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PARTISAN CONFLICT AND PRIVATE INVESTMENT

Marina Azzimonti

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American politics have been characterized by a high degree of partisan conflict in recent years. Combined with a divided government, this has led not only to significant Congressional gridlock, but also to spells of high fiscal policy uncertainty. The unusually slow recovery from the Great Recession during the same period suggests the possibility that the two phenomena may be related. In this paper, I investigate the hypothesis that political discord depresses private investment. To this end, I first present a reduced-form political economy model to illustrate how news about political disagreement affects investment through agents' expectations. I then construct a novel high-frequency indicator of partisan conflict consistent with the model. The index, computed monthly between 1981 and 2015, uses a semantic search methodology to measure the frequency of newspaper articles reporting lawmakers' disagreement about policy. Using a 2SLS approach, I estimate that a 10% increase in the partisan conflict index is associated with a 3.4% decline in aggregate private investment in the US.

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A data appendix is available at:
http://www.nber.org/data-appendix/w21273

Partisan Conflict and Private Investment *

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May, 2015

Abstract

American politics have been characterized by a high degree of partisan conflict in recent years. Combined with a divided government, this has led not only to significant Congressional gridlock, but also to spells of high fiscal policy uncertainty. The unusually slow recovery from the Great Recession during the same period suggests the possibility that the two phenomena may be related. In this paper, I investigate the hypothesis that political discord depresses private investment. To this end, I first present a reduced-form political economy model to illustrate how news about political disagreement affects investment through agents' expectations. I then construct a novel high-frequency indicator of partisan conflict consistent with the model. The index, computed monthly between 1981 and 2015, uses a semantic search methodology to measure the frequency of newspaper articles reporting lawmakers' disagreement about policy. Using a 2SLS approach, I estimate that a 10% increase in the partisan conflict index is associated with a 3.4% decline in aggregate private investment in the US.

JEL Classification: E3, H3.

1 Introduction

American politics have been characterized by a high degree of partisan conflict in recent years. Combined with a divided government, this has led not only 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 (e.g., the 2012 tax-expirations and the fiscal cliff). The unusually slow recovery from the Great Recession during the same period suggests the possibility

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that the two phenomena may be related. Political divisions are relevant for the evolution of private investment for two reasons. First, they make the timing, size, and composition of fiscal policy less predictable. As long as investment is irreversible, uncertainty induces delays in investment decisions (Baker, Bloom, and Davis, 2013). Second, because they cause legislative gridlocks that affect the optimal timing of policy reforms (Alesina and Drazen, 1991). To the extent that these factors erode investors' confidence in the ability of the government to prevent negative outcomes (such as a financial crisis or a war), investment levels will be adversely affected.

In this paper, I investigate the hypothesis that political discord depresses private investment. To this end, I present a reduced-form political economy model to illustrate how news about political disagreement affects investment through agents' expectations. I assume that investment returns depend on the state of the economy, and may take extremely low values during low probability events such as a financial 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 must 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 (due to sub-optimal timing or less effectiveness). Partisan conflict, thus, exacerbates economic risk by increasing the likelihood of rare events.

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) in the sense of Baker, Bloom, and Davis (2013). 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. Agents can obtain imperfectly informative signals about true partisan conflict by reading newspapers. Periods in which a large proportion of articles reporting political discord are observed 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 this prediction, I construct a novel indicator of the degree of partisan conflict that is consistent with the theory, and assess how it affects private investment. The *partisan conflict index* (PCI) is computed monthly for the period 1981-2015 using a methodology similar to that of Baker, Bloom, and Davis (2013).[1] 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. The search is performed in Factiva, a newspaper database containing digitalized copies of all major US newspapers. 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

[1] The Federal Reserve Bank of Philadelphia updates this series monthly, and can be obtained free of charge at https://www.philadelphiafed.org/research-and-data/real-time-center/partisan-conflict-index/

about well-known polemic issues. Interestingly, partisan conflict subsides when the country is at war or subject to national security threats, such as 9/11, the Oklahoma Bombing and the Iraq Wars. This suggests that American politics are very polarized regarding economic policy, but are less divided when it comes to national defense issues. It also indicates the presence of a partisan "rally around the flag" effect.

Quantifying the effects of partisan conflict on investment is non-trivial due to a potential reverse-causality issue. Periods of intense political disagreement may be associated with low investment because policymakers tend to engage in budget battles more fiercely during recessions—when investment is low—, rather than being partisan conflict the cause of depressed investment. I try to address this problem in two ways. First, I exploit the high-frequency at which the index is constructed to estimate the effects using monthly data. The rationale of this approach is that we would expect short-term fluctuations in investment being caused by changes in investors expectations (due to learning about the degree of partisan conflict), rather than expect partisan conflict being caused by monthly swings in investment. Second, I try 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 reported 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 the conflict between policymakers. Because newspaper ad-revenues and employment (in the newspaper sector) 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, ensuring that it is a valid instrument. I find that partisan conflict deters private investment at business cycle frequencies. The 2SLS estimation implies that a 10% increase in partisan conflict is associated with a 3.4% decline in private investment, even after controlling for interest rates and the magnitude of recessions.

