Policy Uncertainty and Corporate Investment

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Using a news-based index of policy uncertainty, we document a strong negative relationship between firm-level capital investment and the aggregate level of uncertainty associated with future policy and regulatory outcomes. More importantly, we find evidence that the relation between policy uncertainty and capital investment is not uniform in the cross-section, being significantly stronger for firms with a higher degree of investment irreversibility and for firms that are more dependent on government spending. Our results lend empirical support to the notion that policy uncertainty can depress corporate investment by inducing precautionary delays due to investment irreversibility. (*JEL* D80, E22, E66, G18, G31, G38)

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> *Business contacts in many parts of the country were reported to be highly uncertain about the outlook for the economy and for fiscal and regulatory policies. Although firms' balance sheets were generally strong, these uncertainties had led them to be particularly cautious and to remain reluctant to hire or expand capacity…*[1]

Politicians and regulatory institutions frequently make decisions that alter the environment in which firms operate. Since businesses often face a significant amount of uncertainty regarding the timing, content, and potential impact of policy decisions, it is important to investigate whether this policy-related uncertainty has important economic consequences. This topic has recently

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[1] From the minutes of the Federal Open Market Committee (FOMC) meeting in September 2012.

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received increased attention from academics, policy makers, and the media, with many commentators arguing that the uncertainty induced by the political system is one of the main reasons for the sluggish recovery following the 2008–2009 financial crisis.[2] We contribute to this debate by empirically investigating the effect of policy-related uncertainty on corporate investments in the United States.

One of the main challenges in this line of research is finding an appropriate measure of policy uncertainty. The overall uncertainty faced by firms has been measured using a variety of variables, such as dispersion in analyst forecasts or volatility of stock returns, input and output prices, total factor productivity, or firm fundamentals.[3] However, measuring the portion of this uncertainty attributed to the political and regulatory system is a daunting task. While some studies have focused on particular types of policy (fiscal, monetary, social security), significantly less work has been done to measure the overall level of policy uncertainty in the economy.

Baker, Bloom, and Davis (2013) (henceforth BBD) fill this gap in the literature by constructing an index of aggregate policy uncertainty as a weighted average of three different components. The first and most heavily weighted component is derived from a count of newspaper articles containing key terms related to policy uncertainty. The second component measures uncertainty about future changes in the tax code using the dollar impact of tax provisions set to expire in the near future. The third and final component uses dispersion in economic forecasts of the CPI and government spending to proxy for uncertainty about fiscal and monetary policy. A visual inspection of the index (Figure 1) reveals that it spikes during events that are ex ante likely to cause increases in policy uncertainty, such as debates over the stimulus package, the debt ceiling dispute, major federal elections, wars, and financial crashes. It also exhibits considerable time-series variation in the periods between such major events. The next section contains a more detailed discussion of the construction of the index and the precautions taken by BBD to ensure that it does in fact capture aggregate policy uncertainty and not some other confounding factors.

We use the BBD index to estimate the effect of policy uncertainty on corporate investments. Besides the classic investment predictors (Tobin's q, cash flows, sales growth), we also control for several macroeconomic proxies for investment opportunities (e.g., forecasted GDP growth, composite leading indicators, and consumer confidence.) This is meant to alleviate endogeneity concerns stemming from the fact that uncertainty tends to be countercyclical and could therefore be capturing the effect of poor economic prospects.[4]

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[2] For example, see Stock and Watson (2012) or "Investment Falls Off a Cliff: U.S. Companies Cut Spending Plans Amid Fiscal and Economic Uncertainty" (*Wall Street Journal*, November 19, 2012).

[3] See, for example, Leahy and Whited (1996), Ghosal and Loungani (1996), Minton and Schrand (1999), Bond and Cummins (2004), Bloom et al. (2012), and Stein and Stone (2012).

[4] See, for example, Bloom et al. (2012).

Additionally, we control for several measures of general economic uncertainty (e.g., the VXO index of implied volatility, cross-sectional dispersion in returns, and the Jurado, Ludvigson, and Ng (2015) index) to ensure that the effect we are estimating can be attributed to the political and regulatory system and not to some other source of uncertainty.

In our study, we find evidence of a persistent, negative relationship between policy uncertainty and investment. In our preferred specification, we estimate that a doubling in the level of policy uncertainty is associated with an average decrease in quarterly investment rates of approximately 8.7% relative to the average investment rate in the sample. This is a sizable effect, considering that during the recent financial crisis, the policy uncertainty index nearly tripled. A counterfactual analysis indicates that the increase in policy uncertainty between 2007 and 2009 may be accountable for roughly one-third of the 32% fall in capital investments observed during this period.

From a time-series perspective, we find that policy uncertainty can affect investment levels up to eight quarters into the future. Indeed, the effect seems to be progressively stronger (more negative) over the first four to five quarters, after which time it begins to decay, becoming positive at longer lags into the future. This is consistent with the idea that once uncertainty is resolved, firms increase investments to satisfy pent up demand. The fact that this rebound occurs over the span of two to three years shows that it can take a significant amount of time to recover from the effects of policy uncertainty.

To assess which one of the three subcomponents of the BBD index is driving this result, we also run our regressions separately using each one of them as our measure of policy uncertainty. We find that most of the explanatory power of the BBD index can be attributed to the news-based component, even though the component measuring tax-related uncertainty also has a significantly negative impact on investment. On the other hand, we find that the component measuring fiscal and monetary policy uncertainty through forecast dispersion is not a significant predictor of investment.

Our findings hold up to a battery of robustness tests. First, we verify that the BBD index is not simply picking up the effect of elections on investments (Julio and Yook 2012). Second, we use the cumulant estimator of Erickson, Jiang, and Whited (2014) to ensure that our results are not an artifact of measurement error in Tobin's q. Third, we address concerns about overfitting the data by showing evidence that the policy uncertainty variable can reliably predict investments out of sample. Fourth, based on the idea that the United States and Canadian economies are tightly linked, we regress the BBD index on a measure of policy uncertainty in Canada (also developed by BBD) to remove possible confounding macroeconomic forces from the index (to the extent that they are common to both countries). We find that all of our results hold if we use the residuals from this regression as our main measure of policy uncertainty. Finally, to further alleviate endogeneity concerns, we show that our results also hold in an IV specification in which a measure of political polarization in the United States Senate is used as an instrument for policy uncertainty.

To identify possible mechanisms through which policy uncertainty propagates in the economy, we investigate whether the negative effect of policy uncertainty on capital investment exhibits heterogeneity in the cross-section. This investigation is motivated by the predictions made by the real options literature, which has received a great deal of attention from both academics and policy makers.[5] This literature emphasizes that if investment projects are (even partially) irreversible, uncertainty shocks can increase firms' incentives to delay investment until some of the uncertainty resolves (e.g., Bernanke 1983; Rodrik 1991; Dixit and Pindyck 1994). If this is the case, the slow-down effect should be stronger for firms with more irreversible investments. To test this prediction, we use four different proxies for investment irreversibility: the ratio of fixed to total assets, a measure of asset redeployability proposed by Kim and Kung (2013), an indicator variable for whether the firm operates in a "durables" industry, and a measure of sunk costs based on rent expense, depreciation, and fixed asset sales. Consistent with the above prediction, we find that the dampening effect of policy uncertainty on capital expenditures is stronger for firms that, according to these proxies, have a higher degree of investment irreversibility.

The second source of cross-sectional heterogeneity we explore is firms' dependence on government spending. If political uncertainty has a negative effect on corporate investments, then this effect should be stronger for firms that rely on the government more for their sales. Following Belo, Gala, and Li (2013), we use the BEA input-output tables to calculate the percentage of an industry's total sales purchased by the government (directly and indirectly). We find that the investments of firms operating in industries with a higher dependence on government spending are significantly more negatively affected by policy uncertainty.

The real options mechanism also makes a prediction about the evolution of the policy uncertainty effect over time. Specifically, even though firms may find it advantageous to delay investments in the face of uncertainty, if the uncertainty persists over a long period of time, firms may be compelled to eventually invest, either because many investment projects cannot be delayed indefinitely, or because the cash flows lost by postponing investments may

5 From the minutes of the Federal Open Market Committee, in April 2008, "Several participants reported that uncertainty about the economic outlook was leading firms to defer spending projects until prospects for economic activity became clearer. The tightening in the supply of business credit was also seen as holding back investment, with some firms apparently reluctant to reduce their liquidity positions in the current environment."
From the remarks of Lawrence Summers, director of the White House National Economic Council, at the Brookings Institution on the Obama administration's economic program and the prospects for the American economy on March 13, 2009, "...unresolved uncertainty can be a major inhibitor of investment. If energy prices will trend higher, you invest one way; if energy prices will be lower, you invest a different way. But if you don't know what prices will do, often you do not invest at all. That is why we must move forwards as rapidly as possible to reduce uncertainty and carefully create a new cap-and-trade regime."

become too large to justify any further delays. To test this hypothesis, we investigate how conditional average investments evolve throughout high-policy-uncertainty spells. Consistent with our prediction, we find that while average investments decrease significantly in the first four to five quarters of a high-policy-uncertainty spell, they then recover to the point that after seven or more quarters of high policy uncertainty, conditional average investments are at the same level as observed during quarters with below-average policy uncertainty.

Our paper is related to the recent studies that use national or local elections as indicators of times with high political uncertainty.[6] The paper closest to ours is Julio and Yook (2012), who use a panel of countries to show that investments tend to drop significantly during election years. We improve on this strand of the literature in several important ways. First, while elections may be good exogenous indicators of higher uncertainty, they do not tell us how much policy uncertainty increases during these elections, and the election indicator variable assumes that policy uncertainty does not change during nonelection years. While this is not an issue for identification purposes, it can be a significant drawback from a measurement standpoint.[7] By using a variable designed to measure the actual level of policy uncertainty at every point in time, our paper should provide a more accurate picture of the magnitude of the effect of policy uncertainty on investments. Second, by studying how this effect varies in the cross-section, we shed light on the mechanisms by which uncertainty affects the economy. We show that firms' investment irreversibility and their reliance on government spending are crucial moderators of the policy uncertainty-investment relationship. Finally, we investigate how this relationship evolves through time and show evidence that policy uncertainty can have a long-lasting impact on the economy, affecting investments for up to two years into the future.

1. Measuring Policy Uncertainty

We measure policy-related economic uncertainty using an aggregate index developed by Baker, Bloom, and Davis (2013). Below we describe how this index is built and why it should be considered a reliable measure of the overall level of policy uncertainty present in the economy.

The BBD index is a weighted average of three components. The first component quantifies the volume of news discussing policy-related uncertainty, every month starting in January 1985. This is done using an automated search

[6] See, for example, Boutchkova et al. (2012), Durnev (2010), Julio and Yook (2012), and Jens (2012).

[7] This is clear to see for at least a couple of reasons. First, an election dummy variable does not take into account the fact that elections at different points in time or in different countries will have different implications for the level of policy uncertainty in the economy. Second, election years do not capture the variation in policy uncertainty that may occur between elections. Intuitively, this variation is likely significant given the infrequency of elections and the many uncertainty-inducing events that happened in nonelection years, such as debates over the stimulus package, the debt ceiling dispute, wars, and financial crashes.

of the archives of ten large newspapers, and counting the number of articles containing at least one of the terms "uncertainty" or "uncertain," at least one of the terms "economic" or "economy," and at least one of the terms "congress," "legislation," "white house," "regulation," "federal reserve," or "deficit." To control for the changing volume of news throughout time, for each of the ten newspapers, each month, the number of policy uncertainty articles is normalized by the total number of articles in that newspaper. These ten series are then normalized to unit standard deviation and summed within each month. The resulting index is then scaled to have an average value of 100 from 1985 to 2009.

The second component of the BBD index measures the level of uncertainty related to future changes in the tax code. This is done using data from the Congressional Budget Office on the tax provisions set to expire in the near future. BBD estimate this level of tax-related uncertainty every year by the discounted value of the revenue effects of all tax provisions set to expire in the following ten years. The third and final component of the BBD index captures forecaster disagreement about future monetary and fiscal policies. The authors use the Survey of Professional Forecasters provided by the Federal Reserve Board of Philadelphia to obtain forecasts of CPI, and purchases of goods and services by federal, state, and local governments. The forecast disagreement index is obtained by taking the average of the interquartile ranges of these two forecasts.

To obtain their overall measure of policy uncertainty, BBD first normalize each of the three components above and then calculate a weighted average of the resulting series, using a weight of one-half for the news-based component, one-sixth for the tax component, and one-third for the forecaster disagreement component. As we can see in Figure 1, this index exhibits clear spikes around events that are ex ante expected to increase policy-related uncertainty, such as recessions (shaded areas), financial crises, and wars.

In panel A of Table 1, we present the correlation coefficients between the overall BBD index and it subcomponents, as well as the correlations with the quarterly growth in real GDP and the VXO index of implied volatility from the CBOE. Not surprisingly, the overall index is highly correlated with each of its components, particularly with the news-based index (0.887). The news component is also strongly correlated with the tax component (0.357), but less so with the measures based on forecaster disagreement (which are themselves strongly correlated). Overall, this suggests that even though there may be some informational overlap between the components of the BBD index, they each contain unique information.

