dependent variable. The second column, denoted by $\hat{P}CI_{sa}$, relaxes the log-assumption by using the raw measure of seasonally adjusted PCI. The value of the coefficient is different. But since PCI is normalized to 100 in 1990, we can see that the size of the effect is similar and still statistically significant (even after controlling for autocorrelation and heteroskedasticity). The third column, $\log(\hat{P}CI)$, uses the non-seasonally adjusted (although still de-trended using an HP-filter) PCI in logs. The coefficient is virtually unchanged. In the fourth column, $\log(\hat{P}CI_n)$, I use an alternative measure for the PCI where I normalize the number of articles on partisan conflict by the total number of articles that include the word 'the' in a given month (hence, the denominator includes *all* the articles published in a given month). This is in contrast to the benchmark variable, which normalizes the number of articles by those including the word 'today.' The effect is significantly larger, as a 10% increase in PCI is associated with a 4.3 % decline in private investment, but the instrument is weaker as seen form the smaller value of the Kleibergen-Paap Wald F-test statistic (under 'weak identification stat' in the table).

Table 5: Robustness

Dependent var.=log $\hat{I}_t$	$\log(\hat{P}CI_{sa})$	$\hat{P}CI_{sa}$	$\log(\hat{P}CI)$	$\log(\hat{P}CI_n)$
Partisan Conflict Index	-0.34***	-0.0032***	-0.35***	-0.43**
	(0.10)	(0.001)	(0.12)	(0.184)
2SLS Tests:				
Weak Identification stat	20.5	10.3	12.3	7.8
Underidentification stat	9.8	3.9	6.7	5.3
Chi-sq(1) P-val	0.002	0.05	0.001	0.021

Notes: Estimation results from the second stage of the 2SLS regressions. First column corresponds to the benchmark measure (see eq.11). Second column corresponds to non-log SA $\hat{P}CI$, while the third uses the non-seasonally adjusted series (in logs). The fourth column uses an alternative measure of de-trended PCI (in logs, non-SA); $\hat{P}CI_n$ is normalized by the total number of news (rather than by those including the word today). Variables are detrended using an HP filter (w = 1600 for quarterly data). Underidentification test corresponds to Kleibergen-Paap rk LM and weak identification test to Kleibergen-Paap rk Wald F statistic. Robust standard errors (controlling for heteroskedasticity and autocorrelation) are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Finally, the results presented in Table 2 are also robust to the introduction of an indicator variable for elections (midterm and/or presidential), and to including a dummy variable indicating that a Democratic President is in power (results omitted, but available upon request from the author). Given the short time-span covered in the sample, there was too little variability in these dummy variables to render them statistically significant. Summarizing, the results seem to be robust to a set of sensible modifications of the benchmark model.

5.4 Firm-level Data Approach

In this section, I exploit the heterogeneity of US publicly traded firms to study the effects of partisan conflict on private investment. To do so, I use a panel of Compustat firms with quarterly data over the period 1985:Q1-2015:Q1. I consider two alternative identification strategies. In the first one, firms are differentiated by their ex-ante exposure to government demand of goods and services, a measure obtained from Belo, Gala, and Li (2013). Their measure is computed using detailed industry level data from the NIPA input-output accounts. Firms which are more exposed to government spending are expected to have lower investment rates when partisan conflict is high (but moderate) through the uncertainty channel. This exercise, in the spirit of Baker, Bloom, and Davis (2015), yields better causal identification than what was presented in previous sections using aggregate investment levels. However, the level of exposure is obtained only at the industry level (i.e., three digit SIC codes) for a specific group of publicly traded companies, making the result less general.

The second identification strategy differentiates firms by their individual contributions to U.S. political campaigns, using an index constructed by Cooper, Gulen, and Ovtchinnikov (2010). These authors showed that firms which devote a larger share of revenues to campaign contributions tend to have abnormal future returns, in particular if the candidates supported hold office in the same state in which the firm is located. We should expect firms that donate more through PACs to have a larger response to innovations to the PCI, as potential gridlock makes it less likely to receive political favors from the candidates supported. A benefit of Cooper, Gulen, and Ovtchinnikov (2010)' contribution index is that it is firm specific (rather than industry specific), but it involves a smaller number of firms than the one used in the first exercise.[29]

Data Firm-level data is obtained from Compustat for the period 1985:Q1-2015:Q1. I exclude all financial firms (SIC codes between 6000 and 6999), utilities (SIC codes between 4900-4999), and government entities (SIC codes greater than or equal than 9000). The capital stock of firm i, K_{it} is measured using net property, plant and equipment (corresponding to PPENTQ in Compustat) in quarter t, whereas investment I_{it} is measured by the growth rate of capital. This is a normalized measure of net investment (i.e. gross investment minus depreciation). Firms' sales are measured by SALEQ in Compustat. All nominal values are converted to 2009-dollars using the quarterly GDP deflator obtained from FRED. Variables expressed in Canadian dollars, i.e. those with CURCDQ=CAD, are converted to US dollars using quarterly exchange rates also obtained from FRED. Firm-quarters with missing or negative PPENT data are excluded.

Investment rates I/K are computed as the ratio between investment in quarter t and

[29] I would like to thank Itay Goldstein for productive conversations leading to this identification strategy.

capital in quarter $t-1$.[30] To limit the impact of outliers and potential data errors, I exclude investment rates that are lower than the 1st percentile or larger than the 99th percentile of the whole sample. This results in 479,620 firm-quarter observations. The investment rate of the median firm is about 3% per quarter in the sample.

Government exposure The first approach differentiates firms by their exposure to government spending. I use Belo, Gala, and Li (2013)'s exposure measure, defined as the proportion of each industry's total output that is purchased directly by the government sector (federal plus state and local), as well as indirectly through the chain of economic links across industries. Indirect effects arise form the fact that in order for a specific sector to make a sale to the government, it uses inputs from other sectors. The authors compute indirect governments spending effects using the Leontief inverse. I use the average exposure over time for each 3-digit SIC industry to construct the variable Exp_i. Even though most of the government exposure is concentrated at low levels, some industries rely heavily on the sales to the government sector. For example, Radio and Television Broadcasting (SIC 483)'s exposure is about 72 %, followed by Ordnance and Accessories (SIC 348) at 66% and Search and Navigation Equipment (SIC 381) at 58%. These industries have also been identified as highly exposed to government policy by Baker, Bloom, and Davis (2015) using data on federal contracts and Nekarda and Ramey (2011) using an alternative measure derived from NIPA accounts.