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 4.2 describes the evolution of partisan conflict over time. The connections between partisan conflict and economic policy uncertainty are discussed in Section 4.3. Section 5 quantifies the effects of partisan conflict on private investment, and Section 6 concludes.

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.[2] 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. 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 switches between left-wing and right-wing governments amplify the cycle. Moreover, 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 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—as investors cannot predict which policies would be undertaken—this need not always be the case. Under extreme values of the PCI, such as during 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. Studies highlighting the effects of time-varying volatility caused by rare events (Gabaix, 2008; Shen 2005; Kelly and Jiang 2014, among others) have mainly focused on how tail risks affect stock market behavior. Moreover, they ignore the effects of political disagreement, which is the main driving force affecting the likelihood of rare events in this paper.

The effects of political news on economic outcomes have been studied by Pastor and Veronesi (2013) and Kelly, Pastor, and Veronesi (2013). 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 driver 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. Finally, I develop a novel index of partisan conflict based on newspaper reports about political disagreement, while Pastor and Veronesi's main explanatory variable is the economic policy uncertainty (EPU) measure developed in Baker, Bloom, and Davis (2013).

In terms of the index construction, while the methodology used to compute the PCI is similar to the one used by Baker, Bloom, and Davis (2013) to measure EPU, the two indexes represent different concepts and are therefore characterized by distinctive features. For example, both indexes rise during the Obamacare debates and the fiscal cliff, but they move in opposite direction during 9/11. The attacks introduced uncertainty in the economy (so EPU was extremely high), but there was very little

[2]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.

disagreement about which policies should be implemented (so PCI was extremely low). Section 4.3 discusses this in further detail.

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 (see Azzimonti, 2015 for details). 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's 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 does not represent an alternative measure of polarization.

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 tangentially related to the literature on the market for news (Gentzkow and Shapiro, 2010) and the influence of the media (Campante and Hojman, 2010, Prat 2015, Prat and Stromberg, 2013, Prior, 2013).

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), 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.[3] The degree of sophistication, or quality of the reform, enhances 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 $TC(x_t)$

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

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, $\partial TC/\partial c > 0$.

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

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 an important determinant 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 ideologically divided 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:

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

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).

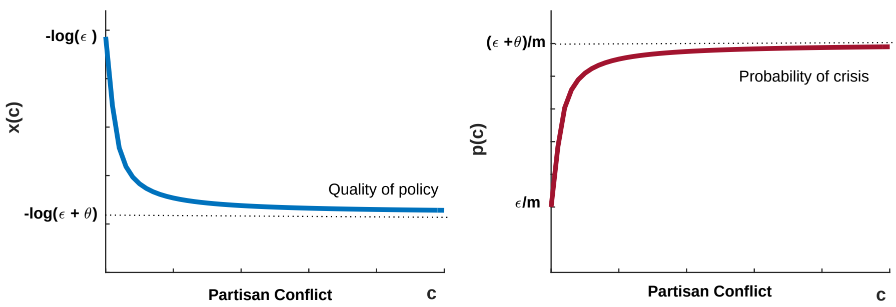

Figure 1: Government policy and probability of a rare-event as a function of partisan conflict.

We can see that when c increases, the quality of preventive measures and reforms goes down. 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 (2013). 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,

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

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.[4] 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 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 , 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.

[4] 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.

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

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

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.

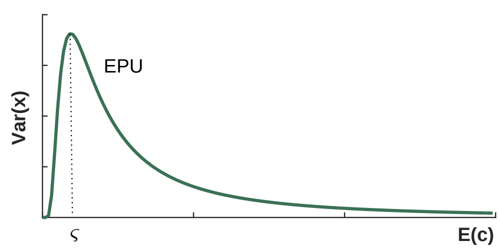

Figure 2: Economic Policy Uncertainty, $Var(x(c))$, as a function of partisan conflict.

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

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

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 $c = 10$).

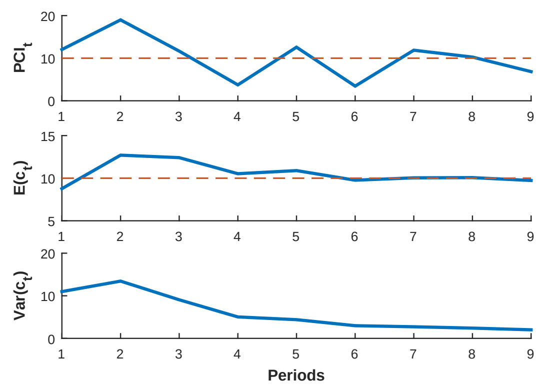

Figure 3: Evolution of signals $\bar{s}_t$, or PCI (first plot), posterior beliefs about partisan conflict, $E(c_t) = \hat{c}_t$ (second plot), and political uncertainty $Var(\hat{c}_t)$ (third plot).