Finally, note that the overall BBD index, as well as its news-based component, are strongly negatively correlated with GDP growth and strongly positively correlated with the VXO index (i.e., with uncertainty about future equity returns.) This provides a first hint at the econometric challenges faced, since it suggests that policy uncertainty is likely to correlate with other measures of economic uncertainty, as well as with firms' investment opportunities. To

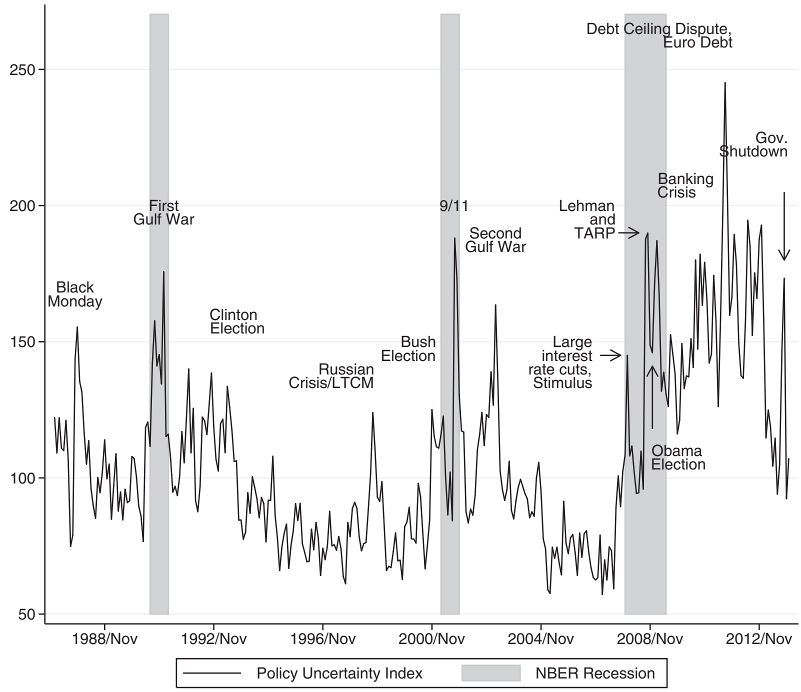

Figure 1
Policy uncertainty index
This figure plots the Baker, Bloom, and Davis (2013) index of policy uncertainty (solid line), together with the NBER recession periods (shaded areas), during the January 1987 to December 2013 period.

the extent that this is simply a feature of the economic environment, later in the paper we discuss the precautions taken to ensure that our inference is not clouded by these confounding effects. However, another possibility is that this correlation is the artifact of measurement error: the BBD index may inadvertently measure low investment opportunities or economic uncertainty that is not policy related. BBD go to great lengths to minimize this possibility. We present a summary of their attempts below.

Since the main component of the BBD index is built using newspaper searches and not by directly estimating the second moment of any economic variable, it is not immediately clear that the BBD methodology can actually produce a reliable measure of uncertainty. To alleviate this concern, as a proof-of-concept exercise, BBD use their news-search methodology to construct an index of equity market uncertainty. To this end, they use the same newspaper search procedure described in the previous section, only this time replacing the terms related to policy with the terms "stock price," "equity price," or "stock market." They find that the level of the resulting index has a correlation of 0.73

Table 1
Summary statistics

Panel A: Correlation matrix

	PU	PU news	PU Tax	PU CPI	PU GOV	Δ GDP	VXO
Policy uncertainty (PU)	1.000						
PU news component	0.887	1.000					
PU tax component	0.626	0.357	1.000				
PU CPI component	0.471	0.153	0.258	1.000			
PU Gov.Purch. component	0.373	0.071	0.156	0.427	1.000		
Real GDP growth	−0.396	−0.393	−0.182	−0.270	0.009	1.000	
VXO	0.383	0.457	0.017	0.210	−0.025	−0.276	1.000

	Panel B1: Sample used in this study				Panel B2: Compustat universe 1987–2013			
	N	Mean	Median	SD	N	Mean	Median	SD
CAPX	441,326	26.5	1.5	87.4	572,204	24	1.1	83.5
PPE	425,108	648	34.2	2,123	639,932	609	24.3	2,075
Total assets	441,326	2,882	267	9,170	661,360	2,886	226	9,418
Operating cash flows	441,326	53.5	2.8	190	544,309	48.7	1.9	183
Sales	441,326	423	48.4	1,187	649,950	397	36.6	1,185
CAPX/Lag total assets	441,326	0.014	0.008	0.020	568,769	0.015	0.008	0.022
Tobin’s q	441,326	1.869	1.350	1.545	643,699	1.937	1.319	1.733
Cash flows/Lag total assets	441,326	0.011	0.015	0.058	541,294	0.006	0.013	0.065
Sales growth	441,326	0.181	0.078	0.581	588,911	0.192	0.080	0.617
PPE/Lag total assets	425,108	0.265	0.187	0.245	617,089	0.259	0.172	0.254

Panel C: Classic investment regressions

	CAPX/TA	CAPX/TA	CAPX/TA
Tobin’s q	0.156***		0.157***
	(24.66)		(24.85)
Cash Flows		0.0517***	0.0533***
		(14.98)	(16.26)
N	441,326	441,326	441,326
R-sq	0.020	0.003	0.023

This table presents summary statistics for the main variables used in our analysis. The data extend from January 1987 to December 2013. Panel A presents correlations between the policy uncertainty index of Baker, Bloom, and Davis (2013), the index’s subcomponents, the quarterly growth rate in real GDP and the CBOE index of implied volatility VXO. All variables in this panel are measured at the monthly frequency, except for the GDP growth rate which is measured quarterly. Panel B presents summary statistics both for the sample used in this study (panel B1) as well as for the entire Compustat universe (panel B2). In panel C we regress quarterly capital investments (CAPX/TA) on Tobin’s q and operating cash flows.

with the VIX index provided by the CBOE, which is a widely accepted measure of uncertainty related to future equity returns.

While the above exercise provides evidence that frequency counts of newspaper articles can in principle yield informative measures of economic uncertainty, it is not clear that the specific search terms used by the BBD index actually provide an accurate measure of policy-specific uncertainty in the economy. To ensure that the best possible set of search terms is used, the authors lead a human audit of 10,463 newspaper articles with the purpose of identifying which of these articles actually discuss an increase in policy uncertainty and which do not. They then run automated searches of the same articles using 32,193 different combinations of key words and choose the combination that minimizes the sum of false positives and false negatives (with respect to the human audit).

The human audit provides two additional important pieces of information. First, the authors find that only 1.8% of the audited articles discuss a decrease in policy uncertainty as opposed to an increase. This is reassuring, considering that automated textual searches are not sophisticated enough to make this distinction on their own. Second, the authors calculate the difference between the index obtained through an automated search (using the optimal key terms) and the index obtained using the human audit. They find that this measurement error is not correlated with either GDP growth or the true index of policy uncertainty (the human audit). This is reassuring from an econometric point of view, since it implies that even though the BBD index may not be a perfect measure of policy uncertainty, the measurement error is not likely to induce a bias in our empirical analysis.

Another issue with the BBD index is the possibility that newspaper articles simply may not be a reliable source of information about the true level of policy uncertainty in the economy. For example, this possibility arises if left-leaning newspapers tend to emphasize policy uncertainty when Democrats are in power, or vice versa. To investigate this issue, BBD use the Gentzkow and Shapiro (2010) media slant index to split the ten newspapers into the five most left-leaning and the five most right-leaning ones. They then run their textual search separately on the two sets of newspapers and find that the two resulting measures of policy uncertainty track each other closely. This suggests that most of the variation in the news-based index is not a result of political slant.

To further address potential biases in newspaper reporting on policy uncertainty, BBD test their methodology on a different source of information altogether: the Beige Books released before FOMC meetings. These books summarize the information gathered by each Federal Reserve Bank on the business conditions in the districts they represent. For each Beige Book since 1985, a human audit was performed on all passages that contained the terms “uncertain” or “uncertainty” to verify how many times these terms were used in the context of policy-related uncertainty. The resulting count yielded an index that had a 0.8 correlation with the overall BBD index described in the previous section. This provides further reassurance that newspaper articles do not contain significant biases in their discussions of policy uncertainty.

2. Data and Methodology

The data used in our empirical analysis come from the quarterly Compustat files and extend from January 1987 to December 2013. The sample period is chosen to match the availability of the policy uncertainty index and the operating cash-flow variable from the statement of cash flows. Our baseline tests are augmentations of panel regressions common to the investment literature:

$$\frac{CAPX_{i,t+l}}{TA_{i,t+l-1}}=\alpha_i+\beta_1 PU_{i,t}+\beta_2 TQ_{i,t}+\beta_3\frac{CF_{i,t}}{TA_{i,t-1}}+\beta_4 SG_{i,t}+\delta M_t+QRT_t+\varepsilon_{i,t+l}. \tag{1}$$

Here, i indexes firms, t indexes calendar quarters, and $l \in \{1,2,3,4\}$ stands for the quarter lead between the dependent and independent variables. The α_i's are firm fixed effects and the *QRT* term contains a set of calendar- and fiscal-quarter dummy variables meant to control for possible seasonality in capital investments. Standard errors are always clustered at the firm and calendar-quarter level to correct for potential cross-sectional and serial correlation in the error term $\varepsilon_{i,t+l}$ (Petersen 2009).

For each firm i, the policy uncertainty variable ($PU_{i,t}$) is measured as the natural logarithm of the arithmetic average of the BBD index in the three months of the firm's fiscal quarter ending in calendar quarter t. Since for each calendar quarter not all firms' fiscal quarters end on the same month, there is some cross-sectional variation in $PU_{i,t}$ for each t (which is why the $PU_{i,t}$ term carries a firm index). However, this variation is minimal, because the vast majority of firms do have fiscal quarters ending at the same time (the last month of the calendar quarter). This means that we cannot include time fixed effects in our specifications, since doing so would mechanically absorb all the explanatory power of the policy uncertainty variable. In the absence of time fixed effects, we control for possible confounding macroeconomic forces explicitly, using various proxies for investment opportunities and general economic uncertainty. For now, we denote these controls by the term M_t in Equation (1), and discuss them in more detail in the following section.[8]

The capital investment (*CAPX*) and operating cash-flow (*CF*) variables are both taken from the statement of cash flows and are normalized by beginning of the period total assets (*TA*). Tobin's q (*TQ*) is measured as the market value of equity plus the book value of assets minus book value of equity plus deferred taxes, all divided by book value of assets. Sales growth (*SG*) is calculated as the year-on-year growth in quarterly sales and is meant as an additional control for investment opportunities.

To be included in our analysis, firms must have nonmissing observations for all the accounting variables in Equation (1) for at least three years. This amounts to a sample of 10,278 unique firms with 441,326 firm-quarter observations. Panel B of Table 1 presents summary statistics for the main accounting variables used in our analysis. To reduce the impact of extreme outliers, all variables have

[8] It is not clear whether our analysis should be performed using the level of policy uncertainty or its first difference. In principle, both approaches could yield interesting results. Conceptually speaking, the EPU level is more appropriate for answering the question "How are firm investments affected when managers face high levels of policy uncertainty?," while a specification in differences is more suited for answering "How are firm investments affected by short-term policy uncertainty shocks?" Ultimately, while both questions are interesting, one of the main reasons we decided to focus on the first is that using quarterly changes can eliminate much of the relevant information contained in the level of uncertainty. Levels help capture the slow-moving, long-lasting relation between policy uncertainty and corporate investment. We believe that short-term changes in uncertainty influence investments when they accumulate to a large enough (or low enough) level of uncertainty. For example, we are not sure what the impact of a decrease (increase) in uncertainty would be if this decrease still leaves us at extremely high (low) levels of uncertainty. For these reasons, we decided to use the policy uncertainty index in levels in our analysis. Furthermore, in unreported tests, we verify that our results are robust to including the first differences of the index in our specifications.

been winsorized at the 1% and 99% level. Comparing panels B1 and B2, we can see that even though we have imposed several filters on the data, our final sample is similar to the entire Compustat universe.

