The Bright Side of Political Uncertainty: The Case of R&D*

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ABSTRACT

We examine the relationship between political uncertainty and R&D investment by exploiting the timing of U.S. gubernatorial elections as a source of plausibly exogenous variation in uncertainty. In contrast to the literature documenting negative effects of political uncertainty on real investment, we find that uncertainty over government policy encourages firm-level R&D. Firms increase R&D investments by an average of 4.6% in election years relative to non-election years. The uncertainty effect is stronger in hotly contested elections, in politically sensitive and hard-to-innovate industries, and in firms subject to higher growth options and greater product market competition. Our findings suggest that, as predicted by models of investment under uncertainty, the real effects of political uncertainty depend on the properties of the investment and the degree of product market competition and therefore the total effect of political uncertainty on the long-run growth of an economy is unclear.

Keywords: Political uncertainty; Gubernatorial elections; R&D; Competition; Preemption

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1. Introduction

Recent research in Finance and Economics has documented that political uncertainty has adverse real effects on the economy[1]. Drawing on real options theory of investment irreversibility, the standard argument is that uncertainty exerts a strong negative effect on capital investment by increasing the value of waiting to invest. The negative relationship between various measures of political uncertainty and fixed investment have led researchers to conclude that policy makers should be mindful of the damage that lengthy debates about policy may inflict on the economy. However, not all investments are expected to decline with increased uncertainty. For example, some investments, such as R&D, may respond differently to uncertainty because of its long time-to-build and high technical uncertainty (e.g., Grossman and Shapiro (1986), Pindyck (1993), and Bar-Ilan and Strange (1996)). In this paper, we use panel data on individual firms to provide novel and causal empirical evidence on how uncertainty affects both the level and the timing of R&D investment. Using the quasi-natural experiment created by the U.S. gubernatorial elections over the 1976 to 2013 period as a source of plausibly exogenous increase in political uncertainty, we show that heightened political uncertainty about government policies encourages firm's R&D investment. This finding implies that in the long-run, there is a bright side to political uncertainty.

A large body of theoretical literature has investigated the effect of uncertainty on investment. However, different theories emphasize different channels, some pointing to a positive relationship and some to a negative relationship. The real options models establish that increased uncertainty depresses current investment by emphasizing that the interaction of capital irreversibility and uncertainty generates positive option value to defer investment (e.g., Bernanke (1983), McDonald and Siegel (1986), Dixit and Pindyck (1994)). The idea is simple: by deferring the project and keeping the option alive, the firm incurs a decrease in current profits but may avoid costly mistakes by waiting for additional information about the uncertain future. Thus, deferring (partly)

[1] For example, Julio and Yook (2012), Gulen and Ion (2015), Baker, Bloom and Davis (2014), and Jens (2013) show that real investment declines with higher political uncertainty, Colak, et al (2014) find lower IPO volume, and Gao and Qi (2013) find higher financing costs.

dissolves uncertainty. Uncertainty increases the value of the deferring option thereby making it optimal to postpone investment. R&D investment is highlighted in this literature as a particularly relevant example of extremely irreversible capital with costly adjustment because R&D is often project-specific and a substantial part of R&D supports the salaries of research personnel (i.e., scientists and engineers) and cannot be recouped if projects fail (e.g., Grabowski (1968) and Dixit and Pindyck (1994)). In this case, the adverse effect of uncertainty on R&D, therefore, is likely to be more severe than on other types of investment.

While the real options literature emphasizes that adjustment costs and partial irreversibility may cause firms to defer R&D investment in the face of heightened uncertainty, subsequent theoretical research has explored several other mechanisms that may restrict a firm's ability to wait and lead to early investment. The uncertainty-investment sensitivity also depends on the type of uncertainty. Pindyck (1993) and Bar-Ilan and Strange (1996) show that uncertainty over the difficulty and the duration of completing a project drives the firm to launch R&D sooner, because R&D projects' high technical uncertainty and long research duration will be dissolved, not by waiting but only by finishing the project. The theoretical rationale for early investment under uncertainty is explained by the "good vs. bad news principle" emphasized in Oi (1961), Hartman (1972, 1976) and Abel (1983), who highlight the fact that firms can expand to exploit good news and contract to insure against bad news, making them potentially risk seeking in an uncertain environment. An additional channel through which uncertainty can potentially spur R&D is emphasized in Bloom and Van Reenen (2002), who analyze patents as options. As patents provide the firm a legal right to prevent imitation and discourage entrants in the product market, investment in R&D that eventually gets embodied in a patent can be (at least partially) recouped by selling the intellectual property rights. This partially offsets the irreversibility of R&D investment and leads to accelerated R&D investment under uncertainty. In this case, filing a patent can be viewed as acquiring a reversibility option on R&D investment.

The intuition for why R&D may respond positively to heightened political uncertainty is s-traightforward. Investments that proceed in stages, such as R&D (Berk, Green and Naik (2004)), change the trade-off between early commitment and delaying investment. Bar-Ilan and Strange (1996) embed investment lags in a standard model of investment under uncertainty. Without investment lags, increases in uncertainty increase the value of waiting but not the opportunity cost of lost cash flows from investing early. Increases in uncertainty increase the probability of bad outcomes and waiting can allow the firm to avoid bad decisions. But since the firm can invest immediately, the opportunity cost of waiting is independent of uncertainty. With investment lags, however, the opportunity cost of waiting also increases with uncertainty since a firm that delays the initial investment also delays when cash flows are received upon completion of the project. The fact that the opportunity cost of waiting increases with uncertainty along with the ability to abandon makes it possible that the incentive to invest early increases with uncertainty, even if abandonment is costly.

Another key feature of R&D investments is that they cannot be held independently of strategic considerations. For example, Kulatilaka and Perotti (1998) develop a strategic growth options model to show that under imperfect competition, increased uncertainty may encourage current investment in future growth options. They consider an initial investment under uncertainty as the acquisition of future growth options, which allow the firm to take competitive advantages.[2] Weeds (2002) considers a real options model with R&D competition and finds that uncertainty leads to early investment when the expected benefit of preemption outweighs the option value of delay.

[2] A firm's competitive advantages can take many forms. As pointed out by Barney (1991), a firm is said to possess a competitive advantage when it is implementing a value creating strategy not simultaneously being implemented by any current or potential competitors. In this regard, R&D does well to generate a firm's competitive advantages, because the outcomes of R&D are valuable, unique and difficult to imitate and substitute (e.g., Porter and Millar (1985), Barney (1991), Lengnick-Hall (1992) and Amit and Schoemaker (1993)). Importantly, R&D is a critical input in innovation and this literature considers firm's innovation activities as the cornerstone of their competitive advantages. The technological change induced by R&D significantly increases the productivity and boosts endogenous growth for firms (e.g., Arrow (1962), Hall (2002), Bond et al. (2003), McGrattan and Prescott (2009, 2010) and Holmes et al. (2011)). This strategic benefit of R&D investment is more pronounced under a competitive environment in which the value of growth options easily expire.

The idea is that due to the threat of preemption induced by strategic rivalry, a firm fears that a competitor may seize an advantage by acting first.

Estimating the effects predicted by the theories of R&D investment under uncertainty has proven challenging due to the difficulty both of measuring uncertainty and of establishing causality. The relatively sparse empirical literature on this issue finds only mixed results. Minton and Schrand (1999) use cash flow volatility as a proxy for uncertainty about future cash flows and find that firms with higher cash flow volatility invest less in R&D. Goel and Ram (2001) consider a panel of OECD countries to show that inflation rate uncertainty tends to reduce aggregate R&D investment. Using cross-sectional data on German manufacturing firms, a series of papers by Czarnitzki and Toole (2007, 2011, 2012) document that current R&D investment falls as uncertainty about sales of new products increases.

While the finding of a negative relationship between firm-specific or macro-based measures of uncertainty and R&D investment is consistent with the existence of real options, those realized (or backward-looking) measures of uncertainty raise a number of identification issues which call into question the reliability of the finding. The first is that of an omitted variable bias. It is possible that an unobservable factor may be causing changes in both uncertainty and firm R&D investment. A second issue is that of a possible reverse causality. For example, the decision to undertake a risky R&D investment project may introduce elevated uncertainty over the firm's future stock returns and/or cash flows.[3] In attempting to address these endogeneity issues, Stein and Stone (2013) use firms' exposure to exogenous variations in energy and currency option-implied volatility derived from firms' equity options as an instrument for firm-specific uncertainty, finding that uncertainty is positively correlated with R&D investment.

[3]There has been criticisms that the choice of volatility in stock returns may be unsuitable as a proxy variable for uncertainty. For example, Shiller (1989) and Schwert (1989) suggest that the volatility in stock market returns may be driven by speculative bubbles as much as by fluctuations in economic fundamentals. Further, Kothari, Laguerre and Leone (2002) provide empirical evidence for reverse causality by showing that investment can lead to heightened uncertainty, and Minton and Schrand (1999) explicitly recognize that their results are particularly susceptible to criticisms related to endogeneity issues and omitted correlated variables, as volatility is only a choice variable chosen as one of several joint managerial decisions.

In this paper, we overcome these empirical challenges by utilizing explicitly a proxy for political uncertainty that is uncorrelated with other determinants of R&D to examine its likely economic impact on R&D investment in a large sample of U.S. publicly listed firms. Specifically, we exploit the quasi-natural experiment created by the U.S. gubernatorial elections over the 1976 to 2013 period as a natural source of plausibly exogenous shocks in political uncertainty. We define political uncertainty as the uncertainty regarding the election outcomes and government policies. We study political uncertainty in the timing of U.S. gubernatorial elections for a number of reasons. First, elections of state governors have implications for corporate decisions.[4] State governors have substantial power in influencing state-level policy-making (e.g., Peltzman (1987) and Ang and Longstaff (2012)). During the election process, politicians with likely different policy preferences are elected. Thus, gubernatorial elections introduce political uncertainty about state leadership and almost all sorts of state government policies such industry regulation, fiscal, monetary and trade policy and taxation, many directly or indirectly affecting firms' R&D decisions.[5] Second, the timing of gubernatorial elections is exogenously determined by law and not affected by general economic conditions. Using gubernatorial elections as a source of political uncertainty mitigates endogeneity concerns that changes in R&D investment may be caused by changes in business cycles or state economic conditions. Third, unlike U.S. presidential elections, gubernatorial elections in different states occur in different years, which provides us with staggered cross-state and time-series variation in the timing of gubernatorial elections to test our main hypothesis. Finally, focusing our analyses on U.S. firms and U.S gubernatorial elections helps to alleviate concerns that omitted variables could lead to a spurious association between R&D investment and political uncertainty, because U.S. firms located in different states share the same national political business cycles, have similar constraints in accessing capital markets, and share common cultural norm-

[4]A growing literature has documented that firms face political uncertainty before elections. See, for example, Durnev (2011), Julio and Yook (2012, 2014) and Gao and Qi (2013) for surveys.

[5]According to the 2014 Global Innovation Index report, political stability and government effectiveness under the political environment category are rated as the top two most influential factors in affecting innovation activities. See `https://www.globalinnovationindex.org/userfiles/file/reportpdf/GII-2014-v5.pdf` for details.

s. Additional discussion on the appropriateness of using gubernatorial elections as the proxy for political uncertainty is provided in §2.1.

We start our empirical investigation by examining whether changes in political uncertainty leads to changes in firms' R&D investments around the election cycle. We do so by exploiting the quasi-natural experiment created by the U.S. gubernatorial elections over the 1976 to 2013 period as a source of plausibly exogenous variation in political uncertainty. Our main results are striking. We find that, controlling for changing firm characteristics and state macroeconomic conditions, firms' R&D intensities, defined as the ratio of R&D expenditure to total assets, increase by an average of 4.6% in election years, relative to the non-election year average across all firms. This suggests that increased political uncertainty related to elections may indeed encourage firm R&D investments in election years, which is consistent with a theoretical literature emphasizing that when investment has strategic value, growth options and strategic preemption may dominate uncertainty's depressing effects on R&D and drive the firm to launch R&D projects earlier in the face of political uncertainty. The results are robust to various empirical specifications, various measures of R&D intensities, a placebo (falsification) test with randomly generated election events, and various susbsamples. In addition, our overall inference is unchanged when we move from OLS estimation of a static model to estimation using the dynamic GMM panel estimator.

