MASTER THESIS

Copenhagen Business School

MSc in Advanced Economics and Finance

TO WHAT EXTENT DOES POLICY UNCERTAINTY AFFECT INNOVATION?

An empirical study of the effect of policy uncertainty on innovation

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16th May 2022

Nr. pages: *109*

Nr. characters: *202 369*

~ The warmest thank you is directed to our supervisor, Marek Giebel, for his support and guidance. ~

ABSTRACT

Measuring innovation through the log of scaled patents, we find a significant negative relationship between policy uncertainty and innovation. This is robust to the use of raw patent counts. We use alternative measures and instrumental variables for the independent variable to address endogeneity and find the estimated relationship between innovation and policy uncertainty to be consistently negative for three of four measurements: the opposite relationship is reported when election data is used as an alternative measure. We decompose policy uncertainty into fiscal and monetary policy, and find that these have opposing effects, where fiscal policy uncertainty is associated with a decrease in innovation, monetary policy uncertainty has the opposite relationship. The impact of policy uncertainty is greater for innovation with more impactful patents and smaller for patents with a higher degree of novelty. Consistent with the precautionary motive to hold cash, we find that the innovation of firms with a lower level of cash holdings have a more adverse reaction to increased policy uncertainty. Moreover, we find the degree of financial constraint to be inconclusive, as it depends on the measure of financial constraint. For instance, we find that the debt to asset ratio indicates that innovation of financially constrained firms is impacted more by increased policy uncertainty compared to that of financially unconstrained firms, however, the interest coverage ratio suggests the opposite relationship. Finally, we find that the sensitivity of innovation to changes in policy uncertainty changes depending on the initial level of policy uncertainty. The sensitivity is bigger for large firms in both high and low policy uncertainty environments, consistent with previous findings that small firms generally have a more stable level of innovation and thrive under uncertainty relative to large firms.

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1 INTRODUCTION

The study of innovation has been of interest throughout time. Solow (1956) showed that capital alone could not fully explain the apparent growth of the economy, and effectively suggested that technological progress and innovation played a central role in the expansion of the economy over time. After this finding, the importance of innovation became indisputable, and naturally, the behavior and determinants of research and development (R&D) have received a lot of exposure in the literature (Griliches (1990), Trajtenberg, Henderson, and Jaffe (1997), Hall, Jaffe, and Trajtenberg (2001), Bernstein (2015), Matray (2020)). Historically, innovation output of a firm is measured by patents, as these are readily available and possible to access (Griliches, 1990). A vast amount of innovation is conducted at firm level, and thus, innovation is affected either directly or indirectly by various economic and strategic effects. The dynamics and complexities behind innovative processes and output make innovation an interesting objective to study. Lemley (2012) introduced the notion of *patent racing*, which denotes the inter-firm competition in the process of inventing and subsequently claiming innovations. Moreover, Sherer (2000) showed that certain industries are more dependent on innovation, partly due to the competition that exists, but also due to the role that the field plays in making contributions to society. For instance, this could be the pharmaceutical and tech industries. The effects of competition and the nature of industries suggest that there are indeed central interactions and factors that impact innovation in the firm and across industries.

Another widely covered topic is that of uncertainty and its implications for the macro- and microeconomic environment. In the context of a firm, having certainty about the future economic climate is often preferred, as it allows for more accurate budgeting and forecasting. In many cases, the decision to take on a project involves the estimation of future cash flows, and the longer the duration of the project, the more uncertain these projections become (Gaspars-Wieloch, 2017). In its essence, uncertainty is merely the inability to have conviction in something, however, the sources of uncertainty can vary greatly. This paper focuses on economic uncertainty that arises from uncertainty regarding the political climate. This type of uncertainty is relevant for firms, as their ability to operate is largely dictated by the regulations and laws that the government decides for and against (Abdurakhmonov, Ridge, and Hill, 2021). Baker, Bloom and Davis (2016) developed an index of policy uncertainty (PUI), which captures economic uncertainty coming from uncertainty regarding policy. Generally, the PUI has spiked periodically throughout time around Black Monday, Bill Clinton-Lewinsky scandal, the Persian Gulf War, the government shutdowns etc. The common trend in the development of the index is that in the first half of the twentieth century, the periods of elevated policy uncertainty were short lived and dispersed. However, in the second half, the index has become increasingly volatile with a much higher frequency of periods with elevated policy uncertainty.

