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Partisan conflict, policy uncertainty and aggregate corporate cash holdings

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ABSTRACT

This paper distinguishes political uncertainty from policy uncertainty shocks and uncovers new empirical facts about how each impacts the aggregate cash holdings of US firms. Our baseline structural vector autoregression model shows that an exogenous one standard deviation shock to political and economic policy uncertainty is followed by 1 and 1.8% increase in aggregate corporate cash-to-total assets after five and eight quarters, respectively. The baseline result also shows that policy uncertainty shocks tend to raise financial market volatility while political uncertainty shocks tend to lower financial market volatility. Moreover, we find evidence that political uncertainty exerts asymmetric effects on aggregate corporate cash holdings, with a shock tending to raise cash holdings under normal financial conditions and lower cash holdings under tight financial conditions. Our main results are robust against a wide range of shock identification schemes as well as against parametric and non-parametric model estimations.

1. Introduction

In recent years, the role of corporate cash holdings and its implication for the US economy and business cycle fluctuations has received increasing attention in the macroeconomics literature. Adao and Silva (2016) show that the increase in firm cash holdings after 1980 has amplified the effect of monetary policy shocks. Bacchetta et al. (2016) study the relationship between the corporate cash ratio and employment. Alfaro et al. (2016) examine how firm cash holdings could exacerbate the impact of a financial uncertainty shock. Uncertainty is often perceived as an important driver of corporate cash holdings. In this paper, we disentangle political uncertainty shocks, proxied by the Partisan Conflict (PC) Index introduced by Azzimonti (2018a), from policy uncertainty shocks, proxied by the news-based Economic Policy Uncertainty (EPU) Index developed by Baker et al. (2016), and provide empirical
evidence that both types of uncertainty matter for aggregate corporate cash holdings in the US.

Using data on all non-financial and non-utility firms from Compustat Quarterly File over the period 1985Q1–2008Q3, we develop a structural vector autoregression (VAR) model that enables us to model the dynamical relationships between cash holdings, political uncertainty, economic policy uncertainty, as well as the real economy. To identify structural political uncertainty shocks from structural economic policy uncertainty shocks, we adopt the Cholesky decomposition as our baseline identification method, with the variable ordering informed by previous research. Our baseline results show that an exogenous one standard deviation (10%) increase in the PC Index is associated with an increase in the aggregate cash-to-total assets ratio that reaches a peak of 1% approximately five quarters after the initial shock. Our results also show that a one standard deviation (20%) shock to the EPU Index causes the aggregate cash ratio to increase by about 1.8% after eight quarters. In addition, a forecast error variance decomposition shows that partisan conflict and economic policy uncertainty shocks together account for up to 18% of the variation in the cash ratio at the 16 quarter horizon. Importantly, these findings are evident even after controlling for aggregate uncertainty, proxied by the VIX index, national financial conditions, proxied by the Adjusted National Financial Conditions Index, and short-term aggregate financial constraints, proxied by the 3-month Commercial Paper-Treasury Bill Spread.

Uncertainty can affect cash holdings through various channels. For example, Bloom (2009) points out that heightened uncertainty could trigger a drop in investment by increasing the real option value of waiting, which could lead to an accumulation of cash. This point is highlighted in Azzimonti (2011), Canes-Wrone and Park (2012) and, Azzimonti (2018b). Moreover, by increasing the risk of default, an increase in uncertainty may raise financial frictions as firms tend to hold more cash as the cost of external financing rises. This is consistent with the precautionary motive. Political and policy uncertainty are particularly relevant to the cash holding behavior of firms. In the model presented in Azzimonti (2018b), partisan conflict could cause the probability in which risk-averse investors believe costly rare events would happen to rise. This could lower expected return and lead to delays in investment decisions, resulting in an increase in cash holdings. In addition, if firms perceive heightened economic policy uncertainty to be long-lasting, they may question the extent of available profitable investment in the future. A preference for cash in the face of uncertainty over future investment is consistent with the model discussed in Almeida et al. (2011).

Our baseline model shows that an economic policy uncertainty shock lowers investment and raises financial market volatility. On the other hand, a partisan conflict shock leads to a brief fall in investment and, interestingly, a decline in both financial market volatility and economic policy uncertainty. This latter result is in line with several findings, both theoretical and empirical, from the literature on political and policy uncertainty. For example, Pastor and Veronesi (2012) demonstrate theoretically that low policy uncertainty leads to low financial market volatility. In another theoretical exercise, Bechtel and Fuss (2008) show that divided government can lower policy risk by reducing the likelihood of any policy changes and confirm their hypothesis using German data. More recently, Azzimonti (2018b) argues that high levels of partisan conflict may potentially lower economic policy uncertainty. Lower economic policy uncertainty can occur if the policy status-quo remains unchanged as a result of gridlock amongst politicians. Finally, these findings are consistent with Gupta et al. (2018b), who show that a rise in US partisan conflict lowers stock market volatility.

We also discover significant asymmetric responses of cash holdings to uncertainty shocks. Particularly, we highlight that a partisan conflict shock exerts a significant impact on investment and output under tight financial conditions, which is also observed for EPU shocks. On the other hand, when a partisan conflict shock occurs during a financially tight period, financial market volatility falls and financial conditions actually loosen, resulting in a 5% decline in the aggregate cash ratio within the first two quarters. However, this asymmetry does not present itself following an EPU shock, where we observe increases in the aggregate cash ratio of 5% by approximately the fifth quarter. Thus, we highlight an important difference between how a political uncertainty shock and an economic policy uncertainty shock impact the cash management decisions of US firms. Our main results are robust against a range of shock identification schemes as well as against parametric and non-parametric model estimations.

Overall, this paper is among the first to concurrently identify structural shocks to political uncertainty and economic policy uncertainty and their implications for corporate cash holdings and the broader macroeconomy. These findings also contribute to a nascent, but growing literature examining the broader consequences of US partisan conflict (see for example Azzimonti, 2018a; Azzimonti, 2018b; Cheng et al., 2016; Gupta et al., 2018a; Gupta et al., 2018b). Finally, this paper complements the findings of Alfaro et al. (2016) who show, among other results, that a rise in financial uncertainty raises corporate cash holdings. In the next section, we will discuss how our paper fits into the relevant literature on this topic.