3. The Average Effect of Policy Uncertainty on Investment

We begin our empirical analysis by estimating several benchmark investment regressions using only Tobin's q and operating cash flows as predictor variables. The results in panel C of Table 1 show that both variables have significant explanatory power, despite the q-theory prediction that only Tobin's q should. This common result has been the source of much debate in the literature, with some authors interpreting it as evidence that financial constraints have a significant effect on investment (e.g., Fazzari, Hubbard, and Petersen 1988), and others arguing that cash flows simply capture the effect of investment opportunities in a way that Tobin's q does not (e.g., Alti 2003; Erickson and Whited 2000). Even though our study is not concerned with the interpretation of the coefficient on cash flows, this debate points to the possibility that Tobin's q is not a perfect measure of investment opportunities. Hence, the concern for our study is that the policy uncertainty variable may also be capturing (at least to some extent) the effects of poor investment opportunities which are missed by the Tobin's q variable. Throughout the paper we discuss several attempts to alleviate this concern. For now however, we begin with a set of baseline estimates of the average effect of policy uncertainty on investment.[9]

In Table 2 we run four specifications of Equation (1), one for each $l \in \{1,2,3,4\}$, to accommodate the possibility that the effect of policy uncertainty on investment may persist over multiple quarters or may manifest itself with a lag (results are in columns (1) to (4) in each panel). We present results for the overall policy uncertainty index in panel A and separately for each of its three components in panels B, C, and D. At this stage, we use two variables to control for possible confounding macroeconomic forces (M_t). First, we use the quarterly growth in real GDP as a proxy for current demand conditions. Second, we use an indicator variable equal to one if a presidential election is scheduled in the current calendar year, to ensure that the policy uncertainty variable is not simply picking up the negative impact of elections on investments documented by Julio and Yook (2012).

To facilitate the comparison of economic magnitudes across covariates, all variables have been normalized by their sample standard deviation. Therefore, each coefficient can be interpreted as the change in the dependent variable (as a proportion of its standard deviation) associated with a one-standard-deviation

9 The benchmark regressions in Table 1 also find that Tobin's q predicts investments better than the cash-flow variable. While this may be at odds with the older investment studies (e.g., Fazzari, Hubbard, and Petersen (1988)), it is not incompatible with the more recent studies in the literature. For example, Chen and Chen (2012) find that operating cash flows were a stronger predictor of investment only until about 1980–1985. Since then, the effect has reversed and Tobin's q is a stronger explanatory variable than cash flows.

Table 2
Policy uncertainty and capital investment

Dependent variable: CAPX/Total assets	Panel A : Overall policy uncertainty index				Panel B : News-based component of policy uncertainty index			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Policy uncertainty	−0.168***	−0.171***	−0.179***	−0.174***	−0.128***	−0.137***	−0.151***	−0.153***
	(−6.67)	(−6.75)	(−7.04)	(−7.11)	(−5.88)	(−6.16)	(−6.32)	(−6.54)
Tobin's q	0.169***	0.159***	0.143***	0.128***	0.171***	0.160***	0.143***	0.128***
	(24.43)	(23.63)	(22.18)	(18.65)	(24.49)	(23.66)	(22.15)	(18.59)
Cash flow	0.0258***	0.0359***	0.0379***	0.0347***	0.0257***	0.0357***	0.0378***	0.0346***
	(10.04)	(13.70)	(14.22)	(13.31)	(9.95)	(13.59)	(14.13)	(13.21)
Sales growth	0.0409***	0.0448***	0.0397***	0.0305***	0.0414***	0.0452***	0.0400***	0.0307***
	(14.69)	(15.52)	(13.84)	(10.54)	(14.38)	(15.41)	(13.90)	(10.62)
GDP growth	0.0111	0.0199**	0.0225**	0.0324***	0.0137*	0.0219**	0.0241***	0.0335***
	(1.43)	(2.31)	(2.48)	(3.39)	(1.76)	(2.55)	(2.63)	(3.44)
Election indicator	0.00448	−0.00517	−0.0155	−0.0251	0.00674	−0.00291	−0.0131	−0.0227
	(0.28)	(−0.33)	(−0.90)	(−1.23)	(0.41)	(−0.18)	(−0.77)	(−1.14)
N	424,785	412,621	401,744	392,679	424,785	412,621	401,744	392,679
R-squared	0.039	0.038	0.033	0.028	0.038	0.037	0.033	0.028
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes	yes	yes
Cluster by firm	yes	yes	yes	yes	yes	yes	yes	yes
Cluster by quarter	yes	yes	yes	yes	yes	yes	yes	yes

(*continued*)

Table 2
Policy uncertainty and capital investment (continued)

Dependent variable: CAPX/Total assets	Panel C : Policy uncertainty related to tax code				Panel D : Policy uncertainty related to government spending and inflation			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Policy uncertainty	−0.0601***	−0.0565***	−0.0536***	−0.0510***	−0.0331	−0.0236	−0.0181	−0.00558
	(−14.12)	(−13.10)	(−11.78)	(−10.54)	(−0.98)	(−0.77)	(−0.62)	(−0.20)
Tobin's q	0.166***	0.156***	0.142***	0.127***	0.177***	0.167***	0.152***	0.138***
	(23.91)	(23.17)	(21.48)	(18.22)	(24.84)	(24.07)	(22.51)	(19.33)
Cash flow	0.0269***	0.0370***	0.0391***	0.0359***	0.0256***	0.0356***	0.0376***	0.0344***
	(10.65)	(14.39)	(14.88)	(13.87)	(9.91)	(13.59)	(14.12)	(13.13)
Sales growth	0.0382***	0.0425***	0.0379***	0.0289***	0.0437***	0.0477***	0.0428***	0.0336***
	(13.41)	(14.63)	(12.93)	(9.77)	(15.12)	(15.82)	(14.15)	(11.21)
GDP growth	0.0146**	0.0238***	0.0276***	0.0374***	0.0217***	0.0312***	0.0348***	0.0452***
	(2.42)	(3.51)	(3.75)	(4.55)	(2.77)	(3.69)	(3.94)	(4.83)
Election indicator	0.00391	−0.00491	−0.0144	−0.0240	0.00927	−0.000173	−0.0103	−0.0201
	(0.29)	(−0.34)	(−0.83)	(−1.12)	(0.56)	(−0.01)	(−0.53)	(−0.89)
N	424,785	412,621	401,744	392,679	424,785	412,621	401,744	392,679
R-squared	0.046	0.044	0.039	0.032	0.038	0.037	0.033	0.028
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes	yes	yes
Cluster by firm	yes	yes	yes	yes	yes	yes	yes	yes
Cluster by quarter	yes	yes	yes	yes	yes	yes	yes	yes

In this table we regress firm-level quarterly investment (CAPX/Lagged Total Assets) on Tobin's q, operating cash flows, sales growth, and the policy uncertainty index from Baker, Bloom, and Davis (2013) (panel A). In panels B through D, we replace the overall policy uncertainty index with each of its three components, respectively. The data are quarterly and extend from January 1987 to December 2013. See Section 2 for a detailed description of how we calculate each variable. In specifications marked (1), the dependent variable has a lead of one period (calendar quarter) with respect to the independent variables in specifications marked (2) it leads two periods, and so forth until (4). All specifications include calendar and fiscal quarter dummies, as well as firm fixed effects. All variables are normalized by their sample standard deviation. Standard errors are clustered at the quarter and firm level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

increase in the right-hand-side variable. Since the policy uncertainty variable is logged, its normalizing constant is absorbed by the firm fixed effects. Hence, its coefficient can be interpreted as the number of standard deviations by which investment changes when policy uncertainty increases by 100%. Column 1 in panel A suggests that when policy uncertainty doubles, investment in the next quarter declines by 0.168 standard deviations. This is a 34-bp decrease, which is equivalent to 24.1% of the average investment level in the sample. Similarly, a doubling of the news-based and tax-code components is associated with a decline in investment of 18.6% and 8.7% with respect to the sample mean. Finally, panel D suggests that uncertainty related to government spending and inflation, at least as captured by forecaster disagreement, does not have a significantly negative effect on corporate investments.[10]

Our baseline results suggest that the majority of the explanatory power of the overall policy uncertainty index comes from its news-based component. This is not surprising, since the news index is in principle designed to capture the uncertainty associated with all policy decisions, including those captured by the tax-code component and by government spending and inflation components. For this reason, and to keep our tables to a reasonable number, we present results using only the news-based index for most of our remaining tests. This also serves to eliminate any possible confusion as to which of the components of the BBD index is driving our results. Nevertheless, our results are qualitatively the same if we use the overall index instead.

3.1 Omitted variables: Investment opportunities

The main challenge in interpreting our baseline results causally is the possibility that the policy uncertainty variable may capture the effect of low investment opportunities. Several authors have found empirical evidence that economic uncertainty is countercyclical.[11] Since policymakers often feel increasing pressure to make policy changes during bad economic conditions, it is plausible that policy uncertainty is also countercyclical and thereby negatively correlated with investment opportunities. If this is the case, the potential for an omitted-variables bias arises if our current control variables do not perfectly capture firms' investment opportunities.

To address this concern, we augment our baseline specifications with several variables that have been used in the literature as proxies for expectations about future economic conditions. First, we use data on one-year-ahead GDP forecasts from the Philadelphia Federal Reserve's biannual Livingstone survey to calculate a proxy for expected GDP growth, as perceived by professional forecasters. This variable is measured every June and December as the

10 In unreported tests, we verify that these results are robust to controlling for measurement error in Tobin's q using the higher-order cummulant estimator of Erickson, Jiang, and Whited (2014).

11 See Bloom (2014) for a survey of the evidence.

percentage change between the mean GDP forecast and the current GDP level. Second, we use the Conference Board's monthly Leading Economic Index, which is based on ten macroeconomic indicators that have been shown to have predictive power over future GDP. Our proxy is a year-on-year log change in this index. Third, we control for consumers' expectations about future economic prospects using the Michigan Consumer Confidence Index from the University of Michigan.[12]

We include these three control variables in our baseline specification from Equation (1), using the news-based component of the BBD index as our policy uncertainty measure. The results, presented in panel A of Table 3, show that policy uncertainty remains a significant predictor of capital investment, even though the economic magnitude of the effect decreases (compared with panel B of Table 2.) Our estimates indicate that a doubling of the level of policy uncertainty is associated with a decline in investment in the next quarter equivalent to 8.7% of the sample mean (0.06 standard deviations).[13] Note that this effect is quite large, considering, for example, that the policy uncertainty index nearly tripled throughout the recent financial crisis (late 2007 to late 2008).

3.2 Omitted variables: Economic uncertainty

A second potential concern with our results is that the BBD index may be capturing the effect of general economic uncertainty and not just the effect of policy-related uncertainty. Since the type of events that tend to increase policy uncertainty (e.g., recessions, wars, financial crises) also tend to increase overall macroeconomic uncertainty, it is possible that when businesses face policy uncertainty, they also face uncertainty about other aspects of their business (e.g. consumer demand.) For identification purposes, it is therefore important to explicitly control for any other sources of uncertainty that may affect firms' investment decisions at the same time that policy uncertainty affects them.

To address this concern, we control for several macroeconomic measures of uncertainty as proposed by Bloom (2009). First, we use the Livingstone survey of professional forecasters mentioned above to calculate a proxy of uncertainty about future economic growth. Specifically, the proxy is calculated every June and December as the coefficient of variation in GDP forecasts obtained from the survey. Second, to proxy for uncertainty about future profitability, we use the within-quarter cross-sectional standard deviation of firm-level profit growth (quarter-on-quarter change in net profit divided by average sales.) Finally, to

[12] In an earlier draft of this paper, we also used the Investor Sentiment Index of Baker and Wurgler (2007), to control for expectations by equity-market participants. Because this index was always statistically insignificant in our regressions, and because it is only available until December 2010, we decided to exclude it in order to preserve our sample size.

[13] Note that all controls from the baseline specification are present in these regressions. Many of them are not reported in order to preserve space, especially considering that their economic magnitudes are very similar to the ones obtained in our previous tests.