Table 6 displays the results for the estimated effects on firms' investment rates of the natural logarithm of partisan conflict interacted with the measure of exposure, $\ln(PCI_t) \times Exp_i$. I control for unobserved characteristics of the firm with firm fixed-effects, as well as unobserved common factors that change over time, with time fixed-effects. The estimated coefficient of -0.0608 indicates for the median firm in the sample, which sells 17% of its output to the government, a 1% increase in partisan conflict is associated with a decline of 0.0103 in their investment rate (computed as -0.0608×0.17).[31] Given that the investment rate of the median firm is 3.4%, a one percent increase in partisan conflict is associated with a 0.3 percent decline in investment (computed as $0.0103/3.4 \times 100$). To put this number in perspective, notice that $\ln(PCI)$ was 4.42 in 2007 and reached 4.97 in 2011. This 55 log point increase, according to the estimation, would have been associated with a 16% decline in investment rates for the median firm.

The second specification in the table considers the effects of investors beliefs' about partisan conflict, rather than the current observation of the signal $\bar{s}_t$, as an independent variable. In the theoretical model, an investor enters the period with a belief about partisan conflict equal to $\hat{c}_{t-1}$. After observing the average signal $\bar{s}_t$, investors update their beliefs according to $\hat{c}_t(\bar{s}_t) = \omega_t \bar{s}_t + (1-\omega_t)\hat{c}_{t-1}$. Their posterior is then a weighted sum between the prior mean $\hat{c}_{t-1}$ and the sample mean $\bar{s}_t$. Given that PCI_t is the empirical counterpart of $\bar{s}_t$, we can use the recursion of the previous equation to compute an empirical counterpart of investors'

[30]Quarter t corresponds to the calendar quarter rather than the fiscal quarter. This is done for consistency with PCI measures.

[31]Median firm is defined as the firm in the third quintile of total deflated sales over the time period.

Table 6: Panel regression with firm fixed-effects and time fixed-effects

Dep. Var.: I/K_{it}	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(PCI_t) \times Exp_i$	-0.0608**					
	(0.0300)					
$\overline{\ln(PCI_t)} \times Exp_i$		-0.0767***	-0.0748**			
		(0.0287)	(0.0275)			
$\ln(PCI_t) \times Cont_i$				-0.00419***		
				(0.00136)		
$\overline{\ln(PCI_t)} \times Cont_i$					-0.00539***	-0.0048***
					(0.00174)	(0.0014)
Observations	432,540	432,540	432,540	35,041	35,041	35,041
Number of firms	11,991	11,991	11,991	661	661	661
EPU	No	No	Yes	No	No	Yes

Notes: The sample period is 1985:Q1-2015:Q1. The dependent variable is the the investment rate I/K of firm i in quarter t. Capital K_{it} is measured with (Net) Property, Plant, and Equipment and investment I_{it} with the change in this variable. The investment rate is defined by I_{it}/K_{it-1}. The independent variables in specification (1) are the natural log of PCI, $\ln(PCI_t)$ interacted with firm exposure Exp_i, firm-fixed-effects and time-fixed effects. Specification (2) considers the empirical counterpart of beliefs $\overline{\ln(PCI_t)}$, computed as the moving average of PCI between elections, interacted with firm exposure. Specification (3) controls for EPU, by interacting $\ln EPU \times Exp_i$. Specifications (4), (5), and (6) are similar to (1), (2), and (3), but considering the interaction between partisan conflict and political contributions instead. All regressions are weighted by average sales of the firm during the sample period. Standard errors are clustered by firm and corrected for heteroscedasticity and autocorrelation; they are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

beliefs $\hat{c}_t$ at date t, which I will denote by $\overline{PCI_t}$, as follows

$$\overline{PCI_t} = \sum_{l=0}^{L} \frac{PCI_{t-l}}{L},$$

where L is the date of the last election.[32] The posterior belief $\overline{PCI_t}$ thus corresponds to the moving average of the partisan conflict index between elections (either midterm or presidential) in the data. For consistency, I will use the moving average of the natural logarithm of PCI instead, $\overline{\ln(PCI_t)}$. The result is presented in the second column of Table 6. The estimated coefficient is still negative and statistically significant. Moreover, a one percent increase in beliefs about partisan conflict has a stronger effect on investment decisions, -0.0767, than a one percent increase in the index itself. The third specification controls for economic policy uncertainty by including the interaction between the natural logarithm of EPU and firm's exposure to government spending Exp_i in a specification similar to (2). The estimated effect of PCI is basically unchanged.

[32] I would like to thank an anonymous referee for this suggestion.

Political contributions In the second identification strategy, publicly traded firms are differentiated by their political contribution practices. I use a contribution index developed by Cooper, Gulen, and Ovtchinnikov (2010), who collect data from the U.S. Federal Election Commission (FEC) to create contributions to political campaigns in the U.S made by corporations through their corporate political action committees (PACs). Under the assumption that firms support a portfolio of candidates on presidential and mid-term elections, it is possible to sum up, over a rolling multiyear window, the number of candidates that each firm supports. Because the ability of the candidate to actually help a particular firm through policy depends on other factors, the index only includes candidates that hold office in the same state in which the firm is headquartered, and it is adjusted by the candidate's strength. In particular, letting $Cont_{it}$ denote the contribution index in period t, we have that

$$Cont_{it} = \sum_{j=1}^{J} I_{jt} \times \frac{NVC_{jt}}{NOV_{jt}} \times H_{jt,t-5},$$

where I_{jt} is a dummy variable that equals one if candidate j is in office at time t, and zero otherwise; NVC_{jt} denotes the number of votes that candidate j's party holds in office at time t whereas NOV_{jt} is the number of votes that candidate j's opposing party holds in office at time t. Hence, the ratio $\frac{NVC_{jt}}{NOV_{jt}}$ reflects the party's strength relative to the opposition. Finally, $H_{jt,t-1}$ is an indicator variable that equals one if candidate j is running for office from the state in which firm i is headquartered and zero otherwise. The variable J denotes the total number of candidates that receive contributions from firm i. The authors compute this index for a series of presidential and mid-term elections between 1984 and 2004. In the estimation, I focus on the *average* value of the index over this interval of time, $Cont_i = \sum_t Cont_{it}$ so it it time-independent. This variable is interacted with the partisan conflict index. Intuitively, firms with high average contribution indexes are relatively more affected by political gridlock, as the ability of the candidates they support to enact favorable policies is lower. Therefore, we expect the coefficient on $\ln(PCI_t) \times Exp_i$ to be negative.