Policy uncertainty is indeed inevitable and difficult to predict due to its arbitrary nature, but gaining an understanding of the interplay between innovation and policy uncertainty could provide insight into complex strategic choices at the firm, and moreover, the real effect of an economic environment characterized by more erratic and volatile uncertainty related to policy. In effect, this paper strives to investigate and answer the research question: *to what extent does policy uncertainty affect innovation?* This is a multidisciplinary study using literature from industrial organization, macro- and microeconomics, and corporate finance. The various literature is relevant to this paper, due to the important interconnections between economic growth and the development occurring at a firm level, as well as the various strategic interactions which impact the decision to innovate. The focus of this paper is monthly innovation by public firms from 1985 to 2019, where innovation is measured by patents. The purpose is to understand how innovation is impacted by policy uncertainty, as well as the potential firm and industry determinants of this relationship.

We begin by showing that the univariate relationship between innovation and policy uncertainty is significantly negative. A one percent increase in policy uncertainty is associated with a 0.113 percent decrease in innovation. It is possible that the negative coefficient is caused by omitted variables related to firm characteristics or general economic uncertainty. To account for this, we include firm and macroeconomic controls where the relationship between innovation and policy uncertainty remains negative and significant at the one percent level. The main specification suggests that a one percent increase in policy uncertainty is associated with a 0.411 percent decrease in innovation.

Breaking down the PUI into two of its constituent components, fiscal and monetary policy uncertainty, we show that there are opposing forces within the index that effectively indicate that innovation is not impacted in the same way by all types of policy uncertainty. In the main specification including macroeconomic and firm controls, the fiscal policy uncertainty has a coefficient of negative 0.111 which is significant at a one percent level, meaning that a one percent increase in fiscal policy uncertainty is associated with a 0.111 percent decrease in innovation. Using monetary policy uncertainty, the coefficient is positive 0.054 and significant at a one percent level, indicating that a one percent increase in monetary policy is associated with a 0.054 percent increase in innovation.

We compare the relationship between policy uncertainty and innovation depending on the quality (impact and novelty) of innovation by splitting the data into subsamples depending on whether or not the patent is above or below the median according to three different measures of innovation: *scaled citations*, *scaled generality* and *scaled originality*. Although scaled citations capture total citations received and scaled generality captures the number of distinct technology classes that an innovation has been cited by, both indicate the relative impact of an innovation. The results are consistent for the two measures, splitting the sample yields the result that the innovation of firms with more impactful patents has a more adverse reaction to increased policy uncertainty. Moreover, the scaled originality, which indicates the level of novelty, suggests that the innovation of firms with patents characterized by a higher degree of novelty has a less adverse reaction to increased policy uncertainty.

Comparing the relationship between policy uncertainty and innovation depending on firm size, we find that the innovation of large firms is significantly more impacted by increased policy uncertainty as opposed to that of small firms. For small firms, we find that a one percent increase in policy uncertainty is associated with a 0.226 percent decrease in innovation, in contrast to a 0.503 percent decrease for large firms. This result is significant at the one percent level. The findings may be consistent with the findings of Bhattacharya, Hsu, Tian and Xu. (2017), who suggest that firms postpone investment in case of increased policy uncertainty, where the ability to postpone and engage in resource planning may be associated with large firms. Moreover, policy uncertainty amplifies information frictions that enlarge problems connected to moral hazard, adverse selection, and misallocation of resources, where these are prevalent in large firms.

Exploring other firm characteristics that may impact the relationship between innovation and the PUI, we use three measures of financial constraint: the *KZ score*, *debt to asset ratio*, and *interest coverage ratio*. Based on the debt to asset ratio, we find that the innovation of financially constrained firms is impacted more by increased policy uncertainty, however, the interest coverage ratio indicates the opposite effect, where the innovation of financially constrained firms is less impacted by increased policy uncertainty as opposed to that of constrained firms. We find that the difference between the subsamples is significant at a one percent level for the debt to asset ratio and at a five percent level for the interest coverage ratio, however, using the KZ score as a measure of financial constraint, it is not possible to conclude that there is a significant difference between the financially constrained and unconstrained firms in the sample. Hence, the effect of the degree of financial constraint is inconclusive and depends on the measure of financial constraint.

Furthermore, we investigate whether the level of cash holdings impact the relationship between the PUI and innovation. High cash holdings may be associated with the agency problem of free cash flows, leading to value destroying behavior and an unorganized effort towards innovation (Jensen and Meckling, 1976). Alternatively, firms may decide to hold more cash due to precautionary motives, which effectively indicates that they are better prepared to withstand uncertainty (Keynes, 1936). Consistent with this, we find that the innovation of firms with higher levels of cash have a significantly less adverse reaction to increased policy uncertainty.

In the final test on determinants of the relationship between innovation and policy uncertainty, we investigate the impact of lobbying activities. A firm is said to have lobbying activities if it has engaged in such activities anytime during the sample period. The idea is that firms engage in lobbying to further their own interest that may stem from potentially unfavorable future states of nature. Although the result indicates that the innovation of lobbying firms has a more adverse reaction to increased policy uncertainty, the difference in the estimators is not statistically significant.