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 $\bar{s}_t$.footnoteThis could also be seen from eq. (5), as a new value of $\overline{s}_t$ increases both the numerator through $\hat{c}_t$ and the denominator through t. This implies that political uncertainty may increase under extremely large realizations of PCI, but that would not necessarily be the case for moderate increases.

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, we will 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).
- 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

$$f_c = E\left[\frac{1}{a}\left(1 - e^{-ar_t}\right)\right]. \tag{6}$$

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 agents who choose $I = 1$,

$$\Upsilon(\bar{s}_t) = \int_0^{f_c(\bar{s}_t)} \frac{1}{\phi} df = \frac{1}{\phi} f_c(\bar{s}_t). \tag{7}$$

With this, 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. (7) 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. 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 will also be affected by the dynamics characterizing the media market.

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 beliefs 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. Agents 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.

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 $\bar{s}_t$, partisan conflict, will be precisely this measure:

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

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 identification 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).

The search is performed 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 4 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.[5] 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 8 in Appendix 7.4 for a decomposition of sources). 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). 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.

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 4 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.

Articles with less than 200 words and republished news are excluded (this is standard in the semantics literature). Note that the search is performed on full articles, not just titles or abstracts.

[5]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 excluded 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.

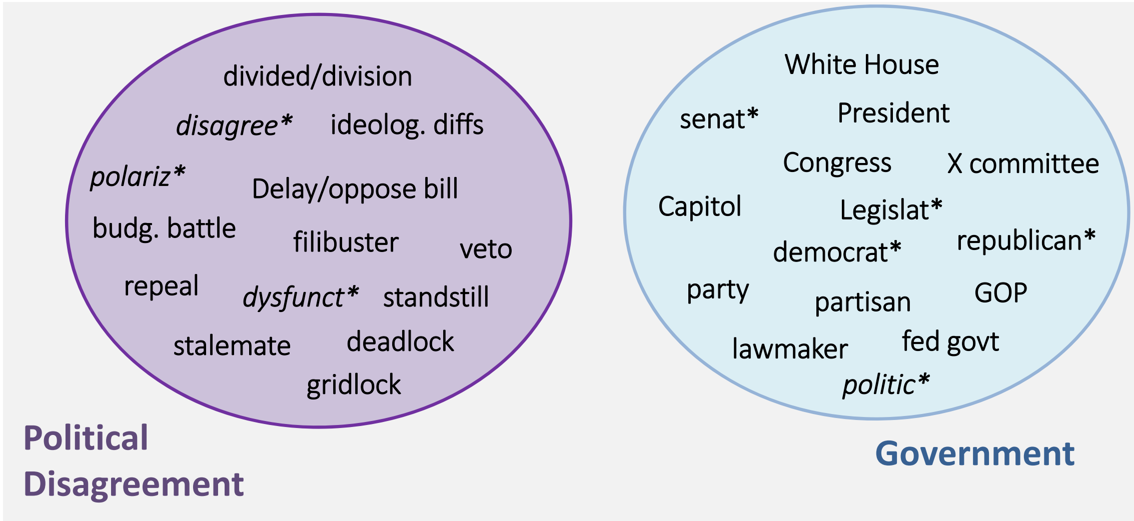

Figure 4: Sample keywords used in the search.

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.

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. Additional words used by the media 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.

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 index, I perform a search every month from January 1981 to December 2013 containing the word "today."[6] 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. Finally, I normalize the PCI such that the average equals 100 in the year 1990.

4.2 The evolution of partisan conflict

In this section, I describe the evolution of the partisan conflict index computed from newspaper counts. The objective of this exercise is to validate the measure by showing that it has a plausible behavior.

[6]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 5.2.2 the estimation results are robust to using this alternative normalization.

The PCI is shown in Figure 5.[7]

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. This is consistent with the evidence provided by McCarty, Poole, and Rosenthal (2006) and Bonica and Rosenthal (2013), who document that legislators' ideology has become more polarized, particularly in recent years. We should expect partisan conflict to intensify when political polarization rises. Intuitively, it should be more difficult for parties to agree on the course of social and economic policy when their ideological differences are large. Moreover, in a related paper (Azzimonti, 2015), I find that partisan conflict is highly correlated with political polarization over a longer horizon, 1890 to 2013.[8] I also show that keeping polarization constant, increases in the PCI trend tend to be larger under a divided government and are negatively related to the share of seats in Congress controlled by the President's party. Short-term increases in partisan conflict are associated with presidential and midterm elections, suggesting that (i) newspapers focus attention to differences between policymakers during the campaign period and (ii) that there is 'posturing,' consistent with the findings in Ash, Morelli, and Van Weelden (2014).

The circles in Figure 5 indicate months associated with presidential elections, while the vertical bars represent those in which Congress held midterm elections. The figure also displays other historical events (with diamonds) that resulted in deviations from the trend. Most noticeable are the Government shutdown in 1995, 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. Interestingly, episodes related to national defense exhibit very little or no partisan conflict. For example, the PCI is 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 suggests a partisan "rally around the flag" effect, as partisan conflict subsides significantly when the country is at war or subject to national security threats.

