The Effect of Economic Policy Uncertainty on Investment*

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Abstract

Exploiting textual information for a large panel of U.S. firms, I study the sensitivity of corporate investment rates to economic policy uncertainty. I find that a doubling of economic policy uncertainty reduces capital expenditure by 25%, but R&D does not respond to policy uncertainty when controlling for industry-specific shocks. Firms might have little reason to delay R&D projects when policy uncertainty idiosyncratically increases because this makes them lose the race for new discoveries against their competitors. Investigating the channels through which policy uncertainty affects investment, I find the sensitivity of investment to policy uncertainty is significantly amplified for firms that are likely to be financially constrained ex-ante. Thus, the key to understanding the relation between investment and policy uncertainty lies in the interaction of policy uncertainty with financial frictions.

Keywords: Policy Uncertainty; Investment; R&D; Financial Constraints.

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1 Introduction

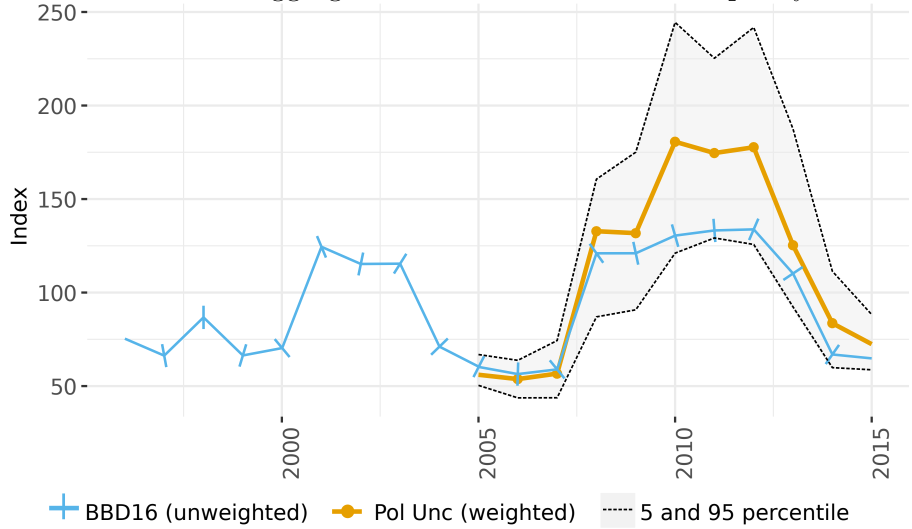
Economic policy uncertainty refers to uncertainty about when and how policies may change and how the changes may impact the business environment. Policy uncertainty has been put forward as a possible cause for the depressed investment rates observed after the financial crisis of 2008 in the US (Gulen and Ion, 2015; Baker et al., 2016). However, the policy uncertainty created by the British referendum to leave the European Union in 2016 left investment largely unaffected (Forbes, 2016). This has re-opened debates about how big the effect of economic policy uncertainty on investment is and through which channels it operates.

This paper presents a novel approach to empirically investigate the effect of economic policy uncertainty on investment and the channels through which the effect is transmitted. My approach relies on the idea that we can sort policy risks into different policy classes such as tax, trade, or spending policy risks. I exploit a 2005 rule of the Securities and Exchange Commission (SEC) which requires US firms to report on their key risk factors in a specific section of their annual report. I measure how exposed a firm is to a policy class by text-mining its risk disclosure section to count mentions of that policy class. I combine this information with newspaper based measures of aggregate policy uncertainty within different policy classes from Baker et al. (2016). This results in an index of economic policy uncertainty for a panel of US firms between 2005 and 2015. My index varies within firms over time because firms are exposed differently to policy classes and uncertainty across policy classes varies. Figure 1 illustrates the evolution of aggregate policy uncertainty and the firm-level variation around it.

To identify the effect of policy uncertainty on investment, I regress investment on my measure of firm-level policy uncertainty while controlling for aggregate and industry-specific shocks and a battery of additional controls. Controlling for aggregate shocks is important because these shocks can simultaneously increase policy uncertainty and depress investment, creating a spurious negative correlation between the two.

I find large reductions in average capital expenditure in the year after an increase in economic policy uncertainty, but, once industry shocks are controlled for, no effect on

Figure 1: Evolution of aggregate and firm-level economic policy uncertainty



Fiscal year average, 5 and 95 percentile of my weighted policy uncertainty index. For comparison, the blue line illustrates the monthly newspaper based index from Baker et al. (2016) [BBD16]). The sample includes all Compustat firms with positive sales and assets, excluding financials and utilities.

R&D rates. My estimates suggest that a doubling in economic policy uncertainty reduces average capital expenditure in the following year by 25%. R&D might be unresponsive to idiosyncratic changes in policy uncertainty because an individual firm cannot delay R&D without loosing out against its competitors in the race for new discoveries. Having established these results, I investigate whether the aggregate estimates mask cross-sectional differences in terms of how firms respond.

Economic policy uncertainty can affect investment through a variety of channels. The previous empirical literature on the investment-uncertainty relation has emphasized the "wait-and-see" channel: when faced with higher uncertainty, firms tend to delay their investment projects where possible, until uncertainty recedes (Bernanke, 1983; Dixit and Pindyck, 1994; Abel and Eberly, 1994; Bloom, 2009). However, uncertainty can also operate through a financial frictions channel. In this case, an increase in idiosyncratic uncertainty raises the default probability of a firm because financial frictions prevent the firm from perfectly insuring itself against downside risk. The firm responds by scaling back its investment (Christiano et al., 2014; Gilchrist et al., 2014; Arellano et al., 2016; Alfaro et al., 2016).

It is possible to shed light on the empirical strength of the financial frictions channels by estimating the effect of economic policy uncertainty on investment for financially constrained and unconstrained firms separately. Financially unconstrained firms are not exposed to financial frictions, but financially constrained firms are. Taking the difference between the estimated investment-uncertainty sensitivities for the two groups allows us to gauge the empirical importance of the financial frictions channel compared to all other channels.

I classify firms as financially constrained if they faced difficulties to finance planned investments in the year before an increase in uncertainty. I measure this using the Hoberg and Maksimovic (2015) index, which is based on large-scale textual analysis of a specific part of annual reports. In that part, firms need to disclose whether they might face difficulties to obtain financing going forward. Using this index, I sort firms into groups of likely constrained and unconstrained firms.[1]

I find the effect of policy uncertainty on capital expenditure to be much stronger for firms that are likely to be financially constrained ex-ante. A doubling of economic policy uncertainty reduces capital expenditure between 30 to 40% for financially constrained firms. Firms that are less likely to be constrained reduce capital expenditures by only 10 to 20% from the group specific mean. Thus, the presence of financial frictions can thus roughly double the effect of policy uncertainty on capital expenditure.

To the extent that R&D rates do respond to higher policy uncertainty, I find the effect to be concentrated among firms that are financially constrained ex-ante. Before controlling for industry specific shocks, the sensitivity of R&D to economic policy uncertainty for constrained firms is more than twice the sensitivity for unconstrained firms. Once industry-specific shocks are controlled for, R&D of likely unconstrained firms becomes insensitive to changes in policy uncertainty. However, constrained firms still respond by lowering their R&D rates when policy uncertainty increases. This suggests that, if anything, R&D is affected by higher policy uncertainty through the financial frictions channel.

The importance of the financial frictions channel for the investment-uncertainty re-

[1] I use the Hoberg and Maksimovic (2015) index because there are serious concerns about the validity of accounting based measures for financial constraints (Farre-Mensa and Ljungqvist, 2016). Nevertheless, I show my results are robust to using rating, size, dividends and age based proxies for constraints as well.

lation suggests that economic policy uncertainty is particularly damaging to investment when financial markets are not operating smoothly. This was likely the case over much of the time period covered in my sample, which may explain the large negative average effects of uncertainty on capital expenditures I find. However, if economic policy uncertainty increases at a time when financial frictions are subdued, its effect on corporate capital expenditure is unlikely to be as large as during the recession following the financial crisis in 2008. As long as financial markets are operating smoothly, we should not be too worried about policy uncertainty, per se.

This paper makes two contributions to the literature on economic policy uncertainty and investment, one substantive and one methodological. On a substantive level, this is the first paper that empirically documents the amplifying role financial frictions play in propagating the effect of policy uncertainty on investment. The potential of financial frictions to transmit the effects of uncertainty on investment has only recently been formally modeled (Christiano et al., 2014; Gilchrist et al., 2014; Arellano et al., 2016; Alfaro et al., 2016). Empirical evidence on the magnitude of this channel is scarce and focuses on uncertainty more generally (Gilchrist et al., 2014; Alfaro et al., 2016; Alessandri and Bottero, 2017). Previous work on the effects of economic policy uncertainty on investment have emphasized the "wait-and-see" channel (Julio and Yook, 2012; Gulen and Ion, 2015). There is, however, some evidence that the supply of funds is negatively affected by policy uncertainty (Francis et al., 2014; Waisman et al., 2015; Bordo et al., 2016). This supports the idea that financial factors play a role in propagating the effect of policy uncertainty on investment. The paper also extends the analysis of the effects of economic policy uncertainty on investment from capital expenditure to R&D expenditure.

On a methodological level, I present a novel approach to estimate the effect of policy uncertainty on capital expenditure and R&D rates. Previous approaches to identify the effect of policy uncertainty on investment used cross-country variation in policy uncertainty induced by elections (Julio and Yook, 2012), lacked genuine firm-level variation in policy uncertainty within a country (Gulen and Ion, 2015), and focused only on capital expenditures. Only recently have firm-level measures of policy uncertainty appeared for the US (Hassan et al., 2016). Unlike my measure, their measure is based on voluntary disclosure of policy risks during earning calls rather than mandatory disclosure in annual reports. Papers that look at the relation between uncertainty and investment more generally often have problems identifying a exogenous variation in uncertainty (Leahy and Whited, 1996; Bulan, 2005; Panousi and Papanikolaou, 2012) or instrument firm-level uncertainty with industry-level measures of uncertainty (Stein and Stone, 2013; Alfaro et al., 2016). The data constructed for this study could also be used to investigate further questions on how policy uncertainty affects firm behaviour.

2 Data

2.1 Overview

My dataset combines accounting information from Compustat for fiscal years 2005 to 2015 with data from several other sources. The textual data on exposure to political risks are based on corporate filings with the SEC and matched to the accounting data using the WRDS-linking tables. Details on the matching process can be found in Appendix A.1.2. Stock market variables come from CRSP and are matched per fiscal year end. I use the WRDS Beta Suite to calculate volatilities using monthly log returns over 12 month windows. I require a minimum of six months of data for an observation to be included in my dataset.

I match the fiscal year averages of the categorical policy uncertainty indices from Baker et al. (2016) to individual firms. These indices offer a measure of economic policy uncertainty in nine different policy classes and will serve as a key input for my firm-level index. The indices are based on monthly counts of newspaper articles that relate to economic policy uncertainty and a specific policy class. All indices are based on the Access World News Database, which covers well over 1000 U.S. newspapers, and are standardized to an average of 100 over the period 1985 to 2010. More details on how the indices are constructed can be found in Section A.2 of the Appendix.

[Table 1 here]

I classify firms as financially constrained if they faced difficulties to finance planned investments in the year before a change in uncertainty using the Hoberg and Maksimovic (2015) index of financial constraints. In theory, such issues might arise because the firm faces an inelastic capital supply curve that turns vertical at some point and shuts the firm out of funding markets (Stiglitz and Weiss, 1981) or because the firm experiences a positive wedge between its internal and external cost of funds (Fazzari et al., 1988). In both cases, the firm cannot implement an investment project it deems profitable and is hence financially constrained.

The Hoberg and Maksimovic (2015) measure is based on automatic textual analysis of the capital and liquidity section in firms' *Management, Discussion & Analysis* (MD&A) part of the annual report. In this section firms need to discuss when they might face difficulties to finance planned investments. Using a number of search terms the authors identify a set of firms as financially constrained. For each firm and year they then calculate the cosine similarity of the term-vector of the current liquidity section to the average term vector of the firms previously identified as being financially constrained. This measure is then purged of boiler-plate information by regressing it on the cosine similarities to the average liquidity section within a given industry and year. The residual of this regression is a continuous measure of financial constraints.

I sort firms into terciles along the Hoberg-Maksimovic constraints measure and define firms in the top tercile as likely financially constrained and firms in the bottom tercile as likely unconstrained. Firms in the bottom tercile of the index might still be constrained. For example, a firm without access to capital markets might not plan any investment and thus would not report any financing issues. Such a firm would rank low in the index. Keeping this in mind, I will still sometimes refer to the firms in the lower tercile as being unconstrained.