2. Related literature

Adopting a macro-econometric methodology, this paper adds to an extensive empirical literature investigating the relationship between different types of uncertainty and the cash holdings practices of firms. The literature examining corporate cash holdings has experienced tremendous growth since the influential study by Opler et al. (1999). As documented by Bates et al. (2009), since 1980, corporate managers have increased cash holdings for precautionary reasons. The precautionary motive has been discussed at least as far back as Keynes (1936). Other important contributions studying the precautionary motive include (Opler et al., 1999; Almeida et al., 2004; Han and Qiu, 2007). Through our study of cash holdings over the period 1985–2008, our paper adds to this literature on the precautionary motive of corporate cash holdings.

In particular, our paper contributes to the investigation of how systematic uncertainty impacts corporate cash holdings. Baum

1 By using the word “systematic” we are referring to a class of uncertainty that affects all firms. This is in contrast to idiosyncratic uncertainty, which would be used to describe firm-specific uncertainty.
et al. (2006, 2008) were concerned with how macroeconomic uncertainty impacted corporate cash management decisions. In the former, the authors showed that heightened macroeconomic uncertainty led to a reduction in the dispersion of cash-to-total assets, including for firms that were financially constrained and firms deemed high growth. In the latter, the authors studied the cash-to-total assets of manufacturing firms and found that cash holdings increased in response to macroeconomic uncertainty. Gao and Grinstein (2014) study a larger set of firms and find that aggregate level uncertainty, as opposed to idiosyncratic uncertainty, has a more pronounced effect on the cash holdings decisions of firms. More recently, Graham and Leary (2017) show that macroeconomic factors, rather than firm-level factors, are more important for explaining the evolution of aggregate cash holdings in the US. Our contribution to this literature is that we disentangle two important sources of systematic uncertainty: policy uncertainty and political uncertainty. Furthermore, we will provide evidence that periods of political uncertainty can be distinct from policy uncertainty and aggregate uncertainty more generally.

Julio and Yook (2012) estimate how corporate investment and cash holdings practices behave during election periods. They find evidence that corporate managers increase cash holdings and decrease investment, both as a percentage of total assets, during election years. These results give us reason to expect an increase in corporate cash holdings during periods associated with political uncertainty. However, by using the PC Index and the EPU Index, we can not only distinguish between two types of uncertainties, as discussed above, but observe political uncertainty for all available years.

Our paper is perhaps most closely related to Alfaro et al. (2016). Their paper builds a partial equilibrium model to show that higher uncertainty not only induces the negative real-options impact on the demand for labor and capital, but also leads firms to hoard cash and cut debt to hedge against future shocks. In particular, they argue that financial frictions roughly double the negative impact of uncertainty shocks on investment and hiring. Using firm-level data regressions, they find evidence that higher financial uncertainty is associated with larger cash holdings. Motivated by these results, we will study the response of corporate cash holdings and other macroeconomic variables to political and policy uncertainty shocks during periods of high and low financial frictions.

In addition, this paper is related to a strand of the macroeconomics literature that uses the working capital channel to motivate how firms hold cash. The earliest work in this area dates back to Christiano (1991), Fuerst (1992), and Christiano and Eichenbaum (1992). Specifically, this channel is based on the assumption that firms’ variable inputs such as labor and capital must be financed by short-term loans, also known as the cash-in-advance constraint. Monetary policy can exert an effect on the real economy because any changes in the interest rate will change firms’ variable production costs, on top of the usual demand mechanism. This paper is also related to Bacchetta et al. (2016), who show a systematic negative co-movement between employment and the corporate cash-to-total assets ratio.

3. Motivation

Given the potential similarities between the various proxies for uncertainty that are available to economists today, it is important to distinguish political uncertainty from policy uncertainty, and aggregate uncertainty more generally. In this section, we will briefly motivate our research question by highlighting theoretical and empirical differences between the various uncertainty proxies used in this paper.

Azzimonti (2018a) points out that political uncertainty and economic policy uncertainty are fundamentally different. There are two types of policy-related uncertainty. The first type represents uncertainty about the types of policies the government might adopt whereas the second type relates to uncertainty over the effects of policies that have already been adopted. Azzimonti (2018a) points out that political uncertainty is only related to uncertainty over what policies would be chosen. Pastor and Veronesi (2012) also distinguish between political uncertainty and impact uncertainty. Theoretically, they model political uncertainty as the standard deviation of the political costs associated with the potential implementation of a new policy and model impact uncertainty as the standard deviation of the impact on the average profitability of firms. In their model, political uncertainty and impact uncertainty are captured by different structural parameters. They show that both types of uncertainty can impact firms’ behaviors in important ways.

As mentioned in Section 1, we use the Partisan Conflict (PC) Index introduced by Azzimonti (2018a) to measure political uncertainty and the news-based Economic Policy Uncertainty (EPU) Index developed by Baker et al. (2016) to measure the degree of policy uncertainty in the US.

The Partisan Conflict Index is created using a multi-staged word search procedure that is described in Azzimonti (2018a). Azzimonti (2018a) performs a monthly search of major English-language US newspapers and counts the number of articles mentioning words associated with both government and political disagreement. For example, words that might be used to describe government include “Congress,” “Republican,” and “Democrat,” while words used to describe political disagreement include “gridlock” and “filibuster” (Azzimonti, 2017, p. 6). The index is refined using a number of procedures meant to reduce the incidence of false-positives.3

The Economic Policy Uncertainty Index is also created using a newspaper search procedure. Specifically, the authors conduct a monthly search of ten major U.S. newspapers and count articles mentioning, in the words of the authors the following trio of terms: ‘uncertainty’ or ‘uncertain’; ‘economic’ or ‘economy’; and one more of ‘Congress’, ‘deficit’, ‘Federal Reserve’, ‘legislation’, ‘regulation’, or ‘White House’ (ibid: p. 1594).4

Despite some similarities, there are important differences between these indices. First, Azzimonti (2018a) searches over a word

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2 Christiano et al. (2010) provide a detailed survey.