4.3 Partisan conflict and economic policy uncertainty

The methodology used to compute the PCI is similar to the one Baker, Bloom, and Davis (2013) 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 (as described before). The database used to perform the search is different as well: while they focus on a balanced panel of 10 newspapers, I use an unbalanced panel of major US newspapers (as defined by Factiva, see Appendix 7.4 for the list of newspapers included).

[7] The series is updated monthly by the Federal Reserve Bank of Philadelphia, and can be found at http://www.philadelphiafed.org/research-and-data/real-time-center/partisan-conflict-index/.

[8] *Historical Partisan Conflict*, the measure used in Azzimonti (2015) is computed annually using news articles from five major newspapers that have been digitalized since 1891. The advantage of such measure is that the long-run trend in partisan conflict can be identified and compared with other slow-moving variables such as polarization or party composition in Congress. The main disadvantage is that the search cannot be refined to the same degree as the one used in this paper, so the indicator is noisier.

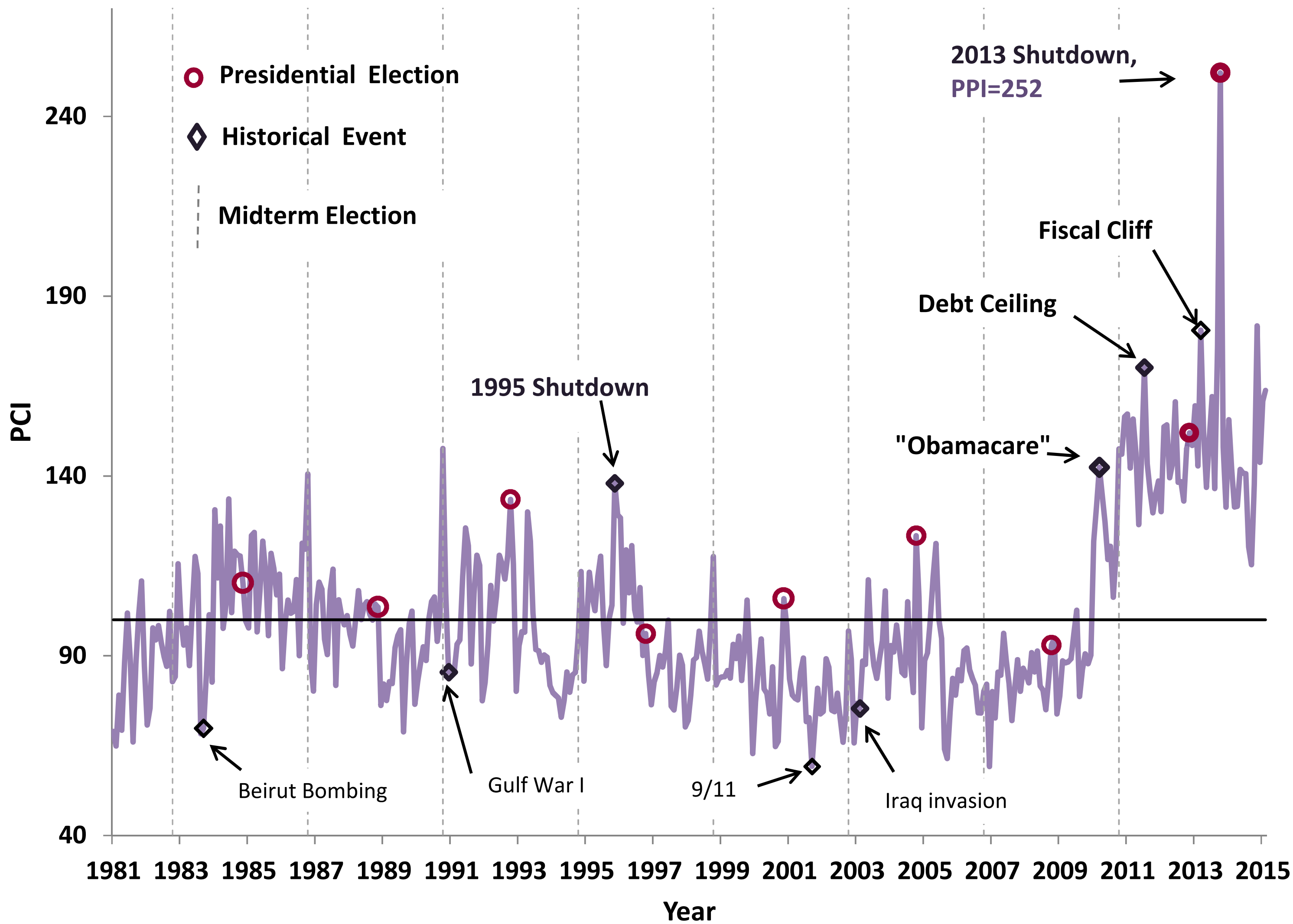

Figure 5: Partisan conflict index (PCI=$\bar{s}_t$), 1981-2015. PCI normalized to 100 in 1990. Circles represent presidential elections (month of election or the month before); diamonds are historical events, and vertical lines are midterm elections.