The two other key variables in my analysis, the investment rates, are defined as capital expenditures ($CAPX$) and R&D expenditures (XRD) scaled by the firm's lagged total capital stock. The total capital stock K is calculated as the sum of intangible capital and gross property, plants and equipment ($K_I + PPEGT$). My measure of intangible capital comes from Peters and Taylor (2017) and is constructed using the perpetual inventory method. For easier interpretation of the uncertainty sensitivities, the rates are expressed in percentage points.

Lastly, I define a number of supplementary variables and apply a few common sample restrictions. Definitions of the additional controls and alternative financial constraints proxies are provided in Appendix A.1.1. As is common in the micro-econometric literature on investment, I drop financials (SIC 6000-7000) and utilities (SIC 4899-5000). I also drop observations with negative assets or negative sales. All data are winsorized at the 1% and 99% levels.

2.2 Firm-level economic policy uncertainty

My index of economic policy uncertainty at the firm level is a weighted average of the uncertainty across different policy classes. Conceptually, the index can thus viewed as a Bartik (1991)-type instrument for policy uncertainty.[2] As weights, I use the lagged ratio of the number of sentences on a specific policy class to the total number of policy related sentences in the mandatory risk disclosure section of the annual report. I will discuss my weighting scheme more thoroughly in the following section.

As a measure for the uncertainty within policy risk classes, I use the logged sub-components of the newspaper based policy uncertainty index from Baker et al. (2016). The index is based on monthly counts of newspaper articles that relate to economic policy uncertainty. For the sub-components of the index the policy uncertainty-related articles are further sorted into nine policy classes. More detail on the aggregate index is found in Section A.2 of the Appendix. For now, a formal definition of my firm-level index might help to fix ideas:

Definition The effective economic policy uncertainty of firm i in fiscal year t is given

[2] Bartik (1991) instruments local employment growth in a state with a weighted average of national industry growth using local industry shares as weights. I depart from a classic Bartik-approach in two ways: first, I am updating the weights in my index for every observation; second, I will take logs of my index to estimate a sensitivity of investment to policy uncertainty. I show that these deviations are inconsequential in Section 4.3 and in the Tables 17 and 18 in the Appendix.

by:

$$Pol_{i,t} = \sum_{c \in C} s_{i,t-1,c} \cdot PU_{c,t}, \tag{1}$$

where:

$c \in C$ is policy risk class c from the set of policy classes $C = \{$*regulation, monetary policy, trade, entitlement programs, national security, taxes, spending, healthcare, debt crisis*$\}$;

$s_{i,c,t-1}$ is the share of sentences on risk class c to all policy-related sentences of firm i in the mandatory risk disclosure section of its preceding annual report;

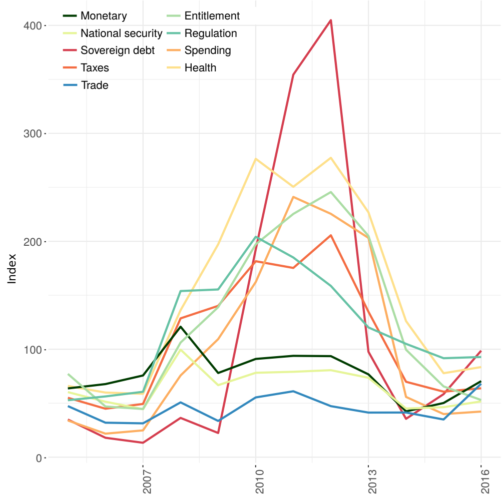
$PU_{c,t}$ is the fiscal year matched economic policy uncertainty within risk class c.

It is useful to illustrate my approach with a concrete example. In its 2010 annual report, General Motors disclosed 21 sentences about policy risks of which eight were about monetary policy, in particular General Motors' exposure to changes in interest rates. For its 2011 report, General Motors changed their risk disclosure. Now only 20 sentences contained policy risk terms and six of them can be associated with monetary policy risks. GM's disclosed exposure to monetary policy risk drops from 40% to 30% from 2010 to 2011.

My index varies at the firm-level after controlling for aggregate shocks, because uncertainty varies across risk classes and firms are differentially exposed to these classes. If uncertainty was identical across policy risk classes, then my index would be the same for all firms in a given year, even if firms were differentially exposed to policy risk classes. If, on the other hand, exposure to policy risk classes was identical across all firms, then my index would also be the same for all firms in a given year, even if policy uncertainty evolves differently across policy classes. In both cases, all variation in policy uncertainty at the firm-level would be absorbed by aggregate time effects.

There are significant differences in how uncertainty evolved in the different policy risk classes during the time period covered by my sample. Figure 2 illustrates this. In the

Figure 2: Policy uncertainty across policy classes



Debt								
0.76	Taxes							
0.83	0.9	Spen-ding						
0.74	0.96	0.93	Health					
0.38	0.63	0.47	0.48	Mone-tary				
0.43	0.76	0.61	0.64	0.86	Nat sec			
0.82	0.94	0.98	0.97	0.46	0.64	Entitle-ments		
0.61	0.91	0.77	0.89	0.61	0.73	0.81	Regu-latory	
0.6	0.58	0.56	0.55	0.53	0.62	0.59	0.61	Trade

The left panel shows the fiscal year averages of matched policy uncertainty for all policy classes as provided by Baker et al. (2016). The right panel shows the corresponding correlation matrix. Based on Compustat matched sample for fiscal year 2005 to 2015. Excludes financials and utilities, as well as observations with negative assets or sales.

left panel, I plot the evolution of uncertainty within the different risk classes. While there clearly is a common factor that drives all time series, there is also an idiosyncratic component in the different measures. Sovereign debt uncertainty, for example, is much more volatile than trade policy uncertainty and shows a different time series pattern. In the right panel, I show the correlation of uncertainty across the different risk classes. Correlation is high between the health, entitlement, spending and regulation risk classes but is much smaller among the other risk types.

Another desirable feature of my economic policy uncertainty index is a positive correlation to other measures of uncertainty at the firm-level. To the extent that changes in policy affect the business environment, the uncertainty that these changes generate should also be reflected in other measures of uncertainty at the firm-level. Table 14 in the Appendix shows that this is the case for measures of stock return, cash flow and sales volatility.

2.2.1 Measuring policy uncertainty exposure

Since 2005 essentially all public firms in the U.S. filing with the SEC need to report important risk factors that could affect their business in a designated section of their annual report.[3] This is stipulated in Item 503(c) of Regulation S-K:

> "§ 229.503 (Item 503) (c) Risk factors. Where appropriate, provide under the caption "Risk Factors" a discussion of the most significant factors that make the offering speculative or risky. This discussion must be concise and organized logically. Do not present risks that could apply to any issuer or any offering. Explain how the risk affects the issuer or the securities being offered. Set forth each risk factor under a subcaption that adequately describes the risk."

The key assumption in my measurement approach is that mandatory risk disclosure is informative on risk exposure. I discuss this assumption in detail in Section 4.1 and provide evidence in favor of the informativeness hypothesis. For now, I will focus on explaining my measurement approach.

I classify each sentence in the risk disclosure sections of firms' annual reports into the policy classes suggested in Baker et al. (2016). I first isolate the mandatory risk disclosure section for all firms in my sample by text-mining their annual reports filed with the SEC. This is a complicated process that is detailed in Appendix A.1.2.[4] The classification of sentences into policy classes is based on the same list of search expressions used to classify newspaper articles in Baker et al. (2016). The expressions used for classification can be general policy terms, such as "taxes", specific regulations or regulatory agencies, such as "minimum wage" or the "Food and Drug Administration". Lastly, a search expression might also refer to a specific event, such as the "Russian Financial Crisis". All search expressions are listed in Appendix A.3. Figure 4 in Appendix A.4 shows the relative importance of each keyword in the search expressions for the final classification. If a sentence qualifies for more than one risk class, I count it towards all of them.[5]

[3] The appendix contains a detailed overview on the structure of Form 10-K and changes in the technical implementation of SEC filings.

[4] A tailored solution to the textual analysis of SEC filings is important, because of the peculiarities associated with the raw data (Loughran and McDonald, 2011, 2016). My technical implementation builds on several open-source libraries. I use JSOUP (https://jsoup.org/) to parse the documents and the natural-language processing toolbox presented in Manning et al. (2014) for the textual analysis part.

[5] A small number of search expressions in Baker et al. (2016) are used for classifying newspaper articles into multiple policy classes. Moreover, sometimes multiple risk factors can be named in one sentence; for

I define exposure to a policy class as the ratio of sentences discussing that policy class to the number of all policy-related sentences in the mandatory risk disclosure section. My weight $s_{i,t,c}$ for policy class c of firm i at time t is then simply the ratio of the number of sentences that contain a search expression related to risk class c to the number of sentences containing a search expression from any policy risk class. Figure 5 in the Appendix gives an overview of how the disclosure data evolves over time.

Extracting text specifically from the mandatory risk disclosure section minimizes the possibility that the policy search terms are not used in a risk-related context. For example, the word "tax" shows up in all sections of the annual report. However, when it appears in the risk disclosure section it is likely because tax-related risks are being discussed.

To give an idea of the kind of sentences my algorithm identifies, Figure 3 shows the forty most common words in the sentences relating to sovereign debt and currency crises. The word cloud reveals that the selected sentences contain words which we would broadly expect to be used when explaining currency and debt crisis-related risks.

Figure 3: Word-cloud currency and debt crisis

Word cloud of thirty most common terms in sentences classified as relating to debt and currency crisis. Covers sentences identified in Item 1A (Risk Factors) for filings between 2005 and 2015. All sentences are transformed to lower case, additional white-space, punctuation and English stop-words are removed.

My disclosure data exhibit intuitive industry patterns in the cross-section. To illustrate this, I show the ten highest ranking industries in terms of relative disclosure about

example in lists where individual points are only separated by semicolons. In such cases, I allow sentences to count into multiple policy risk classes. I adjust the total number of policy sentences accordingly so that the resulting weights in my index will still sum to one.

a policy risk class in Table 2. Industries are defined using the Fama-French 48 industry classification.

[Table 2 here]

The observed industry patterns are in line with the notion that more exposure towards a risk class goes hand-in-hand with more disclosure about that risk class. For example, healthcare and entitlement risks are most important in the healthcare industry. Monetary policy risks cluster in banking, real estate and insurance. Tax policy risks are important for most companies; the shares are quite high for many industries, but are particularly salient in Beer & Liquor as well as Tobacco. In the robustness section, I provide additional evidence on the informativeness of my disclosure data.

3 Policy uncertainty and corporate investments

3.1 Empirical approach

To identify the effect of policy uncertainty on investment rates, I run panel fixed effects regressions of the following type:

$$I_{it+1} = \beta \log(Pol_{it}) + \Theta X_{it} + \alpha_{jt} + \gamma_i + e_{it}, \tag{2}$$

where i, j and t index firms, industries and fiscal years, respectively. The outcome variable I_{it+1} is either the capital expenditure or R&D rates expressed in percentage points with a one period lead. My policy index Pol_{it} is included in logs, so that the coefficient of interest β can be interpreted as the percentage point change in investment rates when policy uncertainty doubles. The vector X_{it} includes a set of firm-level controls. I include firm γ_i and industry specific time α_{jt} fixed effects. The variable e_{it} is the usual error term.

The key challenge in identifying the effect of economic policy uncertainty on investment is to control for negative economic shocks at the industry or the aggregate level.

Such shocks increase economic policy uncertainty (Pástor and Veronesi, 2012, 2013), reduce firms' growth expectations and hence investment going forward.[6] Not taking these shocks into account would lead to a downward bias in the estimated effect of uncertainty on investment.

I control for aggregate shocks using industry-specific fiscal year fixed effects. I define industries using the Fama-French 10 industry classification. Whilst industry-time fixed effect solve the omitted variable problem described in the previous paragraph, they also absorb potentially useful industry variation in policy uncertainty that is not driven by industry-level shocks. The Fama-French 10 industry classification offers a way to control for industry shocks without absorbing too much variation in my index.

I control for firm-specific changes in growth expectations by including a number of common proxies for investment opportunities in my regressions. I include the market to book value, cash flow, sales growth at the firm level and sales growth at the four digit SIC level as additional controls. These factors have been shown to be important predictors of investment in previous research. To the extent that there remain concerns about potential bias due to the correlation between investment opportunities and uncertainty, the concerns are equally valid for most other papers using firm-level data to investigate the investment-uncertainty relation.