3 See Azzimonti (2017, 2018b, 2018a) for a more detailed discussion of how the Partisan Conflict Index is created, including the full list of search terms.

4 See Baker et al. (2016) for a detailed list of these news sources.
list devoted to disagreement between politicians. For example, the PC Index will count articles discussing disagreement between legislators, parties, or legislators and the president, regardless of the source of disagreement. Conversely, the EPU Index will only count an article discussing political disagreement if that disagreement is about uncertainty regarding the economy. In short, the PC Index is a much broader measure of political dysfunction. Furthermore, uncertainty over Federal Reserve policy will not register on the PC Index whereas it will register on the EPU Index.

Second, the PC and EPU indices do not necessarily co-move. As Azzimonti points out, a relatively high level of partisan conflict can be associated with a low level of economic policy uncertainty because observers might reason that the government is in such a state of dysfunction that no meaningful policy will be generated. Conversely, there are periods where economic policy uncertainty is exceptionally high while the PC Index is at a relatively low level. This can be observed in Fig. 1. For example, in the third quarter of 2001, when the US suffered the September 11th terrorist attack, EPU increases to an extremely high level. However, the PC Index decreases, indicating what Azzimonti referred to as a “rally around the flag” effect (Azzimonti, 2017, p. 3). Furthermore, as shown in Table 1 the unconditional correlation between the PC and news-based EPU indices over our sample period is 0.0033. Not only does the PC Index reveal periods of uncertainty that do not register on the EPU Index, and vice versa, but the PC Index is also distinct from the VIX index, a broader measure of aggregate financial market uncertainty. Again, looking to Fig. 1, we see that the PC Index and VIX often move in opposite directions and pick up different types of uncertainties. The raw correlation between PC and VIX is −0.21. On the other hand, the EPU Index and VIX are closely related, displaying similar trends and registering heightened uncertainty during the same historical events.

Preliminary evidence for the impact that political and economic policy uncertainty can have on the corporate cash ratio is provided in Table 2, which shows the dynamic correlations between the cyclical components of the PC Index, the EPU Index, and the aggregate corporate cash ratio between 1985Q1 and 2008Q3. Following the business cycle literature, we detrend the series using the HP filter with the filtering parameter set at 1600. We see significant positive correlations between the corporate cash ratio and lags of the PC Index, with a peak correlation of 0.26 at a four-quarter lag. Interestingly, lags of the EPU Index display positive correlations (0.37 at the eighth lag) before turning significantly negative at the one-quarter lag. Table 2 provides preliminary evidence that there are significant business cycle relationships between the two types of uncertainty and the aggregate corporate cash ratio. We will now proceed to a description of the baseline empirical model.

4. The vector auto-regression model

The effects of uncertainty shocks on the US economy are estimated through our baseline vector auto-regression (VAR) model. We consider the following model:

\[ B(L)y_t = d + e_t, \]

where \( y_t \) is a vector of endogenous variables, \( d \) is a vector of constant terms and \( e_t \) are the reduced-form residuals, fulfilling \( E(e_t) = 0 \) and \( E(e_t e'_t) = \Sigma B(L) \) is given by \( I + B_1L + B_2L^2 + ... + B_L L^N \), where \( N \) is the lag length of the VAR model.

The following variables are included in the VAR model: the Partisan Conflict Index (PC\(_t\)), the news-based Economic Policy Uncertainty Index (EPU\(_t\)), the volatility index (VIX\(_t\)), the Adjusted National Financial Condition Index (ANFCI\(_t\)), real gross domestic product (GDPe\(_t\)), real investment (Inv\(_t\)), the aggregate corporate cash ratio (Cash\(_t\)), the federal funds rate (FFR\(_t\)), and the commercial paper spread (Spread\(_t\)). More specifically, the vector \( y_t \) reads as follows:

\[ y_t = [PC_t, EPU_t, VIX_t, ANFCI_t, GDPe_t, Inv_t, Cash_t, FFR_t, Spread_t]^T. \]

All variables are in log values, except for the Adjusted National Financial Condition Index, the federal funds rate, and the commercial paper spread. We employ quarterly data from 1985Q1 to 2008Q3 in our estimation. The sample starting date is based on the availability of the EPU Index. The end data is chosen to help avoid the potential structural shift in the PC Index and any non-linearities that might be caused by the financial crisis after 2008.  

We use data from Compustat Quarterly File to construct measures of aggregate cash holdings. Compustat provides financial information on all publicly-traded corporations in the United States by corporate observation. Aggregate cash holdings is the aggregate of cash, cash equivalents, and short-term investments. To compute the aggregate cash-to-asset ratio, we divide aggregate corporate cash holdings by aggregate total assets for each quarter.  

Financial firms (SIC 6000-6999) and utilities (SIC 4900-4999) are excluded because the former hold cash related to their unique business practices while the latter hold cash primarily for regulatory purposes. In addition, we exclude firms headquartered outside of the United States. The Economic Policy Uncertainty Index is taken from the “Economic Policy Uncertainty” website and the Partisan Conflict Index is taken from the Federal Reserve Bank of Philadelphia.  

5 We stop our estimation at 2008Q3, as suggested by Nodari (2014), in order to avoid the zero lower bound period, which could potentially bias estimates of the reaction of the federal funds rate to partisan conflict and economic policy uncertainty. We provide a robustness check using a longer sample in the appendix. 

6 Cash, cash equivalents, and short-term investments include non-interest earning assets, low-interest earning assets, and interest-bearing assets as long as they are short-term. 