This additional source of variation is key in the empirical section where an instrument related to advertisement revenues is applied. In addition, Factiva allows me to refine the search by excluding articles which are irrelevant to partisan conflict, reducing the incidence of noisy observations in the measured index. Of particular importance is the ability to filter out foreign news and short articles (those with less than 200 words), as indicated by a human audit.

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 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 6, which depicts the PCI (solid line) together with the news-based EPU index (dashed line), shows that the indexes share a similar trend.

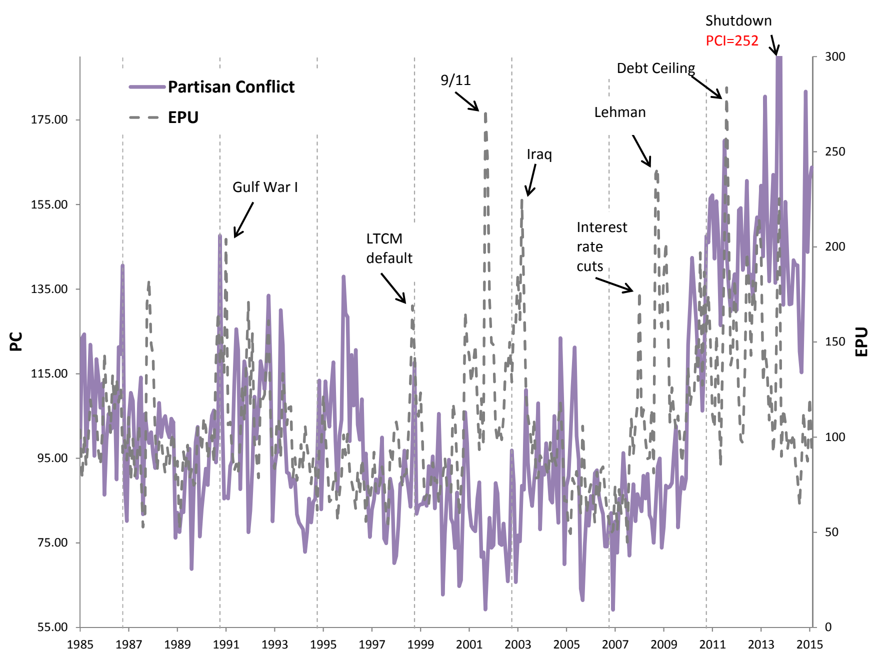

Figure 6: Partisan conflict (solid) and news-based economic policy uncertainty (dashed).

Notes: Vertical lines are midterm elections. Shutdown spike truncated for readability.

Partisan conflict need not, however, always cause economic policy uncertainty. 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 6 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.

Figure 7 shows the relationship between PCI and EPU between 1985 and 2014 (quarterly data), together with the fitted line from a 4th order polynomial approximation. It is the data counterpart of Figure 2, and consistent with the theory, it indicates that the relationship between partisan conflict and economic policy uncertainty may be non-monotonic. The evidence, however, is only suggestive as the declining part seems to be mostly driven by the 2013 shutdown.

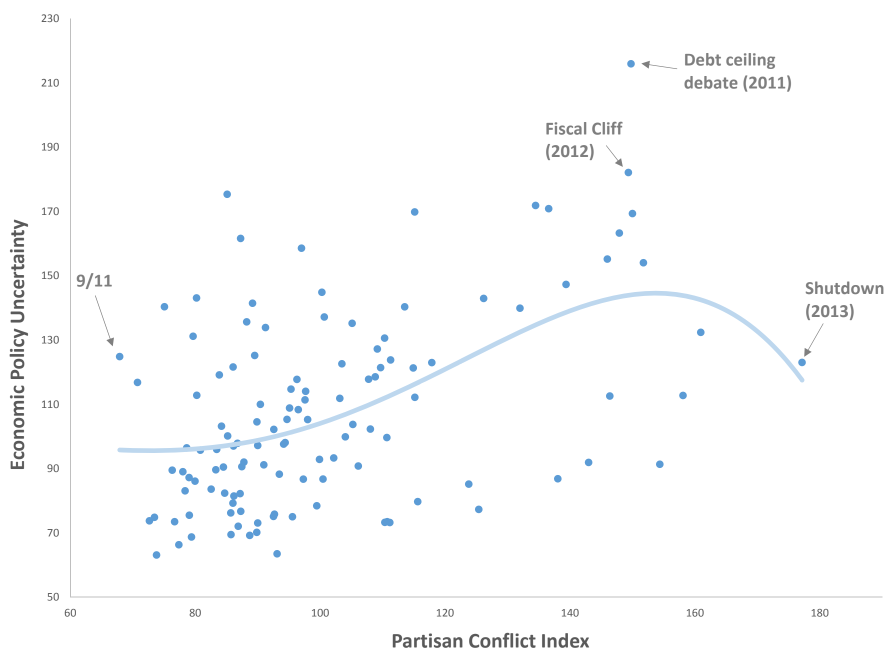

Figure 7: Economic policy uncertainty (News-based) as a function of partisan conflict (dots) for Q1:1985-Q4:2014. The solid line represents the fitted values of a 4th order polynomial.