The fourth column of Table 6 reports the coefficient of $\ln(PCI_t) \times Exp_i$, controlling for firm fixed-effects and time fixed-effects (this is a specification equivalent to the one in column (1), but considering contributions rather than exposure to government spending). The number of observations is much smaller than in the previous section for two reasons. First, because the sample period under consideration is restricted to coincide with the period in which the contribution index is computed, namely 1985:Q1 to 2004:Q4. Second, because only about 9% of Compustat firms engage in contributions through PACs. As a result, the sample consists of only 661 firms and 35,041 firm-quarter observations (relative to 11,991 firms and 432,450 firm-quarter observations in the previous specification). These firms have slightly different characteristics: they tend to be significantly larger (average sales are three times larger) and have lower investment rates (median investment rates are 2.4% versus 3.4% before). The estimated coefficient is negative and significant. Considering that the median firm (measured in terms of sales) in this sample has a contribution index of 2.6, a one percent increase in the partisan conflict index is associated with a decline in the investment rate of $-0.0109 = -0.00419 \times 2.6$. This number is slightly below the one computed when firms were differentiated by their exposure to government spending, but because the investment rate is actually smaller, it corresponds to a 0.45 percent change in the investment rate of the median firm ($0.45 = -0.0109/2.4 \times 100$). The fifth column re-computes Specification (4) but using expected partisan conflict instead of the PCI interacted with the firms' contribution index. This specification is analogous to the one estimated in column (2). As in the previous case, the resulting coefficient -0.00539 is larger, indicating that a one percent increase in expectations about partisan conflict discourages investment even more than a one percent increase in PCI. Notice that the last two specifications are estimated in a period that precedes the Great Recession (e.g. it ends in 2004). This is reassuring, as the effects of news about political discord identified in this paper are not just driven by abnormal trends taking place during the Great Recession. Finally, the last column controls for EPU by including the interaction between $\ln EPU$ and the contribution index $Cont_i$. The negative and statistically significant coefficient on PCI indicates that the findings are not confounding the effects of the EPU indicator.

6 Conclusion and extensions

This paper investigates whether news about partisan conflict negatively affect private investment. I first present a very simple model to illustrate how investors expectations are affected by news about political discord. I then develop an index of partisan conflict based on a semantic-search approach on newspaper articles. I show that the indicator has a plausible behavior, as it is consistent with that of other variables determining the political process (such as polarization and political power), as well as trends in media coverage, and short-term shocks that are expected to affect true partisan conflict. Using historical data (e.g. 1929 to 2013), I show that the index is negatively associated with real aggregate investment in the US. Taking advantage of the high-frequency at which the measure is constructed, I show that higher values of the index are also associated with lower levels of durable goods orders, a widely used proxy for private investment at the monthly frequency. I also estimate the effect of reported partisan conflict on aggregate private investment, both using a simple OLS estimation and an instrumental variables approach. Using the latter, I estimate that a 10% increase in the PCI is associated with a decline of 3.4% in investment. Finally, I show that innovations to the PCI result in lower investment rates at the firm level.

This is a first step towards understanding the effects of political disagreement on the economy, and as such it could be improved in several dimensions. First, the index only considers the frequency of articles reporting political discord but ignores the intensity and relevance of alternative news articles. Second, the analysis makes exclusive use of newspapers, ignoring other sources of news such as cable TV or internet outlets. It may be interesting to study the effect of these alternative sources of information, particularly social media, on investors' expectations in future work. Analyzing the effects of partisan conflict on the US budget cycle (following Alt and Lassen, 2006) or its effects on the composition of durable and nondurable consumption (as in Canes-Wrone and Ponce de Leon, 2014) could also be interesting extensions to this work. Finally, because I wanted to focus on how political disagreement affects investment, the dynamics in partisan conflict is completely exogenous. It would be interesting to model the political game determining partisan conflict more formally.

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7 Appendix

7.1 Posterior Distribution Derivation

Suppose that we observe n signals $s = \{s_1, ..., s_n\}$, which are mutually independent given c, and $s_i \sim exp(c)$. Then, the likelihood is

$$\begin{aligned} L(c|s) &= \prod_{i=1}^{n} \frac{1}{c} e^{-\frac{s_i}{c}} \\ &= \frac{1}{c^n} e^{-\frac{n\bar{s}}{c}}, \end{aligned}$$

where $\bar{s} = \frac{1}{n}\sum_{i=1}^{n} s_i$. A conjugate inverse gamma prior $IG(\alpha, \beta)$ has pdf

$$f(c) = \frac{\beta^{\alpha} c^{-\alpha-1} e^{-\frac{\beta}{c}}}{\Gamma(\alpha)} \qquad x > 0,$$

where $\Gamma(\alpha)$ denotes the Gamma function. By Bayes' rule,

$$\begin{aligned} p(c|s) &\propto p(s|c)p(c) \\ &\propto c^{-\alpha-1} e^{-\frac{\beta}{c}} \frac{1}{c^n} e^{-\frac{n\bar{s}}{c}} \\ &\propto c^{-(\alpha+n)-1} e^{-\frac{\beta+n\bar{s}}{c}} \\ &\sim IG(\alpha+n, \beta+n\bar{s}). \end{aligned}$$