To say something about the empirical importance of the financial frictions channel, I estimate the investment-uncertainty relation separately for financially constrained and unconstrained firms. For the former the financial constraints channel is active, for the latter it is not active. The difference between the estimated effects is a proxy for the empirical importance of the financial frictions channel. I run regressions of the following type:

$$I_{it+1} = \beta \log(Pol_{it}) \times Avg_{it-1} \times Cons_{it-1} + \Theta X_{it} + \alpha_{jt} + \gamma_i + e_{it}, \quad (3)$$

[6] In Pástor and Veronesi (2012), economic policy uncertainty occurs because negative shocks increase the likelihood of a new policy being adopted and agents learn only slowly about its impact. In Pástor and Veronesi (2013), there is an additional layer of uncertainty, because agents do not know which kind of policy will be implemented in response to a shock.

where the variables and indices are defined as before. I now include interactions between the log of policy uncertainty and dummies that indicate in which tercile of the financial constraint measure a firm ranked in year $t-1$. In the above specification, the coefficient on the interaction between $Cons_{it-1}$ and $\log(Pol_{it})$ is an estimate of the difference in the investment-uncertainty sensitivity for financially constrained and unconstrained firms. For the tables in Section 3.3, I alternate the constraint dummies I use so that I get estimates for the base effect for each group as well as the estimates for the differences between groups.

Financially constrained firms might also react stronger to negative demand shocks. I therefore also estimate specifications where the control variables and aggregate time shocks are interacted with the dummies for financial constraints. However, my data does not allow me to credibly estimate a fully interacted regression with industry-specific time shocks.

I address a number of additional concerns with my approach in the robustness section of this paper. In particular, I show in Section 4.2 that my results are not solely driven by the years of the financials crisis and that they are robust to including proxies for systemic risk in the regressions. In Section 4.3, I address the concern that updating the weights in my index introduces a correlation between the error term in my regressions and my measure for policy uncertainty. I show that keeping the weights fixed at the initial period does not affect my estimation results.

In all regressions, I cluster standard errors at the four digit SIC level in case policy uncertainty does not affect firms individually but uniformly across groups.

3.2 The average effect of policy uncertainty on investment

In this section, I present my estimates of the average effect of economic policy uncertainty on capital expenditure and R&D rates. I start with a basic specification that only includes fiscal year and firm-fixed effects for both investment classes. In a next step, I add the firm-level controls before finally estimating my preferred specification including industry-specific time fixed effects. To control for potentially higher systemic risk during periods of elevated policy uncertainty, I run these specifications with and without controlling for total stock return volatility which does not affect the results in a substantial way. The results are shown in Table 3.

[Table 3 here]

An increase in uncertainty significantly reduces capital expenditure rates in the following fiscal year. Using only firm and fiscal year fixed effects, I estimate a sensitivity of capital expendiures to economic policy uncertainty of -1.3. The estimate is significant at the 5% level. I continue by including my firm-level controls which leaves the estimate roughly unchanged. Lastly, I estimate the full specification including industry-time fixed effects. This leaves the estimated sensitivity of capital expenditure to uncertainty again roughly unchanged. The estimate is now significant at the 1% confidence level. A doubling of economic policy uncertainty thus reduces the capital expenditure rate by 1.3 percentage point. This corresponds to a 25% reduction from the mean rate. For comparison, in my sample the average capital expenditure rate drops roughly 3 percentage points from its peak during the financial crisis.

R&D rates do not respond to policy uncertainty once industry-level shocks are controlled for. Column 4 and 5 in Table 3 show the sensitivity of R&D to policy uncertainty using just fiscal year fixed effects and my additional controls. In these specifications, I find a one year ahead sensitivity of R&D rates to policy uncertainty of roughly -0.7 with and without additional controls. The estimates are statistically significant at the 10% level. There is thus slight evidence that R&D and capital expenditure rates respond in similar ways to increases in economic policy uncertainty. Once I control for industry-specific time shocks, however, the sensitivity of R&D rates to policy uncertainty essentially drops to zero and becomes statistically insignificant.

Controlling for industry specific shocks solves a potential omitted variable problem, negative industry shocks increase uncertainty and depress investment, but it also absorbs relevant variation in uncertainty at the industry level. In the case of R&D, the effect estimate before controlling for industry-specific shocks is driven by the healthcare industry. This industry experienced a period of high policy uncertainty in combination with a steep reduction in R&D expenditure during the recession. Other industries spend much less on R&D and the expenditures are also more stable.

One way to interpret the R&D result is thus as follows: there is some evidence for R&D expenditure responding to industry-specific uncertainty but not to uncertainty that is idiosyncratic to the individual firms within an industry.

The literature on patent races offers an explanation why R&D might be less affected by policy uncertainty than capital expenditure. In a race, the winner takes it all. Only the first firm making an invention has a chance to make exclusive use of its discovery for a certain amount of time (Grossman and Shapiro, 1987; Harris and Vickers, 1987). If policy uncertainty affects an individual firm within an industry, there might simply not be an option to delay research when uncertainty increases. The effect of policy uncertainty on investment might then simply be too small to be identified using the variation in my index. Alternatively, policy uncertainty might simply not be relevant for the R&D decision.

The average effect of policy uncertainty on investment estimated here can operate through a variety of channels. For example, managers might shy away from investment either because they are risk averse or because they want to wait until uncertainty recedes. In the next section, I investigate to what extent the presence of financial frictions can amplify the effect of policy uncertainty on investment.

3.3 Financial frictions and the uncertainty-investment relation

In this section, I use the time-varying variation in financial constraints provided by the Hoberg and Maksimovic (2015) index in combination with the variation in policy uncertainty my index provides, to investigate the empirical importance of the financial frictions channel to propagate the effect of policy uncertainty on investment. Economic theory suggests that financially constrained firms should respond stronger to changes in uncertainty, because they cannot insure against changes in downside risks when policy uncertainty idiosyncratically increases.

I start by estimating a variation of Equation 3 where I only include firm and fiscal year fixed effects. I then estimate gradually more stringent specifications. First, I include additional controls. Next, I interact my controls with the financial constraints dummies as well. I then estimate a specification where I control for industry-specific time shocks. Lastly, I run a regression where I interact the fiscal year fixed effects with the dummies for financial constraints. I do this, because financially constrained firms could also react more strongly to first-moment shocks and I want to control for that.

The results for capital expenditure and R&D rates are presented in Table 4 and Table 5 respectively. The first three rows show the estimated sensitivity of investment to policy uncertainty for the top, middle and bottom tercile of firms in the Hoberg and Maksimovic (2015) measure of financial constraints. Rows four and five show the estimated differences across the groups of constrained and unconstrained firms.

In terms of interpretation, the effect of uncertainty on investment for unconstrained firms is my best estimate of the investment-uncertainty relation absent the financial frictions channel. The difference between the estimated sensitivity for the unconstrained and constrained firms is my best estimate for the investment-uncertainty relation in the presence of financial frictions. Comparing this difference to the sensitivity of investment to uncertainty for the unconstrained firms tells us how much the presence of financial frictions can amplify the basic investment-uncertainty relation resulting from all other channels. I will first discuss the results for capital expenditures again and then move to the results on R&D rates.

[Table 4 here]

Economic policy uncertainty has a strong effect on capital expenditures even absent financial frictions. The estimated sensitivity of capital expenditure to uncertainty for financially unconstrained firms lies between -0.8 and -1.0 across most specifications I estimate. However, the estimated sensitivity drops to -0.4 when I interact the fiscal year fixed effects with my dummies for financial constraints. This could be because multicollinearity issues become quite aggravated in this specification which makes the estimates unstable. The estimated effects of economic policy uncertainty on capital expenditure are economically non-trivial and imply a reduction of capital expenditure rates between 10 and 20% from the group specific mean when economic policy uncertainty doubles. Even though the estimated effects are economically large, they are not statistically significantly different from zero in most cases.

The estimated sensitivity of capital expenditure to policy uncertainty for financially constrained firms is two to five times the sensitivity estimated for unconstrained firms. Capital expenditure rates of financially constrained firms are reduced between 30 and 40% from the group specific mean when policy uncertainty doubles. The estimated sensitivities are statistically significant at the 1% level across all specifications. The sensitivity of capital expenditure to policy uncertainty for constrained firms is also statistically significantly larger than the sensitivity for unconstrained firms across all specifications. This suggests that financial frictions can significantly amplify the effect of uncertainty on capital expenditure.

The response of capital expenditure to policy uncertainty is also statistically significantly stronger for constrained firms compared to unconstrained firms in relative terms. Financially constrained firms tend to be high growth firms that exhibit higher investment rates than unconstrained firms (Hoberg and Maksimovic, 2015). The stronger response of capital expenditure to uncertainty of financially constrained firms in absolute terms might simply be due to the higher base rate in that group. To test this, I run one sided t-tests on the difference of the relative change in capital expenditure between constrained and unconstrained firms with respect to the group specific mean after a doubling in policy uncertainty. If constrained firms do not react stronger, the difference in relative effects should not be positive. I provide the results of these tests in Table A.4 in the Appendix. I reject this hypothesis at the 1% confidence level for all specifications except one. When industry-specific time shocks are included, I can only reject the hypothesis at the 10% significance level. The evidence suggests that financially constrained firms are more sensitive to policy uncertainty also in relative terms.

[Table 5 here]

R&D rates of financially constrained firms respond stronger to policy uncertainty than R&D rates of unconstrained firms, but the evidence is patchier than for capital expenditure. The estimated elasticity of R&D rates to uncertainty for financially unconstrained firms lies at roughly -0.4 for most specifications and even turns slightly positive when industry-specific shocks are included. However, none of the estimates is statistically significantly different from zero. Financially constrained firms, on the other hand, exhibit a negative sensitivity of R&D to uncertainty that is statistically significant at the 5% level across all specifications except when industry-specific shocks are included. When industry-specific shocks are included, financially unconstrained firms do not seem to reduce their R&D rates at all, while constrained firms reduce theirs by -0.359 percentage points. The estimated sensitivity, however, is not statistically significantly different from zero.

R&D responds also more to policy uncertainty for financially constrained firms in relative terms. Financially constrained firms spend more on R&D than unconstrained firms. In absolute terms, constrained firms might thus respond stronger to changes in policy uncertainty, even though their R&D rates exhibit the same elasticity to policy uncertainty than the R&D rates of financially unconstrained firms. I test this using one sided t-tests on the difference between the relative response to a doubling in policy uncertainty between constrained and unconstrained firms with respect to their group specific mean. The results of these tests are provided in Table A.4 in the Appendix. I can reject that financially unconstrained firms react the same or stronger than constrained firms at the 1% level for all specifications except one. In the specification where I interact the aggregate time shocks with my dummies for financial constraints, I can reject the above hypothesis only at the 5% level. My results suggest that, to the extent R&D reacts to policy uncertainty at all, the effect operates primarily through the financial frictions channel.

4 Validation, robustness and sensitivity tests

I now turn to providing a set of validation tests of my approach to measure policy uncertainty at the firm-level and robustness as well as sensitivity tests of my main results.

Section 4.1 presents the results of two tests on the informativeness of the risk disclosure data I constructed. In Section 4.2 I run robustness tests on whether my results are driven by the years of the financial crisis, general elections, systemic risk or lobbying. Section 4.3 addresses the concern that updating my index weights might introduce a spurious correlation between investment and my index. Finally, in Section 4.4, I show that my results are not sensitive to how I measure financial constraints or investment.

4.1 Informativeness of disclosure data

My measurement approach builds on the idea that risk disclosure is informative on risk exposure. There are several arguments in favor of this. First, the Sarbanes-Oxley Act of 2002 requires the Securities and Exchange Commission (SEC) to review each company filing at least every three years focusing on disclosure that appears to be insufficient in terms of clarity and explanation. Second, when a company makes a misleading statement or omits relevant information, investors can file a class-action lawsuit against that company until the issue is corrected. Timely and accurate information on a companies' risk landscape reduces the expected costs from such lawsuits (Skinner, 1997; Bozanic et al., 2017). Third, empirical evidence does at least not reject the idea of risk disclosure being informative on risk exposure (Kravet and Muslu, 2013; Campbell et al., 2014; Bao and Datta, 2014; Gaulin, 2016). In this section, I run a number of tests on the validity of my approach to measure economic policy uncertainty at the firm-level.

My first test on informativeness follows Campbell et al. (2014) and relates measures of stock return volatility at the firm level during a fiscal year to the amount of risk disclosure, general and policy specific, at the end of that fiscal year. If risk disclosure is updated in a meaningful way, then years of elevated stock return volatility should be followed by increases in the amount of risk disclosure.

To test this, I regress measures of stock return volatility during a year on measures for the amount of risk disclosure at the end of that year. I measure the amount of risk disclosure in two ways. First, I use the number of sentences on policy in the mandatory risk disclosure section. Second, I use the total number of sentences in the risk disclosure section. My regression specification includes firm and and fiscal year fixed effects. No additional controls are included. The stock return variables are standardized so that the coefficients can be interpreted as the number of additional risk sentences after a one-standard deviation increase in stock return volatility. Table 6 shows the results.