To control for aggregate financial uncertainty, we follow Acharya et al. (2013) in adopting the VIX index in our baseline model. To control for financial conditions, we follow Alessandri and Mumtaz (2017) and adopt the National Financial Conditions Index (NFCI), constructed by the Federal Reserve Bank of Chicago. The NFCI is a broad representation of US aggregate financial conditions. It is computed as a factor from a large set of variables that relate to the money, debt, and equity markets and the leverage of financial intermediaries. In particular, we use the Adjusted National Financial Condition Index (ANFCI). Unlike the NFCI, the ANFCI is isolated from economic conditions and it is only affected by financial conditions. To control for short-term aggregate financial constraints, we follow Acharya et al. (2013) by constructing the commercial paper spread, which is defined as the difference between 3-month commercial paper and treasury yields. Data for the other variables in the model are retrieved from the Federal Reserve Bank of St. Louis (FRED) database.

The summary statistics for the indices used in this paper are reported in Table 3. The VAR model is estimated with two lags as suggested by Akaike information criterion, however, our results are robust to various lag selections. We adopt a standard Cholesky (recursiveness) decomposition approach to identify the structural shocks and impose recursive restrictions on the model residuals. In particular, we follow Bloom (2009) and Caggiano et al. (2014) by ordering the EPU Index before the macroeconomic variables. Azzimonti (2018a) points out that heightened political uncertainty can potentially lead to higher economic policy uncertainty. Thus, we order the PC Index first and before the EPU Index, implying that PC shocks exert

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**Fig. 1.** PC, EPU, and VIX: 1985–2008. Notes: This chart shows the Partisan Conflict Index (PCI), Economic Policy Uncertainty Index (EPU), and VIX. PCI is taken from the Federal Reserve Bank of Philadelphia, EPU is taken from www.policyuncertainty.com, and VIX is constructed according to Bloom (2009). PCI and EPU are measured by the vertical axis on the left hand side and VIX is measured by the vertical axis on the right hand side. All series are measured at a quarterly frequency. Historical events correspond to major PC and EPU shocks identified in Section 7.

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8 Since VIX is unavailable prior to 1986, we follow Bloom (2009) and use the actual monthly return volatilities, which are computed by monthly standard deviation of the daily S&P 500 index normalized to the same mean and variance as the implied volatility index when they overlap in 1986.

9 We thank an anonymous referee for this suggestion.

10 In addition to this variable ordering, in Section 5.3.1 we describe an alternative VAR specification with the PC Index ordered after the EPU Index.
contemporaneous effects on all other variables in the model. The “fast moving” financial variables, such as the VIX index and the commercial paper spread, are ordered after both the PC and EPU indices. This implies that financial variables respond to PC and EPU shocks within the same quarter. In the next section we will discuss the results from the baseline model. In Section 5.3.1, we provide robustness checks for our results to different orderings of the model variables.

5. Baseline results

5.1. Impulse responses

Fig. 2 displays the estimated impulse responses to an unanticipated 10% rise in the PC Index (referred to as a PC shock), amounting to a one standard deviation shock. Following the suggestion of Sims and Zha (1999), we present the impulse responses along with 68% probability bands. The model predicts that a positive shock to the PC Index leads to a short-lived decrease in private investment and an insignificant decrease in real GDP. Moreover, it is predicted that a positive shock to the PC Index exerts a significant effect on the aggregate cash-to-total assets ratio, which rises after the shock and reaches its peak of 1% after five quarters. One plausible reason for the delayed response of the cash-to-total assets ratio is due to portfolio adjustment costs. Firms may not be able to immediately and costlessly adjust how total assets are held. Interestingly, both the EPU and VIX indices drop significantly after a partisan conflict shock. This result is consistent with the findings in Gupta et al. (2018b), who show that a rise in partisan conflict lowers stock market volatility. Our result is also in line with Azzimonti (2018b), who argues that high levels of partisan conflict may lower economic policy uncertainty as politicians are unlikely to reach an agreement and no meaningful policy would be passed.

Fig. 3 shows that an unanticipated 20% rise in the EPU Index (EPU shock), equivalent to a one standard deviation shock, leads to significant economic contractions; that is, investment and output fall by 1% and 0.35%, respectively, five quarters after the shock.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Correlation matrix among uncertainty and financial market indices.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PC</td>
</tr>
<tr>
<td>PC</td>
<td>1.0000</td>
</tr>
<tr>
<td>EPU</td>
<td>0.0033</td>
</tr>
<tr>
<td>VIX</td>
<td>−0.2101</td>
</tr>
<tr>
<td>ANFCI</td>
<td>−0.0630</td>
</tr>
<tr>
<td>CP Spread</td>
<td>0.1229</td>
</tr>
</tbody>
</table>

Note: “PC” denotes the Partisan Conflict Index; “EPU” denotes the Economic Policy Uncertainty Index; “VIX” stands for the volatility index; “ANFCI” denotes the Adjusted National Financial Condition Index; “CP spread” denotes the 3-month Commercial Paper-Treasury Bill spread. The sample is between 1985Q1 and 2008Q3.

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Dynamic correlations between uncertainty and aggregate cash holdings.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>j(Quarterly lag/lead)</td>
</tr>
<tr>
<td></td>
<td>−8</td>
</tr>
<tr>
<td>corr(PC(−j),Cash)</td>
<td>0.02</td>
</tr>
<tr>
<td>[−0.11,0.14]</td>
<td>[0.07,0.31]</td>
</tr>
<tr>
<td>corr(EPU(−j),Cash)</td>
<td>0.37</td>
</tr>
<tr>
<td>[0.25,0.50]</td>
<td>[0.29,0.51]</td>
</tr>
</tbody>
</table>

Note: All quarterly series are expressed in logarithm and HP-filtered with the filtering parameter set at 1600, following the practice of the business cycle literature. Numbers in square bracket correspond to 80% confidence interval estimated with the Newey-West estimator. The sample is between 1985Q1 and 2008Q3.