Let $\hat{\alpha}_0 = \alpha_0$ and $\hat{\beta}_0 = \beta_0$. Then, the posterior parameters evolve according to

$$\alpha_t = \alpha_{t-1} + n \qquad \text{and} \qquad \beta_t = \beta_{t-1} + n\bar{s}_t.$$

To compute the mean and the variance of c, note that

$$\begin{aligned} E(c^k) &= \int_0^{\infty} c^k \frac{\beta^{\alpha} c^{-\alpha-1} e^{-\frac{\beta}{c}}}{\Gamma(\alpha)} dc \\ &= \frac{\beta^{\alpha}}{\Gamma(\alpha)} \int_0^{\infty} c^{k-\alpha-1} e^{-\frac{\beta}{c}} dc \\ &= \frac{\beta^{\alpha}}{\Gamma(\alpha)} \frac{\Gamma(\alpha-k)}{\beta^{\alpha-k}} \int_0^{\infty} \beta^{\alpha-k} c^{-(\alpha-k)-1} \frac{e^{-\frac{\beta}{c}}}{\Gamma(\alpha-k)} dc \\ &= \beta^k \frac{\Gamma(\alpha-k)}{\Gamma(\alpha)} = \beta^k \frac{\Gamma(\alpha-k)}{(\alpha-1)....(\alpha-k)\Gamma(\alpha-k)} \\ &= \frac{\beta^k}{(\alpha-1)....(\alpha-k)}. \end{aligned}$$

This implies that

$$E(c) = \frac{\beta}{\alpha-1},$$

$$E(c^2) = \frac{\beta^2}{(\alpha-1)(\alpha-2)}.$$

Hence, the variance is

$$Var(c) = E(c^2) - [E(c)]^2 = \frac{\beta^2}{(\alpha-1)^2(\alpha-2)}.$$

7.2 Proof Lemma 3.2

Lemma 7.1 *The variance of government policy,*

$$Var(x(c_t)) = Var\left(-\log(\epsilon + \theta e^{-\frac{1}{c_t}})\right), \tag{13}$$

is approximately equal to

$$Var(x(c_t)) \simeq \frac{\theta^2}{(\alpha_0 + tn - 2)} \frac{e^{-\frac{2}{\hat{c}_t}}}{\left(\epsilon + \theta e^{-\frac{1}{\hat{c}_t}}\right)^2 \hat{c}_t^2}, \tag{14}$$

where $\hat{c}_t$ denotes the posterior mean of partisan conflict, $\hat{c}_t = E(c_t)$.

Proof 7.1 *A Taylor series expansion of $x(c_t)$ gives the approximation*

$$x(c_t) \simeq x(\hat{c}_t) + x'(\hat{c}_t)[c_t - \hat{c}_t].$$

Taking the variance of both sides yields:

$$Var(x(c_t)) \simeq \left[x'(\hat{c}_t)\right]^2 Var(\hat{c}_t). \tag{15}$$

We can compute $x'(\hat{c}_t)$ by taking the derivative of $x(\hat{c}_t) = -\log(\epsilon + \theta e^{-\frac{1}{c_t}})$,

$$x'(\hat{c}_t) = -\frac{\theta e^{-\frac{1}{\hat{c}_t}}}{\epsilon + \theta e^{-\frac{1}{\hat{c}_t}}} \frac{1}{\hat{c}_t^2}. \tag{16}$$

Replacing eq. (5) and eq.(16) into eq. (15) yields expression 14. *Q.E.D.*

Using Lemma 7.1, we can see that

$$\frac{\partial Var(x(c_t))}{\partial \hat{c}_t} \simeq \frac{2\theta^2 e^{-\frac{2}{\hat{c}_t}}}{(\alpha_0 + tn - 2)\left(\epsilon + \theta e^{-\frac{1}{\hat{c}_t}}\right)^3 \hat{c}_t^4} \left[\epsilon - \hat{c}_t\left(\epsilon + \theta e^{-\frac{1}{\hat{c}_t}}\right)\right].$$

Let ς denote the solution to

$$\epsilon - \varsigma\left(\epsilon + \theta e^{-\frac{1}{\varsigma}}\right) = 0.$$

Then,

$$\frac{\partial Var(x(c_t))}{\partial \hat{c}_t} \begin{cases} \geq 0 & \text{if} \quad \hat{c}_t \leq \varsigma \\ < 0 & \text{if} \quad \hat{c}_t > \varsigma \end{cases}.$$

Q.E.D.

7.3 Proof to Proposition 3.1

Agents choose $I = 1$ as long as

$$E\left[\frac{1}{a}\left(1 - e^{-ar}\right)\right] \geq f.$$

The cutoff value $f_c(\bar{s})$ is defined by the level of fixed costs at which the equation above holds with equality.

$$f_c(\bar{s}) = E\left[\frac{1}{a}\left(1 - e^{-ar}\right)\right] = \frac{1}{a}\left(1 - E\left[e^{-a(z+\nu)}\right]\right),$$

where

$$E\left[e^{-a(z+\nu)}\right] = E\left[e^{-a\nu}e^{-az}\right] = \left(\hat{p}(\bar{s})e^{-a\log(1-\kappa)} + 1 - \hat{p}(\bar{s})\right) E\left[e^{-az}\right],$$

since $\nu = 0$ with probability $1 - \hat{p}(\bar{s})$ and using the assumption that economic z and political shocks s_i are independent.