Higher stock return volatility during a fiscal year predicts an increase in risk disclosure at the end of the fiscal year. A one standard deviation increase in stock return volatility, idiosyncratic or total, is associated with half an additional policy sentence or five additional general risk sentences. This corresponds to a 3% increase in policy or general risk disclosure from the mean. Risk disclosure is thus updated in a way consistent with realized stock return volatility during a fiscal year.

[Table 6 here]

The predicted increases in disclosure are relatively small, but this is to be expected if disclosure was informative also before an increase in policy uncertainty. Large changes in risk disclosure should only occur if previously unknown risks appear. My results thus suggest that when uncertainty increases, firms adapt their risk disclosure to reflect the latest information, but do not fundamentally change their risk reporting.

As a second test for the informativeness of my risk disclosure data, I investigate the likelihood to obtain my sensitivity estimates of investment to policy uncertainty if the weights I use to construct my index are simply noise. In a simulation exercise, I construct a placebo index using randomly drawn weights from a uniform distribution for each firm, year and policy class. The weights are then standardized so that they sum to one for each firm-year. I use these weights instead of the disclosure-based weights to calculate a placebo index of policy uncertainty for my panel. Using the placebo index, I then re-estimate my base regression with aggregate time-shocks and the usual controls. The estimated sensitivities of investment to policy uncertainty are then stored and the exercise is repeated a thousand times. Table 7 provides an overview of the estimated sensitivities of capital expenditure and R&D to policy uncertainty.

[Table 7 here]

In none of my simulations do I obtain an effect estimate of the same size as in my actual regressions. The largest effect sizes I obtain in the placebo tests are still two to three times smaller than the effect sizes I estimated using the textual disclosure data. Perhaps unsurprisingly, in 95% of the simulations, the estimated effect is not statistically significantly different from zero, even though the standard errors using the simulated weights are considerably smaller than the standard errors in my actual regressions. This exercise suggest that there is at least some relevant information on exposure to policy uncertainty in the textual-data.

4.2 Robustness to alternative explanations

This section presents a series of robustness tests that address some of the key worries for the results presented so far. The results of these tests are presented in Table 8 for capital expenditure and Table 9 for R&D rates. I will now discuss each additional specification in turn.

[Table 8 and 9 here]

A first concern with the results so far is that they might be driven by the years of the financial crisis. In particular, fiscal years 2008 and 2009 were marked by substantial upheaval on financial markets and it might thus not be surprising that firms who report to be vulnerable to a tightening in lending conditions actually react stronger when policy uncertainty increases than other firms. To see whether this drives my results, I re-estimate Equation 3 dropping fiscal years 2008 and 2009 from my sample. The results are provided in the first columns of Tables 8 and 9. For capital expenditures, the results remain unaffected. For R&D rates I still find a significantly stronger reaction of likely constrained firms to policy uncertainty than of likely unconstrained firms. However, the base effect in both groups is not statistically significantly different from zero.

A second concern is that my results are driven by political business cycles. Julio and Yook (2012) show that corporate investment decreases substantially in election years. Besides increasing economic policy uncertainty, election years can affect corporate investments also through other channels. The political business cycle hypothesis states that policy makers use fiscal and monetary policies to stimulate the economy prior to an election which could have a crowding out effect on corporate investment. Additionally, during election years firms might use more resources to build up political connections than during normal years. For that reason, there might be less funds for investment. To see whether my results are driven by election years, I include an additional dummy that is one in years of US general elections in my regressions. The results are shown in the second columns of Table 8 and 9. The estimated sensitivity of policy uncertainty to investment is largely unchanged by this additional control.

A third concern might be that policy uncertainty increases systemic risk in the economy and that this increase might affect financially constrained firms in a more significant way than financially unconstrained firms. For example, firms might report to face difficulties to obtain financing for planned investment because they are more exposed to systemic risks than other firms and therefore lenders are more cautious towards them. This channel would be operative even in the absence of true financial frictions. To see whether this drives my results, I re-estimate Equation 3 additionally controlling for total stock volatility interacted with my dummies for financial constraints. The results are provided in the third column of Table 8 and 9. This reduces the sample size slightly compared to my base sample. However, the estimated coefficients of policy uncertainty remain largely unchanged again.

Fourth, I address the concern that lobbying introduces a reverse causality issue. Low demand could induce a firm to lobby for regulatory change which increases policy uncertainty at a time when investment is likely depressed. Since I control for industry- specific demand shocks, the described endogeneity problem presupposes that individual firms have a substantial impact on policies, which is unlikely. In particular, since I exclude financial firms and utilities from the analysis in the first place. Nevertheless, I show that excluding observations in highly concentrated industries from my sample does not affect by estimates either. I use the Fama-French 48 industry classification to rank industries by the number of firm-year observations they contain in my sample. I then drop the top ten most concentrated industries and rerun my regressions. The results are essentially unchanged.

4.3 Results using constant index weights

In this section, I use an index based on fixed weights for the policy classes to re-estimate the effect of policy uncertainty on investment. Updating the weights in my index in each period potentially introduces a bias in the estimation.

Unobserved shocks that drive policy uncertainty in a class could also drive the reported disclosure shares, for example because of strategic over-reporting of risks in annual reports. Combined with serial correlation in policy uncertainty, the disclosure weights might be correlated with the error term. Note, however, that because I control for industry-specific shocks, the unobserved shocks need to operate at the firm level. Also, because weights are included with a lag in my index definition, the unobserved shocks would have to affect investment two periods ahead at least.

[Table 10 here]

My alternative index is based on the first available exposure information for each firm in my sample. Using this weight, I again calculate the weighted average of policy uncertainty across classes and take logs of the resulting index. The results using this alternative index are provided in Table 10.

The results suggest that updating the weights in my index does not introduce a serious bias in terms of estimation. For capital expenditure, the estimation results using this alternative index are almost identical to the estimation results using my base index. For R&D, I find again some evidence that financially constrained firms respond more cautiously to higher uncertainty than financially unconstrained firms. In this specification, however, I can't identify a statistically significant reduction in R&D rates for either group after controlling for industry-specific shocks.

To further explore how the specific definition of my index affects my results, I provide additional results using alternative index definitions in Tables 17 and 18.

4.4 Sensitivity to financial constraints and investment measures

In this section, I investigate whether my results on the importance of the financial frictions channel are robust to using alternative measures of financial constraints and investment. First, I re-estimate Equation 3 replacing the Hoberg-Maksimovic measure of financial constraints with commonly used accounting based measures. Second, I re-estimate Equation 3 using alternative measures of investment.

For the first part, I construct four commonly used proxies of financial constraints. I classify firms as constrained if they are not paying dividends in a year or do not have a credit rating from S&P. Constrained firms are less likely to pay dividends because they need their internal funds to invest. Firms without a credit rating have more difficulties tapping capital markets. Additionally, I sort firms into terciles according to their age or size. Younger and smaller firms face more information asymmetries and are thus more likely to be constrained. The results of the analysis are presented in Table 11.

[Table 11 here]

In most cases, I do get negative point estimates on the interaction terms which are economically significant. For capital expenditure, the effect of policy uncertainty on investment is statistically significantly different for constrained firms compared to unconstrained firms when I use rating-, dividends-, size- and age-based proxies for financial constraints. For R&D expenditures the estimated sensitivities are statistically significantly different using rating-, dividends-, and age-based proxies for constraints. [7]

On average, my estimated sensitivities of capital expenditure to policy uncertainty for constrained firms are about two times the estimates of likely unconstrained firms. Turning to R&D expenditures, the average effect of uncertainty on R&D rates is not statistically significantly different from zero for constrained and unconstrained firms, although there is slight evidence that constrained firms might be more likely to respond by lowering

[7] In unreported results, I also check whether there are statistically significant differences between firms scoring high on the Kaplan-Zingales (Kaplan and Zingales (1997)) and Wu-Whited (Whited and Wu (2006)) indices. In both cases, I do get a stronger response of financially constrained firms to uncertainty in terms of capital expenditures, but not in terms of R&D expenditures.

R&D. The results are thus comparable to the estimates using the same specification and the Hoberg-Maksimovic measure for financial constraints.

[Table 12 here]

To see how robust my results are to using alternative investment measures, I define two additional measures of investment. First, I scale investment by Total Asset (AT) instead of the Peters and Taylor (2017) measure for the total capital stock. Second, I scale investment by the value of Property, Plants and Equipment (PPEGT). To make the estimated sensitivities comparable across specifications, I standardize the investment rates for my sample. I estimate Equation 3 with industry-time shocks and all controls. The results are provided in Table 12.

The results using these alternative measures are similar to the results in my base estimations. I find financially constrained firms to respond stronger to policy uncertainty in terms of capital expenditure in both new specifications. Turning to R&D, the results are a bit patchier. I find no evidence that financially unconstrained firms reduce their R&D expenditure in a substantial way using any of the alternative measures. Because the "wait-and-see" channel is arguably the most important channel active for financially unconstrained firms, it seems indeed not to be operating for R&D when it comes to policy uncertainty. There is, however, some evidence that financially constrained firms reduce their R&D expenditure in times of high policy uncertainty. The respective coefficient estimate is negative and significant at the 10% level for the R&D measure scaled by PPEGT.

5 Conclusions

Economic policy uncertainty occurs because political decisions frequently modify the business environment. Often, but not always, periods of high economic policy uncertainty coincide with periods of low investment. It is thus important to understand what the effect of policy uncertainty on investment is and through what channels it operates.

Exploiting textual information on exposure to political risk in companies' mandatory risk disclosure, I first estimate the base effect of economic policy uncertainty on investment in a large panel of US firms between 2005 and 2015. I find a doubling in economic policy uncertainty reduces capital expenditure rates by 25%. R&D initially seems to respond in the same way, but the result is not robust to controlling for industry-specific time shocks. A reason might be that an individual firm cannot delay R&D without loosing out against its competitors in the race for new discoveries. Alternatively, policy uncertainty might simply not be relevant for the R&D decision.

Looking at the channels through which effects propagate, I find the effect of policy uncertainty on investment to be significantly stronger for firms which are ex-ante most likely to be financially constrained. For capital expenditure rates, I estimate a sensitivity to uncertainty which is two to five times larger for financially constrained firms compared to financially unconstrained firms. I also find some evidence, that financially constrained firms reduce their R&D expenditures when policy uncertainty increases idiosyncratically.

My results suggest that the investment-uncertainty relation is primarily driven by the interaction of uncertainty with financial market frictions. Economic policy uncertainty is thus particularly damaging to investment when financial markets are not operating smoothly. This was likely the case over the time period covered in my sample, which explains the large negative effects of uncertainty on investment I find on average. If, however, economic policy uncertainty rises at a time when financial frictions are subdued, its effects on corporate investment is unlikely to be as large.

These findings are important because the implications for policy making vary for the different channels through which uncertainty affects investment. If policy uncertainty affects investment primarily by inducing firms to "wait-and-see" with investments until uncertainty recedes, as suggested by the previous literature on the topic, then it might make sense to reduce policy uncertainty as much as possible. For example, it might be better to implement a bad policy quickly so as to create certainty, rather than suffer through the prolonged period of uncertainty it can take to come up with a good policy. If, on the other hand, the financial frictions channel is at the core of the observed negative relation, reducing financial market frictions offers a way to protect investment from elevated policy uncertainty.

My results also suggest that capital expenditure and R&D are affected differently by policy uncertainty. This implies that policy uncertainty might be particularly damaging in countries where investment occurs primarily in physical assets, such as developing and emerging economies, but less so in more advanced economies.

There are several ways how the dataset developed in this study can be used to investigate further questions on the impact of uncertainty on firm behaviour. One interesting avenue of future work is the implication of increased uncertainty for liquidity decisions in firms. Higher uncertainty could trigger an increased demand for precautionary savings; at the same time higher external funding costs increase the demand for internal funds, potentially decreasing cash holdings. The net effect on liquidity is thus unclear. To the extent that an increase in uncertainty affects the funding costs of firms, states of high uncertainty could also induce real option like effects when issuing debt or equity. Firms could choose to wait with issuances until uncertainty recedes again.

Another avenue of future work might be to investigate in more detail how financial markets price political risks. Pástor and Veronesi (2012) and Pástor and Veronesi (2013) argue that the market risk premium for firms exposed to policy uncertainty might be positive or negative. Economic policy uncertainty increases after negative aggregate economic shocks. Intuitively, highly exposed firms should exhibit a positive risk premium. However, they might also profit from an implicit government guarantee in periods of high uncertainty, leading to a negative policy risk premium. The disclosure data generated in this paper, could build a starting point for analysing this and further questions on how markets respond to political uncertainty.