Moreover, the relationship between EPU and PCI is not perfect, exhibiting wide variation around the fitted line. The reason is that measured EPU may fluctuate as a consequence of factors unrelated to government policy and regulation, and thus to partisan conflict. Inspecting Figure 6, we can see that EPU is affected by financial shocks (such as Lehman's collapse or the series of defaults in Latin American countries) and monetary policy (such as interest rate cuts by the Federal Reserve), while the PCI is completely unresponsive to them. This is reasonable, as those events are unrelated to fiscal policy but do introduce economic uncertainty about monetary policy, chosen by an independent authority. Another important difference results from 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 (2013) is only 0.29.[9]

5 Consequences of partisan conflict on the economy

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

5.1 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.[10] 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.'[11] Schwab Advisor Services presented the results of its

[9]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 0.41.

[10]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/.

[11]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.

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.[12]

5.2 Partisan Conflict and Private Investment

We can estimate the effects of political signals (PCI) on economic outcomes (investment) by using a simple specification that controls for prices (the Federal Funds rate) and the state of the economy (such as the NBER's indicator for recessions or total factor productivity). Unfortunately, we cannot interpret the findings of such regression as causal, as partisan conflict may be affected by the business cycle. It is possible that the extent of disagreement between policymakers is higher in periods of high income inequality (typically recessions), where redistributional concerns are heightened. Alternatively, we could think that the rewards to a bipartisan effort may be larger during a severe crisis.

I try to address the issue of reverse causality in two ways: (i) by using high-frequency (e.g., monthly) data, and (ii) by implementing a 2SLS approach. The rationale for the first approach is as follows: business cycle fluctuations and the degree of inequality are slow moving variables. Hence, we would expect that short-term fluctuations in investment are caused by changes in investors expectations (due to learning about the degree of partisan conflict), rather than expect that partisan conflict is caused by monthly swings in investment.

The second 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).

5.2.1 High-frequency Approach

A main prediction of the model presented in Section 3 is that increases in the PCI, $\bar{s}_t$, are associated with reductions in total investment. To quantify the impact of partisan conflict on aggregate investment, I estimate an OLS regression of the following specification

$$I_t = \alpha_0 + \alpha_1 Z_t + \alpha_2 r_{t-1} + \beta PCI_t + \epsilon_t, \tag{8}$$

where I denotes real private investment, r the interest rate, Z indicates the state of the economic cycle, PCI the 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

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

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.

Because I, r, and PCI exhibit noticeable trends over the sample period, they 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. Detrended variables are denoted by dI, dr, and $dPCI$.

The regression results are presented in Table 1. Specification (1) corresponds to the model presented in eq. (8), 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.[13]

Table 1: OLS regression results

Dependent variable: dI_t	(1)	(2)	(3)
$dPCI_t$	−0.076*	−0.0726*	
	(0.05)	(0.038)	
Z_t	−7.20*	−8.59	−8.58
	(4.30)	(6.18)	(6.17)
dr_{t-1}	12.79***	9.71***	9.67***
	(1.36)	(3.17)	(3.18)
PCI_t^H			−0.088**
			(0.038)
PCI_t^L			−0.049
			(0.07)
Observations	275	275	275
R-squared	0.32	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

As we can observe, partisan conflict does indeed cause a decline in private investment at a monthly frequency. The coefficient on $dPCI_t$ is statistically significant at the 6% level.

Specification (3) considers the possibility of non-linear effects of PCI on investment. It is reasonable

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

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 PCI_t^H which equals $dPCI$ when deviations from trend (on either direction) are larger than one standard deviation, denoted by $\sigma(dPCI)$, and it is zero otherwise.[14]. That is,

$$PCI_t^H = \begin{cases} dPCI & \text{if} \quad |dPCI| > \sigma(dPCI) \\ 0 & \text{otherwise.} \end{cases}$$

The complement of this, PCI_t^L equals zero when the index's deviations are low, while $PCI_t^L = dPCI$ when $|dPCI| \leq \sigma(dPCI)$. 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 PCI_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, PCI_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 PCI_t^H and PCI_t^L, in which case about half of the observation would be within one standard deviation from the mean.

5.2.2 Instrumental Variables Approach

In this section I take a different approach to address 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 (2006) 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*

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

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.

5.3 Estimation

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

$$\log I_t = \beta_0 + \beta_0 \log PCI_t + \beta_2 X_t + \epsilon_t, \tag{9}$$

where $\log I_t$ denotes natural logarithm of real private investment, $\log PCI$ is the natural logarithm of the partisan conflict index, and X_t represents a set of control variables. In particular, $X_t = \{Z_{t-1}, r_{t-1}\}$, where Z captures the state of the economy and r denotes the interest rate. 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.[15] 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 7.8). This variable is preferable to the NBER-based recession indicator because it allows us to take into account the intensity of a recession.[16] Investment, interest rates, and partisan conflict have been de-trended using an HP filter, 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.