Because $z \sim N(\mu, \sigma^2)$, we obtain

$$E\left[e^{-az}\right] = e^{-a(2\mu - a\sigma^2)/2},$$

which completes the derivation of $f_c(\bar{s})$. To obtain an expression for $\hat{p}(\bar{s})$, recall that

$$p(c) = \frac{1}{m}\left(\epsilon + \theta e^{-\frac{1}{c}}\right).$$

At the time of making an investment decision, agents do not know the true value of c. Their information set consists of a prior $\hat{\beta}_{t-1}$ and $\hat{\alpha}_{t-1}$, and a set of signals $\{s_t^i\}_{i=1}^n$. Given the signals, agents update their priors so that $\hat{\alpha}_t = \hat{\alpha}_{t-1} + n$ and $\hat{\beta}_t = \hat{\beta}_{t-1} + n\bar{s}_t$, with $\bar{s}_t = \sum_i s_t^i$. Moreover, they know that c is distributed according to an $IG(\hat{\alpha}_t, \hat{\beta}_t)$. Given this distribution, their best guess for the probability of a rare event is

$$\hat{p}(\bar{s}) = E[p(c)|\hat{\alpha}_t, \hat{\beta}_t] = E\left[\frac{1}{m}\left(\epsilon + \theta e^{-\frac{1}{c}}\right)|\hat{\alpha}_t, \hat{\beta}_t\right],$$

Using the fact that $c \sim IG(\hat{\alpha}_t, \hat{\beta}_t)$, we obtain

$$\hat{p}(\bar{s}) = \int_0^\infty \frac{1}{m}\left(\epsilon + \theta e^{-\frac{1}{c}}\right) \frac{\hat{\beta}_t^{\hat{\alpha}_t} e^{-\frac{\hat{\beta}_t}{c}} c^{-\hat{\alpha}_t - 1}}{\Gamma(\hat{\alpha}_t)} dc,$$

where $\Gamma(\hat{\alpha}_t)$ denotes the Gamma function, $\Gamma(\alpha) = \int_0^\infty x^{\alpha-1}e^{-x}\,dx$. This is equivalent to

$$\hat{p}(\bar{s}) = \frac{1}{m}\epsilon + \frac{1}{m}\theta \int_0^\infty e^{-\frac{1}{c}} \frac{\hat{\beta}_t^{\hat{\alpha}_t} e^{-\frac{\hat{\beta}_t}{c}} c^{-\hat{\alpha}_t - 1}}{\Gamma(\hat{\alpha}_t)} dc,$$

Multiplying and dividing by $\tilde{\beta}^{\hat{\alpha}_t}$, where $\tilde{\beta}_t = 1 + \hat{\beta}_t$, and re-arranging, we obtain

$$\begin{aligned}
\hat{p}(\bar{s}) &= \frac{1}{m}\epsilon + \frac{1}{m}\theta \frac{\hat{\beta}_t^{\hat{\alpha}_t}}{(1+\hat{\beta}_t)^{\hat{\alpha}_t}} \underbrace{\int_0^\infty \frac{\tilde{\beta}_t^{\hat{\alpha}_t} e^{-\frac{\tilde{\beta}_t}{c}} c^{-\tilde{\alpha}_t - 1}}{\Gamma(\tilde{\alpha})} dc}_{=1} \\
&= \frac{1}{m}\left(\epsilon + \theta \frac{\hat{\beta}_t^{\hat{\alpha}_t}}{(1+\hat{\beta}_t)^{\hat{\alpha}_t}}\right).
\end{aligned}$$

Q.E.D.

7.4 Sources

Table 7: Newspaper coverage in Factiva

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

Note: This table contains the names of the main US newspapers used in constructing the partisan conflict index, together with the coverage start month in Factiva's database.

The top news sources are The Washington Post, Los Angeles Times, The New York Times, Chicago Tribune, Newsday, Dallas Morning News, The Boston Globe, Tampa Bay Times, and The Wall Street Journal (see Figure 18 for a decomposition).

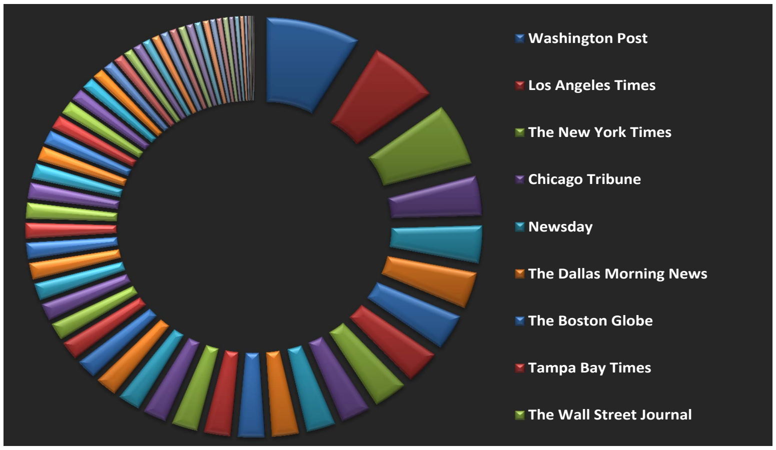

Figure 18: Percentage of news searches in which these subjects are mentioned over the sample.

7.5 Filters

NADVTR	Advertorials	GLIFE	Lifestyle
NEDC	Commentary/opinion	GROYAL	Royal Family
NCOPRO	Country Profile	GCOM	Society/Community/Work
NEDI	Editorial	GWEA	Weather
NITV	Tv listings	NRGN	Routine general news
NLET	Letters	E52	Eurozone currency news
NOBT	Obituaries	GRAPE	Rape
NPEO	People profiles	GJURI	Juri
NPAN	Personal announcements	gdoga	Dog attacks
NRAN	Rankings	gdomv	Domestic violence
NRVW	Reviews	ghara	Harrassment
GSPO	Sports	gprob	Probation
GENT	Entertainment	gtrff	Traffic violations
GAWARD	Awards/Lotteries	gvand	Vandalism

In addition, news items are restricted to at least 200 words. In addition, I exclude editorials and commentaries from the search in an attempt to reduce potential ideological biases (see the work by Gentzkow and Shapiro, 2010, on media slant).

7.6 Boolean Search Query

The exact Boolean search query used in Factiva follows:

((standstill OR stalemat* OR gridlock OR disagree* OR ((fail to OR cannot) /n2/ comprom*) OR polariz* OR dysfunc* OR ideol* differ* OR deadlock* OR budg* w/3 (battle OR fight) OR filibust* OR standoff OR veto* OR (delay OR oppos*) /N4/ bill) AND (white house OR senate OR senator OR Capitol OR congress* OR party OR partisan OR republican* OR GOP OR democrat* OR politic* OR legislat* OR lawmake* OR the president OR ((appropr* OR

finance OR ways w/2 means) /N2/ committee) OR feder* gov*) OR ((divided OR division*) /n5/ (partisan OR congress* OR party))) AND wc>200

Where the operators work as follows:

- *AND*: Retrieves documents containing both terms.
- *OR*: Retrieves documents containing one or more terms.
- *nn*: Links terms based on specified number of words from each other. Words may appear in either order. Example *football /n5/ injury.*
- *w/n*: Links terms based on specified number of words from each other. Terms must appear in order indicated. Example *football w/3 injury.*
- *: Used at the end of a word string. Example *labo** retrieves labor, labour, laboratory.