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6 Tables

Table 1: Summary statistics, Compustat 2005-2015 excl financials and utilities

	N	Mean	S.D.	p5	p50	p95
Capx/K	17701	5.23	8.63	0.128	2.71	18.29
R&D/K	17701	3.86	6.97	0.000	0.255	17.10
Policy Uncertainty	17701	127.98	56.48	48.46	131.02	218.88
Log(Policy Uncertainty)	17701	4.74	0.50	3.88	4.88	5.39
Market To Book	17701	2.57	6.62	0.81	1.53	5.76
Cash Flow/TA	17701	-0.09	1.02	-0.62	0.06	0.19
Sales growth	17701	0.17	0.70	-0.34	0.07	0.81
Prop, Plants & Equipment	17701	1,888	8,387	2	164	7,698
Intangible Capital	17701	1,739	7,895	8	212	6,634
Total Capital	17701	3,627	14,326	18	488	14,756
Total Assets (TA)	17701	3,498	17,451	10	448	13,998
Financial Constraints (HM)	17701	-0.01	0.09	-0.15	-0.01	0.14
Total Stock Return Vol	14823	0.14	0.08	0.05	0.12	0.29
Idiosync Stock Return Vol	14823	0.10	0.06	0.03	0.08	0.22
Cash Flow Volatility	14820	0.03	0.09	0.00	0.01	0.10
Sales Volatility	14812	0.04	0.05	0.00	0.02	0.12

Observations are restricted to sample in base investment regressions. The sample of firms with information on financial constraints is slightly smaller because not all firms have a machine-readable capital and liquidity section and those that don't are unlikely to be unconstrained. Stock market variables are also only available for a reduced sub-sample.

Table 2: Industry rankings based on risk disclosure data

	War and National Security Policy Risks	s_c	Currency Crisis Risk	s_c	Entitlement Risk	s_c
1	Aircraft	27%	Shipping Containers	18%	Healthcare	28%
2	Transportation	18%	Fabricated Products	10%	Medical Equipment	6%
3	Apparel	15%	Machinery	8%	Pharma Products	5%
4	Retail	13%	Steel Works Etc	7%	Insurance	4%
5	Entertainment	12%	Measuring and Control Equipment	7%	Personal Services	3%
6	Recreation	11%	Apparel	7%	Retail	2%
7	Defense	11%	Autos and Trucks	7%	Transportation	2%
8	Utilities	11%	Recreation	6%	Wholesale	2%
9	Computers	9%	Textiles	6%	Business Services	2%
10	Construction	9%	Beer & Liquor	6%	Trading	1%

	Health Policy Risk	s_c	Monetary Policy Risk	s_c	Regulatory Risk	s_c
1	Healthcare	28%	Banking	42%	Non-Metallic and Industrial Metal Mining	57%
2	Medical Equipment	6%	Real Estate	22%	Communication	57%
3	Pharma Products	5%	Insurance	22%	Precious Metals	56%
4	Insurance	4%	Shipping Containers	20%	Utilities	53%
5	Personal Services	3%	Construction Materials	19%	Defense	53%
6	Retail	2%	Business Supplies	18%	Restaraunts, Hotels, Motels	50%
7	Transportation	2%	Shipbuilding, Railroad Equipment	18%	Petroleum and Natural Gas	50%
8	Wholesale	2%	Printing and Publishing	17%	Computers	49%
9	Business Services	2%	Steel Works Etc	17%	Coal	49%
10	Trading	1%	Construction	16%	Business Services	47%

	Spending Policy Risk	s_c	Tax Policy Risk	s_c	Trade Policy Risk	s_c
1	Aircraft	16%	Beer & Liquor	56%	Apparel	6%
2	Defense	10%	Tobacco Products	48%	Steel Works Etc	6%
3	Computers	3%	Trading	47%	Textiles	5%
4	Textiles	3%	Real Estate	40%	Business Supplies	3%
5	Construction	3%	Fabricated Products	40%	Agriculture	2%
6	Shipbuilding, Railroad Equipment	3%	Textiles	39%	Personal Services	2%
7	Construction Materials	3%	Entertainment	37%	Food Products	2%
8	Electronic Equipment	3%	Petroleum and Natural Gas	37%	Electrical Equipment	2%
9	Rubber and Plastic Products	2%	Construction	36%	Chemicals	1%
10	Steel Works Etc	1%	Coal	36%	Fabricated Products	1%

The table shows the industry averages of the exposure weights per risk class. Weights are defined as the number of sentences per risk class over all policy-related sentences in a firm's risk disclosure section. The industry classification used is Fama-French 48 and the sample includes all Compustat firms including financials between 2005 and 2015.

Table 3: Base investment results

	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$
$\log(Pol_t)$	-1.293**	-1.360**	-1.375***	-0.707*	-0.757*	0.0396
	(0.602)	(0.586)	(0.438)	(0.372)	(0.400)	(0.146)
Market To Book		2.131***	2.021***		1.652***	1.642***
		(0.688)	(0.598)		(0.441)	(0.422)
Obs	17,701	17,701	17,701	17,701	17,701	17,701
R^2	0.042	0.051	0.124	0.018	0.036	0.086
	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$
$\log(Pol_t)$	-1.271**	-1.308**	-1.327***	-0.864*	-0.894*	-0.0681
	(0.634)	(0.594)	(0.453)	(0.442)	(0.466)	(0.167)
Total Return Volatility		-0.403***	-0.281***		-0.165**	-0.185*
		(0.146)	(0.0959)		(0.0802)	(0.0945)
Observations	15,253	15,253	15,253	15,253	15,253	15,253
R^2	0.046	0.069	0.153	0.021	0.047	0.117
Controls	No	Yes	Yes	No	Yes	Yes
FE	Year	Year×Indu	Year×Cons	Year	Year×Indu	Year×Cons
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC	SIC	SIC

Investment rates are expressed in percentage points. Pol_t is my measure of economic policy uncertainty and included as log so that the coefficient estimates can be interpreted as semi-elasticities. Additional controls are market to book value, sales growth, cash flow and industry sales growth at the SIC 4-digit level. All regressions include firm fixed effects. *Year* refers to fiscal year end fixed effects. Year fixed effects can be interacted with the Fama-French 10 industry classification (Year×Indu) or with the dummies for financial constraints (Year×Cons). The top panel shows regression results without controlling for stock return volatility, the bottom panel the results with controlling for stock return volatility. The sample covers Compustat firms between 2005 and 2015, excluding financial and utilities. Observations with negative assets and sales have been dropped. Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$.

Table 4: Financial Frictions: Capx Regressions

	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$
Uncons	-0.788	-0.871	-0.881	-1.030**	-0.355
	(0.586)	(0.569)	(0.564)	(0.414)	(0.534)
Avg	-1.159**	-1.235**	-1.229**	-1.367***	-1.169*
	(0.560)	(0.544)	(0.546)	(0.436)	(0.645)
Cons	-2.069***	-2.101***	-2.103***	-1.915***	-2.889***
	(0.733)	(0.717)	(0.718)	(0.548)	(0.995)
Avg-Uncons	-0.372*	-0.364*	-0.349*	-0.337*	-0.814
	(0.198)	(0.193)	(0.192)	(0.195)	(0.593)
Cons-Uncons	-1.281***	-1.230***	-1.222***	-0.885**	-2.533***
	(0.386)	(0.386)	(0.389)	(0.348)	(0.856)
Observations	17,701	17,701	17,701	17,701	17,701
R^2	0.044	0.053	0.053	0.126	0.058
Controls	No	Yes	Yes×Cons	Yes×Cons	Yes×Cons
FE	Year	Year	Year	Year×Indu	Year×Cons
Firm FE	Yes	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC	SIC

Estimated sensitivity of $Capx_{t+1}$ to policy uncertainty at time t. Pol_t is included as log. Firms are sorted into unconstrained, average, and constrained firms based on whether they rank in the bottom, middle or top tercile of the Hoberg-Maksimovic measure of financial constraints. The base regression (1) is gradually saturated by adding additional controls (2), interacting the controls with financial constraints (3), adding industry-specific time shocks (Year×Indu) (4). In column (5) fiscal year fixed effects are interacted with the financial constraint dummies (Year×Cons). Controls are the market to book value, cash flows, sales growth and industry sales growth at the SIC-4 digit level. All regressors are included at time t. Based on Compustat firms between 2005 and 2015. Financials and utilities are excluded. Negative sales and assets are dropped. Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$ respectively.

Table 5: Financial Frictions: R&D Regressions

	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$
Uncons	-0.372	-0.432	-0.468	0.228	-0.315
	(0.271)	(0.297)	(0.308)	(0.171)	(0.244)
Avg	-0.703*	-0.764*	-0.757*	-0.00506	-0.602
	(0.393)	(0.425)	(0.431)	(0.169)	(0.437)
Cons	-1.161**	-1.181**	-1.218**	-0.359*	-1.540**
	(0.481)	(0.500)	(0.519)	(0.183)	(0.727)
Avg-Uncons	-0.332*	-0.332*	-0.289	-0.233	-0.286
	(0.183)	(0.182)	(0.178)	(0.144)	(0.361)
Cons-Uncons	-0.790***	-0.749***	-0.750***	-0.587***	-1.224*
	(0.273)	(0.261)	(0.263)	(0.154)	(0.722)
Observations	17,701	17,701	17,701	17,701	17,701
R^2	0.021	0.038	0.047	0.096	0.054
Controls	No	Yes	Yes×Cons	Yes×Cons	Yes×Cons
FE	Year	Year	Year	Year×Indu	Year×Cons
Firm FE	Yes	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC	SIC

Estimated sensitivity of $R\&D_{t+1}$ to policy uncertainty at time t. Pol_t is included as log. Firms are sorted into unconstrained, average, and constrained firms based on whether they rank in the bottom, middle or top tercile of the Hoberg-Maksimovic measure of financial constraints. The base regression (1) is gradually saturated by adding additional controls (2), interacting the controls with financial constraints (3), adding industry-specific time shocks (Year×Indu) (4). In column (5) fiscal year fixed effects are interacted with the financial constraint dummies (Year×Cons). Controls are the market to book value, cash flows, sales growth and industry sales growth at the SIC-4 digit level. All regressors are included at time t. Based on Compustat firms between 2005 and 2015. Financials and utilities are excluded. Negative sales and assets are dropped. Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$ respectively.

Table 6: Amount of disclosure and volatilities

	Policy Risk Disclosure			General Risk Disclosure		
	I Vol (CAPM)	I Vol (FF)	Total Vol	I Vol (CAPM)	I Vol (FF)	Total Vol
Volatility	0.340*	0.350	0.418**	4.259***	3.957***	4.528***
	(0.206)	(0.220)	(0.212)	(1.269)	(1.183)	(1.167)
Observations	15,148	15,148	15,148	15,148	15,148	15,148
Controls	No	No	No	No	No	No
FE	Year	Year	Year	Year	Year	Year
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC	SIC	SIC

Higher stock return volatility during a year is associated with more risk disclosure in the annual report for that year. Based on regressing the amount of policy (1-3) or general (4-6) risk disclosure on idiosyncratic and total stock return volatility. *I Vol* is idiosyncratic stock return volatility calculated using either a CAPM or a Fama-French (FF) specification in twelve month rolling regressions. *Tot Vol* is total stock return volatility. All stock measures are calculated using the WRDS Beta Suite over a twelve month window and matched per fiscal year end to the data. *Policy Risk Disclosure* is the number of sentences on policy risks found in the overall risk disclosure section of a firm's annual report. *General Risk Disclosure* is the number of sentences in the risk disclosure section. Volatility measures are standardized, so that the coefficients can be interpreted as changes in the number of sentence after a one standard deviation increase in volatility. The usual sample restrictions apply. $Year$ refers to fiscal year end fixed effects. Standard errors clustered at the industry level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.01$.

Table 7: Estimated investment-uncertainty sensitivities using simulated data

		Percentiles			Smallest	Largest
		5	50	95		
CAPX	Sensitivity	-0.19	0.01	0.20	-0.37	0.40
	t-Stat	-1.61	0.07	1.69	-3.13	3.49
R&D	Sensitivity	-0.09	0.00	0.16	-0.16	0.17
	t-Stat	-1.65	0.10	1.77	-2.78	3.35

Simulation results from regressing investment on a placebo index of policy uncertainty. The placebo index is calculated as defined in Section 2.2 except that it uses randomly drawn weights for each policy class, firm and year observation. The weights are drawn from a uniform distribution and normalized so that they sum to one in each firm-year . The regressions include firm- and fiscal year fixed effects as well as the usual controls. The data is based on 1000 repetitions.