Our identification strategy behind the primary results assumes that political uncertainty is on average higher in election years relative to non-election years. While this seems to be a reasonable assumption, there is some concern for possible reverse causality in this estimation. In order to establish causality and cross-validate our main hypothesis, we further exploit variations in the degree of political uncertainty induced by elections and their likely economic impact across states and over time. The impact of electoral uncertainty on R&D should depend on both the predictability of an election's outcomes and the probability that a policy shift will occur. Hotly contested elections introduce exogenous shocks and can be viewed as better proxies for political uncertainty. (e.g., Snowberg, Wolfers and Zitzewitz (2007)). The idea is that hotly contested elections entail more uncertainty about the eventual winner and future policy and therefore are associated with a higher degree of political uncertainty, which in turn causes a greater spike in election year R&D. Following Julio and Yook (2012) and Jens (2013), we measure hotly contested elections using vote difference and term-limit expiration, which we describe in detail in subsection 3.2. Consistent with the prediction, we find that the positive effect of political uncertainty on R&D intensity is mainly driven by hotly contested elections in which the electoral uncertainty and competition are likely to be high. Although our identification strategy is less vulnerable to potential reverse causality, this finding further helps strengthen the causality that indeed runs from political uncertainty to R&D, further confirming the main hypothesis.

Political uncertainty is not the only economic channel through which firm's R&D investment can be affected around the timing of gubernatorial elections. Starting from Nordhaus (1975) and Rogoff (1987), models of political business cycles argue that incumbents may opportunistically adopt expansionary fiscal and monetary policies to generate low unemployment rate and high economic growth before elections, in order to appease voters and increase chances of being re-elected. Under this scenario, our results may merely reflect the peaks and troughs of the political business cycle. For example, they might reduce state taxes and increase public expenditures, which may also contribute to the election year spike in R&D investment (Atanassov and Liu (2016)). Thus, the political business cycles hypothesis predicts that average economic activity should be higher just prior to the election. If the opportunistic political business cycles hypothesis is the driving force behind our main findings, we expect to see that the election year increase in R&D should be less pronounced in *term-limited* elections in which incumbents are ineligible for re-election and are supposed to have little incentive to manipulate firm investment to influence election outcomes. To directly test the opportunistic political cycle hypothesis, we distinguish elections in which incumbents are eligible for re-election and elections in which incumbents face term limits. We find that there is a even larger increase in R&D investment before term-limited elections. A larger increase before term-limited elections is thus consistent with the political uncertainty hypothesis but not the hypothesis that firms are manipulating investment.

It is well known that the Democratic and Republican parties in the U.S. political system have different political agendas that influence economic outcomes and corporate activities differently. In terms of R&D policy, Democrats tend to engage in specific, identifiable goals, such as safe and clean energy, to foster innovation. In contrast, Republicans prefer to create the general conditions and incentives to encourage innovation in many areas. For example, they may prefer low corporate taxes, tax incentives for R&D performance, and free trade regimes to encourage innovation, while eschewing subsidies for specific technologies and sectors (Kahin and Hill (2013)). As such, a natural question that follows is whether incumbent's party affiliation (i.e., Republican vs. Democrat) alters the patterns of R&D around elections. To address this question, we explore the interactions between political uncertainty and political regime and examine how such interactions affect firm's R&D investment. Consistent with an increase in political uncertainty stimulating firm's R&D investment, we find that the increasing pattern in R&D is only present in election years where the political uncertainty is supposed to be high, but doesn't exist in post-election years once political uncertainty is resolved. While incumbent Republican regime is on average associated with more R&D over *the entire sample period*, we find little evidence that political regimes affect the R&D sensitivity to political uncertainty around the election cycle.

We further explore the mechanisms through which uncertainty affects innovation by examining firm characteristics that should result in firms being particularly sensitive to increases in political uncertainty. We expect that the election year increase in R&D is more pronounced for firms operating in *politically sensitive industries*, because these firms are more likely to face regulatory changes that affect their business operations and corporate decisions (Kostovetsky (2009)). Consistent with the expectation, we find that politically sensitive industries have approximately a 6.6% increase in R&D intensities in election years (relative to the non-election year average across these industries), while is figure is only 3.0% for non-sensitive industries. These results support the view that firms operating in politically sensitive industries are particularly sensitive to increases in political uncertainty.

To better understand the economic mechanisms behind our main results, we further conduct several cross-sectional tests to exploit settings where the positive effect of political uncertainty on a firm's R&D intensity is predictably larger. We first consider rival preemption. The R&D project' value will be greatly destroyed when a competitor completes the similar product first, especially in competitions for patents (e.g., Weeds (2002)). Thus, the positive effect of political uncertainty on R&D is expected to be especially strong for firms subject to a high level of product market competition. We then consider growth options, which provide firms the ability to expand the "upside potential" in the future (e.g., Kulatilaka and Perroti (1998) and Pindyck (1988)). To the extent that R&D investments generate potential growth options, we expect that under imperfect competition, firms with higher growth options have stronger incentives to preemptively invest in the election year R&D in order to maintain and enhance their competitive advantages over competitors in the future. Also, R&D projects' high degree of technical uncertainty and long time-to-build may create valuable call options on investment that outweigh uncertainty's discouraging effects due to irreversibility and in turn lead to early investments (e.g., Grossman and Shapiro (1986), Pindyck (1993), and Bar-Ilan and Strange (1996)). Building on this intuition, we expect that the election year increase in R&D is larger for firms operating in hard-to-innovate industries in which R&D projects' technical uncertainty tends to be high and the product development cycle is usually long. Consistent with the theoretical literature predicting that an increase in uncertainty stimulates R&D investment, we find that the positive relation between political uncertainty about future government policies and firms' R&D intensities is strongest in subsamples of firms that: (1) face greater product market competition, (2) have higher growth options (e.g., high Q and high-tech firms), or (3) operate in hard-to-innovate industries.

Our study timely contributes to the wide debate over the impact of uncertainty on both the level and the timing of R&D investment. On the one hand, different theories emphasize different channels, some pointing to a positive relationship and some to a negative relationship. On the other hand, existing empirical evidence on this issue is surprisingly little and also mixed, due to the difficulty both of measuring uncertainty and of establishing causality. In this paper, we revisit the relationship between uncertainty and R&D investment by exploiting the quasi-natural experiment created by the U.S. gubernatorial elections over the 1976 to 2013 period as a source of plausible exogenous increase in political uncertainty. Contrary to conventional wisdom drawing on real options theory, we find novel and causal empirical evidence that political uncertainty indeed encourages firm R&D investment in election years. This is consistent with a theoretical literature emphasizing that when investment has strategic value, growth options and strategic preemption may dominate uncertainty's depressing effects on R&D and drive the firm to launch R&D projects earlier in the face of uncertainty. To establish causality, we use term-limited elections in which incumbents are ineligible for re-elections to test against the alternative *political business cycles hypothesis* explaining the changes in R&D investment around elections. We find no evidence that this hypothesis is operating in our sample of firms.

The paper also increases our understanding of the drivers of corporate innovation. On the innovation input side, prior studies have examined how corporate R&D investment is influenced by a firm's industry (Scherer (1984) and Beck and Levine (2002)), corporate strategy (Baysinger and Hoskisson (1989), Hoskisson and Hitt (1988) and Baysinger et al. (1991)), institutional ownership (Baysinger et al. (1991), Graves (1988) and Hansen and Hill (1991)), internal and external finance (Himmelberg and Petersen (1994), Brown et al. (2009) and Hall and Lerner (2009)), CEO characteristics (Barker and Mueller (2002), Coles, Daniel and Naveen (2006) and Hirshleifer, Teoh and Low (2012)), board compositions (Kor (2006)), shareholder protection (John, Litov and Yeung (2008) and Brown, Martinsson and Petersen (2013)), and an active acquisition market (Phillips and Zhdanov (2013) and Bena and Li (2014)) to name just a few factors. On the innovation output side, existing research has focused on firm- and market-specific factors in determining firm patenting activity, including incentive compensation for managers (Manso (2011)), institutional ownership (Aghion et al. (2013)), anti-takeover provisions (Atanassov (2013)), the choice of financing (Atanassov (2016)), access to the equity market (Gao et al. (2014) and Hsu et al. (2014)), firms' information environment (He and Tian (2013)), banking competition (Cornaggia et al. (2015)), investors' tolerance (Tian and Wang (2014)), stock liquidity (Fang et al. (2014)), ownership structures (Ferreira, Manso and Silva (2014)), and debt covenant violations (Gu et al. (2014)), among others. Although these studies enhance the understanding of the mechanisms that motivate firms to innovate, the role of politics, especially political uncertainty, is largely overlooked. In this paper, we identify a new determinant of corporate innovation and provide casual evidence that political uncertainty created by elections has a significant and positive effect on corporate R&D investment policy, supporting the view that strategic preemption and growth options motive is particularly important.

Lastly, the paper contributes to a growing body of literature on the role of politics, especially political uncertainty, in shaping firm performance and corporate decisions. From the perspective of asset pricing, Boutchkova et al. (2012), Pastor and Veronesi (2012, 2013), Belo et al. (2013) and Brogaard and Detzel (2015) study the impact of political uncertainty on stock returns. From the perspective of corporate finance, Julio and Yook (2012) show that firms tend to reduce investment prior to national elections around the world, due to the rising political uncertainty related to elections. Similar findings have been documented for U.S. public firms around U.S. gubernatorial elections by Jens (2013). Cao et al. (2015) show that firms strategically time cross-border acquisitions and diversify political uncertainty abroad before national elections. Using U.S. gubernatorial election data, Gao and Qi (2013), Liu and Ngo (2013), Colak et al. (2014), and Dai and Ngo (2014) further investigate the impact of political uncertainty on the financing costs of public debts, bank failure rate, IPO activity, and accounting conservatism respectively. As far as we know, we are the first to relate firm-level R&D dynamics to political uncertainty created by U.S. gubernatorial elections. While recent research largely suggests that political uncertainty about government policies has negative real and financial effects, we document the bright side of political uncertainty in that it indeed encourages R&D investment in innovative growth options.

2. Data

The primary source for the U.S. gubernatorial election data is the CQ Press Electronic Library. Firm-specific accounting variables are obtained from Compustat database. Our initial sample contains all domestic firms listed on NYSE, AMEX, and NASDAQ markets. Since we analyze the relation between political uncertainty and firm R&D investment, we also include in the analysis all the over-the-counter (OTC) traded domestic firms, which tend to be small technology stocks and deserve close examination.[6] Our sample period runs from 1976 to 2013 as the accounting treatment of R&D expense reporting was not standardized by FASB until 1975 (e.g., Financial Accounting Standards Board Statement No. 2), as also noted in Li (2011). We focus on annual R&D expenditure since quarterly R&D data are generally unavailable until 1989.[7] The sample only includes firm-year combinations with *non-missing* R&D expense and positive total assets.[8] We omit firms not headquartered in any of the 48 U.S. states and firms with missing data for the main vari-

[6]OTC traded firms account for roughly 30% of the firm-year combinations in our final sample and on average have significantly higher R&D intensities (measured by R&D expenses as a percentage of total assets) than those of exchange traded firms. For example, the mean value of R&D intensity is 0.0968 for OTC traded firms, while this figure is only 0.0780 for exchange traded firms (the difference is significant at the 1% level). In the robustness tests, we show that the exclusion of OTC traded firms do not alter our results.

[7]We note that quarterly R&D has a strong cyclical trend based on the firm's financial year. Although we focus on annual R&D expense data in the main tests, in unreported analysis, we show that our results are robust to using quarterly R&D expense data. Results are available upon request.

[8]R&D expense may be subject to measurement biases from missing value in the Compustat database. Chemmanur and Tian (2013) report that about 50% of Compustat firms do not report R&D expenses in their financial statements (partly due to firms not reporting R&D spending when it is trivial). Koh and Reeb (2015) empirically document that missing R&D does not necessarily imply that these firms have no substantive R&D activities. Therefore, in the main tests, we only use firm-year observations with non-missing R&D expense. In unreported analysis, we show that our baseline results still hold after replacing missing values of R&D expense with zero, which is a conventional approach in the existing literature (e.g., Bound et al. (1984), Brown and Petersen (2011) and Hirschey et al. (2012)). Results are available upon request.

ables used in the analysis.[9] Further, observations with book assets less than $5 million (inflation adjusted to 2013) are excluded. We combine accounting data from the Compustat database and the U.S. gubernatorial election data by election year and firm headquarter state. There is a potential issue with this approach in that Compustat only reports the current state of a firm's headquarters, not its historical headquarters, which introduces measurement error if the firm has relocated. Nevertheless, the number of firms that relocate is on average small and should introduce only a small amount of noise to our results.[10] Finally, we collect information on state macroeconomic conditions such as annual GDP growth rate and unemployment rate from the U.S. Bureau of Economic Analysis (BEA). By applying these selection criteria, We end up with a sample of 90,637 firm-year observations between 1976 and 2013. Our overall sample ensures that we have a representative sample for a large cross-section of firms over a long time horizon. Below, We describe main variables, sample selection and data collection procedures. Appendix A provides detailed information on definitions, construction, and data sources of variables.