Table 3
Alternative macroeconomic controls for investment opportunities and economic uncertainty

	Panel A : Add controls for investment opportunities				Panel B : Add controls for economic uncertainty			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Policy uncertainty (news)	−0.0600**	−0.0659**	−0.0785***	−0.0860***	−0.0909***	−0.0963***	−0.110***	−0.122***
	(−2.15)	(−2.55)	(−2.85)	(−3.05)	(−3.11)	(−3.56)	(−3.79)	(−4.04)
GDP growth	0.00393	0.00843	0.00843	0.0175*	0.00275	0.00677	0.00686	0.0156*
	(0.49)	(1.00)	(0.97)	(1.91)	(0.43)	(0.98)	(0.93)	(1.83)
Expected GDP growth	0.00837	0.0131*	0.0152**	0.0161**	0.000461	0.00507	0.00644	0.00591
	(1.26)	(1.96)	(2.16)	(2.22)	(0.08)	(0.83)	(1.04)	(0.93)
Leading economic index	−0.00326	0.00799	0.0156**	0.0205***	−0.0552***	−0.0415***	−0.0339***	−0.0283***
	(−0.41)	(1.08)	(2.53)	(3.22)	(−5.01)	(−3.84)	(−3.20)	(−2.69)
Consumer confidence	0.00318***	0.00263***	0.00224***	0.00167**	0.00105	0.000590	0.000265	−0.000421
	(4.25)	(3.99)	(3.28)	(2.21)	(1.48)	(0.86)	(0.39)	(−0.53)
GDP forecast dispersion					−0.00710	−0.00836	−0.00855	−0.00992
					(−0.85)	(−1.05)	(−1.03)	(−1.32)
Profit growth SD					−0.0366**	−0.0335**	−0.0224*	−0.0111
					(−2.49)	(−2.45)	(−1.71)	(−0.79)
VXO					0.0211**	0.0194**	0.0148*	0.0113
					(2.39)	(2.33)	(1.72)	(1.20)
Return SD					0.0163**	0.0169**	0.0179***	0.0228***
					(2.30)	(2.42)	(2.76)	(3.45)
JLN uncertainty measure					−0.0727***	−0.0700***	−0.0765***	−0.0861***
					(−3.97)	(−4.19)	(−4.77)	(−5.65)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
N	424,785	412,621	401,744	392,679	418,118	409,503	401,744	392,679
R-squared	0.040	0.039	0.035	0.030	0.044	0.043	0.039	0.034

In this table we present results obtained from estimating our baseline investment equation using several alternative macroeconomic proxies for investment opportunities (panel A) and economic uncertainty (panel B). The proxies for investment opportunities are: the realized real GDP growth, the expected GDP growth calculated biannually from the Livingstone survey of the Philadelphia Federal Reserve Bank, the Leading Economic Index released by The Conference Board, and the Michigan Consumer Confidence Index developed by the University of Michigan. The proxies for economic uncertainty are the coefficient of variation of the biannual GDP forecasts from the Livingstone survey of the Philadelphia Federal Reserve Bank, the cross-sectional standard deviation in firm-level profit growth, the monthly VXO implied volatility index from the CBOE, the cross-sectional standard deviation in firm-level monthly stock returns, and the comprehensive measure of macroeconomic uncertainty of Jurado, Ludvigson, and Ng (2015). See Section 3 for details on how each proxy was constructed. In specifications marked (1), the dependent variable has a lead of one period (calendar quarter) with respect to the independent variables in specifications marked (2) it leads two periods, and so forth until (4). All specifications include calendar and fiscal quarter dummies, as well as firm fixed effects. All variables are normalized by their sample standard deviation. Standard errors are clustered at the quarter and firm level; t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

capture information about uncertainty as perceived by the equity markets, we use the monthly cross-sectional standard deviation of stock returns and the VXO (implied volatility) index from the Chicago Board Options Exchange.[14] In addition to these proxies, we also use a comprehensive measure of aggregate uncertainty developed by Jurado, Ludvigson, and Ng (2015). Their measure is based on the comovement in the unforecastable component of a large number of economic variables.

We introduce all five of these proxies in our baseline specification from Equation (1), along with all of the macroeconomic proxies for investment opportunities discussed in the previous section. The results, reported in panel B of Table 3, show that a negative relationship between investments and policy uncertainty remains statistically significant at all four lags. Using these estimates, a doubling in policy uncertainty is associated with a reduction in investment next quarter equivalent to 13.2% of the sample mean (0.09 standard deviations). The fact that the explanatory power of the policy uncertainty index is not absorbed by any of our proxies for aggregate economic uncertainty is particularly reassuring, since some of these proxies, such as the one developed by Jurado, Ludvigson, and Ng (2015), should in principle also capture the level of policy-related uncertainty in the economy. The results of these tests not only strengthen the robustness of the policy uncertainty effect on investments but also suggest that the BBD index contains information about macroeconomic uncertainty not captured by any of the other measures commonly used in the literature.

3.3 Out-of-sample predictability

In this section, we investigate whether policy uncertainty can be used to reliably predict investments out of sample. For this purpose, we use the methodology developed by Clark and West (2007) to test if adding policy uncertainty to several predictive investment models improves their out-of-sample fit. Specifically, we consider the following benchmark models:

$$M_0: INV_{i,t+l} = \alpha_i + \varepsilon_{i,t+l},$$

$$M_1: INV_{i,t+l} = \alpha_i + \theta X_{i,t} + \varepsilon_{i,t+l},$$

$$M_2: INV_{i,t+l} = \alpha_i + \theta X_{i,t} + \gamma IO_{i,t} + \varepsilon_{i,t+l},$$

$$M_3: INV_{i,t+l} = \alpha_i + \theta X_{i,t} + \gamma IO_{i,t} + \delta GEU_{i,t} + \varepsilon_{i,t+l},$$

where $INV_{i,t}$ is our main investment variable ($CAPX_{i,t+l}/TA_{i,t+l-1}$), $X_{i,t}$ contains all controls in our baseline specification, except for policy uncertainty (Tobin's q, operating cash flow, sales growth, real GDP growth, the election

[14] Following Bloom (2009), to ensure our proxies are not influenced by time-series changes in the characteristics of newly listed firms when calculating standard deviations of profit growth and returns, we only use firms that are in our sample for at least 20 years.

indicator, and the quarter dummies), $IO_{i,t}$ contains the investment opportunities proxies from Section 3.1, and $GEU_{i,t}$ contains the proxies for general economic uncertainty from Section 3.2. Note that M_0 is a random walk model at the level of the firm, M_1 is our baseline model with the policy uncertainty variable taken out, and M_2 and M_3 are the models tested in Sections 3.1 and 3.2 (once again without the policy uncertainty variable). For each $j \in \{0,1,2,3\}$, let $M_{j,pu}$ be the model obtained from adding policy uncertainty as a control variable to model M_j.

Clark and West (2007) propose a test statistic for evaluating if two nested models have equal predictive accuracy and show simulation evidence that it has an approximately normal distribution. To implement their test, for each $j \in \{0,1,2,3\}$, we estimate models $M_{j,pu}$ and M_j every quarter starting in January 1992, each time using data from the past 20 quarters. For each quarter t and each firm i, we store the l quarter-ahead prediction errors from $M_{j,pu}$ and M_j as $PE^{j,pu}_{i,t,l}$ and $PE^{j}_{i,t,l}$, respectively. The test statistic proposed by Clark and West (2007) is an adjusted difference in mean square prediction errors (MSPE), which simplifies to

$$Adj.\Delta MSPE^j_l = \frac{2}{N}\sum_{i,t} PE^j_{i,t,l}(PE^j_{i,t,l} - PE^{j,pu}_{i,t,l}), \tag{2}$$

where N is the total number of predictions made by each model. To obtain this statistic and to control for the fact that the prediction errors may be correlated within firm and within quarter, we simply regress the vector of quantities $2PE^j_{i,t,l}(PE^j_{i,t,l} - PE^{j,pu}_{i,t,l})$ on a constant, clustering the standard errors at the firm and quarter level.

Table 4 summarizes our findings on the out-of-sample predictive power of the news-based component of the BBD index. In panel A, we report the test statistics $Adj.\Delta MSPE^j_l$ defined above, with each row corresponding to a different benchmark model ($j \in \{0,1,2,3\}$) and each column corresponding to a different prediction horizon ($l \in \{1,2,3,4\}$). The results show that the policy uncertainty variable significantly increases the predictive accuracy of all four benchmark models for predictions of up to four quarters into the future. In panel B, we use the same methodology described above to test whether the models used in our study ($M_{1,PU}$, $M_{2,PU}$, and $M_{3,PU}$) outperform the predictive performance of a simple random walk (M_0). The results indicate that this is in fact the case for all three models (rows) at all four horizons (columns).

Having shown that the policy uncertainty index can be reliably used to forecast investment out of sample, we now run a counterfactual exercise as an alternative way to gauge the economic consequences of policy uncertainty. For this purpose, we compare the investment levels predicted by our model from 2006 onward, with the investment levels predicted if policy uncertainty had stayed at its 2006 level. This comparison should give us an estimate of the economic impact of policy uncertainty during the financial crisis.

Table 4
Out-of-sample predictability

Parsimonious model	Larger model	Panel A: Predictive improvement when adding News-based policy uncertainty index to benchmark models			
		(1)	(2)	(3)	(4)
M_0	$M_{0,pu}$	0.00586***	0.00694***	0.00551***	0.00595***
		(3.28)	(3.97)	(3.77)	(3.94)
M_1	$M_{1,pu}$	0.00314***	0.00365***	0.00394***	0.00408***
		(4.03)	(4.37)	(4.33)	(4.23)
M_2	$M_{2,pu}$	0.000298***	0.000302***	0.000236***	0.000158*
		(3.33)	(3.62)	(3.06)	(1.67)
M_3	$M_{3,pu}$	0.000193**	0.000145**	0.000113*	0.000140**
		(2.52)	(2.53)	(1.93)	(2.11)
Parsimonious model	**Larger model**	**Panel B: Predictive improvement when adding controls to random walk model**			
		(1)	(2)	(3)	(4)
M_0	$M_{1,pu}$	0.0521***	0.0500***	0.0423***	0.0344***
		(17.28)	(18.02)	(18.09)	(16.16)
M_0	$M_{2,pu}$	0.0567***	0.0542***	0.0467***	0.0391***
		(17.24)	(17.37)	(16.12)	(15.13)
M_0	$M_{3,pu}$	0.0605***	0.0571***	0.0488***	0.0411***
		(16.81)	(16.95)	(15.43)	(13.66)

In this table we use the methodology of Clark and West (2007) to test if the policy uncertainty variable improves the out-of-sample predictive accuracy of the following benchmark models:

$$M_0: INV_{i,t+l} = \alpha_i + \varepsilon_{i,t+l},$$

$$M_1: INV_{i,t+l} = \alpha_i + \theta X_{i,t} + \varepsilon_{i,t+l},$$

$$M_2: INV_{i,t+l} = \alpha_i + \theta X_{i,t} + \gamma IO_{i,t} + \varepsilon_{i,t+l},$$

$$M_3: INV_{i,t+l} = \alpha_i + \theta X_{i,t} + \gamma IO_{i,t} + \delta GEU_{i,t} + \varepsilon_{i,t+l}.$$

For each $j \in \{0,1,2,3\}$, $M_{j,pu}$ is the model obtained by adding the news-based policy uncertainty variable to model M_j. In panel A, we test if $M_{j,pu}$ is more accurate than M_j for each $j \in \{0,1,2,3\}$. The entries in the table are differences in mean square prediction error between the parsimonious model and the larger model. Larger values represent stronger evidence that the larger model is more accurate. In panel B we test if models $M_{j,pu}$, $j \in \{1,2,3\}$ provide more accurate predictions than the random walk model M_0. t-statistics are in parentheses. Standard errors are clustered at the firm and calendar quarter level to account for possible correlation in prediction errors within firm and within quarter.

To predict investment rates out of sample, we first run our baseline regression from Equation (1) using the investment irreversibility proxies from Section 3.1 as additional macroeconomic controls. Using only the firms that are present in our sample in the first quarter of 2007, we predict investment rates one quarter ahead, as:

$$\frac{\widehat{CAPX_{i,t+1}}}{TA_{i,t}} = \widehat{\alpha_i} + \widehat{\beta}_1 PU_{i,t} + \widehat{\beta}_2 TQ_{i,t} + \widehat{\beta}_3 \frac{CF_{i,t}}{TA_{i,t-1}} + \widehat{\beta}_4 SG_{i,t} + \widehat{\delta} M_{i,t} + \widehat{QRT}_t. \quad (3)$$

We obtain aggregate investment rates for each calendar quarter from 2004 to 2011 by taking cross-sectional weighted averages of the firm-level fitted values, using the firms' total assets in the previous quarter as weights. The resulting time series is plotted as the solid line in the top panel of Figure 2. We then apply the same averaging procedure to the the fitted values obtained

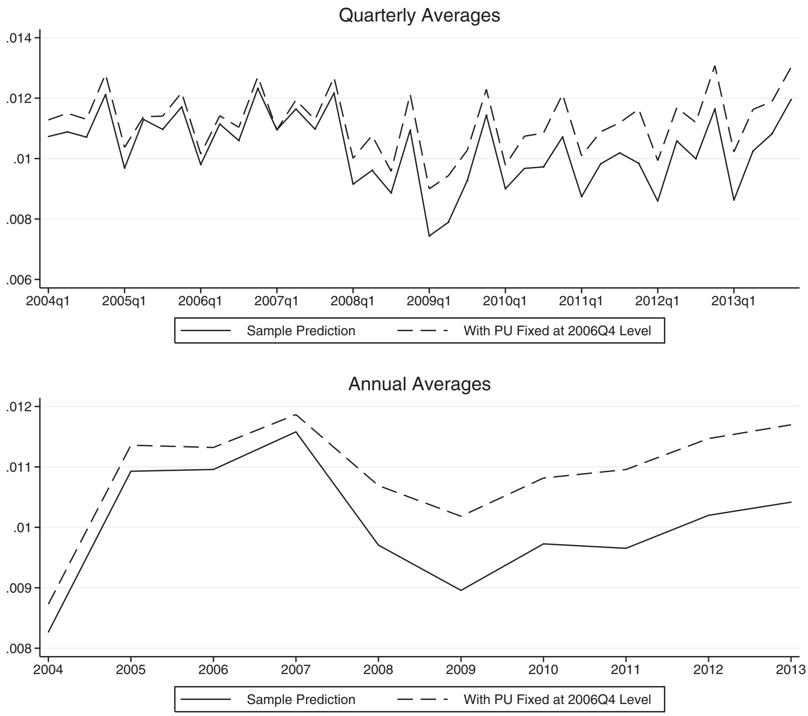

Figure 2
Predicted capital investment levels
This figure depicts quarterly (top) and annual (bottom) cross-sectional weighted averages of fitted values from our baseline model. These fitted values are calculated both using the realized levels of policy uncertainty (solid line), as well as by keeping the policy uncertainty index fixed at the level observed in the last quarter of 2006 (dashed line). The averages are calculated using the previous quarter total assets as weights. Throughout, we use only the firms that are in the sample in the first quarter of 2007.

if the policy uncertainty index remained at the level it had been during the last quarter of 2006. This second time series is plotted as the dashed line in the top panel of Figure 2. In the bottom panel of the figure, we take annual, rather than quarterly, weighted averages for each of the two sets of fitted values described above. Both graphs suggest that if policy uncertainty had remained at its pre-2007 levels, the fall in investment from 2007 to 2009 would have been smaller by roughly one-third.