Table 8: Robustness: Capital Expenditures

$Capx_{t+1}$	No Crisis	No election	Stock Vol	Lobby
Uncons	-0.988**	-1.141**	-0.999**	-0.664
	(0.447)	(0.494)	(0.435)	(0.461)
Avg	-1.275***	-1.335**	-1.210***	-1.210***
	(0.446)	(0.520)	(0.443)	(0.464)
Cons	-1.967***	-2.095***	-1.943***	-1.550**
	(0.597)	(0.672)	(0.564)	(0.605)
Avg-Uncons	-0.286	-0.194	-0.210	-0.546**
	(0.192)	(0.206)	(0.204)	(0.222)
Cons-Uncons	-0.979***	-0.953**	-0.944***	-0.887**
	(0.346)	(0.379)	(0.303)	(0.408)
Observations	13,426	13,676	15,253	12,865
R^2	0.121	0.122	0.158	0.144
Controls	Yes×Cons	Yes×Cons	Yes×Cons	Yes×Cons
FE	Year×Indu	Year×Indu	Year×Indu	Year×Indu
Firm FE	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC

No Crisis shows the results without fiscal years 2008 and 2009. *No Election* drops observations during election years 2008 and 2012. *Stock Vol* additionally controls for stock return volatility interacted with the financial constraints dummies. *Lobby* drops observations from the 20% most concentrated industries (Fama-French 48). Controls are the market to book value, cash flows, sales growth and industry sales growth at the SIC-4 digit level interacted with the financial constraint dummies. Year×Indu refers to fiscal year end dummies interacted with the Fama-French 10 industry classification. Year×Cons interacts the fiscal year ends with the dummies for financial constraints. Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$ respectively.

Table 9: Robustness: R&D

$R\&D_{t+1}$	No Cris	No election	Stock Vol	Lobby
Uncons	0.260	0.383**	0.174	0.324
	(0.208)	(0.187)	(0.195)	(0.240)
Avg	0.0866	0.178	-0.163	-0.0404
	(0.207)	(0.193)	(0.187)	(0.229)
Cons	-0.274	-0.215	-0.432**	-0.315
	(0.208)	(0.191)	(0.213)	(0.238)
Avg-Uncons	-0.173	-0.204	-0.337*	-0.364*
	(0.148)	(0.147)	(0.177)	(0.194)
Uncons-Cons	-0.534***	-0.597***	-0.606***	-0.639***
	(0.145)	(0.169)	(0.176)	(0.203)
Observations	13,426	13,676	15,253	12,865
R^2	0.103	0.109	0.123	0.094
Controls	Yes×Cons	Yes×Cons	Yes×Cons	Yes×Cons
FE	Year×Indu	Year×Indu	Year×Indu	Year×Indu
Firm FE	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC

No Crisis shows the results without fiscal years 2008 and 2009. *No Election* drops observations during election years 2008 and 2012. *Stock Vol* additionally controls for stock return volatility interacted with the financial constraints dummies. *Lobby* drops observations from the 20% most concentrated industries (Fama-French 48). Controls are the market to book value, cash flows, sales growth and industry sales growth at the SIC-4 digit level interacted with the financial constraint dummies. Year×Indu refers to fiscal year end dummies interacted with the Fama-French 10 industry classification. Year×Cons interacts the fiscal year ends with the dummies for financial constraints. Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$ respectively.

Table 10: Results using index with fixed exposure weights

	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$
Uncons		-0.806*	-1.046***	-0.415
		(0.457)	(0.369)	(0.415)
Avg	-1.351***	-1.155**	-1.381***	-1.071*
	(0.395)	(0.458)	(0.399)	(0.588)
Cons		-2.035***	-1.941***	-2.818***
		(0.638)	(0.529)	(0.964)
Avg-Uncons		-0.349*	-0.336*	-0.656
		(0.188)	(0.190)	(0.554)
Cons-Uncons		-1.229***	-0.895**	-2.403***
		(0.386)	(0.347)	(0.875)
	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$
Uncons		-0.287	0.274*	-0.243
		(0.250)	(0.160)	(0.203)
Avg	0.115	-0.566	0.0620	-0.387
	(0.136)	(0.371)	(0.160)	(0.386)
Cons		-1.026**	-0.291*	-1.297**
		(0.454)	(0.164)	(0.634)
Avg-Uncons		-0.279	-0.212	-0.144
		(0.176)	(0.140)	(0.320)
Cons-Uncons		-0.739***	-0.565***	-1.054*
		(0.260)	(0.149)	(0.637)
Observations	17,701	17,701	17,701	17,701
Controls	Yes	Yes×Cons	Yes×Cons	Yes×Cons
FE	Year×Indu	Year	Year×Indu	Year×Cons
Firm FE	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC

Estimation results using an index with fixed weights. The instrument is constructed by calculating a weighted average of policy uncertainty for each firm using the first available disclosure information as weight. Unlike in my index, weights are then not updated anymore in future periods. Policy uncertainty is again included as log. Controls are Tobin's Q, cash flow, sales growth and industry sales growth. In some specifications, controls are additionally interacted with the dummies for financial constraints. *Year* refers to fiscal year end fixed effects which can be interacted with the Fama-French 10 industry classification (Year×Indu) or with the dummies for financial constraints (Year×Cons). Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$ respectively.

Table 11: Robustness using alternative constraint measures

$Capx_{t+1}/K_t$	Rating	Dividend	Size	Age
$\log(Pol_t)$	-0.511	-0.897**	-0.839**	-1.092***
	(0.396)	(0.421)	(0.412)	(0.397)
$Avg \times \log(Pol_t)$			-0.572**	-0.00949
			(0.225)	(0.219)
$Cons \times \log(Pol_t)$	-0.730***	-0.749***	-0.548**	-0.541**
	(0.211)	(0.222)	(0.278)	(0.267)
Observations	16,507	17,701	17,701	16,050
R^2	0.141	0.129	0.154	0.149
$R\&D_{t+1}/K_t$	Rating	Dividend	Size	Age
$\log(Pol_t)$	0.167	0.181	0.173	0.128
	(0.204)	(0.209)	(0.206)	(0.201)
$Avg \times \log(Pol_t)$			-0.197*	-0.0991
			(0.113)	(0.110)
$Cons \times \log(Pol_t)$	-0.135	-0.232**	-0.125	-0.699***
	(0.108)	(0.110)	(0.139)	(0.135)
Observations	16,507	17,701	17,701	16,050
R-squared	0.083	0.087	0.093	0.115
Controls	Yes×Cons	Yes×Cons	Yes×Cons	Yes×Cons
FE	Year×Indu	Year×Indu	Year×Indu	Year×Indu
Firm FE	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC

This table provides robustness regressions using alternative proxies for financial constraints. Based on standard sample with some variation due to the availability of alternative constraint measures. *Rating* is 1 if the firm owned as S&P long-term credit rating at time t. *Dividend* is 1 if the firm paid dividend at time t. *Size* and *Age* is sorted into terciles over the sample period with larger and older firms considered to be less financially constrained. Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. All regressions include firm and time fixed effects. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$ respectively.

Table 12: Robustness using alternative investment measures

	CAPX/K	CAPX/AT	CAPX/PPEGT	XRD/K	XRD/AT	XRD/PPEGT
$log(Pol_t)$	-0.0794**	-0.0822**	-0.0242	0.0227	-0.0250	0.0147
	(0.0322)	(0.0386)	(0.0340)	(0.0162)	(0.0162)	(0.0154)
$Avg \times \log(Pol_t)$	-0.0274*	-0.0326*	-0.00154	-0.0217	0.0115	0.00181
	(0.0152)	(0.0167)	(0.0162)	(0.0136)	(0.0104)	(0.00841)
$Cons \times \log(Pol_t)$	-0.0702***	-0.0729***	-0.0555**	-0.0540***	0.0189	-0.0218*
	(0.0271)	(0.0245)	(0.0219)	(0.0145)	(0.0162)	(0.0122)
Observations	17,656	17,656	17,656	17,656	17,656	17,656
R^2	0.126	0.132	0.074	0.095	0.112	0.021
Controls	Yes×Cons	Yes×Cons	Yes×Cons	Yes×Cons	Yes×Cons	Yes×Cons
FE	Year×Indu	Year×Indu	Year×Indu	Year×Indu	Year×Indu	Year×Indu
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC	SIC	SIC

Robustness regressions using alternative proxies for investments. Outcome variables are standardized to make the coefficient estimates comparable between the specifications used. Estimates include firm and industry-time fixed effects and my standard controls. Based on the standard sample and kept fixed between the regressions. Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. The sample size is slighlty reduced due to the availability of the alternative investment measures. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$ respectively.

A Appendix

A.1 Data appendix

A.1.1 Variable definitions

Additional controls:

Cash ratio. Cash and Short-Term Investments (CHE) over lagged total assets (AT).

Cash flows. Operating Income Before Depreciation minus interest and related expenses minus income taxes minus dividends ($OIBDP - XINT - TXT - DVC$) scaled by lagged total assets (AT).

Sales growth. Growth in net sales/turnover ($SALE/l.SALE - 1$)

In. Sale G. Sales growth averages per SIC four-digit code.

Additional proxies for financial constraints

Size. Smaller issuances have higher transaction costs (proportionally), so external financing becomes relatively more expensive for small firms. Less analyst coverage leads to more adverse selection issues. Large firms are more diversified and hence less risky. Size is measured as log of total assets, inflation corrected.

Age. Younger firms might have higher financing needs and are thus more likely to be financially constrained. Age is measured as the number of years since the IPO date as indicated in CRSP.

Dividends. A dummy that is one if the firm paid dividends (DVC) in a given year.

Bond ratings. A dummy that indicates whether a firm had a S&P bond rating in a given year ($SPLTICRM$).

A.1.2 Data extraction algorithm and matching

Using the quarterly master index files available on the SEC server, I identify all 10-K and 10-KSB filings between 2005 and 2016.[8] A filing can contain multiple documents and I parse filings to only select Form 10-K documents or their exhibits. In particular, I remove all XBRL and all non-ASCII documents included in the filing. Following, Loughran and McDonald (2011), I parse the HTML structure of each document and remove all tables if they contain less than 15% word characters. This reduces the probability that later I parse numerical information into sentences. The remaining file is then transformed into raw text. In the process, I remove/replace common words, such as *Table of Contents*, duplicate spaces, Unicode and special characters. Next, I use regular expressions to identify "Item 1a: Risk Factors" and "Item7: Management & Discussion and Analysis" in each filing. This potentially results in multiple matches per filing. For now I proceed with all available matches. Each match is parsed into sentences using the libraries described in Manning et al. (2014) and processed sentence by sentence. For each sentence, I check whether it contains any of the keywords of Baker et al. (2016); if so, I store the sentence in my database. I also store document length, section length, and some others sentence characteristics.

This produces 82529 instances of Item 1A and 211634 instances of Item 7 – the number for the former is smaller, since it has only become mandatory in 2005 to disclose this information and small firms can still opt out under some circumstances. Sometimes my algorithm identifies several sections of the same type in a filing. For example, because a given section is filed both in the main part of the report as well as in the exhibits, or because my algorithm erroneously identified parts of the table of contents as a section. I first delete matches which are shorter than 10 lines; which is the case for 3615 matches for Item 1A and 17594 matches of Item 7. Lacking an objective way to distinguish between the remaining matches, I then simply average over the number of identified policy risk sentences per filing and section. This leaves me with 78356 instances of Item 1A and 192312 instances of Item 7 in a total of 218131 distinct filings.

[8]Specifically, I download all 10-K/A, 10K405, 10-K405/A, 10-KSB, 10-KSB/A, 10-KSB40 and 10-KSB40/A between the 2005 and 2016.

To match the text data to Compustat, I use the tables provided in the WRDS SEC Analytics databases. The WRDS SEC Linking table provides me with a link between the unique SEC identifier *CIK* and the Compustat identifier *gvkey*, as well as information on the quality of the link. I drop observations which were not linked or flagged to be weak links (flag variable in linking table not equal 2 or 3). This still leaves me with multiple links from a *CIK* to a *gvkey*. For example, between June 1995 and March 2008, Activision, a video game producer, filed under the *CIK* 718877, which is linked to *gvkey* 1111. In December 2007 it was announced that Activision would merge with Vivendi, another game producer and owner of Blizzard Entertainment. The merger was agreed on in July 2008. The merged company was named "Activision Blizzard" and is coded in the linking table as having filed under *CIK* 718877 since June 1995 as well. Issues like this affects 1.1% of the monthly links and potentially lead to some filings being used as exposure measures for multiple firms. Since I don't know which links are most appropriate to use, I allow for duplicate use of filings; however, my results are not sensitive to this. I match *gvkey*'s for 177357 unique filings; due to duplicate links I end up with 195326 matched filings. I get 66743 unique (73918 with duplicates) Item 1A and 154835 unique (170699 with duplicates) Item 7 matches which can be linked to Compustat. I complement all filings with information on the firm's fiscal year end using the WRDS Header data.[9] The matching process can still result in multiple filings for a given firm / fiscal year combination. For example, if a firm files its annual report in one month and then posts a correction or an appendix the next month, wherein it repeats the content

[9]The fiscal years are constructed as follows: using the parsed header data from the WRDS database, I match in the companies fiscal year ends (day and month), which was valid at the time of the filing. For each filing I check whether, in the current year, the end of the reporting period has already passed or not. If it hasn't passed yet, the fiscal year is said to end in the year before the report was filed – otherwise I assume the report refers to the fiscal year ending in the same year as it was filed. As an example, assume a report was filed in March for a company with a reporting period ending in November. In that case I assume, it refers to the fiscal year that ended the year before the report was filed. If, however, the reporting period of this firm ends in February, I would assume that the report refers to the fiscal year that ended in the same year as the report was filed. Finally, to make this matchable to Compustat, I construct the fiscal year variable as the year in which the fiscal year ended minus one, if the reporting period ends before July and as the year of the fiscal period end otherwise. For some filings I was not able to obtain the reporting period ends via WRDS. There I just assume that everything filed before July refers to the (Compustat) fiscal year before the filing year and everything after to the same as the filing year. I cross-checked this approach using the data from Loughran and McDonald (2011), where the fiscal year is provided [up to 2014] and ended up with a correlation coefficient above 0.98.

of the initial report. In these cases I keep, for each section, the filing which has been published closest to the identified fiscal year end. Having a unique match between a filing and a given *gvkey* and *fiscal year*, I can now match the text date to the Compustat universe.