2.1. Gubernatorial Elections

The timing of U.S. gubernatorial elections is exogenously determined by law. Every state but Louisiana holds its gubernatorial election on the first Tuesday following the first Monday in November.[11] Currently, the vast majority of the states hold gubernatorial elections every four years, with the exception of Vermont and New Hampshire, which choose to run their gubernatorial elections every two years. Five states, including Louisiana, Kentucky, Mississippi, New Jersey, and

[9]Howells (1990) and Breschi (2008) show that firms usually locate their R&D facilities close to headquarters and do not disperse them geographically. In addition, two states, New Hampshire (NH) and Vermont (VT), are excluded in the analysis as they follow a two-year gubernatorial term throughout the sample period.

[10]For example, Pirinsky and Wang (2006) find only 118 examples of relocation in a sample of more than 5,000 firms over 15 years. Heider and Ljungqvist (2015) identify that only 4% of firms' headquarter states are misrecorded in Compustat for fiscal year 2011. In the robustness tests, we show that our results are robust to using an alternative measure of firm's headquarter state location based on Garcia and Norli (2012)'s dataset on the state-level operations of individual firms.

[11]The election timing of Louisiana may differ every year due to the adoption of the open primary system, where all the candidates for an office run together in one election. See Wikipedia for more detailed discussion about elections in Louisiana: `http://en.wikipedia.org/wiki/Elections_in_Louisiana`

Virginia, elect their state governors in odd-numbered years just preceding a presidential election. Other states run their gubernatorial elections in even-numbered years to coincide either mid-term elections or presidential elections. In thirty-eight states, governors are limited to two consecutive terms. In some cases, states have changed the length of their gubernatorial election cycle. For example, the state of Arizona and the state of Rhode Island switched from a two-year election cycle to a four-year election cycle in 1986 and 1994 respectively.[12]

We use U.S. gubernatorial elections as the main proxy for the measures of political uncertainty. We focus on gubernatorial elections in the baseline analysis, instead of the presidential elections or the economic policy uncertainty index developed by Baker, Bloom and Davis (2014) for several reasons. First, gubernatorial elections are pre-scheduled and thus can be viewed as mostly exogenous events where political uncertainty arises. Using such a setting mitigates possible endogeneity between political uncertainty and general economic conditions, which may also affect corporate R&D decisions, and allows us to make causal inferences regarding the real impact of political uncertainty on R&D investment. Second, unlike presidential elections, gubernatorial elections in different states occur in different years. Therefore, substantial across- and within-state variations exist in addition to the time series variation in the timing of gubernatorial elections. For example, there are total 437 gubernatorial elections conducted in 48 states during the sample period of 1976 to 2013.[13] In contrast, there are only 10 president elections during the same period, which is not an adequate sample to yield any meaningful statistical inferences. On the other hand, as a country level index, there is little cross-sectional variation in the economic policy uncertainty index by construction. Besides, the index itself may not be purely exogenous in the sense that firm R&D investment behavior could also impact news coverage, government policy and economic forecasts,

[12]The only special election in the sample period took place in California in 2003. It resulted in voters replacing incumbent Democratic Governor Gray Davis with Republican Arnold Schwarzenegger. We treat this observation as all other election observations, and its inclusion has no effect on the results.

[13]Since we are interested in analyzing the change in R&D dynamics in both election and post-election years, we exclude New Hampshire and Vermont in the analysis, which follow a two-year gubernatorial term.

which constitute the key underlying components of the index. [14] This said, gubernatorial elections, as mostly exogenous events, are less subject to measurement biases resulting from survey sampling or model estimation inherited in the construction of the economic policy uncertainty index.

Our study considers 437 gubernatorial elections in 48 states held between 1976 and 2013. Detailed election information is obtained from a variety of sources. The primary source for election and regime change data is the CQ Press Voting and Elections Collection, which is part of the CQ Press Electronic Library.[15] This database contains information on election date, the names of Republican/Democract candidates and the independent candidates (if any), incumbent party affiliation, whether the incumbent governors seek re-election, whether the incumbents are subject to term limit expiration, other reasons if the incumbents don't participate in the election (e.g., defeated in primary or retired or simply not running for re-election), the winning candidate/party affiliation, the percentage vote for each candidate and the vote margin of the election. We further supplement the gubernatorial election data with Wikipedia for cases in which election information is missing from the CQ Electronic Library.

[Insert Table 1 about here]

Panel A of Table 1 summarizes our gubernatorial election data for the sample period from 1976 to 2013. There are 437 gubernatorial elections in total, distributed quite evenly across the 48 U.S. states. As discussed earlier, the distribution of elections offers a great deal of both cross-sectional and time-series variations to test their effects on firm R&D policies. Following the identification of Julio and Yook (2012) and Jens (2013), we classify an election as being more uncertain if it is a close election, where the victory margin, defined as the percentage vote difference between the first place candidate and the second place candidate, is less than 5%. We also distinguish elections where incumbents are eligible for re-elections and elections where incumbents face term limits.

[14] See Baker, Bloom and Davis (2014) for more detailed discussion on the construction of the the economic policy uncertainty index: `http://www.policyuncertainty.com/methodology.html`

[15] The CQ Press Electronic Library database is available at `http://library.cqpress.com/elections/`

We expect elections where incumbents face term limits to be more uncertain. Further discussion on the appropriateness of the measures of the degree of electoral uncertainty is provided in §3.2. Of the 437 elections, 99 are defined as close. The average close election has a vote differential of 2.4%. In 120 elections, incumbent governors do not seek re-election due to term-limit expirations. Further, close elections are 50% more likely than non-close elections to be term limited elections (38.4% vs. 24.3%).

2.2. Firm and State Variables

We obtain firm characteristics data from Compustat North America Fundamentals Annual files for the period from 1976 to 2013. The U.S. Securities and Exchange Commission (since 1972) and the Financial Accounting Standards Board (since 1974) has required all material R&D expenses to be disclosed on the firm's financial statements. On the Compustat database, R&D expenses represent all costs incurred during the financial year that relate to the development of new products or services. In this paper, the main variable of interest is R&D intensity, measured as the ratio of firm's R&D expense to its total assets. To isolate the effect of political uncertainty and firm R&D policies, we control for a set of firm characteristics that are likely to correlate with firm's R&D policies following Atanassov (2013) among others: *Market-to-book (Q)* is the market value of equity plus book value of assets minus book value of equity and deferred taxes, divided by total assets; *Cash Flow* is measured by income before extraordinary items plus depreciation and amortization, scaled by total assets; *Profitability* is the EBITDA-to-assets ratio; *Tangibility* is the net property, plant, and equipment (PPENT) divided by total assets; *Leverage* is the book value of debt divided by total assets.[16] These definitions are standard in the literature. Profitability and Q are included to capture firms' operating profitabilities and growth opportunities. Cash flow and leverage ratio are added to control for the possible effects of internal financing and capital

[16]Throughout the analysis, we use contemporaneous total assets to normalize firm characteristics variables. However, we obtain quantitatively and qualitatively similar results using lagged total assets as the alternative scaling factor. Results are unreported for brevity and are available from the authors upon request.

structure decisions on R&D intensity. In the empirical specification, we also follow Hall and Ziedonis (2001) and include *Ln(Sales)* to control for firm size. Following Aghion et al. (2005), we control for industry concentration using the *Herfindahl* index calculated at the 3-digit SIC level. we also use the squared Herfindahl index, $Herfindahl^2$, to control for possible nonlinear effects of industry concentration. We construct the firm age, *Ln(Age)*, that measures the age of the firm as the number of years that it appears in the Compustat database.

State-level variables are also included in the analysis to account for the general economic conditions within a state: the annual change in state GDP and annual state unemployment rate, both from the U.S. Bureau of Economic Analysis (BEA) website.[17] The sample period is from 1976 to 2013, which is chosen to match the availability of annual R&D expense data in Compustat database. All continuous variables are winsorized at the 1st and 99th percentiles to remove the influence of extreme outliers.[18] Appendix A provides detailed variable descriptions as well as the variable sources.

Panel B of Table 1 presents descriptive statistics on the main firm and state variables used in the regression analyses. The mean (median) firm has a R&D-to-assets ratio of 8.3% (3.2%), which is slightly lower than that reported in Brown et al. (2009), as their sample only consists of R&D intensive firms operating in the high-tech sectors. In addition, an average firm in our sample has a Q of 1.9, a cash flow of -3.5%, a ln(age) of 2.3 years, a ln(sales) of $4.5 million, a profitability of 2.3%, a tangibility of 23.2%, a leverage ratio of 21.5% and a Herfindahl concentration index of 25.3%. The reported firm characteristics are typical of Compustat public firms and are generally comparable to previous studies (e.g., Atanassov (2013) and Cornaggia et al. (2015)).[19] The last

[17] BEA website is available at `http://www.bea.gov/`

[18] The results are robust to alternatively winsorizing firm characteristics at the 5th and 95th percentiles.

[19] We note that the *negative* cash flow and the low profitability is driven by the OTC firms, which account for roughly 30% of the firm-year observations in our final sample. The average cash flow and profitability are negative (positive) for OTC (exchange) traded firms. Specifically, for OTC traded firms, the mean of inflation adjusted (to 2013) firm size is $181.4 million, the mean of R&D-to-assets ratio is 9.7%, the mean of Q is 2.0, the mean of cash flow is -16.9%, the mean of ln(age) is 2.0 years, the mean of ln(sales) is $3.1 million, the mean of tangibility is 22.8%, the mean of profitability is -9.6% and the mean of leverage is 27.7%. For exchange traded firms, the mean of inflation adjusted (to 2013) firm size is $2010.2 million, the mean of R&D-to-assets ratio is 7.8%, the mean of Q is 1.9, the mean of cash

two columns in Panel B of Table 1 also reports some summary statistics on the state-level macroeconomics. For example, the average annual GDP growth rate is 6.2% and average unemployment rate is 6.3% respectively.

3. Empirical Results

This section presents our empirical findings related to changes in R&D intensity around gubernatorial election cycles. We begin with the univariate analysis, followed by a multiple regression framework controlling for firm characteristics and state economic conditions. To better understand the economic channels through which political uncertainty affects R&D policy, we further exploit variation in the sensitivity of R&D intensity to political uncertainty across elections, political regimes, industries, and firms. We then perform a number of additional tests to ensure that our baseline results are robust to various subsamples and alternative model specifications. We also address alternative explanations and possible concerns related to our empirical analysis.

3.1. R&D Intensity around Gubernatorial Elections

Panel C of Table 1 summarize the mean R&D intensity around gubernatorial elections. We first note that in non-election years, the unconditional average R&D intensity, measured by R&D expenses as a percentage of total assets, is 0.0827. The R&D-to-assets ratio increases by 0.0023 to 0.0850 in election years. The increase, statistically significant at the 5% level, represents a 2.8% upsurge in the unconditional mean R&D intensity relative to non-election years in the overall sample of firms. Panel D provides a more detailed examination of corporate R&D dynamics across the gubernatorial election cycle. The annual mean R&D intensity before and after the election year are reported, with year 0 indicating the election year. The non-election years show no significant

flow is 1.7%, the mean of ln(age) is 2.4 years, the mean of ln(sales) is $5.1 million, the mean of tangibility is 23.4%, the mean of profitability is 6.9% and the mean of leverage is 19.1%.

pattern in R&D, aside from a small reduction in year 1, the year immediately following the election. Similar to the results in Panel C, the mean R&D intensity in election years is significantly higher than that in nonelection years. Later in this section, we investigate the post-election R&D patterns in more detail. Although the univariate evidence appears to support the view that electoral uncertainty leads to a temporary upsurge in corporate R&D investment, these unconditional relations should be interpreted with caution since the effects of firm and state variables are not taken into consideration.