4. Cross-Sectional Heterogeneity

In the second part of our empirical analysis, we ask whether all firms are equally affected by policy uncertainty. We explore two reasons why this might not be the case. First, if reversing investment decision is not equally costly for all firms in the economy, then we should expect some cross-sectional variation in their reluctance to invest in the face of uncertainty. Second, if firms differ with respect to their dependence on government spending, then political uncertainty should translate into different levels of demand uncertainty for different firms. If demand uncertainty has a negative effect on investments, then the effect of policy uncertainty should depend at least in part on the sensitivity of firms' sales to government spending. We test these two hypotheses below.

4.1 Investment irreversibility

The evidence from Section 3 that shows a negative relationship between policy uncertainty and investment has an intuitive explanation: all else equal, in order to reduce the uncertainty associated with investment profitability and make a more informed decision, managers have an incentive to postpone investments that can be delayed. Since, all else equal, higher ex ante uncertainty implies a stronger incentive to wait until more information is revealed, on average, we should observe a negative relationship between investment levels and uncertainty.[15] Notice, however, that the "all else equal" qualifier hides an important cross-sectional prediction: even though the benefit of waiting for more information is a function of the level of uncertainty observed, this function should be moderated significantly by the ease with which the firm can reverse its investments. Intuitively, a firm that can reverse its investments at no cost has no benefit from waiting until more information is revealed, and so its investment levels will not be influenced by the the level of uncertainty. On the contrary, a firm with completely irreversible investments would have a lot more to gain from waiting until some of the uncertainty is reduced, since they have more to lose if the project proves unprofitable and downscaling is necessary.

To test this prediction, we use several different proxies to measure the degree to which a firm's investments are irreversible (its costs of adjusting capital downwards). First, we use the firm's capital intensity ratio measured as net PPE divided by total assets. The assumption is that firms with high capital intensity tend to invest in projects that require large upfront costs, often for physical assets that are specific to their line of business. We acknowledge that this is a rough proxy, since it does not explicitly take into account determinants of adjustment costs, such as asset specificity or mobility (Kessides 1990). For example, costs to adjusting fixed assets are not as high if there is an active secondhand market for those assets. To address these shortcomings, we discuss below three additional proxies for investment irreversibility.

First, based on the argument that more redeployable capital has a higher liquidation value, we use an industry-level measure proposed by Kim and Kung (2013) as a proxy for the salability of assets across industries. To calculate this variable, we use the 1997 capital flows table from the Bureau of

[15] The real options literature formalizes this intuition. If a firm has the option to delay an investment, it will make that investment only when its NPV is higher than the value of the option to delay. As with financial options, the value of the real option to delay increases with the uncertainty associated with the value of the underlying asset. Hence, higher uncertainty implies investments need to clear a higher threshold before they are undertaken.

Economic Analysis (BEA). This table contains data on the capital expenditures of 123 industries, broken down into 180 asset categories. We first calculate a redeployability score for each asset category as the percentage of the 123 industries using it. The redeployability score for each industry is then calculated as a weighted average of the redeployability scores of the asset categories in which that industry invests. The weight given to each asset category is its percentage contribution to the industry's total expenditures. The intuition is that firms in industries with more redeployable assets will benefit from a more active secondhand market for these assets and will therefore be able to recover a higher proportion of their investments.[16]

Second, we draw on the industrial organization literature (Kessides 1990; Farinas and Ruano 2005) to build an industry-level measure of cost sunkness based on firms' rent expense and depreciation expense and their past sale of PPE. The reasoning is that sunk costs should be lower for firms which rent a higher proportion of their physical assets, for firms with rapidly depreciating capital, and for firms with assets with a more liquid secondhand market. We measure these three characteristics using firms' rent expense, their depreciation expense, and their sales of PPE in the past 12 quarters, all normalized by PPE at the beginning of the current quarter. We then aggregate these three proxies up to the three-digit SIC level by taking the industry-level means of the firm-level values. Finally, similar to Farinas and Ruano (2005), we combine the three proxies into one sunk-cost index, which, at any time t, takes a value of 0, 1, or 2, where 0 is for industries which have all three proxies above their cross-sectional medians at time t; 2 is for industries which have all proxies below these medians; and 1 is for the remaining industries. Thus, higher values of the index are associated with a higher degree of cost sunkness and therefore with higher levels of investment irreversibility.

Third, following Almeida and Campello (2007), we construct a proxy for asset liquidation values based on firms' sales cyclicality. Borrowing from Shleifer and Vishny (1992), the intuition is that firms operating in highly cyclical industries will tend to be simultaneously affected by negative demand shocks in bad economic times. Hence, such firms should experience lower recovery values for their used assets, because the buyers that should have the highest valuations for these assets (the firms in the same industry) are likely disinvesting themselves. Following this line of reasoning, we use the methodology in Sharpe (1994) to classify firms into high- and low-cyclicality industries, as a proxy for high and low investment irreversibility. To do this, we calculate the correlation between each firm's quarterly sales and GNP (over our entire sample period) and then aggregate these correlations at the three-digit SIC level by taking averages of the firm-level correlations. Finally, we create an indicator variable

[16] The 123 industries are based on the North American Industry System (NAICS). We match these industries to Compustat firms using the NAICS code, first merging at the five-digit level, and then sequentially merging the unmatched observations at the four-, three-, and two-digit level.

that equals one for industries with correlations above the sample median, and zero for the rest of the industries. Not surprisingly, given the well-documented cyclicality of durable goods industries, this methodology amounts to a nearly perfect split between durables and nondurables.

To test whether firms' investment irreversibility has a significant impact on the relationship between policy uncertainty and corporate investment, we add the interactions of the above four proxies with the news-based index of policy uncertainty to our baseline specification:

$$\frac{CAPX_{i,t+l}}{TA_{i,t+l-1}} = \alpha_i + \gamma_t + \beta_1 PU_{i,t} \cdot IR_{i,t} + \beta_2 IR_{i,t} + \beta_3 TQ_{i,t} + \beta_4 \frac{CF_{i,t}}{TA_{i,t-1}} + \beta_5 SG_{i,t} + \varepsilon_{i,t+l}. \quad (4)$$

We estimate this regression separately for each of the four irreversibility proxies discussed above ($IR_{i,t}$), and we present the results in the first four columns of Table 5 (panel A). Once again, the columns are marked (1) through (4) to indicate the lead, l, between the dependent and independent variables. For expositional clarity, we only report the coefficient of interest for each regression (β_1). The results provide strong empirical evidence that investment irreversibility magnifies the effect of policy uncertainty on investment. By design, for all four proxies discussed above, higher values signify higher levels of investment irreversibility. Hence, the results in the first four columns of Table 5 all indicate that the more irreversible a firm's investments, the more these investments are negatively affected by policy uncertainty.

Note that, for the purpose of these tests, we are no longer interested in estimating the average effect of policy uncertainty on investment. This allows us to replace the policy uncertainty term in Equation (1) with a time fixed effect (γ_t in Equation (4)); this has the added benefit of controlling for any macroeconomic, cross-sectionally invariant forces, which may confound the effect of policy uncertainty.[17] However, the time fixed effects do not control for the possibility that these confounding forces may also operate through the investment irreversibility channel. For example, going back to our previous discussion of omitted variables biases, if changes in investment opportunities have a stronger effect on firms with more irreversible investments, then the β_1 coefficient in Equation (4) will be biased away from zero.

To account for this possibility, we repeat the above tests, this time including in each regression the interactions between the choice of irreversibility proxy $IR_{i,t}$ and all the proxies for investment irreversibility discussed in Section 3.1. The results, reported in the last four columns of Table 5 (panel A), provide further support to the idea that the effect of policy uncertainty on investment depends significantly on firms' investment irreversibility even after controlling

[17] This explains the absence of the vector of macroeconomic controls M_t from Equation (4).

Table 5
Cross-sectional heterogeneity in the effect of policy uncertainty

	No controls for interactions with investment opportunities				Controlling for interactions with investment opportunities			
Panel A : Interactions with investment irreversibility proxies								
	Panel A1 : Property, plant, and equipment (PPE)							
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
PU news x PPE	−0.146***	−0.157***	−0.145***	−0.146***	−0.131***	−0.128***	−0.109***	−0.115***
	(−15.70)	(−16.82)	(−15.72)	(−15.91)	(−11.57)	(−11.31)	(−9.90)	(−10.45)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
	Panel A2 : Asset redeployability (AR)							
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
PU news x AR	−0.0656***	−0.0757***	−0.0710***	−0.0746***	−0.0623***	−0.0649***	−0.0557***	−0.0620***
	(−10.43)	(−11.32)	(−10.71)	(−11.49)	(−9.08)	(−9.04)	(−7.85)	(−8.99)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
	Panel A3 : High vs. low sunk costs							
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
PU news x Sunk index	−0.0328***	−0.0481***	−0.0367***	−0.0353***	−0.0396***	−0.0527***	−0.0417***	−0.0436***
	(−4.25)	(−6.10)	(−4.68)	(−4.46)	(−4.48)	(−5.70)	(−4.62)	(−4.81)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
	Panel A4 : Durables vs. nondurables							
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
PU News x Durable index	−0.0589***	−0.0744***	−0.0750***	−0.0833***	−0.0336**	−0.0482***	−0.0393***	−0.0446***
	(−4.68)	(−5.76)	(−5.75)	(−6.39)	(−2.23)	(−3.12)	(−2.60)	(−2.94)
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Panel B : Interactions with sensitivity to government spending (SGS)								
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
PU news x SGS	−0.0148*	−0.0346***	−0.0401***	−0.0310***	−0.0194*	−0.0427***	−0.0438***	−0.0317***
	(−1.72)	(−3.72)	(−4.34)	(−3.43)	(−1.89)	(−3.95)	(−4.27)	(−3.10)
Controls	yes	yes	yes	yes	yes	yes	yes	yes

In this table we regress firm-level quarterly investment (CAPX/Lagged Total Assets) on Tobin's q, operating cash flows and sales growth, to which we add the investment irreversibility proxies discussed in Section 4.1, as well as their interaction with the news-based policy uncertainty index from Baker, Bloom, and Davis (2013) (see Equation (4)). For expositional clarity, we show only the coefficient estimates of the variables of interest (the interaction between policy uncertainty and the irreversibility proxies). In the last four columns, in all panels, we also control for interactions between all our proxies for investment opportunities from the previous table, and the investment irreversibility proxy used in each panel. In specifications marked (1), the dependent variable has a lead of one period (calendar quarter) with respect to the independent variables in specifications marked (2) it leads two periods, and so forth until (4). All specifications include calendar-quarter fixed effects, as well as firm fixed effects. All variables are normalized by their sample standard deviation. Standard errors are clustered at the quarter and firm level; t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

for the possibility that investment opportunities may also operate through the irreversibility channel.[18]

4.2 Dependence on government spending

A second dimension of cross-sectional heterogeneity that may influence the effect of policy uncertainty on investment is the degree to which firms' revenues depend on government spending levels. Intuitively, holding everything else constant, the same level of policy uncertainty should translate to a higher level of demand uncertainty for firms that are more dependent on government contracts for their sales. Hence, if policy uncertainty causes delays in investment, it should do so more severely for firms with a higher sensitivity to government spending.

To test this hypothesis, we quantify the percentage of an industry's sales that can be attributed to government purchases by using data from the Benchmark Input-Output Accounts, released by the BEA.[19] Specifically, let g_i be the total dollar amount of product from industry i sold directly to the government sector (federal, local, and state governments). Also, let $a_{i,j}$ be the dollar amount of input from industry i needed to produce one dollar of final use of industry j's product. Finally, let x_i be the total amount of input from industry i needed, directly and indirectly, to satisfy the total government sector demand. It can easily be shown that:

$$x_i = \sum_j a_{i,j} \cdot g_j, \tag{5}$$

where j runs through all the industries in the economy. To calculate these quantities, we obtain the g_j's from the use table and the $a_{i,j}$'s from the industry-by-commodity table in the I-O accounts. We measure each industry's dependence on government spending by the ratio x_i/y_i, where y_i is the industry's total output obtained from the use tables. These measures are updated every five years, starting in 1982, when new I-O accounts are released.