Finally, *wc* determines the number of words included in the article. In addition, I apply other exclusions and filters, as detailed in the main text.

7.7 A representative article

Tampa Bay Times

POLITIFACT
BUSINESS

SHUTDOWN CAUSED SOME CEOS TO DELAY HIRING FOR SIX MONTHS

JULIE KLIEGMAN

Times Staff Writer
473 words
27 October 2013
Tampa Bay Times
STPT
SOUTH PINELLAS
2D
English

The statement

"Half of all CEOs say that the shutdown and the threat of shutdown set back their plans to hire over the next six months."

President Barack Obama, Oct. 17 in a public address

* * *

The ruling: MOSTLY TRUE

The White House pointed us to a recent Business Roundtable survey.

"Fifty percent of responding CEOs indicated that the ongoing **disagreement** in **Washington** over the 2014 budget and the **debt ceiling** is having a negative impact on their plans for hiring additional employees over the next six months," the report reads.

On its face, that's in line with what Obama said, but we wanted to see how Business Roundtable acquired its results. Their report notes, "Responses were received from 134 member CEOs, 63 percent of the total Business Roundtable membership."

Business Roundtable's membership tends to be larger companies. Spokeswoman Amanda DeBard told us CEOs are invited based on revenue, industry and market capitalization, so it's safe to say the poll responses don't reflect a random sample of U.S. businesses.

7.8 Robustness to the set of words

In this subsection, I analyze whether the PC indicator is robust to restricting the search to involve specific terms related to fiscal policy. The article search focuses on political disagreement, without being specific about particular policy terms. For a robustness check, I recomputed the historical index conditioning articles to involve specific public policies. The index is computed using articles containing at least one word at the intersection of the following three categories: (i) political disagreement, (ii) government, and (iii) public policy.

The terms involved in the first two categories are identical to the ones used to construct the historical index. The list of terms used in the third category can be found below.[33]

On average, these articles correspond to about 60% of the total number of counts obtained in the original search, with the ratio increasing to over 76% since 2006.

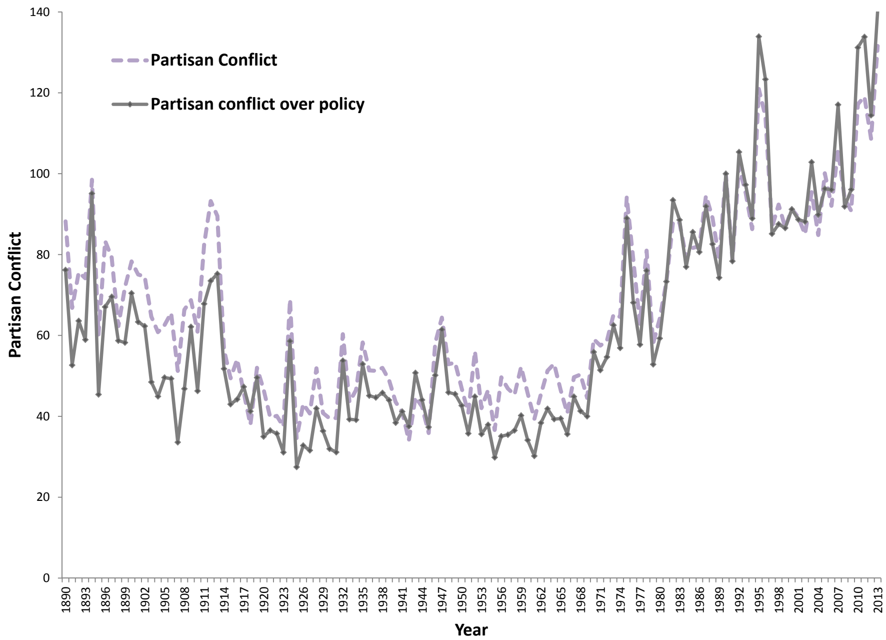

Figure 19: Partisan conflict: historical series (dashed) vs. partisan conflict over specific policies (solid).

The resulting index (computed following the methodology described in Section 4.1), *Partisan conflict over policies*, can be found together with the historical series in Figure 19. When conditioning the search to contain specific policy terms, the resulting index is on average lower than the historical one until about 1968, year after which the two series become virtually identical. This is consistent with the observation that race and religion (rather than wealth) were the dominant determinants of political ideology before the 1970s. For example, the policy terms listed above do not capture terms related to the debate on voting participation that lead to the Voting Rights Act of 1965.

Keywords The list of terms used in the robustness check are summarized below.

- **Govt policy**: tax (taxation, taxes, taxed), tariff, fiscal stimulus, health care, social security, debt ceiling (or limit), welfare, Medicare, Medicaid, part d, affordable care act,

[33]The list includes all the policy terms used in Baker et.al. (2015), plus the following additional terms: tax (taxation, taxes, taxed), budget, war, constitutional amendment, immigration, sovereign debt, monometallist, bimetallist, (silver or gold) coinage, duty (or duties), alcohol (or liquor) prohibition, federal credit, grant in aid, commerce competition, and commerce clause.

food stamps, AFDC, tanf, oasdi, earned income tax credit, EITC, public assistance, nutritional assistant program, head start program, entitlement program, wic program, government subsidies, deficit, budget, national (federal or sovereign) debt, government policy, public policy, government spending (or expenditures), entitlement spending (or expenditures), unemployment insurance (or benefits), disability insurance (or benefits), health insurance (or benefits), medical insurance reform, constitutional reform, welfare reform, duty (or duties).