We next investigate corporate R&D policy in a multivariate setting to control for firm characteristics and state economic conditions. We employ a standard difference-in-difference (DD) framework to evaluate changes in corporate R&D intensity across gubernatorial election cycles that cannot be explained by other explanatory variables. The main regression model is specified as follows:

$$\text{R\&D Intensity}_{ijt} = \alpha_i + \gamma_t + \beta_0 \times \text{Election Dummy}_{j,t} + \sum \varphi_\mathbf{i} \mathbf{X_i} + \sum \delta_\mathbf{j} \mathbf{S_{jt}} + \varepsilon_{ijt} \qquad (1)$$

where i indexes firms, j indexes states, and t indexes years. The dependent variable is the firm-level R&D intensity, measured as the ratio of R&D expenditures to total assets. The main variable of interest is the election dummy, $Election_{j,t}$, which takes on a value of one if a gubernatorial election occurred in state j in year t. The above DD model uses firms in states without an upcoming election as the control group for a treated sample of firms in states about to elect a governor. The coefficient estimate on the election dummy, β_0, is thus designed to capture changes in R&D intensity in election years between the treated and control samples. To control for firm characteristics and state economic conditions, we include a set of control variables motivated by Aghion et al. (2005) and Atanassov (2013), who identify potential determinants of R&D investment, both in the cross-section and over time. $\mathbf{X_i}$ is a vector of firm characteristics, which include Q, Cash flow, Ln(Age), Ln(Sales), Tangibility, Profitability, Leverage, Herfindahl, Herfindahl^2. $\mathbf{S_{jt}}$ is a vector of state macroeconomic variables, including annual state GDP growth rate and state unemployment rate. Appendix A provides details on variable descriptions as well as variable sources. In addition, we include both firm and year fixed effects in the baseline R&D regression to account for any time-invariant unobservable variation. This specification captures the within-firm variation in corporate R&D intensity around gubernatorial election event years. Following Petersen (2009), we compute heteroskedasticity-adjusted standard errors clustered by firm in all specifications.[20]

[Insert Table 2 about here]

Table 2 summarizes the results for our baseline R&D regression specification. The first column reports the regression of R&D intensity on the election dummy alone, without firm and year fixed effects. In columns (2) to (8), we sequentially include firm and year fixed effects and additional variables describing firm characteristics and state macroeconomic conditions. The coefficient estimates on the election year dummy are positive and statistically significant across all specifications, suggesting that political uncertainty stimulates firm R&D spending in election years. Depending on the specification, the increases in conditional R&D intensity range between 0.0036 to 0.0047. The estimates reported in column (8), which represent the baseline specification throughout the rest of analysis, show that R&D intensities increase by 0.0038 on average in election years, after controlling for firm and state variables. In terms of magnitude, the coefficient estimate translates into an economically significant 4.6% (=0.0038/0.0827*100%) increase in firms' R&D-to-assets ratio in election years, relative to the average R&D intensity in non-election years. Table 2 also shows that the signs on the estimated coefficients on the control variables are mostly consistent with previous findings in the literature, except cash flow variable.[21] R&D intensity is positively related to Q and firm age, sales, tangibility, GDP growth and unemployment, but negatively

[20]This specification is the most appropriate in a panel with a large cross-section of firms but a small number of periods (Petersen (2009)). For robustness, we repeat our analysis with standard errors clustered at both firm and year levels and find slightly weaker but still significant results.

[21]Unlike Brown et al. (2009), we find that cash flow has a negative effect on R&D intensity. Recall that the negative cash flow firms account for roughly 30% of the firm-year observations in our final sample. While (in unreported tests) we show that cash flow is positively (negatively) associated with R&D intensity for the subsample of positive (negative) cash flow firms, the overall effect is dominated by the negative cash flow firms in the full sample, as also noted in the

related to cash flow, profitability and book leverage. Other control variables are generally not related. Overall, the results from the baseline specification show that political uncertainty associated with gubernatorial elections creates a positive impact on firms' R&D spending, which is consistent with a theoretical literature emphasizing that the positive "preemption/growth" effect outweighs the negative "option" effect of uncertainty on R&D spending in a competing setting.

For the remainder of the paper, we only indicate which control variables are included in the regression specifications but may not report the coefficient estimates to preserve space. However, the coefficient estimates for the control variables remain largely unchanged for our various specifications.

3.2. Degree of Electoral Uncertainty and R&D Intensity

We have so far established the fact that R&D intensity is systematically higher in election years in the overall sample, which supports the hypothesis that when facing political uncertainty created by elections, firms tend to increase R&D spending in the fear of competitive preemption. In order to cross-validate the main hypothesis and deepen the understanding of political uncertainty, we further exploit variation in the degree of political uncertainty and their likely economic impact across states and over time. The impact of electoral uncertainty on R&D intensity should depend on both the predictability of an election's outcomes and the probability that a policy shift will occur. Highly unpredictable elections introduce exogenous shocks and are considered as better proxies for political uncertainty. (e.g., Snowberg et al. (2007)). Motivated by these arguments, we expect that the stimulating effects of political uncertainty on firm R&D spending should be more

summary statistics in Panel B of Table 1. Our findings are thus consistent with the theoretical and empirical literature predicting a U-shaped relationship between cash flow and capital investment (e.g., Cleary et al. (2007)): investment increases monotonically with internal funds if they are large but decreases if they are very low. In unreported analysis, we are able to replicate the coefficient estimates on cash flow reported in Brown et al. (2009) if we use their cash flow definition $\left(\text{i.e., Cash Flow} \doteq \frac{\text{IB+DP+XRD}}{\text{AT}}\right)$, sample selection and estimation strategy.

pronounced in elections characterized by higher levels of electoral uncertainty. We examine these predictions in this subsection.

We consider two empirical measures that capture the degree of electoral uncertainty. The first measure is the the victory margin, defined as the percentage vote differences between the first place candidate and the second place candidate. The idea is that closer elections, indicated by smaller victory margins, entail more uncertainty about the eventual winner and future government policy and therefore can be associated with higher levels of political uncertainty, which should cause a greater increase in election year R&D spending. To incorporate differences in the degree of electoral uncertainty, we create an indicator variable, *close election*, which is set to one if the victory margin is less than 5% and zero otherwise. It is an *ex post* measure of how close the election was, but should capture the *ex-ante* uncertainty levels of election outcomes well. Of the 437 elections covered in my analysis, 99 (approximately 23%) are identified as close elections. This metric has been used extensively in the literature. For example, Julio and Yook (2012) and Jens (2013) use this measure to analyze changes in corporate investment around close elections.

The second measure considers elections in which incumbent governors are not eligible for re-elections due to term-limit expirations. Previous studies extensively document that the advantage of incumbency is an important predictor of any executive or legislative elections' outcomes (e.g., Cover (1977), Gelman and King (1990) and Ansolabehere and Snyder (2002)). Consistent with this argument, we find that incumbents in our sample win more than 80% of the gubernatorial races when they run for re-elections. Thus, it is reasonable to assume that if an incumbent governor is not a candidate on the election ballot due to term limit, the electoral uncertainty and competition surrounding the election are likely to be high. To capture the variation in incumbency advantage, we define an indicator variable, *term limit*, which is set to one if incumbents face term limit expirations and zero otherwise. We identify 120 gubernatorial elections (approximately 27%) with the indicator variable equal to one.

[Insert Table 3 about here]

Table 3 reports the results of the R&D regression with an interaction term between the election dummy and our measures of electoral uncertainty. In columns (1) and (2), we perform subsample analysis by splitting the full sample into two groups according to election closeness.[22] While the positive political uncertainty–R&D intensity relation is present for both close election and non-close election subsamples, the larger coefficient estimate in the close election subsample analysis implies a much stronger effect of political uncertainty on R&D spending in close elections (7.0% vs. 3.4%). To directly assess the effects of higher political uncertainty caused by close elections on firm R&D spending in election years, in column (3) of Table 3, we follow Julio and Yook (2012) and add to our baseline regression an interaction term between election dummy and close election dummy. As indicated in column (3), the interaction term is large, positive and statistically significant, consistent with the hypothesis that the magnitude of R&D spending is increasing in the degree of electoral uncertainty surrounding the election. In economic terms, the coefficient estimate on the interaction term implies that the average R&D intensities increase by almost 7.3% ((0.0029+0.0031)/0.0827*100%) in hotly contested elections. Columns (4) to (6) replicate the analysis in the first three columns but using term limit to proxy for electoral uncertainty. We find similar results.

Overall, we find that the positive effect of political uncertainty on R&D intensity is mainly driven by hotly contested elections in which the electoral uncertainty and competition are likely to be higher. Although our main identification strategies are less vulnerable to potential reverse causality, the findings in this subsection help strengthen the causality that indeed runs from political uncertainty to R&D investment, further confirming the main hypothesis.

[22] Please note that non-election years are included in in the subsample analysis as a benchmark group.

3.3. Republican vs. Democrat

Prior studies document that financial markets behave differently under different political regimes (i.e., Republican vs. Democrat).[23] A natural question that follows is whether the incumbent's party affiliation alters the pattern of R&D spending around elections. To address this question, we create a regime dummy variable to indicate whether the incumbent governor is a Republican or not. The party identification of the governor is the party of the governor who held office for the majority of the year. Since gubernatorial elections usually take place at the beginning of November followed by inaugurations of the new governors in the following January or February, the party of the election year will be the party of the incumbent, while the party of the following year will be the newly elected governor's party. To provide a more detailed estimation of the impact of political regime on the R&D sensitivity to political uncertainty around the *full election cycle*, we further add to our baseline R&D regression model a post-election year dummy, which is set equal to one for the year immediately following the election year. We also interact this post-election dummy with the regime indicator in the regression analysis.

To investigate the role of political regime, we follow Julio and Yook (2012) and estimate an augmented version of the baseline R&D regression model:

$$\begin{aligned} \text{R\&D Intensity}_{ijt} = {} & \alpha_i + \gamma_t + \beta_0 \times \text{Election}_{j,t} + \beta_1 \times \text{Election}_{j,t} \times \text{Regime}_{j,t} \\ & + \beta_2 \times \text{Post-election}_{j,t+1} + \beta_3 \times \text{Post-election}_{j,t+1} \times \text{Regime}_{j,t} \\ & + \beta_4 \times \text{Regime}_{j,t} + \sum \boldsymbol{\varphi_i X_i} + \sum \boldsymbol{\delta_j S_{jt}} + \varepsilon_{ijt} \end{aligned} \tag{2}$$

[23]For example, Alesina and Rosenthal (1995) and Alesina et al. (1997) show that on average, annual GDP is higher under Democratic term. Santa-Clara and Valkanov (2003) find that excess stock returns are higher and real interest rates are lower under Democratic than Republican presidencies after controlling for business-cycle variables and risk factors. Belo et al. (2013) report that during Democratic presidencies, firms with high government exposure experience higher cash flows and stock returns, and that the opposite is true during Republican presidencies. In a recent study, Giuli and Kostovetsky (2014) further show that Democratic-leaning firms are more socially responsible than Republican-leaning firms.

where $\text{Regime}_{j,t}$ is an indicator variable set equal to one if the party affiliation of the incumbent governor of state j in year t is Republican and zero if it is Democrat. The timing of the two election dummy variables is set to capture the firms' R&D dynamics around the full election cycle. The coefficient estimates of the interaction terms, β_1 and β_3, should pick up the added effects of Republican regime on the magnitude of R&D sensitivity to political uncertainty in *election years* and *post-election years* respectively. The coefficient estimate on the regime indicator variable β_4 alone should capture the underlying difference in R&D spending between Republican regime and Democrat regime over the entire sample period.

[Insert Table 4 about here]

Table 4 summarizes the estimation results. In columns (1) to (3), we estimate this specification on the full sample, the Republican subsample ($\text{Regime}_{j,t} = 1$) and the Democratic subsample ($\text{Regime}_{j,t} = 0$) without including interaction terms. In column (4), we interact the regime indicator with the two election timing dummies in the full sample to directly assess the the role of political regime. Across all specifications in Table 4, we find that the election dummy remains positive and statistically significant, while the post-election dummy is insignificant. These results indicate that while firm R&D spending surges in election years due to the increase in political uncertainty created by elections, it shows no discernible pattern in post-election years when political uncertainty is resolved. Further, column (4) reports a positive and significant coefficient estimate on the regime indicator, implying that on average firms tend to invest more in R&D under Republican regime over the full sample period. However, the interaction terms are not significant, suggesting there is no difference in R&D spending between Republican regime and Democratic regime around the election cycle.

In the final two rows of Table 4, we also include for all specifications a test of whether the net change in R&D around the election cycle is significantly different from zero. This is simply a test of whether the sum of the coefficients on the election timing dummies (and the interaction terms) are zero. The table shows that the political uncertainty induced R&D cycles are present across different political regimes and represent a net increase in R&D spending around the elections.