Since industries are identified by I-O codes in the I-O accounts, we use the concordance tables provided by the BEA to merge our measures of sensitivity to government spending with the Compustat data. The merging is done by three-digit SIC codes before 2002 and by NAICS codes thereafter. When multiple I-O industry codes concord to the same three-digit SIC or NAICS code, we take a weighted average of the corresponding exposures to government spending, in which the weights are given by the total outputs of the I-O industries involved.

[18] In unreported results, we also verify that these result are robust to controlling for interactions between investment irreversibility and general economic uncertainty.

[19] Our methodology closely follows that of Belo, Gala, and Li (2013).

Our empirical tests are analogous to the ones used in the previous section:

$$\frac{CAPX_{i,t+l}}{TA_{i,t+l-1}} = \alpha_i + \gamma_t + \beta_1 PU_{i,t} \cdot SGS_{i,t} + \beta_2 INT_{i,t} + \beta_3 TQ_{i,t} + \beta_4 \frac{CF_{i,t}}{TA_{i,t-1}} + \beta_5 SG_{i,t} + \varepsilon_{i,t+l}. \tag{6}$$

Here, $SGS_{i,t}$ stands for the measure of sensitivity to government spending described above and the $INT_{i,t}$ term is a vector collecting all the proxies for investment irreversibility from the previous section, as well as our measure of dependence on government spending. The β_1 coefficients from Equation (6) are reported in the first four columns of panel B in Table 5. The last four columns of the panel present the β_1 coefficients obtained after including in Equation (6) the interaction between $SGS_{i,t}$, and all the proxies for investment opportunities described in Section 3.1. Overall, our results suggest that the negative relationship between policy uncertainty and corporate investment is significantly stronger for firms more dependent on government spending.

Taken together, the evidence presented in this section finds strong empirical support for the idea that not all firms are affected by uncertainty in the same way. An accurate assessment of the economic consequences of policy uncertainty must take into account cross-sectional differences in firm characteristics that induce exposure to uncertainty. While this study investigates two such characteristics—investment irreversibility and sensitivity to government spending—we do not claim to have exhausted the list of factors that moderate the effects of uncertainty. Our intention is to provide evidence, based on solid theoretical underpinnings, that average estimates can mask a strong cross-sectional dispersion in firm-level exposure to policy-related uncertainty.

5. The Evolution of the Policy Uncertainty Effect over Time

Our results from Section 3 show that policy uncertainty affects investments at least four quarters into the future. In this section, we take a closer look at how the relationship between policy uncertainty and investments evolves over time. A natural starting point in this direction is to extend our previous analysis to include further lags between the two variables. To this end, we estimate a separate regression of investments on all the control variables discussed in Sections 3 and 4, each time extending the lag between the dependent and independent variables by one quarter. We run a total of 24 regressions, corresponding to lags 1 through 24, and we plot the coefficients of the policy uncertainty variable in the top panel of Figure 3.

The results reveal not only that policy uncertainty has a negative effect on investment levels up to five quarters into the future, but also that this relationship weakens for longer lags, becoming significantly positive after 13 quarters and staying that way for lags of up to 22 quarters. This is consistent with the idea that while uncertainty may cause delays in investments, once the

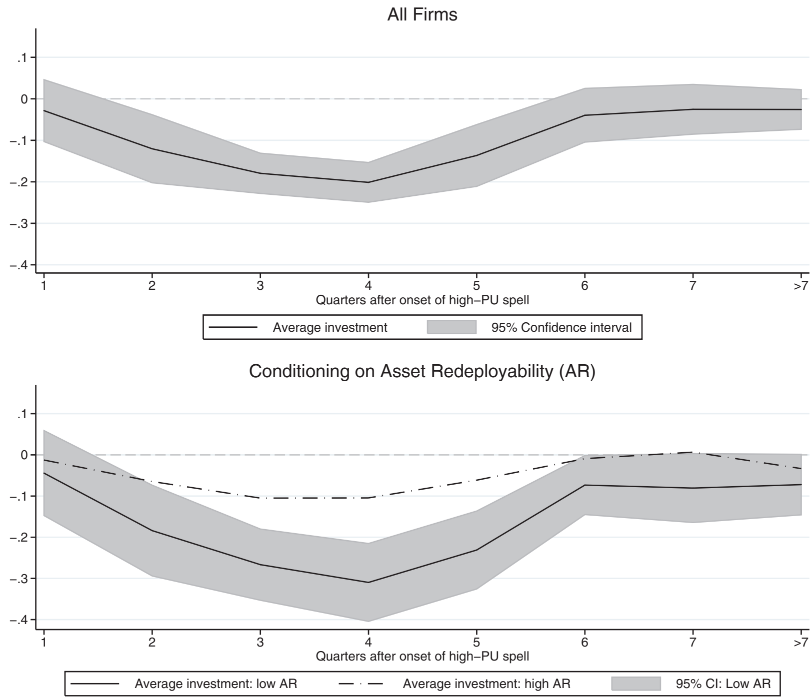

Figure 3
Effect of policy uncertainty on future investment
This figure depicts the effect of policy uncertainty on future levels of corporate investments. In the top panel, this effect is calculated by regressing corporate investments on policy uncertainty and controls, using our entire sample of firms. The horizontal axis represents the lag between the dependent and independent variables in each regression. In the bottom panel, the effect is calculated separately for firms in the top three deciles of asset redeployability (dashed line) and for firms in the bottom three deciles of asset redeployability (solid line). Please see Section 5 for details.

uncertainty is resolved, investment levels increase to satisfy pent up demand. While this subsequent investment rebound seems to fully compensate for the initial delay, it is important to notice that this recovery period is quite long (almost three years). Overall, these results suggest that policy uncertainty can cause significant long-term fluctuations in investments of up to six years in duration.

As detailed in Section 4, we have reason to believe that different firms are affected by policy uncertainty to varying degrees. This suggests that the dynamic pattern discussed above could hide a significant amount of variation in the cross-section. To investigate this possibility, we rerun the above analysis separately for firms with high and low levels of investment irreversibility. In the interest of space, we report results using only the asset redeployability proxy, though we verify that the general result is similar for all the other proxies.[20] The bottom panel of Figure 3 shows that, indeed, firms with low asset redeployability (bottom three deciles) exhibit a significantly stronger investments-uncertainty relationship than do firms with high asset redeployability (top three deciles), at both the short and long horizon.

Another approach to investigating the dynamic relationship between policy uncertainty and investments is to estimate vector autoregressions (VARs) at the aggregate level and calculate an impulse response function (IRF) to quantify how a shock to policy uncertainty affects future levels of investment. This approach has the added benefit of accounting for possible feedback loops between our main variables. To this end, we estimate a VAR using the log of the news-based component of the policy uncertainty index, as well as the Michigan Consumer Confidence Index and aggregate versions (cross-sectional means) of Tobin's q, operating cash flows to total assets, sales growth, and capital investments to total assets.[21] We also include the election-year indicator and the quarter dummies as exogenous variables. The VAR is run on quarterly data from 1987Q1 to 2013Q4, using eight lags. To calculate the IRF, we obtain orthogonal shocks using a Cholesky decomposition based on the exact variable ordering above.[22]

The resulting IRF is reported in the top panel of Figure 4. We find that at the aggregate level, a one unit shock to policy uncertainty has a significantly negative effect on capital investments for up to ten quarters into the future, although we do not observe a rebound in investments in the quarters after this period. Like the previous analysis, we test if these results mask any significant cross-sectional variation by running separate VARs for aggregate date using only high or low asset-redeployability firms. As shown in the bottom panel of Figure 4, we find that investments of firms with high asset redeployability exhibit virtually no response to policy uncertainty shocks, while firms with low asset redeployability exhibit a more amplified response.

6. The Effect of Prolonged Periods of High Uncertainty

As already discussed, the main mechanism by which we believe uncertainty affects investment is the real options channel. In Section 4, we explored implications of this hypothesis for the cross-section of investment rates. In this section, however, we explore a time-series prediction of the real options mechanism. Specifically, if uncertainty lowers investments by increasing the

[20] We chose the asset redeployability proxy in favor of the others because it is significantly less coarse than the "durables" and "sunkness" proxies, and unlike the PPE-based proxy, it does not ignore asset specificity.

[21] We restrict ourselves to using only the Michigan Consumer Confidence Index as a proxy for investment opportunities to keep the number of parameters to a reasonable level. Nevertheless, our results are robust to using all of the proxies discussed in Section 3.1.

[22] It is a well-known fact that IRFs are sensitive to the ordering of the variables in the Cholesky decomposition. Our results are qualitatively similar if we place the policy uncertainty as the last variable in the ordering as opposed to the first.

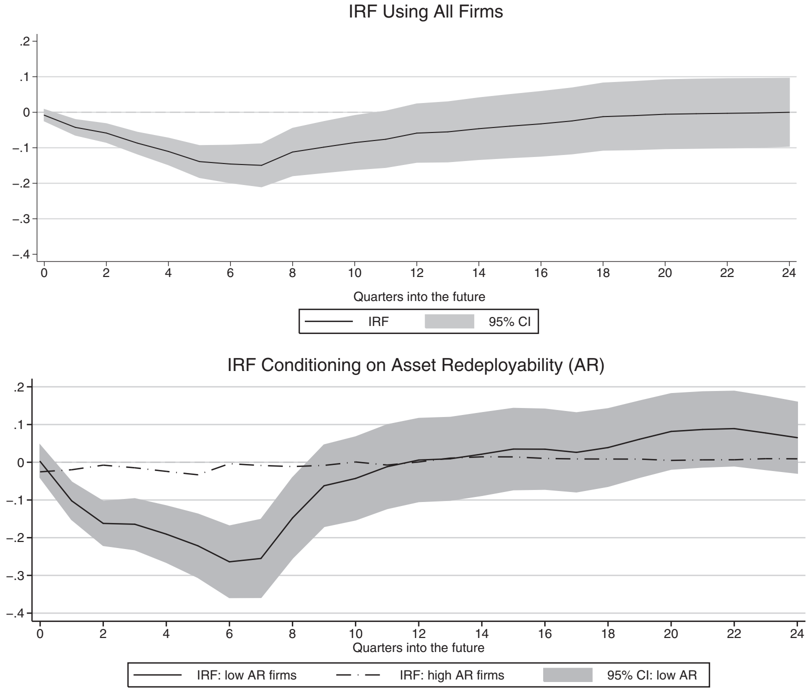

Figure 4
Estimated effect of a policy uncertainty shock on aggregate investment
This figure depicts impulse response functions (IRFs) quantifying the effect of increasing policy uncertainty by one unit on aggregate corporate investments. The IRFs are obtained from estimating vector auto-regressions (VARs) using the following variables: policy uncertainty, the Michigan Consumer Confidence Index, and aggregate measures of Tobin's q, operating cash flows to total assets, sales growth, and capital investments to total assets. In the top panel, the aggregation is done using our entire sample of firms. In the bottom panel, we estimate separate VARs, using variables obtained by aggregating over only firms in the top three deciles of asset redeployability (dashed line) and only the bottom three deciles of asset redeployability (solid line). Please see Section 5 for details.

value of the option to wait, then after long periods of high uncertainty, the relationship between uncertainty and investment should weaken. This is because many investments cannot be delayed indefinitely, and as time lapses, the cash flows forgone by delaying investment can outstrip the value of waiting for more information.

To test this prediction, we use a somewhat conservative definition of "high" policy uncertainty as meaning above average, and we define a high-policy-uncertainty "spell" as an uninterrupted sequence of quarters, all experiencing high policy uncertainty. Unfortunately, even under this conservative definition, our sample period does not exhibit many prolonged periods of high policy uncertainty. For example, we observe a single spell that is longer than eight quarters. This feature of the data makes it difficult to pin down the exact way in which the policy uncertainty effect on investment is affected by long high-policy-uncertainty spells. Nevertheless, we can still test the directional prediction that the effect of policy uncertainty tapers off by investigating the average investment levels at different times during high-policy-uncertainty spells. If it is indeed the case that the effect of policy uncertainty is weaker after long periods of high policy uncertainty, then, controlling for everything else, average investment levels should increase during the latter parts of high-policy-uncertainty spells.