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Summary statistics for uncertainty and financial market indices.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>PC</td>
<td>92.84</td>
</tr>
<tr>
<td>EPU</td>
<td>99.91</td>
</tr>
<tr>
<td>VIX</td>
<td>19.78</td>
</tr>
<tr>
<td>ANFCI</td>
<td>−0.24</td>
</tr>
<tr>
<td>CP Spread</td>
<td>0.48</td>
</tr>
</tbody>
</table>

Note: “PC” denotes the Partisan Conflict Index; “EPU” denotes the Economic Policy Uncertainty Index; “VIX” stands for the volatility index; “ANFCI” denotes the Adjusted National Financial Condition Index; “CP spread” denotes the 3-month Commercial Paper-Treasury Bill spread. The sample is between 1985Q1 and 2008Q3.
Such a result is consistent with the findings in the literature. The short-term interest rate falls significantly as well. In addition, the aggregate cash ratio increases by 1.8% eight quarters after the shock, although it does lead to a short-lived fall in the cash ratio on impact. Compared with the PC shock, an EPU shock imposes a larger and more delayed effect on the cash-to-total assets ratio. Moreover, as pointed out by Pastor and Veronesi (2012), as the impact of a policy becomes more uncertain, firms would need to learn about the potential effect of the new policy before they make any significant changes to their business decisions. This could delay the response of the cash ratio to an EPU shock. It is also important to point out that unlike a PC shock, an EPU shock leads to a rise in aggregate volatility and a tightening of financial conditions on impact.

5.2. Forecast error variance decomposition

Table 4 reports the forecast error variance decomposition (FEVD) for our variables for horizons between 2 and 32 quarters implied by the baseline model. The table shows that PC shocks play a limited role in explaining the output variations, but EPU shocks are more important for the short-run fluctuations in the cash ratio and other real variables, explaining 14% of the variation in investment, 16% of the variation in GDP, and a little over 8% of the variation in the cash ratio at the 8 quarter horizon. Importantly, both political

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**Fig. 2.** Impulse responses to a political uncertainty (PC) shock. Notes: Political Uncertainty is proxied by the Partisan Conflict Index developed in Azzimonti (2018a). Impulse responses to a one standard deviation shock to Partisan Conflict Index. Solid lines: median responses. Grey shaded areas: 68% probability bands.

**Fig. 3.** Impulse responses to an economic policy uncertainty (EPU) shock. Notes: Economic Policy Uncertainty is proxied by the Economic Policy Index developed in Baker et al. (2016). Impulse responses to a one standard deviation shock to Economic Policy Uncertainty Index. Solid lines: median responses. Grey shaded areas: 68% probability bands.
and economic policy uncertainty shocks together explain a considerable fraction of the forecast variance in the aggregate cash ratio: PC shocks explain 4% and EPU shocks explain 14% of variations at the 16 quarter horizon. Hence, if we consider only PC and EPU shocks together in our baseline model, which includes the VIX index, the ANFCI, real GDP, real investment, the cash ratio, the federal funds rate and the commercial paper spread, we find that they explain about 18% of the variation in cash holdings.

Table 4 also displays the share of variation in the aggregate cash ratio explained by different structural shocks. The table shows that a VIX shock plays a very limited role in explaining the variations in the cash ratio. On the other hand, shocks to the ANFCI and the federal funds rate play a more important role in driving the cash ratio, accounting for 11 and 18%, respectively, at the 16 quarter horizon.

On the whole, the results show that both PC and EPU shocks are a non-trivial source of disturbance to the aggregate corporate cash ratio. Our baseline results show that EPU shocks lead to a larger rise in the aggregate cash ratio and generate deeper economic contractions when compared to PC shocks. In the next subsection, we present a battery of robustness checks and alternative shock identification schemes that largely uphold our baseline results.

5.3. Robustness checks to baseline results

5.3.1. Alternative model specifications

We conduct several robustness checks and re-examine the results under alternative VAR specifications. Our robustness checks include: (i) replacing the news-based EPU Index with the “Overall EPU Index”; (ii) augmenting the baseline model with the consumer sentiment index; (iii) augmenting the baseline model with the TED spread, a common proxy for aggregate funding liquidity; (iv) augmenting the baseline model with the liquidity shocks uncovered by Bacchetta et al. (2016); (v) augmenting the baseline model with a factor extracted from a large panel of US economic variables, arguably summarizing the overall economic conditions and hence mitigating the problem of variable omission; (vi) estimating the baseline with four lags instead of two; (vii) ordering the PC and EPU indices, respectively, as the last variables; (viii) re-estimating the baseline model with a longer sample ending in 2014Q4 while accounting for the potential structural shift in the PC Index after 2008Q4 and (ix) re-estimating the baseline model with a new definition of cash holdings that excludes short-term investments.\footnote{Both (iii) and (iv) are motivated by Bacchetta et al. (2016) and are intended to account for adverse liquidity shocks.} Due to the large number of figures that accompany these additional tests, all of the robustness checks mentioned in this subsection are available in the appendix. It is worth noting that our main results reported in Section 5 remain robust.

Note: Panel A shows the forecast error variance decomposition for all variables that is explained by a PC shock. Panel B shows the forecast error variance decomposition for all variables that is explained by an EPU shock. Panel C shows the forecast error variance decomposition for the aggregate cash ratio that is explained by each shock. The unit is in percent.

Table 4 also displays the share of variation in the aggregate cash ratio explained by different structural shocks. The table shows that a VIX shock plays a very limited role in explaining the variations in the cash ratio. On the other hand, shocks to the ANFCI and the federal funds rate play a more important role in driving the cash ratio, accounting for 11 and 18%, respectively, at the 16 quarter horizon.

On the whole, the results show that both PC and EPU shocks are a non-trivial source of disturbance to the aggregate corporate cash ratio. Our baseline results show that EPU shocks lead to a larger rise in the aggregate cash ratio and generate deeper economic contractions when compared to PC shocks. In the next subsection, we present a battery of robustness checks and alternative shock identification schemes that largely uphold our baseline results.