- **Regulation**: prescription drugs, drug policy, food and drug admin, FDA, Gramm-Rudman, Bank supervision, thrift supervision, malpractice reform, constitutional reform, financial reform, medical insurance reform, welfare reform, tort reform, constitutional amendment, Glass-Steagall, Dodd-Frank, housing financial services committee, capital requirement, security exchange commission, sec, deposit insurance, fdic, fslic, ots, occ, firrea, truth in lending, monometallist, bimetallist, (silver or gold) coinage, alcohol (or liquor) prohibition.

- **Labor**: minimum (or living) wage, union rights, card check, national labor rel. board, nlrb, collective bargaining, right to work, closed shop, worker compensation, maximum hours, wages and hours, advanced notice requirement, affirmative action, overtime requirements, at-will employment, Davis-Bacon, equal employment opportunity, eeo, osha, immigration.

- **Competition**: monopoly, patent, copyright law, federal trade commission, ftc, unfair business practice, cartel, competition law, price fixing, price discrimination, class action, antitrust, merger policy, competition policy, commerce competition, and commerce clause..

- **Environment**: carbon tax cap and trade, pollution controls, environmental restrictions, clean air act, clean water act, energy policy, drill* restrict*.

- **Trade**: dumping, trade policy (act, agreement, or treaty), duty (or duties), import tariff (or barrier).

- **Defense**: national security, military invasion (conflict, embargo, or procurement), war, armed forces, police action, base closure, saber rattling, naval blockade, no-fly zone, defense spending (or expenditures), military spending (or expenditures).

7.9 Partisan Conflict and Income inequality

Another variable frequently associated with political disagreement is income inequality. When income is unequally distributed, disagreement over redistributive policy is likely to arise in a democratic society, intensifying partisan conflict. Figure 20 shows that the evolution of partisan conflict is remarkably similar to that of income inequality, proxied by the share of income held by the top 1%, in the postwar period. The increase in inequality observed since the late 1960s may be an important determinant of the rising trend in partisan conflict. This is consistent with McCarty, Poole, and Rosenthal (2003), who show that partisanship became more stratified by income between 1956 and 1996. Prior to this period, according to the authors, race and religion (rather than income and wealth) were the dominant determinants of political ideology.

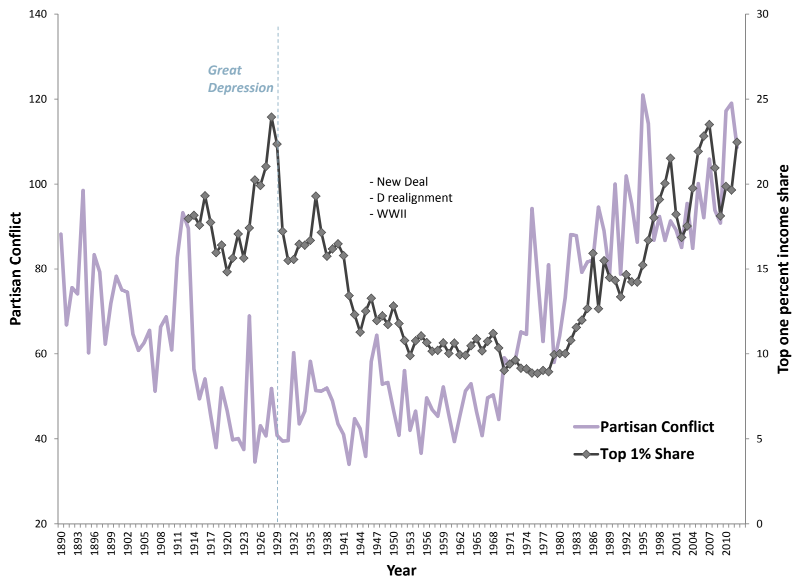

Figure 20: Historical partisan conflict and income inequality, 1944-2012.

Notes: Income inequality measured by the share of income held by the top 1%, from Alvaredo, Atkinson, Piketty, and Saez's dataset. Data downloaded from *http://topincomes.parisschoolofeconomics.eu/*.

In an attempt to estimate the effect of income inequality on HPC, I augmented Specification (2) to include the first difference in the trend component of inequality $\Delta Top1\%_c$, lagged one period. The variable was, however, statistically insignificant. Including two-period or three-period lags did not change this finding (results are omitted but available upon request). An issue with this approach that causality cannot be established, as argued by McCarty, Poole, and Rosenthal (2006). According to the authors, political disagreement can also affect income inequality by hampering support for redistributive policies. This view is supported by the behavior of partisan conflict and inequality in the late 1920s. Figure 20 shows that income inequality peaks right before the Great Depression, but exhibits a declining trend starting in 1929. Initially, inequality lowers due to the erosion of wealth in the top percentiles following the stock market crash. In addition, corporate taxes were raised and the top-bracket tax rate was increased from 25% to 63% under Hoover's presidency. This resulted in further reductions in the share of income held by the top 1%. From 1933 onwards, the size of the welfare state was expanded to unprecedented levels in US history under the New Deal. Interestingly, these novel redistributive policies were approved in a period of unusually low levels of partisan conflict. PC scores were low for two reasons. First, polarization declined sharply during the 74th Congress (e.g., between 1935 to 1937) under Roosevelt's presidency (see Figure 8). Second, both chambers had a Democratic supermajority.

We conclude that the relationship between the trend observed in partisan conflict and that of inequality is not coincidental. Low levels of partisan conflict ease the implementation of policies that reduce inequality, while low inequality creates incentives for parties to move toward the center. An example of the latter is given by the Democratic realignment that resulted from the New Deal. See Musto and Yilmaz (2003) for an interesting exploration of the relationship between inequality and voting outcomes and Vlaicu (2014) for a theoretical model explaining how inequality may shape polarization.