To formalize this intuition, we obtain estimates of conditional averages of capital investment at different times during high-policy-uncertainty spells by including in our investment regressions a set of indicator variables, each identifying how deep we are into a spell at any given time. Specifically, for each calendar quarter t, we measure how long policy uncertainty has been high leading up to t by looking backward and counting the number of consecutive quarters with above-average policy uncertainty up to quarter t. Denoting this quantity by N_t, we then construct a series of eight dummy variables I^j such that for each $j \in \{1,2,...,7,\}$, for any quarter t, $I_t^j = 1$ if $N_t = j$ and 0 otherwise, while $I_t^8 = 1$ if $N_t > 7$ and 0 otherwise. This last indicator variable will capture the conditional average investment in the those quarters when policy uncertainty has been higher than average for at least eight quarters. We include all of these dummy variables in a one-quarter-ahead investment regression:

$$\frac{CAPX_{i,t+1}}{TA_{i,t-1}} = \alpha_i + \sum_{j=1}^{8} \gamma_j I_t^j + \beta_1 TQ_{i,t} + \beta_2 \frac{CF_{i,t}}{TA_{i,t-1}} + \beta_3 SG_{i,t} + \delta M_t + QRT_t + \varepsilon_{i,t+1}. \tag{7}$$

The eight γ_j coefficients are plotted in the top panel of Figure 5, and they tell us the conditional average investment levels at different times during high-policy-uncertainty spells. Note that the indicator variable, which is excluded from regression 7, is I_0, which equals one when $N_t = 0$, i.e., when policy uncertainty is below-average. Hence, all of these conditional averages are relative to the average investment levels in quarters with below-average policy uncertainty. To minimize the possibility that the pattern observed in Figure 5 is an expression of other confounding forces, we include in the vector of controls M_t all the investment opportunity proxies from Section 3.1, all the economic uncertainty proxies from Section 3.2, and all the investment irreversibility and government sensitivity proxies from Section 4.

The results, depicted in the top panel of Figure 5, show that as we progress deeper into high-policy-uncertainty spells, the average investment levels become progressively lower than those observed in quarters with below-average policy uncertainty. However, we find that this difference starts attenuating after four quarters of continuously high policy uncertainty, to the point of insignificance after six quarters or more into the spell. This rebound in average investments at the later end of high-policy-uncertainty spells supports the real options prediction that, after prolonged periods of uncertainty, the value of further delaying investments decreases, weakening the negative relationship

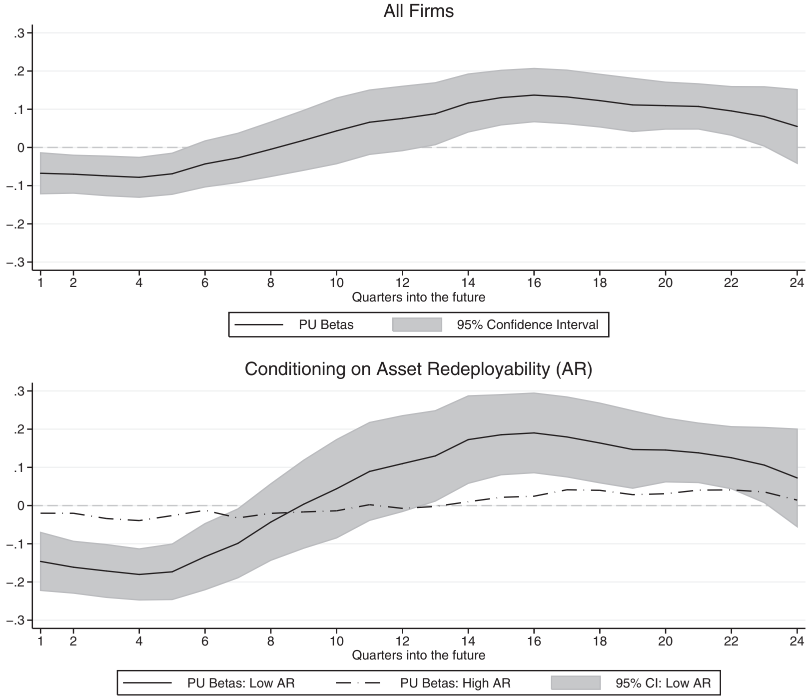

Figure 5
Conditional average investment throughout high PU spells
This figure depicts conditional average investment levels during spells of high policy uncertainty. We say that policy uncertainty is high if it exceeds its sample average. The horizontal axis represents how deep into a spell of high policy uncertainty a given quarter is. The average investment levels depicted are conditional on all the main control variables introduced in our paper (please see Section 6 for details). In the top panel, the averages are calculated using all the firms in our sample. In the bottom panel, we calculate these averages separately using only firms in the top three deciles of asset redeployability (dashed line) and only firms in the bottom three deciles of asset redeployability (solid line).

between uncertainty and investment. Once again, in the bottom panel of Figure 5, we separately repeat the analysis for the subsample of firms with high versus low asset redeployability, and we find that the dynamic pattern documented above is significantly more pronounced for firms with high asset redeployability.

7. Further Tests to Mitigate Endogeneity Concerns

The extant literature on corporate investments has long recognized the difficulty of disentangling uncertainty from investment opportunities as predictors of future investment. A further challenge is to ensure that we identify the effect of policy-driven uncertainty and not the effect of other sources of economic uncertainty. Our approach to these challenges so far has been to explicitly control for these two confounding forces using various proxies for investment opportunities and general economic uncertainty. The efficacy of this approach crucially depends on the accuracy of the proxies used. In the remainder of this section, we present several alternative methods of addressing the possibility that the proxies do not fully alleviate the endogeneity concerns inherent in our analysis.

7.1 Canadian policy uncertainty

One concern with the BBD index is that it may inadvertently capture economic uncertainty that is not policy related, but that may nevertheless affect corporate investments. If this is the case, our tests will suffer from a measurement error bias. As explained in Section 1, BBD have gone to great lengths to minimize this possibility. In this section, we attempt to further alleviate measurement-error concerns by leveraging the similarities between the Canadian and United States economies.

The extensive international trade activity between the United States and Canada has created a tight link between the two economies (see, for example, Romalis 2007).[23] For this reason, we expect many of the shocks that affect general economic uncertainty in the United States to also affect general economic uncertainty in Canada, albeit to a lesser extent. If this is the case, and if indeed the BBD index is in part a measure of non-policy-related economic uncertainty, then we can eliminate this contaminating part of the index by extracting the component of the United States policy uncertainty index orthogonal to the Canadian policy uncertainty index. We do this by running the following monthly time-series regression:

$$USPU_t = \alpha + \beta_1 CANPU_t + \beta_2 TQ_t + \beta_3 CF_t + \beta_4 SG_t + \theta INT_t + \delta M_t + QRT_t + \varepsilon_t. \tag{8}$$

Here, $USPU_t$ and $CANPU_t$ are the news-based policy uncertainty measures developed by BBD for the United States and Canada. TQ_t, CF_t, and SG_t stand for the average levels of Tobin's q, operating cash flows, and sales growth in the economy. The term INT_t is a vector including the economy-wide averages for the variables used in Section 4 as proxies for firms' investment irreversibility and dependence on government spending.[24] Finally, QRT_t is a vector of fiscal and calendar quarter dummies, and M_t collects the election year indicator, real GDP growth, and the three macroeconomic proxies for investment opportunities described in Section 4.1. As argued above, the residual term ε_t should represent a cleaner measure of policy uncertainty in the United States, having been purged of general uncertainty shocks affecting

[23] For example, the correlation between the nominal GDP growth rates of the United States and Canada is 0.78.

[24] These averages are calculated for each calendar quarter in our sample period and then assigned to all three months in that quarter.

both countries. In fact, this procedure serves to eliminate the effects of any other confounding forces present in both measures of policy uncertainty ($USPU_t$ and $CANPU_t$).

We aggregate the monthly residuals in Equation (8) to the quarter level using the same methodology as before: for each firm i, let $RPU_{i,t}$ be the natural logarithm of the arithmetic average of the residuals corresponding to the three months of firm i's fiscal quarter ending in calendar quarter t. In Table 6 we repeat the main tests from Sections 3 and 4, using $RPU_{i,t}$ as our measure of policy uncertainty. In panel A we present estimates from regressions of the form:

$$\frac{CAPX_{i,t+l}}{TA_{i,t+l-1}} = \alpha_i + \beta_1 RPU_{i,t} + \beta_2 TQ_{i,t} + \beta_3 \frac{CF_{i,t}}{TA_{i,t-1}} + \beta_4 SG_{i,t} + \theta INT_t + \delta M_t + QRT_t + \varepsilon_{i,t+l}. \tag{9}$$

In the interest of space, we report only the coefficients on the macroeconomic controls.[25] The effect of policy uncertainty on investments remains significant in all specifications, even though the economic magnitude decreases. However, note that, to the extent that $CANPU_t$ captures some of the variation in policy uncertainty in the United States and not just in Canada, the coefficients in Table 6 underestimate the strength of true relationship between policy uncertainty and investment.

As a falsification test, we estimate Equation (9) using Canadian firm-level accounting data from the Worldscope database and the $RPU_{i,t}$ measure of United States policy uncertainty. If we have extracted a component of the BBD index, which is orthogonal to any macroeconomic forces common to both countries, $RPU_{i,t}$ should not affect investments in Canada, since these macroeconomic confounding forces would likely influence Canadian firms as well. The results, shown in the last column of panel A, confirm that $RPU_{i,t}$ is not a significant predictor of investments for Canadian firms.

In panel B of Table 6, we test whether the policy uncertainty and investment relationship remains stronger for firms with more irreversible investments or a higher dependency on government spending, even when we use the new residual-based measure $RPU_{i,t}$. To this end, we run panel regressions

[25] The standard errors are bootstrapped to account for the fact that the policy uncertainty measure is estimated and the estimation error was ignored. To also account for the fact that our error term may exhibit correlation both within firm and within calendar quarter, we use a sequence of cluster bootstraps as suggested by Cameron, Gelbach, and Miller (2011): in the first bootstrap we resample with replacement from firm clusters; in the second we resample with replacement from quarter clusters, and in the third we resample with replacement from the entire dataset. The final variance matrix is calculated by adding the variance matrices obtained in the first two bootstraps and subtracting the variance matrix from the last.

Table 6
Using Canadian policy uncertainty to mitigate endogeneity concerns

Panel A: Average policy uncertainty effect

Dependent variable: CAPX/Total assets	Without first moment controls				With first moment controls				Canada sample
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)
Policy uncertainty (news)	−0.0247***	−0.0260***	−0.0292***	−0.0330***	−0.0233***	−0.0236***	−0.0261***	−0.0297***	−0.00940
	(−3.38)	(−2.78)	(−3.17)	(−3.87)	(−3.39)	(−2.97)	(−3.49)	(−4.25)	(−0.36)
Election indicator	0.00395	−0.000548	−0.00583	−0.0117	0.00267	−0.000897	−0.00569	−0.0111	
	(0.55)	(−0.07)	(−0.69)	(−1.16)	(0.31)	(−0.11)	(−0.74)	(−1.41)	
GDP growth	0.0299***	0.0389***	0.0410***	0.0491***	0.0102	0.0134*	0.0114	0.0182**	
	(4.59)	(5.18)	(5.52)	(6.38)	(1.43)	(1.71)	(1.53)	(2.33)	
Expected GDP growth					0.00114	0.00681	0.00979	0.0114	
					(0.15)	(0.83)	(1.12)	(1.27)	
Leading economic index					−0.00125	0.0107	0.0185***	0.0244***	
					(−0.15)	(1.20)	(2.81)	(3.37)	
Consumer confidence					0.0591***	0.0556***	0.0550***	0.0493***	
					(7.88)	(7.36)	(8.28)	(6.44)	
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	342,950	333,001	323,863	316,025	342,950	333,001	323,863	316,025	12,144
R-sq	0.045	0.038	0.032	0.027	0.049	0.043	0.039	0.033	0.044
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes	yes	yes	yes	yes	No
Clustering	Cluster-bootstrapped standard errors using firm and quarter/year clusters								

In this table we replicate our main results in Tables 3 and 5, using as our policy uncertainty variable the OLS residuals obtained from regressing the news-based policy uncertainty index in the United States on the news-based policy uncertainty index in Canada, as well as on cross-sectional averages of the control variables used in Table 4. Panel A presents the average effect of this measure of policy uncertainty on capital investments in the United States. Panel B shows interaction effects of this policy uncertainty measure with investment irreversibility (a replication of the last four columns in Table 5). For expositional purposes, the table shows only the variable of interest from each regression. In specifications marked (1), the dependent variable has a lead of one period (calendar quarter) with respect to the independent variables in specifications marked (2) it leads two periods, and so forth until (4). We bootstrap the standard errors using a series of cluster-bootstraps as in Cameron, Gelbach, and Miller (2011). t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6
Using Canadian policy uncertainty to mitigate endogeneity concerns (continued)

Panel B: Investment irreversibility

	Panel B1 : Property, plant, and equipment (PPE)			
	(1)	(2)	(3)	(4)
PU news x PPE	−0.0219***	−0.0299***	−0.0256***	−0.0238***
	(−3.06)	(−4.04)	(−3.45)	(−3.82)
Controls	yes	yes	yes	yes
	Panel B2 : Asset redeployability (AR)			
	(1)	(2)	(3)	(4)
PU news x Asset redeployability	−0.0138***	−0.0227***	−0.0191***	−0.0177***
	(−2.62)	(−4.51)	(−3.70)	(−3.62)
Controls	yes	yes	yes	yes
	Panel B3 : High vs. low sunk costs			
	(1)	(2)	(3)	(4)
PU news x Sunk index	−0.0114***	−0.0162***	−0.0161***	−0.0146***
	(−2.62)	(−3.38)	(−3.77)	(−3.29)
Controls	yes	yes	yes	yes
	Panel B4 : Durables vs. nondurables			
	(1)	(2)	(3)	(4)
PU news x Durable index	−0.00421	−0.00679**	−0.00594*	−0.00590*
	(−1.10)	(−2.12)	(−1.71)	(−1.67)
Controls	yes	yes	yes	yes
Panel C : Sensitivity to government spending (SGS)				
	(1)	(2)	(3)	(4)
PU news x Sensitivity to gov. spending	−0.00835*	−0.0162***	−0.0174***	−0.0150***
	(−1.70)	(−3.84)	(−4.54)	(−3.87)
Controls	yes	yes	yes	yes
	All panels B and C			
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Clustering	Cluster-bootstrapped standard errors using firm and quarter clusters			

of the form:

$$\frac{CAPX_{i,t+l}}{TA_{i,t+l-1}} = \alpha_i + \gamma_t + \beta_1 RPU_{i,t} \cdot H_{i,t} + \beta_2 H_{i,t} + \beta_3 TQ_{i,t}$$
$$+ \beta_4 \frac{CF_{i,t}}{TA_{i,t-1}} + \beta_5 SG_{i,t} + \varepsilon_{i,t+l}. \tag{10}$$

Here, $H_{i,t}$ stands either for one of the irreversibility proxies in Section 4.1 (panel B) or for the measure of dependence on government spending in Section 4.2 (panel C). Once again, to preserve space, we only report the coefficient of interest from each regression (β_1). The results suggest that the interaction effects documented in Section 4 remain significant even when we use the $RPU_{i,t}$ measure of policy uncertainty. The interaction with the durables versus nondurables indicator becomes marginally significant at some lags (panel B4), but as mentioned above, these results are likely underestimating the effect of policy uncertainty on investments.