The first stage estimation equation follows

$$\log PCI_t = \alpha_0 + \alpha_1 \log Ads_{t-4} + \alpha_2 X_t + \eta_t, \tag{10}$$

[15] 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).

[16] Data constraints (in particular the lack of a series for output and investment at the monthly level) prevented me from using TFP in Section 5.2.1.

where $X_t = \{Z_{t-1}, r_{t-1}\}$ as above, and $\log Ads_{t-4}$ represents the 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 was 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).

Results from the 2SLS are presented in Table 2, along the coefficients from a simple OLS estimation of eq. (9).

Table 2: 2SLS regression results

Dependent variable	*OLS* $\log I_t$	First Stage $\log(PCI)_t$	Second Stage $\log I_t$
Instrument: $\log Ads_{t-4}$		-1.08^{***}	
		(0.24)	
$\log(PCI)_t$	-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, indicating that there are no concerns about weak instruments in this application. 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 (0.10). This implies that a 10 percent increase in the PCI result in a 3.4 percent 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. 9), where I use the seasonally adjusted PCI (in logs) as the main dependent variable. The second column, denoted by PCI_{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, $\log(PCI)$, uses the non-seasonally adjusted PCI in logs. The coefficient is virtually unchanged. In the fourth column, $\log(PCI_n)$, 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).

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.

6 Conclusion and extensions

Partisan conflict has increased substantially in the United States since the mid-1970s. Commentators and researchers suggest that the deep ideological division between the two main parties may have been an important factor affecting the aggregate economy, in particular by slowing the recovery from the 2007-09 recession. This paper investigates whether these claims are supported by the data. I first present a very simple model to illustrate how news reports about political discord may erode investors' expectations about the ability of the government to prevent rare events, which discourages investment. I then develop a novel index of partisan conflict based on a news-search approach. Taking advantage

Table 3: Robustness

Dependent var.=log I_t	$\log(PCI_{sa})$	PCI_{sa}	$\log(PCI)$	$\log(PCI_n)$
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.9). Second column corresponds to non-log SA PCI, while the third uses the non-seasonally adjusted series (in logs). The fourth column uses an alternative measure of PCI (in logs, non-SA); PCI_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.

of the high-frequency at which the measure is constructed, I show that higher values of the index are 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 at the quarterly level, 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.

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, it would be interesting to investigate whether the main conclusions are robust to considering a longer time-series. There is a set of newspapers that have been digitalized from 1891, in which the same methodology could be applied (this is work in progress at the moment). Third, 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.

References

[1] Ash, E., Morelli, M., and Van Weelden, R. (2014). "Elections and Divisiveness: Theory and Evidence," Mimeo.

[2] Azzimonti, M. (2015). "The causes of partisan conflict," Mimeo.

[3] Azzimonti, M. and Talbert, M. (2013) "Polarized business cycles," *Journal of Monetary Economics*, 67, 47-61.

[4] Alesina, A. and Drazen, A. (1991) "Why are stabilizations delayed?" *American Economic Review*, 81(5), 1170-1188.

[5] Alesina, A. and Rosenthal, H. (1995) *Partisan Politics, Divided Government, and the Economy.* Cambridge University Press.

[6] Alt, J. and Lassen, D. (2006) "Transparency, political polarization, and political budget cycles in OECD countries," *American Journal of Political Science*, 50(3), 530-550.

[7] Bachmann, R., Elstner, S., and Sims, E. (2013) "Uncertainty and economic activity: Evidence from business survey data," *American Economic Journal: Macroeconomics*, 5(2), 217-249.

[8] Baker, S. and Bloom, N. (2013) Does uncertainty reduce growth? using disasters as natural experiments, *NBER Working Paper* 19475.

[9] Baker, S., Bloom, N., and Davis, S. (2013) "Measuring economic policy uncertainty," mimeo.

[10] Barro, R. (2006) "Rare disasters and asset markets in the twentieth century," *The Quarterly Journal of Economics*, 121(3), 823-866.

[11] Barro, R. (2009) "Rare disasters, asset prices, and welfare costs," *American Economic Review*, 99(1), 243-264.

[12] Bloom, N. (2009) "The impact of uncertainty shocks," *Econometrica*, 77(3), 623-685.

[13] Bonica, A. and Rosenthal, H. (2013) "Ideology and interests in the political marketplace," *American Journal of Political Science*, 57(2), 294-311.

[14] Campante, F. and D. Hojman (2010) "Media and Polarization." mimeo Harvard.

[15] Canes-Wrone, C. and Park, J.K. (2011) "Electoral business cycles in OECD countries," *American Political Science Review*, 106(1), 103-122.

[16] Canes-Wrone, C. and Ponce de Leon, C. (2014) "Elections, uncertainty, and economic outcomes," mimeo.

[17] Fernández-Villaverde, J., Guerrón, P. Kuester, K., and Rubio-Ramírez, J. (2012) "Fiscal volatility shocks and economic activity," mimeo.

[18] Fernández-Villaverde, J., and Rubio-Ramírez, J. (2010) "Macroeconomics and volatility: Data, models, and estimation," mimeo.