A.1.3 Background on Form 10-K filings

A precise understanding of the history of the SECs electronic filing system is essential to understand the possibilities of text analysis based on 10-K filings. The SEC began to mandate electronic filings through its Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) on February 1993. The process to move files onto the EDGAR system began on April 26, 1993. On December 19, 1994, the Commission made the EDGAR rules final and applicable to all concerned parties. On January 30, 1995 phase-in commenced. Ending May 6, 1996, all public domestic companies were required to make their filings on EDGAR, except for filings made in paper because of a hardship exemption. We can thus speak of a reasonably complete dataset from at least 1997 onwards. The key facts of the phase-in of EDGAR are presented below.

- On June 28, 1999 the Commission started accepting HTML documents as well as supplemental PDF documents in EDGAR filings. As a consequence, filings became increasingly bigger after 1999.

- Since May 30, 2000, the SEC accepts HTML documents with image and graphic files included as ASCII code. Unlike the appended PDF documents in the filings, it is not straightforward to exclude these sections from textual analysis, since they occur within a given document (and are not separate documents). The SEC also allowed the extended use of hyperlinks – new hyperlinks can link between documents in one filing.

- Since November 4, 2002 foreign issuers *have to* make their filings via EDGAR. This could potentially introduce a shift in our sample, however, non-U.S. public companies usually file their annual reports with the SEC on different forms than

10-K, so the problem should be minor.

- Since March 16, 2005 the SEC allows voluntary submissions in XBRL (eXtensible Business Reporting Language) format as exhibits to specified EDGAR filings under the Exchange Act and the Investment Company Act. We exclude XBRL information from our text analysis; for future research it might interesting to note, that XBRL is a machine readable data structure and that the SEC provides us with lists of companies that use XBRL in their reporting. Potentially one could make use of the accounting data provided in XBRL format.

The SEC's acceptance of HTML, images, XBRL and PDF documents as filings has significantly affected the file size of filings. The full year of 10K data for 1997 takes up 3.82 GB of disk space. Ten years later, the full 10K data for 2007 takes up 20.1GB of disk space. The year 2014 take up 117GB of disk space.

Table 13: Overview of contents in 10-K document. Information obtained via: http://www.sec.gov/answers/reada10k.htm, accessed June 15, 2015.

Parts	Item	Name	Description
Part 1	*1*	Business	Description of the company’s business.
	1A	Risk Factors	List of most sigificant risks to company or its securities. Risks might apply to company or economoy as a whole. Usually it is not addressed how company manages risks.
	1B	Unresolved Staff Comments	Explanation of comments received by SEC staff on previously filed reports that have not been resolved.to see whether the SEC has raised any questions about the company’s statements that have not been resolved.
	2	Properties	Company’s significant properties (main plants, mines, other physical properties)
	3	Legal Proceedings	Information about significant pending lawsuits or other legal proceedings, other than ordinary litigation.
	4	empty	No information here; reserved for future regulation.
Part II	*5*	Market for Registrant’s Common Equity, Related Stockholder Matters and Issuer Purchases of Equity Securities	Information on equity securities: number of holders, shares, dividends etc.
	6	Selected Financial Data	Covers selected financial information of the past five years.
	7	Management's Discussion and Analysis of Financial Condition and Results of Operation	Company's perspective on business results of past financial year; risks can be discussed i.e. assessed and how managed
	7A	Quantitative and Qualitative Disclosures about Market Risk	Exposure to market risk, such as interest rate risk, foreign currency exchange risk, commodity price risk or equity price risk. The company may discuss how it manages its market risk exposures.
	8	Financial Statements and Supplementary Data	
	9	Changes in and Disagreements with Accountants on Accounting and Financial Disclosure	Discuss any disagreements with accountants. Many investors view this disclosure as a red flag.
	9A	Controls and Procedures	Information on disclosure controls and procedures and its internal control over financial reporting.
	9B	Other information	
Part III	*10*	Directors, Executive Officers and Corporate Governance	
	11	Executive Compensation	Detailed disclosure about the company’s compensation policies and programs including compensation paid to top executive officers in past year.
	12	Security Ownership of Certain Beneficial Owners and Management and Related Stockholder Matters	Information about the shares owned by the company’s directors, officers and certain large shareholders, and about shares covered by equity compensation plans.
	13	Certain Relationships and Related Transactions, and Director Independence	Information about relationships and transactions between the company and its directors, officers and their family members.
	14	Principal Accountant Fees and Services	Disclose the fees they paid to their accounting firm for various types of services during the year.
Part IV	*15*	Exhibits, Financial Statement Schedules	List of the financial statements and exhibits included as part of the Form 10-K.

A.2 Measuring uncertainty within different policy classes

As measures for the uncertainty within policy risk classes, I use the newspaper based indices from Baker et al. (2016). The indices are based on monthly counts of newspaper articles that relate to economic policy uncertainty and a specific policy class. All indices are based on the Access World News Database, which covers well over 1000 U.S. newspapers, and are standardized to an average of 100 over the period 1985 to 2010. I now turn to explain the approach used to classify news articles into different policy classes.

Articles are classified as referring to economic policy uncertainty based on a simple filter. To be labeled as an article on economic policy uncertainty, a story needs to contain at least one keyword from each of the following three sets: (A) "economy" or "economic", (B) "uncertainty" or "uncertain" and (C) "legislation" "deficit" "regulation" "congress" "federal reserve" or "white house". Baker et al. (2016) test the accuracy of this classification scheme by comparing it to an index based on manually classifying over 10,000 articles. On an annual basis, the computer-based index correlates with the human-based index with a correlation coefficient of 0.8.

In a second step, articles on economic policy uncertainty are further sorted into nine different risk classes. The available risk classes are: (1) regulation, (2) monetary policy, (3) trade, (4) entitlement programs, (5) national security, (6) taxes), (7) healthcare, (8) spending and (9) currency and debt crisis.

This more detailed classification is achieved using a distinct set of keywords for each risk class. For example, if an article identified as referring to economic policy uncertainty also contains the words "interest rates" it would be labeled as an article on *monetary policy uncertainty*. The keyword lists are provided in the next section.

A.3 Search terms

Debt crisis [15 keys]: sovereign debt, currency crisis, currency crash, currency devaluation, currency revaluation, currency manipulation, euro crisis, eurozone crisis, european financial crisis, european debt, asian financial crisis, asian crisis, russian financial crisis, russian crisis, exchange rate

Entitlement programs [23 keys]: entitlement program, entitlement spending, government entitlements, social security, medicaid, medicare, government welfare, welfare reform, unemployment insurance, unemployment benefits, food stamps, adfc, tanf, wic program, disability insurance, part d, oasdi, supplemental nutrition assistance program, earned income tax credit, eitc, head start program, public assistance, government subsidized housing

Taxes [4 keys]: taxes, tax, taxation, taxed

Healthcare [16 keys]: medicaid, medicare, health insurance, malpractice tort reform, malpractice reform prescription drugs, drug policy, food and drug administration, fda, medical malpractice, prescription drug act, medical insurance reform, medical liability, part d, affordable care act, obamacare

Monetary policy [27 keys]: federal reserve, the fed, money supply, open market operations, quantitative easing, monetary policy, fed funds rate, overnight lending rate, bernanke, volker, greenspan, yellen, central bank, interest rates, fed chairman, fed chairman, lender of last resort, discount window, European central bank, ecb, bank of england, bank of japan, boj, bank of china, bundesbank, bank of france, bank of italy

National security [18 keys]: national security, war, military conflict, terror, terrorism, defense spending, military spending, police action, armed forces, base closure, military procurement, saber rattling, naval blockade, military embargo, no fly zone, september 11th, september 11, military invasion

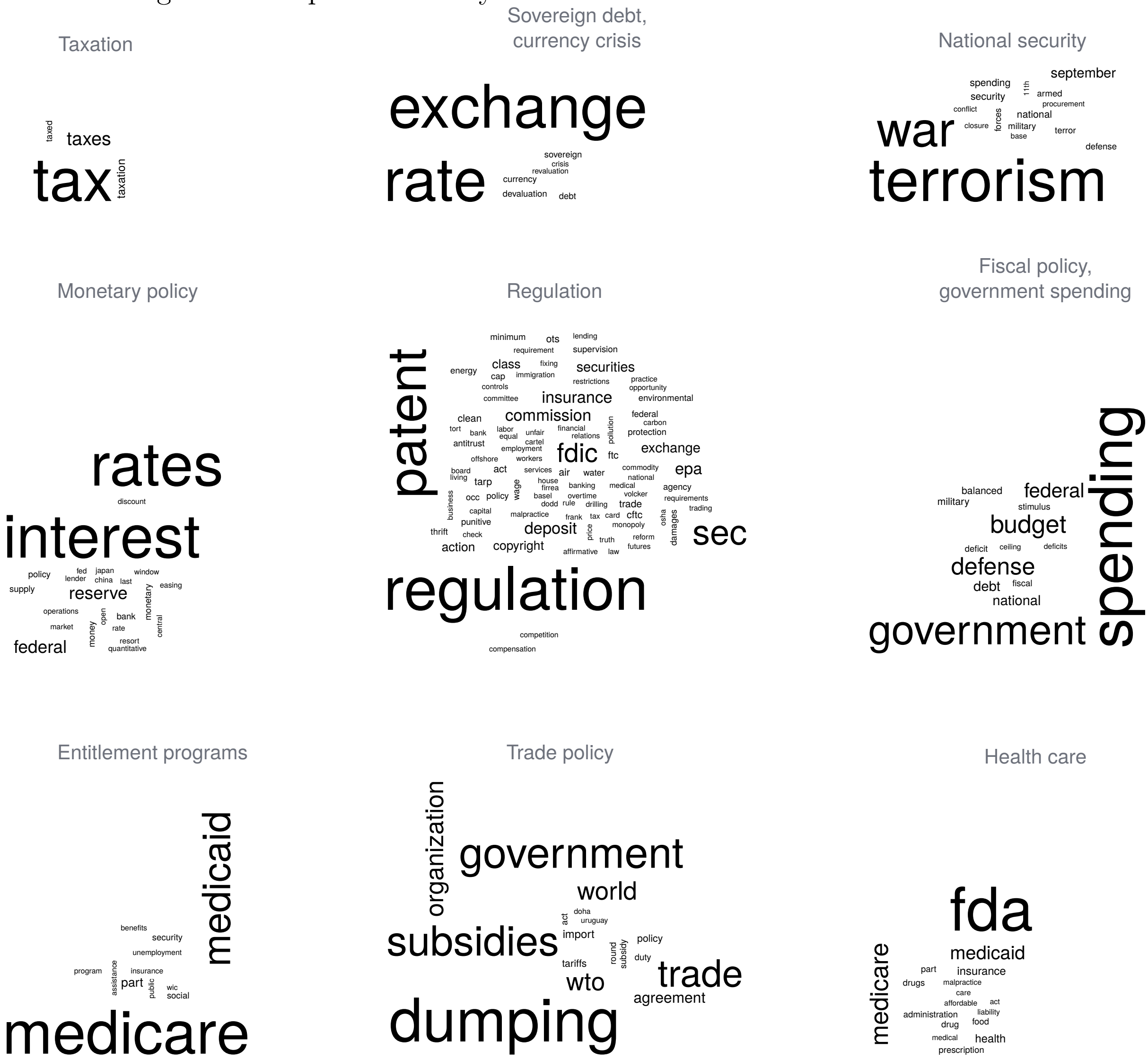
Spending [16 keys]: government spending, federal budget, budget battle, balanced budget, defense spending, military spending, entitlement spending, fiscal stimulus, budget deficit, federal debt, national debt, Gramm Rudman, debt ceiling, fiscal footing, government deficits, balance the budget