7.2 Instrumental variable analysis

The classic approach used in the literature to address endogeneity concerns is through the use of instrumental variables. In the context of our study, a proper instrument is a variable that carries a significant relationship with policy uncertainty and affects investment only through this relationship. In this section we propose one such variable, based on a methodology commonly used in the political science literature to quantify the level of political polarization in the Unites States Senate.

Our measure of partisan polarization is based on the DW-NOMINATE scores of McCarty, Poole, and Rosenthal (1997). These scores are designed to track legislators' ideological positions over time. From McCarty (2011), "[…] DW-NOMINATE scores, are calculated based on a statistical model that uses data about who votes with whom and how often to locate legislators on ideological scales. Conservatives are those who generally vote with other conservatives, liberals are those who vote with other liberals, and moderates are those who vote with liberals and conservatives. The polarization measure for each chamber is simply the average distance between Democratic and Republican legislators on this scale." In particular, we focus on the first dimension of the DW-NOMINATE scores, which can be interpreted as the legislators' position on government intervention in the economy (Poole and Rosentahl 2000). Our instrument is calculated as the average of these scores for the Republican party members in the Senate minus the average for the Democratic party members in the Senate.[26]

Partisan polarization has been argued to "make it harder to build legislative coalitions, leading to policy gridlock" and to "produce greater variation in policy" (McCarty 2012).[27] Hence, holding everything else constant, we expect that higher levels of political polarization will result in a higher uncertainty related to policy decisions and therefore that our polarization measure satisfies the relevance condition as an instrument. On the other hand, it is not immediately apparent how the level of disagreement between politicians on the liberal-conservative dimension should drive firm investment in a way other than through its effect on political uncertainty. We thus feel fairly confident that our instrument satisfies the exclusion restriction as well.

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[26] In an earlier draft of this paper we also used an analogous measure of polarization for the members of the House of Representatives. However, we found that the two measures of polarization (for the House and the Senate) have a correlation of 91%, and hence, we decided to use only the Senate polarization measure since it had slightly higher F-statistics in first-stage regressions.

[27] See also Rosenthal (2004), Gilmour (1995), Groseclose and McCarty (2000), and McCarty, Poole, and Rosenthal (2006).

In Table 7, we replicate our main results from Sections 3 and 4 using the above political polarization measure as an instrument for policy uncertainty. Since both the policy uncertainty variable and its instrument are cross-sectionally invariant, their values are repeated for all firms within each time period. This means that the usual two-stage least-squares methodology is not appropriate in this context, since it would mechanically overstate the correlation between the endogenous variable and its instrument. To circumvent this problem, we run a time-series regression in the first stage and a panel regression in the second stage, bootstrapping the standard errors to address the issues associated with using estimated regressors. Specifically, the first-stage regression takes the form:

$$PU_t = \alpha + \beta_1 POLAR_t + \beta_2 TQ_t + \beta_3 CF_t + \beta_4 SG_t + \theta INT_t + \delta M_t + QRT_t + \varepsilon_t. \tag{11}$$

This is the same monthly time-series regression as in Equation (8) in the previous section, except that the residual-based policy uncertainty variable RPU_t has been replaced by the measure of political polarization described above ($POLAR_t$). The F-statistic for the β_1 coefficient in Equation (11) is 17.72, suggesting that our instrument satisfies the relevance condition.[28] In panel A of Table 7 we re-estimate the average effect of policy uncertainty on corporate investment using the fitted values from Equation (11) to capture the exogenous variation in policy uncertainty:

$$\begin{aligned}\frac{CAPX_{i,t+l}}{TA_{i,t+l-1}} = \alpha_i + \beta_1 \widehat{PU_{i,t}} + \beta_2 TQ_{i,t} + \beta_3 \frac{CF_{i,t}}{TA_{i,t-1}} \\ + \beta_4 SG_{i,t} + \theta INT_t + \delta M_t + QRT_t + \varepsilon_{i,t+l}.\end{aligned} \tag{12}$$

Note that the firm-level policy uncertainty term $\widehat{PU_{i,t}}$ is obtained by taking the natural logarithm of the arithmetic average of the fitted values from Equation (11) corresponding to the three months of firm i's fiscal quarter ending in calendar quarter t. Panel A in Table 7 shows the β_1 coefficients obtained from running second-stage regressions as in (12), using leads of up to four quarters ($l \in \{1,2,3,4\}$).[29] Our results show that the relationship between policy uncertainty and corporate investment remains significantly negative under this alternative IV specification. To test whether the relationship significantly depends on firms' investment irreversibility and on their sensitivity

[28] For brevity, we do not report the results from the first-stage regressions, but they are available upon request. The standard errors in the first-stage regressions are adjusted for autocorrelation using the Newey and West (1987) procedure with 12 lags.

[29] We account for the fact that the policy uncertainty variable $\widehat{PU_{i,t}}$ was estimated by bootstrapping standard errors using the same methodology as in Section 7.1.

Table 7
Using instrumental variables to mitigate endogeneity concerns

Dependent variable: CAPX/Total assets	Panel A: Average policy uncertainty effect			
	(1)	(2)	(3)	(4)
Policy uncertainty (news)	−0.0327***	−0.0314***	−0.0264**	−0.0223*
	(−2.99)	(−2.81)	(−2.23)	(−1.88)
Controls	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes
Quarter dummies	yes	yes	yes	yes
Clustering	Cluster-bootstrapped standard errors using firm and quarter clusters			
Dependent variable: CAPX/Total assets	**Panel B: Investment irreversibility**			
	Panel B1 : Property, plant, and equipment (PPE)			
	(1)	(2)	(3)	(4)
PU news x PPE	−0.126***	−0.135***	−0.133***	−0.129***
	(−9.30)	(−10.99)	(−9.61)	(−10.69)
Controls	yes	yes	yes	yes
	Panel B2 : Asset redeployability (AR)			
	(1)	(2)	(3)	(4)
PU news x Asset redeployability	−0.0469***	−0.0515***	−0.0514***	−0.0498***
	(−11.69)	(−14.62)	(−13.58)	(−13.46)
Controls	yes	yes	yes	yes
	Panel B3 : High vs. low sunk costs			
	(1)	(2)	(3)	(4)
PU news x Sunk index	−0.210***	−0.213***	−0.201***	−0.194***
	(−3.86)	(−3.52)	(−3.49)	(−3.39)
Controls	yes	yes	yes	yes
	Panel B4 : Durables vs. nondurables			
	(1)	(2)	(3)	(4)
PU news x Durable index	−0.185***	−0.194***	−0.161***	−0.153***
	(−4.05)	(−5.28)	(−3.97)	(−3.92)
Controls	yes	yes	yes	yes
	Panel C : Sensitivity to government spending (SGS)			
	(1)	(2)	(3)	(4)
PU news x Sensitivity to gov. spending	−0.170***	−0.170***	−0.148***	−0.0867**
	(−3.76)	(−4.29)	(−4.52)	(−2.53)
Controls	yes	yes	yes	yes
	All panels B and C			
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Clustering	Cluster-bootstrapped standard errors using firm and quarter clusters			

In this table we replicate our main results from Tables 3 and 5 using a two-stage least-squares approach, with a measure of political polarization in the United States Senate as an instrument for policy uncertainty. Panel A presents the average effect of policy uncertainty on capital investments in the United States. Panel B shows interaction effects of policy uncertainty with investment irreversibility (a replication of the last four columns in Table 5). For expositional purposes, the table only shows the variable of interest from each regression. In specifications marked (1), the dependent variable has a lead of one period (calendar quarter) with respect to the independent variables in specifications marked (2) it leads two periods, and so forth until (4). We bootstrap the standard errors using a series of cluster-bootstraps as in Cameron, Gelbach, and Miller (2011). t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

to government spending, we use panel regressions of the following form:

$$\frac{CAPX_{i,t+l}}{TA_{i,t+l-1}} = \alpha_i + \gamma_t + \beta_1 \widehat{PU_{i,t}} \cdot H_{i,t} + \beta_2 INT_{i,t} + \beta_3 TQ_{i,t} + \beta_4 \frac{CF_{i,t}}{TA_{i,t-1}} + \beta_5 SG_{i,t} + \varepsilon_{i,t+l}. \tag{13}$$

We run these second-stage regressions for each choice of proxy for investment irreversibility or dependence on government spending (H_t) and report the β_1 coefficients in panels B and C of Table 7. Note that the vector $INT_{i,t}$ includes all five of the $H_{i,t}$ proxies and that the time fixed effect γ_t replaces all stand-alone macroeconomic controls. Consequently, the appropriate first-stage regression for these tests is given by Equation (11), with all macroeconomic controls M_t discarded. The F-statistic from this time-series regression is 20.34, suggesting once again that we do not have a weak instrument problem. The second-stage results reported in panels B and C of Table 7 show that investment irreversibility and the dependence on government spending remain significant moderators of the policy uncertainty-investment relationship.

8. Conclusion

In this study, we analyze the effect of policy-related uncertainty on the capital investments of U.S. public corporations, paying close attention to the way this effect manifests itself differently across firms. To capture the overall level of policy uncertainty in the economy, we employ a measure developed by Baker, Bloom, and Davis (2013); the measure is based in large part on frequency counts of key terms in newspaper articles. Using this measure, we document a strong negative relationship between policy uncertainty and capital investments. This result is robust to controlling for alternative measures of investment opportunities and macroeconomic uncertainty, as well as to using several methods of identifying exogenous variation in policy uncertainty.

To investigate the degree to which the negative effect of policy uncertainty on investment varies in the cross-section, we rely on real options theories, which suggest that uncertainty increases the benefits from delaying investment. Moreover, it does so more severely for firms with a high degree of investment irreversibility. We find strong evidence in support of this prediction using several different proxies for investment irreversibility. Another dimension of cross-sectional heterogeneity we explore is firms' sensitivity to government spending. Using the BEA Input-Output Accounts to calculate the fraction of an industry's sales that can be attributed to government-sector demand, we find that firms that are more dependent on government spending are significantly more negatively affected by policy uncertainty.

Analyzing how policy uncertainty affects investment over longer horizons, we find that the effect becomes progressively stronger (more negative) up to 4–5 quarters into the future, after which time it decays and eventually becomes positive. While this rebound is consistent with firms increasing investments to satisfy pent up demand, we show that it takes two to three years for investments to recover from the initial effects of policy uncertainty. We also find that the uncertainty-investment relationship weakens after prolonged periods of continuously high policy uncertainty. This is consistent with the idea that many investment projects cannot be delayed indefinitely, as well as with the fact that as time goes by, cash flows lost from delaying investments can outstrip the benefits of waiting for uncertainty to subside.

Our results have three main implications. First, they suggest that when making policy decisions, regulators should be mindful of the fact that the uncertainty surrounding these decisions can be just as damaging as making the wrong decision. Second, our results indicate that in assessing the possible impact of policy-related uncertainty on corporations, we should be aware of the fact that different firms will be affected to different degrees, depending on characteristics such as investment irreversibility and reliance on government spending. Third, we find that policy uncertainty can have long-lasting effects, impacting investment levels for up to eight quarters into the future.

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