5.3. Robustness checks to baseline results

5.3.1. Alternative model specifications

We conduct several robustness checks and re-examine the results under alternative VAR specifications. Our robustness checks include: (i) replacing the news-based EPU Index with the “Overall EPU Index”; (ii) augmenting the baseline model with the consumer sentiment index; (iii) augmenting the baseline model with the TED spread, a common proxy for aggregate funding liquidity; (iv) augmenting the baseline model with the liquidity shocks uncovered by Bacchetta et al. (2016); (v) augmenting the baseline model with a factor extracted from a large panel of US economic variables, arguably summarizing the overall economic conditions and hence mitigating the problem of variable omission; (vi) estimating the baseline with four lags instead of two; (vii) ordering the PC and EPU indices, respectively, as the last variables; (viii) re-estimating the baseline model with a longer sample ending in 2014Q4 while accounting for the potential structural shift in the PC Index after 2008Q4 and (ix) re-estimating the baseline model with a new definition of cash holdings that excludes short-term investments.\footnote{As discussed in Section 4, cash holdings includes short-term investments. However, a PC or EPU shock could potentially affect cash holdings through its impact on the valuation of equity. To address this concern, we construct an alternative aggregate cash-to-assets ratio that excludes short-term investments. We thank an anonymous referee for this suggestion.} Due to the large number of figures that accompany these additional tests, all of the robustness checks mentioned in this subsection are available in the appendix. It is worth noting that our main results reported in Section 5 remain robust.

Table 4

Forecast error variance decomposition.

Panel A: share of variation in all variables explained by structural PC shock

<table>
<thead>
<tr>
<th>Horizon (Quarters)</th>
<th>PC t</th>
<th>EPU t</th>
<th>VIX t</th>
<th>ANFCI t</th>
<th>GDP t</th>
<th>Inv t</th>
<th>Cash t</th>
<th>FFR t</th>
<th>Spread t</th>
</tr>
</thead>
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<tr>
<td>2</td>
<td>94.04</td>
<td>1.25</td>
<td>1.36</td>
<td>0.05</td>
<td>0.85</td>
<td>2.04</td>
<td>0.32</td>
<td>1.76</td>
<td>0.01</td>
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<tr>
<td>8</td>
<td>85.33</td>
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<td>2.38</td>
<td>0.23</td>
<td>0.26</td>
<td>1.19</td>
<td>4.49</td>
<td>3.00</td>
<td>0.12</td>
</tr>
<tr>
<td>16</td>
<td>78.06</td>
<td>3.98</td>
<td>3.21</td>
<td>1.00</td>
<td>0.25</td>
<td>1.23</td>
<td>4.02</td>
<td>2.81</td>
<td>0.48</td>
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<tr>
<td>32</td>
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<td>0.42</td>
<td>1.51</td>
<td>3.36</td>
<td>2.47</td>
<td>0.58</td>
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</table>

Panel B: share of variation in all variables explained by structural EPU shock

<table>
<thead>
<tr>
<th>Horizon (Quarters)</th>
<th>PC t</th>
<th>EPU t</th>
<th>VIX t</th>
<th>ANFCI t</th>
<th>GDP t</th>
<th>Inv t</th>
<th>Cash t</th>
<th>FFR t</th>
<th>Spread t</th>
</tr>
</thead>
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<tr>
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<td>66.15</td>
<td>15.24</td>
<td>12.77</td>
<td>15.74</td>
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<td>8.04</td>
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<td>23.12</td>
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<tr>
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<td>52.97</td>
<td>15.84</td>
<td>15.01</td>
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<td>7.12</td>
<td>10.97</td>
<td>31.19</td>
<td>22.61</td>
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</table>

Panel C: share of variation in cash explained by all shocks

<table>
<thead>
<tr>
<th>Horizon (Quarters)</th>
<th>Cash t</th>
<th>Cash t</th>
<th>Cash t</th>
<th>Cash t</th>
<th>Cash t</th>
<th>Cash t</th>
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</tr>
</thead>
<tbody>
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<td>91.97</td>
<td>2.29</td>
<td>0.86</td>
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<tr>
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</tr>
<tr>
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<td>4.02</td>
<td>14.07</td>
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<td>11.06</td>
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<td>2.27</td>
<td>46.78</td>
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<td>3.28</td>
</tr>
<tr>
<td>32</td>
<td>3.36</td>
<td>10.97</td>
<td>0.34</td>
<td>21.43</td>
<td>8.02</td>
<td>3.27</td>
<td>35.02</td>
<td>14.24</td>
<td>3.35</td>
</tr>
</tbody>
</table>

Note: Panel A shows the forecast error variance decomposition for all variables that is explained by a PC shock. Panel B shows the forecast error variance decomposition for all variables that is explained by an EPU shock. Panel C shows the forecast error variance decomposition for the aggregate cash ratio that is explained by each shock. The unit is in percent.
5.3.2. Sign restrictions

We also attempt to relax the strict timing assumptions implied by Cholesky decomposition by imposing sign and zero restrictions on the contemporaneous impulse response functions, based on the algorithm proposed by Arias et al. (2014). The sign restrictions approach is attractive since it allows the identification to remain agnostic with respect to the responses of the key variables of interest. Moreover, the results based on the sign and zero restrictions approach are not sensitive to the ordering of the variables. Table 5 displays the restrictions we impose. The sign restrictions are motivated by the theoretical predictions in the literature, a detailed discussion of which is found in the appendix. However, the key feature is that we are agnostic about the response of the cash ratio to the uncertainty shocks.

The resulting impulse responses are reported in the appendix. Our baseline results remain robust: policy uncertainty shocks cause significant business cycle fluctuations. Political and policy uncertainty shocks also cause a persistent rise in the aggregate cash ratio, although the rise is no longer significant.\(^{15}\) It is worth noting that, in response to PC shocks, both VIX and the financial conditions index see a persistent decrease. This is in line with our baseline results and implies that our main results are not sensitive to alternative identification methods.