7.10 Gallup and partisan conflict

Figure 21 depicts the PC index (left axis) together with the disapproval ratings (right axis), a series collected by Gallup in which respondents are asked, "Do you approve or disapprove of the way Congress is handling its job?" The shaded area represents the percentage of surveyed people who disapprove of Congress's actions.[34]

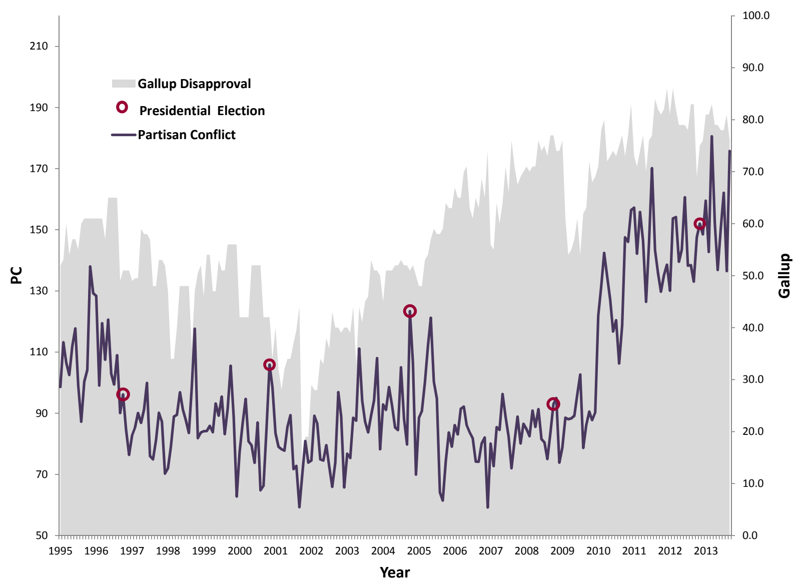

Figure 21: Partisan conflict and Congress disapproval ratings (Gallup).

The low levels of PC observed during military conflicts or national security threats coincide with low disapproval rates, suggesting that partisan warfare was not present during those episodes. The two series follow a similar pattern, exhibiting an upward trend toward the end of the sample, but they behave differently in periods when presidential elections are held (displayed with circles). During those months, partisan conflict intensifies, while—as should be expected—the disapproval ratings remain fairly stable.

[34]Data can be found at http://www.gallup.com/poll/1600/congress-public.aspx#1.

7.11 Partisan Conflict and Expectations

Partisan conflict affects investment decisions through expectations in our model. As agents observe an increasing number of newspaper articles reporting political disagreement, expectations about the quality of government policy and regulation worsen. This, in turn, negatively affects expected returns which induces them to invest less. In addition, high levels of partisan conflict may increase uncertainty about economic policy, as argued in the previous section.

Testing the effect of political signals on investor expectations is unfeasible due to the lack of consistent time series. There is, however, anecdotal evidence contained in survey data indicating that perceptions about intense political disagreement may affect investors' behavior. For example, increased uncertainty about future tax rates or government regulations were attributed as the second most important reason behind a slowing in growth in demand according to the Manufacturing Business Outlook Survey conducted by the the Federal Reserve Bank of Philadelphia on July 2012. Uncertainty about regulations and government policies were highly ranked cited factors among firms restraining hiring, according to the same survey during February 2011 and January 2012.[35] According to a poll conducted by Bloomberg on January 2013 'the state of the U.S. government's finances is the greatest risk to the world economy and almost half [of the survey participants] are curbing their investments in response to continuing budget battles.'[36] Schwab Advisor Services presented the results of its Independent Advisor Outlook Study, which surveyed almost 900 RIAs representing \$204 billion in assets under management, on April 2012. Independent investment advisors reported that according to their clients, evidence of a recovery and the end to political gridlock would boost investing confidence. Finally, political discord in Washington was the top item affecting investment climate in the US, according to 88% of individuals surveyed by Gallup and Wells Fargo during August 15-24, 2014.[37]

7.12 Construction of Total Factor Productivity

I compute the Solow residual to proxy the contribution of technological progress to output growth in the estimations. This residual is constructed as follows:

$$S_t = \log(Y_t) - 0.36\log(K_t) - 0.64\log(L_t),$$

where Y_t denotes output, K_t is the stock of capital, and L_t is private industries' employment in period t. The Solow residual represents the amount of output produced net of expenditures in the main factors of production: capital and labor.

Economic variables are obtained at the quarterly level for the sample period Q1:1981 to Q2:2013 from the Bureau of Economic Analysis (BEA). Output and investment are seasonally adjusted and expressed in billions of 2005 dollars. They correspond to Gross Domestic

[35] The information was obtained from the 'Manufacturing Business Outlook Survey Historical Data' webpage at the Federal Reserve Bank of Philadelphia, https://www.philadelphiafed.org/research-and-data/regional-economy/business-outlook-survey/historical-data/.

[36] See the article U.S. Budget Discord Is Top Threat to Global Economy in Poll, published by Bloomberg on January 23rd 2013. The poll is based on 921 Bloomberg customers.

[37] The second and third items were conflict in the Middle-East and high unemployment levels.

Product (Y_t) and Gross Private Domestic Investment (I_t), respectively, and are converted in real terms using the GDP deflator. Total employment (L_t) is expressed in thousands of employees in the nonfarming sector (seasonally adjusted series).

The specification above assumes a capital share of 0.36 and a labor share of 0.64, close to the long-run empirical averages of the capital and labor income shares. The series for capital is constructed using the perpetual inventory method:

$$K_{t+1} = I_t + (1-\delta)K_t,$$

where δ is a constant depreciation rate of capital (set to 0.012, implying an annual depreciation rate of about 5%) and I_t is real investment. The initial capital stock is chosen so that the capital-to-output ratio in the first period (Q1:1981) equals the average capital-to-output ratio over our sample period Q1:1981 to Q2:2013,

$$\frac{K_{Q1:1981}}{Y_{Q2:2013}} = \frac{1}{131} \sum_{Q1:1981}^{Q2:2013} \frac{K_t}{Y_t}.$$

The resulting series is then used to compute the Solow residual. Detrended measures of the Solow residual capture productivity shocks, which are considered the main factor causing fluctuations in the economy (i.e., real business cycles) in the macroeconomics literature, and will be referred to as TFP in the rest of the paper. To construct the TFP measure Z, I HP-filtered the Solow residual using the weight $w = 1600$, standard for quarterly series.