Overall, we find little evidence that political regimes affect the R&D sensitivity to political uncertainty around the election cycle, although the two parties in the U.S. political systems have different agendas about their R&D and innovation policies.[24]

3.4. Politically Sensitive Industries

To better understand the economic channels through which political uncertainty induced by upcoming gubernatorial elections affects firm R&D policies, we exploit variations in the sensitivity of R&D intensity to political uncertainty across industry and firm characteristics. In this subsection, we first examine whether politically sensitive industries exacerbate or attenuate the positive impact of political uncertainty on firm R&D spending around the election cycle.

Firms are likely to differ from each other with respect to their sensitivity to political uncertainty. For example, both Julio and Yook (2012) and Jens (2013) find that the adverse effect of political uncertainty on firm investment is stronger in politically sensitive industries. Boutchkova et al. (2012) document that equity return volatility is higher around elections in politically sensitive industries. We thus expect that the election year increase in R&D should be more pronounced for firms operating in politically sensitive industries, because these firms are more likely to face regulatory changes that affect their business operations and corporate decisions (Kostovetsky (2009)). Following the identification of Herron et al. (1999), we classify firms operating in tobacco products, pharmaceuticals, health care services, defense, petroleum and natural gas, telecommunications, and transportation industries as politically sensitive, where Fama French 48 industries is used as

[24]As noted in Kahin and Hill (2013), Democrats tend to engage in specific, identifiable national goals, such as safe and clean energy, exploring and learning about space, or wiring the nation. They are also willing to create new programs that provide targeted resources to the private sector to directly subsidize early-stage commercial innovation. In contrast, Republicans prefer to create the general conditions for, and incentives to encourage, innovation in many areas. For example, they prefer low corporate taxes, tax incentives for R&D performance, and free trade regimes to encourage innovation, while eschewing subsidies for specific technologies and sectors.

the industry classification. We then set a *sensitive industry* dummy to one if a firm belongs to one of these politically sensitive industries.

[Insert Table 5 about here]

To test the hypothesis, we perform subsample analyses for firms operating in politically sensitive industries and those in non-sensitive industries separately. We also interact the sensitive industry dummy with the election year dummy in the baseline R&D regression to directly compare the two types of industries. Table 5 reports the estimation results from this analysis. Consistent with the expectation, coefficient estimates in columns (1) and (2) indicate that politically sensitive industries experience approximately a 6.6% increase in R&D intensity in election years (relative to the nonelection year average across these industries), while this figure is only 3.0% for non-sensitive industries. Overall, the results presented in this subsection support the view that firms operating in politically sensitive industries are particularly sensitive to the increases in political uncertainty created by upcoming election.

3.5. Product Market Competition

The positive effect of political uncertainty on firm R&D spending is also affected by a firm's competitive environment. A key feature of R&D investments is that they cannot be held independently of strategic considerations. To the extent that strategic rivalry introduces the threat of preemption, a firm fears that a competitor may seize an advantage by acting first. For example, Weeds (2002) considers a real options model with R&D competition and finds that uncertainty may indeed encourage firm R&D investments when the expected value of strategic preemption outweighs the option value of waiting. Based on their findings, we conjecture that product market competition may further amplify the positive effect of political uncertainty on firm R&D spending in election years. In this subsection, we empirically test this hypothesis.

We examine two types of product market competition measures for our tests. The first measure is the *Herfindahl Index (HHI)*. The industry-level measure is calculated as $HHI = \sum_{i=1}^{N} S_i^2$, where S_i is the market share of firm i's sales within a 3-digit SIC industry and the summation is performed over the total number of N firms in that industry.[25] By construction, HHI measures the degree of product market concentration and a *lower* product market concentration indicates higher competition and vice versa (Haushalter, Klasa and Maxwell (2007)). Since HHI is at the industry level and may not closely capture the dynamic interactions between competitors, we also consider the product market fluidity measure in our second test. The firm level measure, fluidity, is a text-based measure of product market threats developed in Hoberg, Phillips, and Prabhala (2014), which captures firm's product similarity from its rivals. The fluidity data is obtained from the Hoberg-Phillips data library and covers a large sample of U.S. public firms for the period from 1997 to 2011.[26] For our purpose, product market fluidity is a suitable proxy for product market competition and a *higher* fluidity reflects a greater product market threats from rivals.

[Insert Table 6 about here]

To test the hypothesis, we separately estimate the impact of political uncertainty on R&D spending for firms with above and below sample median HHI and product market fluidity each year. We also interact each competition measure with the election year dummy to directly assess the role of product market competition. The first three columns of Table 6 present the estimation results based on the HHI measure, while the last three columns replicate the analysis using product market fluidity measure. For both measures, the results are consistent with our conjecture and show that product market competition amplifies the positive effect of political uncertainty on firm R&D spending in election years. We compare the economic magnitudes of the coefficients on

[25] HHI is calculated based on 3-digit SICs for the reported results. When alternatively classifying industries using 2-digit SICs, Fama and French (1997) 48-industries, or Hoberg and Phillips (2010) FIC-300 industries, we obtain similar results.

[26] We would like to thank Jerry Hoberg and Gordon Phillips for generously providing this data on their website: `http://www.rhsmith.umd.edu/industrydata/`.

the election dummy across the two subgroups (high vs. low product market competition). For example, based on the product market fluidity measure, coefficient estimates reported in columns (4) and (5) indicate that for firms operating in high competitive environments (high fluidity), the election year increase in R&D is 5.3% relative to the nonelection year average R&D across those firms, compared to only a 3.6% increase for firms operating in low competitive environments (low fluidity). Overall, the results in Table 6 confirm that the election year increase in R&D is much larger for firms facing more competitive pressure in the product markets, due to the threat of preemption induced by strategic competition.

3.6. Growth Opportunities

The R&D sensitivity to electoral uncertainty should also depend on firms' growth opportunities. For example, Kulatilaka and Perotti (1998) develop a strategic growth option model and theoretically predict that under imperfect competition, increased uncertainty may actually encourage firm investment in growth options. Prior literature documents that firms can reap growth opportunities from investing in R&D projects, because R&D activities lead to either new products or more efficient production processes, which enable the firms to either open a new market or reduce production costs, and hence to gain larger market shares and make more profits. To the extent that R&D investments generate potential growth options, we conjecture that under political uncertainty, firms with higher growth opportunities have stronger incentives to invest in R&D in order to maintain or enhance their competitive advantages over competitors in the future.

To test the hypothesis, we draw from the literature and use firm-specific Q and high-tech industry to proxy for firms' growth opportunities. Q represents the divergence between the market value and book value of firms' capital stock. The basic idea is that firms with abundant growth opportunities have relatively high market value compared to their physical assets and thus tend to have high Q. This metric has been used extensively in the literature as an indicator of firm-level growth opportunities. For example, Lang and Stulz (1994) show that diversified firms have a lower Q ratio than focused firms because the market penalizes the value of the diversified firm assets. Cao et al. (2008) use this measure to gauge firm growth options and find that the long-term trend in idiosyncratic risk vanishes after controlling for growth options. Further, Kogan and Papanikolaou (2010) empirically document that Q is a good proxy for growth opportunities. *High Q* is an indicator variable set equal to one for firms with above industry median Q each year.

High-tech firms account for the overwhelming share of R&D activity (Hirschey et al. (2012)). The contribution of these firms to technological progress through R&D and innovation has been found to be crucial (Acs and Audretsch (1990)). High-tech firms as opposed to non high-tech firms are supposed to have more *growth options* and in turn should be more affected by political uncertainty. To test the hypothesis, we follow Brown et al. (2009) and classify firms operating in drugs (283), office equipment and computers (357), communication equipment (366), electronic components (367), scientific instruments (382), medical instruments (384), and software (737) as high-tech firms, where the classification is based on 3-digit SIC codes. We set a *high-tech* industry dummy variable to one if a firm belongs to one of these seven high-tech industries.

[Insert Table 7 about here]

To assess the role of growth options, we split the full sample into high vs. low growth subgroups based on median Q each year or the high-tech industry indicator, and re-estimate the baseline R&D model on each subgroup separately. We also interact each growth options proxy with the election dummy directly. Table 7 presents the estimation results from this analysis. Each column is based on such a growth options proxy, indicated by the column heading. The coefficient estimates on the interaction terms between election year dummy and the proxy for high growth options are positive and statistically significant, suggesting that much of the election year increase in firm R&D spending comes from the subsample of firms with high growth options. For example, when median Q is used as the proxy for growth options, coefficient estimates in columns (1) and (2) indicate that high growth firms (high Q subgroup) increase R&D intensities by an average of 4.3% in election years relative to the corresponding nonelection year group average. By contrast, this figure is roughly 3.8% for low growth firms (low Q subgroup). In addition, we notice from column (3) that the *high Q* indicator alone is large, positive and statistically significant, indicating that high growth firms on average exhibit higher R&D intensities. This is consistent with Hirshleifer et al. (2012) among many others, who report that high growth firms tend to undertake more R&D projects. The last three columns of Table 7 consider high-tech industry subsample as an alternative proxy for growth options and deliver similar results. The positive effect of political uncertainty on R&D spending is always somewhat stronger for high growth firms. For example, the coefficient estimates reported in columns (4) and (5) translate into a 4.6% (3.3%) increase in election year R&D intensities for high-tech (non high-tech) firms, relative to their corresponding nonelection year group average.

Overall, the results reported in this subsection are consistent with a theoretical literature emphasizing that when investment has strategic value, growth options may dominate uncertainty's depressing effects and drive the firm to launch R&D project earlier (e.g., Kulatilaka and Perotti (1998)). The results are also consistent with the empirical evidence in Driver, Temple and Urga (2008). They document that industries with high R&D intensity (e.g., high-tech firms and high growth firms) tend to indicate a positive effect of uncertainty on investment.

3.7. Hard-to-Innovate Firms

In this subsection, we continue to test alternative mechanisms that can shed light on the interpretation of our main findings by performing subsample analyses.

We explore the idea of hard-to-innovate industries in which the R&D processes are characterized by long time-to-build and high degree of technical uncertainty. Grossman and Shapiro (1986) show that firms prefer investment projects with less certain effort required to reach a payoff, and

Pindyck (1993) confirms that R&D projects' technical uncertainty (i.e., the difficulty of completing a project) may actually promote firm R&D investment.[27] Further, Bar-Ilan and Strange (1996) show numerically that if firms have long delays in completing projects, for example due to time-to-build, then uncertainty may have a positive impact on investment, if it expands the upside of future outcomes. The basic idea is that R&D projects' high degree of technical uncertainty and long investment lags between project inception and completion cannot be reduced simply by postponing investment, unlike uncertainties related to purely exogenous factors such as the input costs of raw materials. High levels of technical uncertainty and long investment lags thus create competitive pressure for firms to invest earlier. Building on these theoretical predictions, we expect to observe a much stronger impact of political uncertainty on firm R&D spending in these hard-to-innovate industries, where the R&D processes are typically long, very costly and highly uncertain (e.g., Holmstrom (1989) and Hall and Lerner (2009)).

Following the work of Hall, Jaffe, and Trajtenberg (2005) and Tian and Wang (2014), we classify firms operating in pharmaceuticals, medical instrumentation, chemicals, computers, communications, and electrical industries as hard-to-innovate firms. While easy-to-innovate industries include software programming, internet applications and other miscellaneous industries. We then set a *hard-to-innovate* industry dummy to one if a firm belongs to one of those above mentioned hard-to-innovate industries. To test the hypothesis, we divide the full sample into hard-to-innovate and easy-to-innovate subsamples and re-estimate the baseline R&D model separately. We compare the economic magnitudes of the coefficients on the election dummy across the two subsamples. We also add to the baseline R&D model an interaction term between the hard-to-innovate dummy and the election dummy.

[Insert Table 8 about here]

[27] In Pindyck (1993), technical uncertainty is resolved only for R&D active firms, leading firms to invest sooner in an uncertain environment. A numerical experiment further leads Pindyck (1993) to conclude that "Thus for many investments, and particularly for large industrial projects where input costs fluctuate, increasing uncertainty is likely to depress investment. The opposite will be the case only for investments like R&D programs, where technical uncertainty is far more important."

Table 8 reports the estimation results from this analysis. The results indicate that there is a significant difference in the marginal impact of political uncertainty on firm R&D spending across industries. Coefficient estimates in columns (1) and (2) suggest that firms in the hard-to-innovate category experience approximately a 4.5% increase in election year R&D intensities compared with the corresponding nonelection year group average R&D, while the increase is only 3.6% for firms in the easy-to-innovate group. In addition, the coefficient on the interaction term in column (3) is positive and statistically significant, indicating that the difference in the coefficient estimates of the election year dummy between the two subgroups is significant. Overall, the results presented in this subsection lend support to our hypothesis that R&D projects' high degree of technical uncertainty and long investment lags amplify the positive effect of political uncertainty on R&D spending.