6. Non-parametric estimation: local projection

The methodology we have implemented thus far is parametric in nature. In this section, we adopt a non-parametric impulse response estimation approach to estimate the impacts of PC and EPU shocks. More specifically, we use the local projection (LP) method proposed by Jordà (2005). One advantage of using local projections over VAR models is that local projections are less prone to model misspecification (Jordà, 2005). Moreover, unlike in a VAR setting, the estimation of reduced-form equations for all variables is not required. An additional benefit to the LP methodology is that it provides us with a convenient way to study the potential nonlinear nature of uncertainty shocks. This will be explored in more detail in the next section.\(^{14}\)

We first rely on a statistical method to construct “exogenous” uncertainty shocks. Following Bloom (2009) and Caggiano et al. (2014), we adopt a Hodrick-Prescott (HP) filter to identify “big spikes” in the uncertainty series. In particular, we adopt the smoothing parameter to be \(\lambda = 1600\) and isolate the large spikes of the realizations above 1 standard deviation of the HP-filtered trend.\(^{12}\) Some of the major PC and EPU shocks identified by this approach are included in Fig. 1. These identified shocks are associated with financial crises and political events, such as wars, 9/11, and elections, which are likely driven by exogenous factors. In the appendix, we show that these results remain robust to the use of the procedure developed by Hamilton (2018).

We then estimate the impulse response functions using local projection methods. We consider the following series of regressions:

\[
y_{t+h} = \alpha_0 + \theta_i \nu_i + X_{t-1} + u_{t+h}, \quad h \geq 0
\]

where \(h\) refers to the horizon, \(y\) is the endogenous variables of interest, \(\alpha_0\) is a constant term, \(\nu_i\) is the constructed exogenous structural shock and \(u_{t+h}\) is the model residual. \(\nu_i\) is a dummy variable that takes the value of 1 when the PC (or EPU) Index is 1 standard deviation larger than its HP-filtered value, and 0 otherwise. \(X_i\) is a vector of control variables that include two lags of the following variables: the PC Index, the EPU Index, the VIX index, the ANFCI, real gross domestic product, real investment, the aggregate corporate cash ratio, the federal funds rate, and the commercial paper spread.\(^{16}\)

The coefficient \(\theta_i\) represents the response of \(y\) at time \(t + h\) to an exogenous shock at time \(t\). We use OLS to estimate a series of regressions for each horizon and the estimated standard errors of \(\theta_i\) are used to compute the error bands. We adopt the Newey-West variance estimator to account for the serial correlations among the residuals.

Figs. 4 and 5 report the impulse response functions — in general the responses are less smooth, as noted by Ramey and Zubairy (2018), since local projections do not impose any restrictions among impulse responses. However, the baseline results are mostly robust to this non-parametric estimation. Specifically, a PC shock induces a drop and quick rebound in investment and output. This drop, rebound, and overshoot behavior in investment and output is due to an increase in the real option value of waiting, as pointed out by Bloom (2009). A PC shock also leads to a hump-shaped rise in the aggregate cash ratio. On the other hand, the economic contraction implied by the EPU shock is somewhat weaker under our non-parametric estimation. However, the persistent increase in the aggregate cash ratio remains robust and statistically significant.

7. Asymmetric responses of uncertainty shocks under different financial conditions

In this section, we will take advantage of the flexibility afforded by the non-parametric methodology from Section 6 and study potential asymmetries in the nonlinear impact of political and economic policy uncertainty shocks, respectively. As discussed in the

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\(^{12}\) The statistical insignificance can be explained by the substantial increase in “uncertainty” in the estimation because sign restrictions identify a set of models rather than uniquely pinning down a single structural model, as noted by Fry and Pagan (2011) and Baumeister and Hamilton (2015).

\(^{14}\) In principle, we can use a nonlinear VAR – for example an interacted VAR model where the coefficients are interacted with financial regime variables. However, we choose not to adopt this approach because it would require us to estimate significantly more parameters with a relatively short data sample.

\(^{15}\) Bloom (2009) and Caggiano et al. (2014) use the threshold value of 1.65 instead of 1 to isolate uncertainty shocks. Our results remain robust when we use 1.65 as the threshold value.

\(^{16}\) We also estimate a model that controls for a wider range of corporate accounting variables that are relevant to cash holding in the corporate finance literature. These variables, taken from Opler et al. (1999) and Bates et al. (2009), include the market-to-book ratio, cash flow, net working capital ratio, leverage, and size. These results are available in the appendix.
previous section, this approach is preferable to using a nonlinear VAR, which would be computationally expensive.

As pointed out by Alfaro et al. (2016), heightened financial uncertainty often leads to cash hoarding and this effect tends to be stronger during periods of high financial frictions. We adopt the Adjusted National Financial Conditions Index (ANFCI) as a proxy for aggregate financial conditions. Financial conditions are defined as “tight” when the ANFCI is above zero and as “loose” or “normal” when it is equal to or below zero. We interact Eq. (2), the original linear local projections model, with this proxy:

Table 5

<table>
<thead>
<tr>
<th></th>
<th>PCt</th>
<th>EPUt</th>
<th>It</th>
<th>VIXt</th>
<th>ANFCIt</th>
<th>GDPt</th>
<th>FFRt</th>
<th>Casht</th>
<th>Spreadt</th>
</tr>
</thead>
</table>

Note: This table reports the sign and zero restrictions imposed on the contemporaneous impulse responses in order to identify the two structural shocks of interest. Entries with “?” indicate that no restrictions are imposed and we are agnostic about the signs. Explanations on these restrictions are found in the appendix.

Fig. 4. Impulse responses to a political uncertainty (PC) shock using local projections. Notes: Political uncertainty is proxied by the Partisan Conflict Index developed in Azzimonti (2018a). Grey shaded areas: one standard error confidence bands.