Trade [15 keys]: import tariffs, import duty, import barrier, government subsidies, government subsidy, wto, world trade organization, trade treaty, trade agreement, trade policy, trade act, doha round, uruguay round, gatt, dumping

Regulation [77 keys]: regulation, banking supervision, glass steagall, tarp, bank supervision, thrift supervision, dodd frank, financial reform, commodity futures trading commission, cftc, house financial services committee, basel, capital requirement, volcker rule, bank stress test, securities and exchange commission, sec, deposit insurance, fdic, fslic, ots, occ, firrea, truth in lending, union rights, card check, collectice bargaining law, national labor relations board, nlrd, minimum wage, living wage, right to work, closed shop, wages and hours, workers compensation, advance notice requirement, affirmative action, at will employment, overtime requirements, trade adjusted assistance, davis bacon, equal employment opportunity, eeo, osha, antitrust, anti trust, competition policy, merger policy, monopoly, patent, copyright, federal trade commission, ftc, unfair business practice, cartel, competition law, price fixing, class action, healthcare lawsuit, tort reform, tort policy, punitive damages, medical malpractice, energy policy, energy tax, carbon tax, cap and trade, cap and tax, drilling restrictions, offshore drilling, pollution controls, environmental restrictions, clean air act, clean water act, environmental protection agency, epa, immigration policy

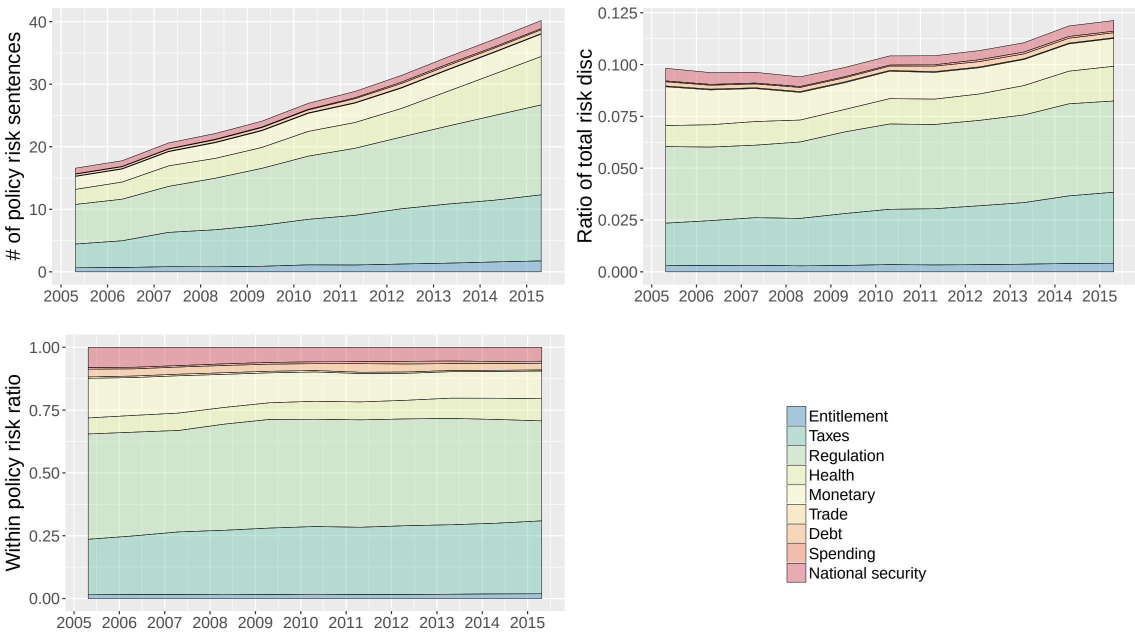
A.4 Additional figures and tables

Figure 4: Frequencies of keywords for different risk classes in Item1A



Word clouds of terms used to classify sentences into different policy uncertainty categories. Covers all annual reports filed with the SEC in 2010. Note that the word clouds are not based on n-grams but only on single words. The word trade, for example, is common in the "Regulation" and the "Trade Policy" class, but is only used to classify sentences into either category when it occurs combined with other terms, such as "trade adjusted trust" or "federal trade commission".

Figure 5: Evolution of risk exposure.



Based on matched filings between 2005 and 2015, including financials and utilities. The top left panel shows the number of policy risk-related sentences in each fiscal year split into the different risk categories. The number of sentences increases monotonically over time. The top right panel shows the ratio of sentences referring to a particular policy risk class as share of total risk disclosure. The bottom left panel shows disclosure per class as share of policy risk-related disclosure.

Table 14: Correlation with other uncertainty measures

	Id Vol_t (FF)	Id Vol_t (Capm)	Total Vol_t	Cash Vol_t	Sales Vol_t
Pol_t	0.0399**	0.0359**	0.0171	0.0104***	0.0253*
	(0.0166)	(0.0157)	(0.0157)	(0.00386)	(0.0143)
Observations	14,812	14,812	14,812	14,812	14,812
R^2	0.216	0.235	0.327	0.007	0.008
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Cluster	SIC	SIC	SIC	SIC	SIC

Higher levels of policy uncertainty are associated with high firm-level volatility. *Id Vol* is idiosyncratic volatility of monthly log returns calculated using either a CAPM or a Fama-French (FF) specification in twelve month rolling regressions and matched per fiscal year-end for each firm. *Tot Vol* is the corresponding total volatility measure. All stock measures are calculated using the WRDS Beta Suite. *Cash Vol* is the standard deviation of fiscal year matched quarterly cash flow data. *Sales Vol* is the standard deviation of fiscal year matched quarterly sales data. *Pol* is the disclosure weighed policy uncertainty index. All regressions include fiscal year end and firm fixed effects. Sample includes all Compustat firms with positive sales and assets between 2005 and 2015, excluding financials and utilities. Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$.

Table 15: Relative difference between sensitivities in sub-groups

	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$
Uncons	-18%	-20%	-20%	-23%	-8%
Cons	-34%	-35%	-35%	-32%	-39%
Difference	-16%***	-15%***	-15%***	-8%*	-39%**
H_0 : Diff$\geq$ 0	0.001	0.003	0.003	0.100	0.008
Obs	17,701	17,701	17,701	17,701	17,701
Controls	No	Yes	Yes×Cons	Yes×Cons	Yes×Cons
FE	Year	Year	Year	Year ×Indu	Year×Cons
Firm FE	Yes	Yes	Yes	Yes	Yes

Uncons and *Cons* are the estimated sensitivities of investment to policy uncertainty scaled by their group-specific means. *Difference* is the relative sensitivity for the constrained firms minus the relative sensitivity for the unconstrained firms. H_0*: Diff* ≥ 0 shows the p-values from a one sided t-test on the hypothesis that the relative difference in effects is larger zero. Rejecting the null implies that financially constrained firms respond stronger to changes in policy uncertainty also in relative terms. The sample covers Compustat firms between 2005 and 2015, excluding financial and utilities. Observations with negative assets and sales have been dropped. Additional controls are market to book value, sales growth, cash flow and industry sales growth. All regressions include firm fixed effects. *Year* corresponds to fiscal year end fixed effects and *Year*×*Indu* are fiscal year end fixed effects interacted with the Fama-French 10 industry classification. Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$.

Table 16: Relative difference between sensitivities in sub-groups

	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$
Uncons	-12%	-14%	-16%	8%	-11%
Cons	-24%	-24%	-26%	-7%	-32%
Difference	-12%***	-10%**	-10%***	-15%***	-21%**
H_0 : Diff≥ 0	0.003	0.011	0.007	0.000	0.025
Obs	17,701	17,701	17,701	17,701	17,701
Year FE	Yes	Yes	Yes	Yes $\times$Indu	Year$\times$Cons
Controls	No	Yes	Yes$\times$Cons	Yes$\times$Cons	Yes$\times$Cons
Firm FE	Yes	Yes	Yes	Yes	Yes

Uncons and *Cons* are the estimated sensitivities of investment to policy uncertainty scaled by their group-specific means. *Difference* is the relative sensitivity for the constrained firms minus the relative sensitivity for the unconstrained firms. H_0*: Diff* ≥ 0 shows the p-values from a one sided t-test on the hypothesis that the relative difference in effects is larger zero. Rejecting the null implies that financially constrained firms respond stronger to changes in policy uncertainty also in relative terms. The sample covers Compustat firms between 2005 and 2015, excluding financial and utilities. Observations with negative assets and sales have been dropped. Additional controls are market to book value, sales growth, cash flow and industry sales growth. All regressions include firm fixed effects. *Year* corresponds to fiscal year end fixed effects and *Year*$\times$*Indu* are fiscal year end fixed effects interacted with the Fama-French 10 industry classification. Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$.

Table 17: Results using alternative index definition (I)

	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$
Uncons		-0.789	-0.941**	-0.489
		(0.503)	(0.392)	(0.519)
Avg	-1.284***	-1.106**	-1.254***	-0.931
	(0.418)	(0.483)	(0.412)	(0.569)
Cons		-2.002***	-1.832***	-2.607***
		(0.656)	(0.539)	(0.882)
Avg-Uncons		-0.317*	-0.314	-0.442
		(0.192)	(0.194)	(0.554)
Cons-Uncons		-1.213***	-0.891**	-2.117***
		(0.387)	(0.352)	(0.808)

	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$
Uncons		-0.339	0.256	-0.312
		(0.276)	(0.162)	(0.213)
Avg	0.0685	-0.616	0.0349	-0.468
	(0.140)	(0.398)	(0.168)	(0.399)
Cons		-1.069**	-0.315*	-1.211*
		(0.483)	(0.183)	(0.656)
Avg-Uncons		-0.277	-0.221	-0.156
		(0.177)	(0.143)	(0.321)
Cons-Uncons		-0.730***	-0.571***	-0.899
		(0.261)	(0.153)	(0.629)
Observations	17,701	17,701	17,701	17,701
Controls	Yes	Yes×Cons	Yes×Cons	Yes×Cons
FE	Year×Indu	Year	Year×Indu	Year×Cons
Firm FE	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC

Estimation based on policy uncertainty measured as the weighted average of the log of policy uncertainty across classes. Weights are the lagged time-varying disclosure shares. Controls are Tobin's Q, cash flow, sales growth and industry sales growth. In some specifications, controls are additionally interacted with the dummies for financial constraints. *Year* refers to fiscal year end fixed effects which can be interacted with the Fama-French 10 industry classification (Year×Indu) or with the dummies for financial constraints (Year×Cons). Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$ respectively.

Table 18: Results using alternative index definition (II)

	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$	$Capx_{t+1}$
Uncons		-0.751*	-0.993***	-0.534
		(0.415)	(0.355)	(0.416)
Avg	-1.302***	-1.069***	-1.308***	-0.900*
	(0.382)	(0.411)	(0.381)	(0.514)
Cons		-1.965***	-1.891***	-2.542***
		(0.590)	(0.523)	(0.857)
Avg-Uncons		-0.319*	-0.315*	-0.366
		(0.189)	(0.190)	(0.514)
Cons-Uncons		-1.215***	-0.898**	-2.009**
		(0.384)	(0.351)	(0.817)

	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$	$R\&D_{t+1}$
Uncons		-0.189	0.304**	-0.236
		(0.225)	(0.150)	(0.180)
Avg	0.144	-0.455	0.103	-0.296
	(0.128)	(0.347)	(0.156)	(0.357)
Cons		-0.905**	-0.245	-1.000*
		(0.427)	(0.162)	(0.572)
Avg-Uncons		-0.266	-0.201	-0.0599
		(0.175)	(0.139)	(0.290)
Cons-Uncons		-0.716***	-0.549***	-0.765
		(0.257)	(0.147)	(0.559)
Observations	17,701	17,701	17,701	17,701
Controls	Yes	Yes×Cons	Yes×Cons	Yes×Cons
FE	Year×Indu	Year	Year×Indu	Year×Cons
Firm FE	Yes	Yes	Yes	Yes
Cluster	SIC	SIC	SIC	SIC

Estimation based on policy uncertainty measured as the weighted average of the log of policy uncertainty across classes. Weights are fixed at the first disclosure observation for each firm. Controls are Tobin's Q, cash flow, sales growth and industry sales growth. In some specifications, controls are additionally interacted with the dummies for financial constraints. *Year* refers to fiscal year end fixed effects which can be interacted with the Fama-French 10 industry classification (Year×Indu) or with the dummies for financial constraints (Year×Cons). Standard errors in parentheses, clustered at the 4-digit SIC industry to account for the possibility that policy uncertainty affects narrowly defined industries uniformly. The 10%, 5% and 1% significance levels are marked by $*$, $**$ and $***$ respectively.