[19] Gabaix, X. (2008) "Variable Rare Disasters: A Tractable Theory of Ten Puzzles in Macro-Finance," *The American Economic Review*, 98(2), 64-67.

[20] Gelman, A., Carlin,J., Stern, H., and Rubin, D. (2003) *Bayesian Data Analysis*, 2nd edition. Chapman and Hall/CRC Press. .

[21] Gentzkow M. and Shapiro, S. (2006) "Media Bias and Reputation.," *Journal of Political Economy*, 114(2), 280-316.

[22] Gentzkow M. and Shapiro, S. (2010) "What determines media slant? Evidence from U.S. daily newspapers," *Econometrica*, 78(1), 35-71.

[23] Groseclose, T. and J. Milyo (2005) "A measure of media bias," *The Quarterly Journal of Economics*, 120(4), 1191-1237.

[24] Jamieson, K. and J. Cappella (2008) *Echo Chamber: Rush Limbaugh and the Conservative Media Establishment*. New York, NY: Oxford University Press.

[25] Jensen, J., Kaplan, E., Naidu, S., and Wilse-Samson, L. (2012) "Political polarization and the dynamics of political language: Evidence from 130 years of partisan speech," *Brookings Papers on Economic Activity*, Fall 2012, 1-81.

[26] Kelly, B. and Jiang, H. (2014) "Tail Risk and Asset Prices, " *The Review of Financial Studies*, 27(10), 2841-2871.

[27] Kelly, B., Pastor, L., and Veronesi, P. (2013) "The Price of Political Uncertainty: Theory and Evidence from the Option Market," mimeo.

[28] McCarty, N., Poole, E., and Rosenthal, H. (2006) *Polarized America: The dance of ideology and unequal riches*, The MIT Press.

[29] Pastor, L. and Veronesi, P. (2013) "Political Uncertainty and Risk Premia," *Journal of Financial Economics*, 110(3), 520-545.

[30] Prat, A. (2015) "Media Power." Mimeo

[31] Prat, A. and Stromberg, D. (2013) "The Political Economy of Mass Media." Mimeo

[32] Prior, M. (2013) "Media and Political Polarization.", *Annual Review of Political Science*, 16, 101-127.

[33] Persson, T. and Svensson, L. (1989) "Why a stubborn conservative would run a deficit: Policy with time-inconsistent preferences," *Quarterly Journal of Economics*, 104(2), 325-345.

[34] Shen, W. (2015) "News, disaster risk, and time-varying uncertainty," *Journal of Economic Dynamics and Control*, 51, 459-479.

[35] Stokey, N. (2013) "Wait-and-See: Investment Options under Policy Uncertainty, " *NBER Working Paper* 19630.

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,*

$$Var(x(c_t)) = Var\left(-\log(\epsilon + \theta e^{-\frac{1}{c_t}})\right), \tag{11}$$

is approximately equal to

$$Var(x(c_t)) \simeq \frac{\theta^2}{(\alpha_0 + tn - 2)} \frac{e^{-\frac{2}{\hat{c}_t}}}{\left(\epsilon + \theta e^{-\frac{1}{\hat{c}_t}}\right)^2 \hat{c}_t^2}, \tag{12}$$

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:

$$Var(x(c_t)) \simeq \left[x'(\hat{c}_t)\right]^2 Var(\hat{c}_t). \tag{13}$$

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

$$x'(\hat{c}_t) = -\frac{\theta e^{-\frac{1}{\hat{c}_t}}}{\epsilon + \theta e^{-\frac{1}{\hat{c}_t}}} \frac{1}{\hat{c}_t^2}. \tag{14}$$

Replacing eq. (5) and eq.(14) into eq. (13) yields expression 12. *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 4: 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 8 for a decomposition).

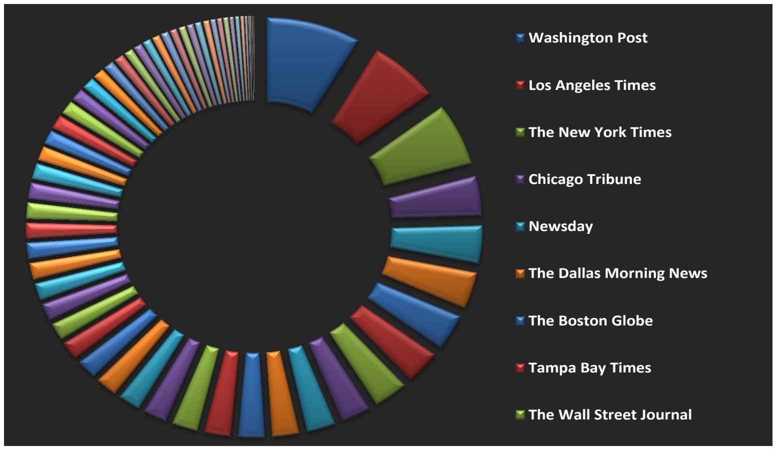

Figure 8: Percentage of news searches in which these subjects are mentioned over the sample.

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.

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 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 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.