3.8. Robustness Tests

In this subsection, we perform several additional tests to ensure that the preceding results are robust to various subsample and subperiod analyses, variable definitions and alternative model specifications. Panel A of Table 9 presents estimation results using the baseline R&D models across all specifications. Panel B of Table 9 further estimate one-step dynamic panel generalized method of moments (GMM) in first differences to eliminate firm effects.

First, there might be potential concerns with the one-way clustering of standard errors by firm only used in the baseline regression specification (Petersen (2009)). To address this concern, in column (1), Panel A of Table 9, we experiment with calculating standard errors based on two-way clustering by both firm and year and re-estimate the baseline model. We find slightly weaker but qualitatively the same results.[28]

[28]As noted in Petersen (2009) and Thompson (2011), two-way clustering of standard errors is only valid provided: (i) Both N and T are "large"; and (ii) The aggregate shocks must dissipate over time. In such cases, clustering by two dimensions will likely produce unbiased standard errors. Apparently, our sample only satisfies the second requirement but doesn't fit the first, as in our sample N exceeds 9,000 firms but the average T is around 10 years with a maximum of

Second, as mentioned earlier, OTC firms tend to be small technology stocks. The average inflation adjusted (to 2013) firm size of an OTC stock is $181.4 million, as compared with $2,010.2 million for the exchange-listed sample. The small size of these OTC firms may result in ratios that are highly variable and very large (in absolute value), which could give them disproportionate impact on the results. To account for this problem, we perform subsample analysis by splitting the full sample into exchange traded firms (exchg = 11, 12, 14) and OTC traded firms (exchg = 13, 19). Columns (2) and (3) of Panel A report results from this analysis. In both cases, the coefficient estimates on the election dummy are significant and of similar magnitude as that in the overall sample. This finding indicates that our results are unlikely to be driven by those small technology stocks, instead, the positive impact of political uncertainty on R&D spending is present for both exchange traded and OTC traded firms.

Third, we perform several robustness tests on the sample selection. For example, columns (4) and (5) of Panel A show that the positive effect of political uncertainty on R&D intensity remains after removing observations during the dot-com bubble period (1999-2000) or financial crisis period (2007-2008) respectively. To ensure that our results are not driven by a small number of large states with disproportionate representation in our sample, in column (6), we drop the three states with the highest number of firms (namely, California, Massachusetts and New York together make up about 35.5% of the total sample) and re-estimate the models. Our conclusions are not sensitive to exclusion of these states. Similarly, in column (7), we exclude firms operating in business services, electronic equipment and pharmaceutical products industries and find qualitatively the same results.[29] These robustness checks help mitigate the concerns that our results might be driven by a small number of dominant states or industries.

[Insert Table 9 about here]

38 years. As such, we choose to report the baseline results based on standard errors computed from one-way clustering by firm only, which is the most appropriate in a panel with a large cross-section of firms but a small number of periods (Petersen (2009)).

[29] Industry classification is based on Fama-French 48 industries.

While we control for various measures of time-varying firm characteristics and state economic conditions, there may be some concern that our results might be coming from some underlying regional or nonlinear time trends in our data, which is not captured by the election year dummy variables alone. In column (8), Panel A of Table 9, we perform a random placebo (falsification) test to rule out this possibility. Specifically, we falsify the gubernatorial election dates by randomly assigning the election years to each state following a four-year cycle. We also require that the relative frequency of randomly assigned election events each state matches the relative frequency of actual gubernatorial elections. In doing this, we end up with a random placebo dummy variable that looks like the actual election year indicator used in the previous regressions, except that the timing is randomly selected across states. Thus, if a temporal regional or nonlinear trend were driving the results in our earlier specifications, we would expect a positive and significant coefficient on the random dummy variable. Column (8) of Panel A reports the estimates from this random placebo test. All of the estimates on the control variables are similar as in the earlier specifications. As expected, the coefficient estimate on this random dummy variable is close to zero and insignificant, indicating that the variation in R&D intensity is specific to the actual election years and not due to some temporal regional or nonlinear trends in the data.

An alternative to the fixed effects OLS estimation of a static model is the dynamic panel GMM estimation developed by Arellano and Bond (1991) and this method has been used in several recent studies on corporate investment (Brown et al. (2009) and Guariglia et al. (2011)). To address the influence of potential dynamic endogeneity, we estimate one-step GMM models in first differences and report the estimation results in Panel B of Table 9. The GMM models includes one lag of the dependent variable in column (1) and two lags of the dependent variable in column (2) respectively. Aggregate year dummies are included in all regression specifications. T-statistics are based on robust, firm-clustered standard errors. AR(1) and AR(2) are tests for first-order and second-order autocorrelation in the first-differenced residuals, under the null hypothesis of no autocorrelation.

Sargan is a test of the null hypothesis that the overidentification restrictions (all instruments) are valid.

As noted in Panel B of Table 9, coefficient estimates on election year dummy are positive and statistically significant for both cases, indicating that our main results do not change after controlling for possible dynamic endogeneity effects using the dynamic panel GMM estimator. While current R&D investment is significantly and positively related to R&D investment lagged one year, it is generally not related to R&D investment lagged two years. The AR(1) and AR(2) tests indicate that the residuals in first differences are correlated, but there is no serial correlation in second differences. However, it is worth noting that the instruments (e.g., the lags of the left-hand-side endogenous variable and the first difference of all right-hand-side exogenous variables) do not pass the Sargan over-identification tests and may not be completely exogenous.[30]

In untabulated tests, we experiment with additional robustness checks. First, we use R&D expenditure scaled by net sales as an alternative measure of R&D intensity and show that our main finding is robust to the new measure. Second, we add to our final sample those missing R&D observations from the Compustat database and find that the election year increase in R&D-to-assets ratio is not driven by the propensity of firms to strategically report R&D spending in election years. Third, our results are robust to using an alternative measure of firm's headquarter state location based on Garcia and Norli (2012)'s dataset on the state-level operations of individual firms. Garcia and Norli (2012) measure the state exposure of a firm's business operations to each U.S. state by conducting a textual analysis to record instances where state names occur in its annual 10-K filings.[31] Further, we repeat the analysis based on Julio and Yook (2012) international sample and find that our results stay unchanged. Finally, we show that our conclusions remain unchanged if we only use the subsample of "innovative" firms that are required to have at least one

[30] In fact, Arellano and Bond (1991) report that the one-step Sargan test tends to overreject in the presence of heteroskedasticity.

[31] The dataset of Garcia and Norli (2012) enables us to examine the effect of political uncertainty on the operations of individual firms across states. In our sample, we find that about 67.5% of firms' Compustat headquarter state location is identical to the main state of firms' operations as reported in Garcia and Norli (2012).

patent granted over the sample period from 1980 to 2004 in the Compustat/NBER patent merged database.[32]

It is ultimately impossible to completely rule out endogeneity in our (or any other) empirical setting. Nevertheless, the results presented in this subsection are consistent with the baseline results, indicating a strong positive and causal association between political uncertainty about future policy and corporate R&D spending.

4. Conclusion

The real effects of uncertainty on R&D investment by firms have been of longstanding concern to both academics and practitioners, given that corporate investment in R&D is an important ingredient of innovation and economic growth. While the real options literature emphasizes that adjustment costs and partial irreversibility may cause firms to defer R&D investment under increased uncertainty, subsequent theoretical research has explored several other mechanisms (e.g., investment lags, rival preemption and growth options) that may restrict a firm's incentive and ability to wait, leading to early investment. In this paper, we investigate how an exogenous increase in political uncertainty arising from the timing of U.S. gubernatorial elections impacts firms' R&D investment decisions. We find novel and casual empirical evidence that firms respond to increased political uncertainty by preemptively investing more in R&D in election years. Moreover, the results from additional analyses suggest that reverse causality and the alternative political business cycles hypothesis are unlikely to drive this finding. Further investigation reveals several potential channels of the causal impact. The positive relation between political uncertainty and R&D investment is especially strongest for firms that: (1) operate in politically sensitive industries, (2)

[32] In order to minimize the truncation bias in the NBER patent/citation database, we follow the conventional approach (e.g., Hall, Jaffe, and Trajtenberg (2001)) and stop our sample period in 2004 for this analysis. In addition, consistent with the orientation of R&D efforts towards innovation, we find that facing political uncertainty, firms use their R&D dollars more efficiently by generating more and better patents (as proxied by number of patents and citations per patent) post election.

face greater product market competition, (3) have higher growth options, or (4) belong to hard-to-innovate industries.

Our paper highlights that the relationship between investment and political uncertainty depends on the nature of investment and product market competition. Unlike (partly) irreversible fixed investment, R&D is stimulated by increasing political uncertainty. As such, the long-run implications of political uncertainty is not clear and warnings to policy makers about avoiding lengthy debate about future policy is not entirely warranted.

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Appendix A: Variable Descriptions

Variable	Definition	Source
R&D Intensity and Innovation Output Measures		
R&D Intensity	Calculated as firms' research and development expenditure (XRD from COMPUSTAT) divided by book value of total assets (AT from COMPUSTAT), measured at the end of fiscal year t.	COMPUSTAT
Patent Count	Natural logarithm of one plus the patent count. Patent count is defined as number of patent applications filed in year t of each firm. Only patents that are later granted are included. This variable measures innovation quantity. The patent count is set to zero for companies that have no patent information available from the NBER patent database.	NBER Patent Database
Citation Count	Natural logarithm of one plus the citation count. Citation count is defined as number of citations received by patent applications filed in year t of each firm. This variable measures patent quality. Only patents that are later granted are included. The citation count is set to zero for companies that have no citation information available from the NBER patent database.	NBER Patent Database
Generality	Natural logarithm of one plus the sum of generality scores of all patents filed by firm i in year t. Generality measures firm level innovation output by considering the versatility of a firm's patents. An individual patent's generality score is defined as one minus the Herfindahl index of the 3-digit technology class distribution of the citing patents (forward citations). A higher value of generality score thus indicates that the focal patents impact a broader set of technological areas.	NBER Patent Database
Originality	Natural logarithm of one plus the sum of originality scores of all patents filed by firm i in year t. Originality measures firm-level innovation output by considering the creativity of a firm's patents. An individual patent's originality score is defined as one minus the Herfindahl index of the 3-digit technology class distribution of the cited patents (backward citations). A higher value of originality score thus indicates that the focal patents build on a broader set of technological areas.	NBER Patent Database
Gubernatorial Elections		
Election (0)	Indicator variable takes on a value of one if a gubernatorial election occurred in that state in that year.	CQE Library
Post-election (+1)	Indicator variable takes on a value of one for the one-year period after a gubernatorial election occurred in that state.	CQE Library
Republican (R)	Indicator variable set equal to one if the incumbent governor is a Republican in state j in year t.	CQE Library
Democrat (D)	Indicator variable set equal to one if the incumbent governor is a Democrat in state j in year t.	CQE Library
Close Election	Indicator variable set equal to one if the victory margin, defined as the vote difference between the first place candidate and the second place candidate, is less than 5%. We classify this type of elections as high uncertainty elections.	CQE Library
Term-limited Election	Indicator variable set equal to one if the incumbent governors are not eligible for re-election due to term-limit expiration. We identify term-limited elections as high uncertainty elections.	CQE Library
Firm Specific and State Economics variables		
Ln(Asset)	Defined as natural logarithm of the book value of total assets (AT from COMPUSTAT) measured at the end of fiscal year t.	COMPUSTAT
Ln(Age)	Defined as natural logarithm of one plus the number of years of the corporation has existed from the IPO year to year t.	COMPUSTAT
Ln(Sales)	Defined as natural logarithm of one plus the net sales/turnover (SALE from COMPUSTAT) measured at the end of fiscal year t.	COMPUSTAT
Profitability	Defined as earnings before interest, taxes, depreciation and amortization (EBITDA from COMUSTAT) divided by book value of total asset (AT), measured at the end of fiscal year t.	COMPUSTAT
Continued on next page		