Fig. 5. Impulse responses to an economic policy uncertainty (EPU) shock using local projections. Notes: Economic Policy Uncertainty is proxied by the Economic Policy Index developed in Baker et al. (2016). Grey shaded areas: one-standard-error confidence bands.
\[
y_{t+h} = I_h [\alpha_h^T + \delta_h^T v_t] + (1 - I_h) [\alpha_h^L + \delta_h^L v_t] + X_{t-1} + u_{t+h} \quad h \geq 0
\]

where \(I_h\) is an indicator function that takes the value of 1 when the financial condition is tight and 0 otherwise. \(X_{t-1}\) includes the interaction terms between the lagged control variables and the lagged indicator functions. The coefficients \(\delta_h^T\) and \(\delta_h^L\) capture the effect of an uncertainty shock on the variable of interest under tight and loose financial conditions, respectively.\(^{17}\)

As in the linear local projection model, we employ data from 1985Q1 to 2008Q3. The results are reported in Figs. 6 and 7, where we observe interesting differences between how the aggregate cash ratio responds to different uncertainty shocks. Fig. 6 shows that when a PC shock is felt during loose or normal financial conditions, the aggregate cash ratio increases to a peak of approximately 3% by the third quarter, which is qualitatively consistent with what we observed in Figs. 2 and 4. However, the increase in cash is relatively short-lived. While several of the additional variables in the model move in the predicted directions – investment and GDP fall – they are not statistically different from zero. Conversely, when a PC shock occurs during tight financial conditions, we see a starkly different response. Following the shock, the aggregate cash ratio falls significantly upon impact, reaching a 5% decline by the second quarter and a 9% decline by the fifth quarter. Furthermore, both the EPU Index and VIX decrease significantly within a few quarters while GDP and investment fall as well.

This last observation is crucial for explaining the decline in the cash ratio. The decline in policy uncertainty after a partisan conflict shock is indeed supported by previous research, both theoretical and empirical. Bechtel and Füss (2008) develop a theoretical model showing that divided government leads to a reduction in economic policy uncertainty and financial market risk. They find empirical evidence for their theoretical claim using German political and economic data. More relevant to our findings, though, is the recent work by Gupta et al. (2018b), who observed that US stock market volatility was lower in the presence of a PC shock. Given the observed relationship between VIX and the EPU Index, it is not surprising that we also observe a decline in uncertainty over economic policy. This result is also consistent with the theoretical model developed by Pastor and Veronesi (2012), which shows that lower policy uncertainty leads to lower financial market volatility. For several of the moderate-to-large spikes in the PC Index, observed in Fig. 1, we see declines, sometimes rather sharp, in economic policy uncertainty. Hence, it is possible that when the economy is already in a financially tight state, a PC shock precipitates lower economic policy uncertainty and financial market volatility, leading financial conditions to loosen, which could potentially relax the borrowing constraints faced by firms. As a consequence, firms choose to reduce the percentage of assets held as cash in lieu of other uses.

Fig. 7 shows the impulse response functions following an EPU shock under tight and loose financial conditions, respectively. Not surprisingly, an EPU shock leads to an increase in VIX under both tight and loose financial conditions. Under loose financial conditions, ANFCI is mostly indistinguishable from zero, except for a short-lived decrease early on. However, we also observe a large increase in ANFCI upon the impact of an EPU shock during tight financial conditions. During tight financial conditions, the aggregate cash ratio appears to increase significantly approximately three quarters following the shock and, during loose financial conditions, the increase in cash begins around the fifth quarter. Under both tight and loose conditions, the cash ratio reaches a peak of approximately 5% by the fifth quarter. Although the median impact response of the cash ratio to an EPU shock is larger under tight financial conditions, the difference in the response of the cash ratio under both tight and loose financial conditions is not statistically significant. The reason for why the cash ratio increases to approximately the same level under both financial condition regimes is likely related to the close relationship between VIX and the EPU Index during the sample period. An exogenous event that causes a shock to economic policy uncertainty is also likely to increase financial market volatility. Since this volatility is quite high under both loose and tight conditions, we see the increase in cash.

8. Conclusion

In this paper, we distinguish political uncertainty from policy uncertainty and investigate the impacts of these two different types of uncertainty on the cash holdings of corporate firms in the US. By using various models, both parametric and non-parametric, we find that both types of uncertainties exert a significant impact on the aggregate cash ratio. Moreover, together, they explain a considerable portion of the variation in the cash ratio in our sample. Our main results are upheld by a series of robustness checks.

We also find that the impact of political uncertainty on the aggregate cash ratio displays asymmetry. In particular, we find political uncertainty shocks lower economic policy uncertainty and financial volatility significantly under tight financial conditions, leading to a decline in corporate cash holdings. However, a similar response is not observed after a policy uncertainty shock. Our empirical results add to the recent literature that relates uncertainty and corporate cash holdings, and lays the groundwork for further theoretical investigation into their relationships in the future. Another interesting extension is to consider measures of local and state partisan conflict that would help researchers measure the response of cash holdings of firms within and across states. We leave this for future research.\(^{18}\)

\(^{17}\) In the appendix, we provide robustness checks replacing the Aggregate Financial Conditions Index with two liquidity indicators, following Bacchetta et al. (2016) and Chiu (2014). The results are broadly robust.

\(^{18}\) We thank an anonymous referee for this interesting suggestion.
Fig. 6. Asymmetric impulse responses to a political uncertainty (PC) shock using local projections — financial conditions (ANFCI). Notes: Impulse responses to a partisan conflict dummy shock. Dashed lines: responses under loose financial conditions. Lines with Diamonds: responses under tight financial conditions. Grey shaded areas and solid lines represent one standard error confidence bands in tight and loose financial conditions, respectively.

Fig. 7. Asymmetric impulse responses to an economic policy uncertainty (EPU) shock using local projections — financial conditions (ANFCI). Notes: Impulse responses to an economic policy uncertainty dummy shock. Dashed lines: responses under loose financial conditions. Lines with Diamonds: responses under tight financial conditions. Grey shaded areas and solid lines represent one standard error confidence bands in tight and loose financial conditions, respectively.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jmacro.2018.08.010.

References