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Variable	Definition	Source
Tangibility	Defined as total net property, plant and equipment (PPENT from COMPUSTAT) divided by book value of total asset (AT), measured at the end of fiscal year t.	COMPUSTAT
Q	Defined as [the market value of equity (PRCC_F $\times$ CSHO from COMUSTAT) plus book value of assets (AT) minus book value of equity (CEQ from COMUSTAT) minus balance sheet deferred taxes (TXDB from COMUSTAT)] divided by book value of asset (AT), measured at the end of fiscal year t.	COMPUSTAT
Cash Flow	Firm's cash flows. It is defined as income before extraordinary items (IB from COMUSTAT) plus depreciation and amortization (DP from COMUSTAT) divided by book value of asset (AT), measured at the end of fiscal year t.	COMPUSTAT
Leverage	Firm's leverage ratio. It is defined as book value of debt (DLTT+DLC from COMUSTAT) divided by book value of total assets (AT) measured at the end of fiscal year t.	COMPUSTAT
CAPEX	Firm's capital expenditure. It is defined as capital expenditure (CAPX from COMUSTAT) divided by book value of total assets (AT), measured at the end of fiscal year t.	COMPUSTAT
Herfindahl Index (HHI)	An industry-level measure of product market competition, calculated as $HHI = \sum_{i=1}^{N} S_i^2$, where S_i is the market share of firm i's sales within a 3-digit SIC industry at the end of fiscal year and the summation is performed over all firms in that industry. By construction, HHI measures the degree of product market concentration and a lower product market concentration indicates higher competition and vice versa.	COMPUSTAT
GDP Growth	State level annual GDP growth rate, obtained from the U.S. Bureau of Economic Analysis (BEA) database.	BEA
Unemployment Rate	State level annual unemployment rate, obtained from the U.S. Bureau of Economic Analysis (BEA) database.	BEA
Politically Sensitive Industries (PSIs)	Indicator variable set equal to one for firms that belong to the following industries: Tobacco Products (5), Pharmaceuticals (13), Health Care Services (11), Defense (26), Petroleum and Natural Gas (30), Telecommunications (32) and Transportation (40), where the industry classifications are based on Fama French 48 industries.	Herron et al. (1999)
Product Market Fluidity	A text-based measure of product market threats/similarity developed by Hoberg et al. (2014). It is calculated as the dot product between the words used in a firm's business description from 10-K filings and the change in the words used by its rivals. The fluidity data is from Hoberg et al. (2014) and covers a large sample of U.S. public firms from 1997 to 2011. A higher fluidity reflects a greater product market threats from rivals.	Hoberg et al. (2014)
High-Tech Industries	Indicator variable set equal to one for firms operating in the following high-tech industries: drugs (283), office equipment and computers (357), communication equipment (366), electronic components (367), scientific instruments (382), medical instruments (384), and software (737). The above industry classification is based on 3-digit SIC codes as defined in Brown et al. (2009).	Brown et al. (2009)
Hard-to-innovate Industries	Indicator variable set to one for firms that belong to pharmaceutical, medical instrumentation chemicals, computers, communications, and electrical industries. The industry classification is based on 3-digit SIC codes (Hall, Jaffe, and Trajtenberg (2005) and Tian and Wang (2014)).	Hall et al. (2005)

Table 1

Summary Statistics

Panel A reports summary statistics for gubernatorial elections held between 1976 and 2013 in 48 U.S. states (New Hampshire and Vermont are excluded from the sample). Panel B reports summary statistics for the firm and state economics characteristics used in the analysis. Panel C reports summary statistics for R&D intensity in both election years and nonelection years, where R&D intensity is defined as R&D expenses scaled by book value of total assets. Panel D reports the annual mean R&D intensity around the elections, where year 0 indicates the actual gubernatorial election year. See the Appendix for variable descriptions as well as the variable sources.

Panel A: Election Characteristics				
	N	Mean	Median	Std. Dev.
Gubernatorial Elections	437			
Incumbent Republican (R)	198			
Incumbent Democrat (D)	233			
Incumbent Other (O)	6			
Victory Margin (%)	437	15.65	11.92	13.17
Close Election (%)	99	2.41	2.54	1.41
Term-limited Election	120			
Panel B: Firm and State Economics Variables				
	N	Mean	Median	Std. Dev.
R&D Intensity	90,637	0.0833	0.0320	0.1469
Q	90,637	1.9348	1.1691	2.6592
Cash Flow	90,637	-0.0352	0.0679	0.3723
Ln(Age)	90,637	2.2958	2.3979	0.8393
Ln(Sales)	90,637	4.5355	4.3941	2.2644
Tangibility	90,637	0.2321	0.1865	0.1913
Profitability	90,637	0.0231	0.1017	0.3008
Leverage	90,637	0.2154	0.1581	0.2553
Herfindahl	90,637	0.2531	0.1788	0.2224
GDP Growth (%)	90,637	6.1847	5.8000	3.5363
Unemployment (%)	90,637	6.2797	5.9000	1.9861
Panel C: Mean R&D Intensity in Election Years versus Non-election Years				
Election Years	21,636	0.0850	0.0314	0.1527
Non-election Years	69,001	0.0827	0.0322	0.1451
Difference		0.0023		
T-statistics		2.00**		
Panel D: Mean R&D Intensity around Election Years				
Year		-1	0	+1
N		21,675	21,636	22,030
R&D Intensity		0.0826	0.0850	0.0819

Table 2
Political Uncertainty and R&D Intensity: Baseline Results

The unit of observation is at firm-year level. The dependent variable in all regressions is R&D intensity, defined as the ratio of R&D expenditure to total assets. Independent variables include Q, Cash flow, Ln(Age), Ln(Sales), Tangibility, Profitability, Leverage, Herfindahl, Herfindahl^2, State GDP growth rate and unemployment rate and and the Election year indicator (year 0). See Appendix A for variable descriptions as well as the variable sources. Variable of interest is the election year indicator. We use baseline regression specification and control for firm and year fixed effects. Standard errors are clustered at the firm level and corrected for heteroskedasticity. T-statistics are reported in square brackets below coefficient estimates. Data is for the period 1976 to 2013. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D Intensity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Election Dummy	0.0038***	0.0041***	0.0047***	0.0043***	0.0043***	0.0036***	0.0036***	0.0038***
	[6.25]	[6.60]	[7.48]	[8.16]	[8.11]	[7.53]	[7.51]	[7.72]
Q			0.0038***	0.0034***	0.0036***	0.0035***	0.0035***	0.0036***
			[7.46]	[8.01]	[8.22]	[8.86]	[8.87]	[8.91]
Cash Flow				-0.1576***	-0.1540***	-0.0462***	-0.0462***	-0.0462***
				[-24.53]	[-23.81]	[-7.48]	[-7.48]	[-7.48]
Ln(Age)					0.0106***	0.0023*	0.0024*	0.0033**
					[7.88]	[1.78]	[1.83]	[2.50]
Ln(Sales)					-0.0068***	0.0026***	0.0026***	0.0028***
					[-6.80]	[2.70]	[2.70]	[2.88]
Tangibility						0.0839***	0.0839***	0.0837***
						[12.36]	[12.36]	[12.34]
Profitability						-0.2111***	-0.2111***	-0.2117***
						[-21.30]	[-21.30]	[-21.32]
Leverage						-0.0134***	-0.0134***	-0.0132***
						[-3.19]	[-3.20]	[-3.13]
Herfindahl							0.0066	0.0035
							[0.59]	[0.31]
Herfindahl^2							-0.0116	-0.0090
							[-1.19]	[-0.94]
GDP Growth								0.0005***
								[4.84]
Unemployment								0.0008***
								[3.43]
Constant	0.0905***	0.0823***	0.0748***	0.0700***	0.0765***	0.0451***	0.0446***	0.0336***
	[64.80]	[561.51]	[72.12]	[74.24]	[22.50]	[11.50]	[9.98]	[6.14]
N	90,637	90,637	90,637	90,637	90,637	90,637	90,637	90,637
R^2	0.000	0.000	0.008	0.250	0.253	0.345	0.346	0.346
Firm FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3
Subsample Analysis: Degree of Electoral Uncertainty and R&D Intensity

This table examines whether the degree of electoral uncertainty amplifies the effect of political uncertainty on firm level R&D intensity. We use *election closeness* and *term limit expiration* to proxy for the degree of electoral uncertainty. Specifically, *close election* is an indicator variable set equal to one if the victory margin, defined as the vote difference between the first place candidate and the second place candidate, is less than 5% and zero otherwise. *Term-limited election* is an indicator variable set equal to one if the incumbent governors are not eligible for re-election due to term limit expiration and zero otherwise. We identify close elections and term-limited elections as high uncertainty elections. For each indicator, we first perform subsample analysis by splitting the full sample into two subgroups according to the indicator and then examine the interaction between the election year dummy and the indicator. Each column is based on such a political regime indicator, denoted by the column heading. The unit of observation is at firm-year level. The dependent variable in all regressions is R&D intensity, defined as the ratio of R&D expenditure to total assets. Independent variables include Q, Cash flow, Ln(Age), Ln(Sales), Tangibility, Profitability, Leverage, Herfindahl, Herfindahl^2, State GDP growth rate and unemployment rate and and the Election year indicator (year 0). See Appendix A for variable descriptions as well as the variable sources. Variables of interests are the election year indicator and the interaction term. We use baseline regression specification and control for firm and year fixed effects. Standard errors are clustered at the firm level and corrected for heteroskedasticity. T-statistics are reported in square brackets below coefficient estimates. To save space, we suppress the estimates of firm specific and state economics control variables. Data is for the period 1976 to 2013. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D Intensity					
	Election Closeness			Term Limit		
	Non-close Election	Close Elections	Interacted	Without Term Limit	With Term Limit	Interacted
	(1)	(2)	(3)	(4)	(5)	(6)
Election Dummy	0.0028***	0.0058***	0.0029***	0.0032***	0.0056***	0.0032***
	[4.97]	[6.03]	[5.14]	[6.13]	[4.57]	[6.16]
Election × Indicator			0.0031***			0.0024*
			[2.76]			[1.82]
N	84,803	74,835	90,637	85,960	73,678	90,637
R^2	0.344	0.342	0.346	0.340	0.347	0.346
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specific Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Economics Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4
Political Uncertainty and R&D Intensity: Political Regime

This table examines whether incumbent governor's party affiliation (i.e., Republican vs. Democrat) affects the pattern of firm level R&D intensity around elections. *Regime* is an indicator variable set equal to one if the governor is a Republican in state j in year t, and zero otherwise. In column (1), we include a post-election indicator in our baseline regression specification to provide a more detailed estimation of the dynamics of R&D intensity around the full election cycle. To investigate the cross-sectional heterogeneity in party affiliation, we then split the full sample into two subgroups based on the regime indicator and perform subsample analysis in columns (2) and (3). In column (4), we further add to the baseline regression interaction terms between regime indicator and election year dummy, and between regime indicator and post-election year dummy. Each column is based on such a political regime indicator, denoted by the column heading. The unit of observation is at firm-year level. The dependent variable in all regressions is R&D intensity, defined as the ratio of R&D expenditure to total assets. Variables of interests are the two interaction terms, *election* $\times$ *regime indicator* and *post-election* $\times$ *regime indicator*, along with the election year (0) and post-election year (+1) dummies, with year 0 being the year the actual election occurred. We use baseline regression specification and control for firm and year fixed effects. To save space, we suppress the estimates of firm specific and state economics control variables. See Appendix A for variable descriptions as well as the variable sources. Standard errors are clustered at the firm level and corrected for heteroskedasticity. T-statistics are reported in square brackets below coefficient estimates. Data is for the period 1976 to 2013. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D Intensity			
	Full Sample	Republican Regime	Democratic Regime	Interacted
	(1)	(2)	(3)	(4)
Election Dummy (0)	0.0037***	0.0035***	0.0036***	0.0037***
	[6.99]	[4.22]	[5.22]	[5.39]
Post-election Dummy (+1)	-0.0002	-0.0003	-0.0001	-0.0003
	[-0.35]	[-0.39]	[-0.13]	[-0.42]
Election $\times$ Regime Indicator				-0.0000
				[-0.04]
Post-election $\times$ Regime Indicator				0.0002
				[0.19]
Regime Indicator				0.0018*
				[1.82]
N	90,637	47,036	43,601	90,637
R^2	0.346	0.347	0.347	0.346
Constant	Yes	Yes	Yes	Yes
Firm Specific Controls	Yes	Yes	Yes	Yes
State Economics Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Tests for linear combinations of coefficients				
Election + Post-election	0.0035***	0.0032**	0.0035***	0.0035***
t-statistics	[4.02]	[2.54]	[3.02]	[2.77]

Table 5
Industry Characteristics: Politically Sensitive Industries

This table examines the cross-sectional variations of politically sensitive industries on firm level R&D intensity in election years. Specifically, *politically sensitive industries (PSIs)* is an indicator variable set equal to one if firms fall into the following industries: Tobacco Products (5), Pharmaceuticals (13), Health Care Services (11), Defense (26), Petroleum and Natural Gas (30), Telecommunications (32) and Transportation (40), as used in Herron et al. (1999) and Julio and Yook (2012). Fama French 48 industries is used as the industry classification. In the first two columns, we perform subsample analysis by splitting the full sample into two subgroups according to the politically sensitive industry indicator and then examine the interactive effects between the election year dummy and the politically sensitive industry indicator in the last column. Each column is based on such a subsample, indicated by the column heading. The unit of observation is at firm-year level. The dependent variable in all regressions is R&D intensity, defined as the ratio of R&D expenditure to total assets. Independent variables include Q, Cash flow, Ln(Age), Ln(Sales), Tangibility, Profitability, Leverage, Herfindahl, Herfindahl^2, State GDP growth rate and unemployment rate and and the Election year indicator (year 0). See Appendix A for variable descriptions as well as the variable sources. Variables of interests are the election year dummy and the interaction term. We use baseline regression specification and control for firm and year fixed effects. Standard errors are clustered at the firm level and corrected for heteroskedasticity. T-statistics are reported in square brackets below coefficient estimates. To save space, we suppress the estimates of firm specific and state economics control variables. Data is for the period 1976 to 2013. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D Intensity		
	Politically Sensitive Industries (PSIs)		
	Politically Sensitive	Non-sensitive	Interacted
	(1)	(2)	(3)
Election Dummy	0.0125***	0.0020***	0.0021***
	[5.65]	[5.36]	[5.51]
Election × PSIs			0.0116***
			[4.69]
N	12,788	77,849	90,637
R^2	0.523	0.261	0.346
Constant	Yes	Yes	Yes
Firm Specific Controls	Yes	Yes	Yes
State Economics Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 6
Industry Characteristics: Product Market Competition

This table examines whether product market competition amplifies the effect of political uncertainty on firm level R&D intensity. We use *Herfindahl-Hirschman Index (HHI)* and *product market fluidity* to proxy for the degree of product market competition. Specifically, the industry-level measure, HHI, is calculated as $HHI = \sum_{i=1}^{N} S_i^2$, where S_i is the market share of firm i's sales within a 3-digit SIC industry and the summation is performed over the total number of N firms in that industry. By construction, HHI measures the degree of product market concentration and a lower product market concentration indicates higher competition and vice versa. The firm level measure, fluidity, is a text-based measure of product market threats, which captures firm's product similarity from its rivals. The fluidity data is from Hoberg, Phillips, and Prabhala (2014) and covers a large sample of U.S. public firms from 1997 to 2011. A higher fluidity reflects a greater product market threats from rivals. For each product market competition indicator, we first perform subsample analysis by splitting the full sample into two subgroups according to the indicator and then examine the interaction between the election year dummy and the indicator. Each column is based on such a product market competition indicator, denoted by the column heading. The unit of observation is at firm-year level. The dependent variable is R&D intensity, defined as the ratio of R&D expenditure to total assets. Independent variables include Q, Cash flow, Ln(Age), Ln(Sales), Tangibility, Profitability, Leverage, Herfindahl, Herfindahl^2, State GDP growth rate and unemployment rate and and the Election year indicator (year 0). See Appendix A for variable descriptions and the variable sources. Variables of interests are the election year indicator and the interaction term. We use baseline regression specification and control for firm and year fixed effects. Standard errors are clustered at the firm level and corrected for heteroskedasticity. T-statistics are reported in square brackets below coefficient estimates. To save space, we suppress the estimates of firm specific and state economics control variables. Sample period is from 1976 to 2013 (1997 to 2011) for the HHI (fluidity) measure. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D intensity					
	Herfindahl-Hirschman Index (HHI)			Product Market Fluidity		
	Low HHI	High HHI	Interacted	High Fluidity	Low Fluidity	Interacted
	(1)	(2)	(3)	(4)	(5)	(6)
Election Dummy	0.0056***	0.0009**	0.0014***	0.0087***	0.0018***	0.0023***
	[6.60]	[2.08]	[3.00]	[5.73]	[3.49]	[3.66]
Election × Indicator			0.0045***			0.0067***
			[4.53]			[4.08]
Indicator			0.0063***			-0.0027*
			[4.75]			[-1.71]
N	44,901	45,736	90,637	18,525	18,525	37,050
R^2	0.416	0.247	0.346	0.461	0.232	0.416
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specific Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Economics Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7
Industry Characteristics: Growth Options

This table examines whether growth options exacerbate or attenuate the positive effect of political uncertainty on firm level R&D intensity. Following the literature, we use firm-specific Tobin's Q and whether firms belong to a high-tech industry to measure firms' growth opportunities. Specifically, Tobin's Q represents the ratio of the market value of assets to the book value of assets. A higher Q indicates higher growth and investment opportunities for the firm, and vice versa. *High Q* is an indicator variable set equal to one for firms with above industry median Q each year. High-tech firms as opposed to non high-tech firms are supposed to have more growth options. *High-tech industry* is an indicator variable set equal to one for firms operating in the following seven high-tech industries: drugs (283), office equipment and computers (357), communication equipment (366), electronic components (367), scientific instruments (382), medical instruments (384), and software (737). The classification is based on 3-digit SIC codes as defined in Brown et al. (2009). For each growth options indicator, we first perform subsample analysis by splitting the full sample into two subgroups according to either the median industry Q or the high-tech industry indicator. To facilitate comparison, we then examine the interaction between the election year dummy and the growth options indicator in the baseline R&D regression specification. Each column is based on such a growth options indicator, denoted by the column heading. The unit of observation is at firm-year level. The dependent variable is R&D intensity, defined as the ratio of R&D expenditure to total assets. Independent variables include Q, Cash flow, Ln(Age), Ln(Sales), Tangibility, Profitability, Leverage, Herfindahl, Herfindahl^2, State GDP growth rate and unemployment rate and and the Election year indicator (year 0). See Appendix A for variable descriptions and the variable sources. Variables of interests are the election year indicator and the interaction term. We use baseline regression specification and control for firm and year fixed effects. Standard errors are clustered at the firm level and corrected for heteroskedasticity. T-statistics are reported in square brackets below coefficient estimates. To save space, we suppress the estimates of firm specific and state economics control variables. Data is for the period 1976 to 2013. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D intensity					
	Tobin's Q			High-Tech Firms		
	High Q	Low Q	Interacted	High-Tech	Non High-Tech	Interacted
	(1)	(2)	(3)	(4)	(5)	(6)
Election Dummy	0.0041***	0.0026***	0.0025***	0.0071***	0.0010***	0.0008**
	[4.96]	[4.58]	[4.33]	[7.15]	[2.81]	[2.07]
Election × Indicator			0.0021**			0.0069***
			[2.07]			[6.49]
Indicator			0.0149***			–
			[14.58]			–
N	45,321	45,316	90,637	39,092	51,545	90,637
R^2	0.372	0.288	0.350	0.405	0.220	0.346
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specific Controls	Yes	Yes	Yes	Yes	Yes	Yes
State Economics Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8
Industry Characteristics: Hard-to-Innovate Industries

This table examines the cross-sectional variations of hard-to-innovate industries on firm level R&D intensity in election years. Following the work of Hall, Jaffe, and Trajtenberg (2005) and Tian and Wang (2014), we classify firms in pharmaceuticals, medical instrumentation, chemicals, computers, communications, and electrical industries as hard-to-innovate industries. while easy-to-innovate industries include software programming, internet applications and other miscellaneous industries. We therefore set a *hard-to-innovate* indicator to one if a firm belongs to one of these hard-to-innovate industries. To test the hypothesis, we first perform subsample analysis by splitting the full sample into two industry subgroups (hard- vs. easy-to-innovate) according to the hard-to-innovate indicator. To facilitate comparison, we then add to the baseline R&D regression an interaction term between the election year dummy and the hard-to-innovate indicator. Each column is based on such a subsample, indicated by the column heading. The unit of observation is at firm-year level. The dependent variable in all regressions is R&D intensity, defined as the ratio of R&D expenditure to total assets. Independent variables include Q, Cash flow, Ln(Age), Ln(Sales), Tangibility, Profitability, Leverage, Herfindahl, Herfindahl^2, State GDP growth rate and unemployment rate and and the Election year indicator (year 0). See Appendix A for variable descriptions as well as the variable sources. Variables of interests are the election year indicator and the interaction term. We use baseline regression specification and control for firm and year fixed effects. Standard errors are clustered at the firm level and corrected for heteroskedasticity. T-statistics are reported in square brackets below coefficient estimates. To save space, we suppress the estimates of firm specific and state economics control variables. Data is for the period 1976 to 2013. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable: R&D intensity		
	Hard-to-Innovate Industries		
	Hard-to-Innovate	Easy-to-Innovate	Interacted
	(1)	(2)	(3)
Election Dummy	0.0077***	0.0020***	0.0022***
	[5.40]	[5.14]	[5.29]
Election × Hard-to-Innovate			0.0067***
			[4.26]
N	21,618	69,019	90,637
R^2	0.480	0.243	0.346
Constant	Yes	Yes	Yes
Firm Specific Controls	Yes	Yes	Yes
State Economics Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 9
Political Uncertainty and R&D Intensity: Robustness Tests

This table presents robustness tests for the baseline R&D intensity results shown in Table 2. The unit of observation is at firm-year level. The dependent variable in all regressions is R&D intensity, defined as the ratio of R&D expenditure to total assets. Independent variables include Q, Cash flow, Ln(Age), Ln(Sales), Tangibility, Profitability, Leverage, Herfindahl, Herfindahl^2, State GDP growth rate and unemployment rate and and the Election year indicator (year 0). See Appendix A for variable descriptions as well as the variable sources. Variable of interest is the election year indicator. In Panel A of Table 9, we use baseline R&D regression specification and control for firm and year fixed effects. Specifically, in column (1), we cluster standard errors by firm and year following Petersen (2009). Column (2) reports regression results based on the subsample of firms listed on NYSE, Amex and Nasdaq only (Exchg = 11, 12, 14), while column (3) presents the results based on the over-the-counter (OTC) traded firms (Exchg = 13, 19). In columns (4) and (5), we remove observations in the dot-com bubble period (i.e., 1999-2000) and financial crisis period (i.e., 2007-2008) respectively. Column (6) excludes firms headquartered in California, Massachusetts and New York and Column (7) excludes firms operating in business services, electronic equipment and pharmaceutical products industries, where industry classification is based on Fama French 48 industries. In column (8), we present regression results from a placebo (falsification) test, where election events are randomly generated every four years for each state. Standard errors in columns (2) to (9) are clustered at the firm level and corrected for heteroskedasticity. In Panel B of Table 9, we further estimate one-step GMM in first differences to eliminate firm effects. The GMM models includes one lag of the dependent variable in column (1) and two lags of the dependent variable in column (2) respectively. Aggregate year dummies are included in all regression specifications. T-statistics are based on robust, firm-clustered standard errors. AR(1) and AR(2) are tests for first-order and second-order autocorrelation in the first-differenced residuals, under the null hypothesis of no autocorrelation. Sargan is a test of the null hypothesis that the overidentification restrictions (all instruments) are valid. T-statistics are reported in square brackets below coefficient estimates. To save space, we suppress the estimates of firm specific and state economics control variables. Data is for the period 1976 to 2013. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Baseline R&D Regressions								
	Dependent variable: R&D intensity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Election Dummy	0.0038**	0.0033***	0.0051***	0.0032***	0.0044***	0.0025***	0.0016***	0.0005
	[2.16]	[6.55]	[4.52]	[6.34]	[8.89]	[4.85]	[4.09]	[0.66]
N	89,570	65,264	25,373	83,909	85,760	58,504	63,400	80,797
R^2	0.275	0.362	0.343	0.354	0.329	0.323	0.260	0.355
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Specific Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Economics Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Dynamic R&D Regressions		
	Dependent variable: R&D Intensity	
	(1)	(2)
Election Dummy	0.0032***	0.0029***
	[6.27]	[5.64]
R&D Intensity$_{t-1}$	0.2021***	0.1984***
	[10.70]	[9.29]
R&D Intensity$_{t-2}$		-0.0145
		[-1.25]
N	69,626	61,401
AR(1) (*p*-value)	(0.00)	(0.00)
AR(2) (*p*-value)	(0.12)	(0.16)
Sargan (*p*-value)	(0.00)	(0.00)
Year Dummies	Yes	Yes
Firm Specific Controls	Yes	Yes
State Economics Controls	Yes	Yes