To understand the nuances of the relationship between innovation and policy uncertainty, we introduce an interaction effect between the change in the PUI and a dummy variable indicating whether there is a high or a low level of policy uncertainty. The idea is to test if firms are more or less sensitive to changes in the PUI when there is a high level of policy uncertainty. We find that a change in the PUI at low levels of policy uncertainty is associated with more innovation, where a change in the PUI at high levels of policy uncertainty is associated with less innovation. Furthermore, we investigate the sensitivity depending on firm size and find that large firms are more sensitive to changes in the PUI relative to small firms at both high and low levels of policy uncertainty.

The PUI measure may be endogenous, as it potentially captures economic uncertainty that is unrelated to policy uncertainty. While macroeconomic controls are included to mitigate the risks of this, previous tests do not entirely rule out this concern. To address the potential endogeneity issue, we follow Kaviani, Kryzanowski, Maleki, and Savor (2020) by estimating different model specifications to establish causality between policy uncertainty and innovation. For the first model specification, we exploit the close economic ties between the US and Canada by regressing the US PUI on the Canadian PUI, in order to capture the residuals with the aim of obtaining a measure that better captures policy uncertainty as distinct from general economic uncertainty. Significant at a one percent level, we find that a one percent increase in policy uncertainty is associated with a 0.116 percent decrease in innovation. In the second model specification, we exploit the relative legislative power and polarization in the Senate and the House of Representatives. Relative legislative power indicates the voting power that the Democratic and Republican Parties have in terms of the number of seats in the House and Senate and reflects the level of opposition that may be expected in a law-making process. If one party has superior voting power, then it is more likely to cause less policy uncertainty than if the voting power was more even. The level of polarization indicates how different the political views of the Democratic and Republican Parties are. If these views are opposing, the ideological gap increases and the permanence of a policy is more uncertain. When using the instruments, the relationship between innovation and policy uncertainty remains negative. Lastly, we define a presidential election dummy equalling one three months before an election, including the month of, and zero otherwise. The idea is that policy uncertainty is heightened around times of political change, which is captured in the months leading up to the election. Inconsistent with previous results, we find that the election period is associated with more innovation. We repeat this for a five month dummy as opposed to three months and report a similar result.

To test if the main findings are robust to other definitions of innovation, we use raw *patent counts*. We use a *negative binomial model* in order to account for the discrete nature of patent counts and opt not to use the *poisson regression model* due to violation of the mean-variance assumption that instead implies overdispersion. We find that a one percent increase in policy uncertainty is associated with an expected decrease of 0.184 percent in the expected value of innovation, holding the other variables constant.

The remainder of the paper is structured as follows: section 2 covers the foundational theories that are central for the understanding of the concepts in this paper. Section 3 outlines the data approach, variable descriptions and sign predictions. Section 4 lays out the econometric methodology. Section 5 presents the results. Section 6 discusses, and section 7 presents further research ideas. Section 8 concludes.

2 LITERATURE REVIEW

2.1 The Importance of Innovation

Innovation and the development of new goods, services, and procedures have been a major part of economic activity throughout time. Different economic orientations like macroeconomics, microeconomics, industrial organization, and international economics identify innovation as an essential variable in diverse models, theories, and analyses. As a result of the increasing importance of innovation as a research area and the multidisciplinary nature of the topic, the economics of innovation can be seen as a distinct area of applied economics (Hall and Rosenberg, 2010). Swann (2009) argues that economists inadequately understand the economics of innovation and that the widespread implications of innovation on the economy and the society outweighs the focus devoted to the research field.

2.1.1 Innovation and Macroeconomics

Solow (1956) derives a model of long-run growth for a closed economy. The economy produces an output $Y(t)$ which is created by two factors of production: capital (K) and labor (L) and is assumed to have a constant return to scale. A fraction of the output of each instant is consumed, and the rest is saved and invested. The fraction of saved outputs, s, is assumed to be constant, meaning that the savings rate can be denoted $sY(t)$. The stock of capital is denoted $K(t)$, and the net investments are defined as the rate at which the capital stock increases instantaneously:

$$\frac{dK}{dt} = \dot{K} = sY$$

The exogenous population growth of the labor force increases at a constant rate of n. Furthermore, the real wage is adjusted such that all available labor is employed. Within the neoclassical growth model, savings increase the capital stock and thus generate economic growth. By analyzing the implications of different savings rates, population growth, and depreciation, the main implication of the model is that long-run economic growth cannot be supported by capital investments only. For economic growth to be sustained, innovation and technology growth are fundamental (Greenhalgh and Rogers, 2010).

The shortcoming of the neoclassical model is that the growth of technology is exogenous in the model. This insight led to the development of endogenous growth models, which attempt to endogenize the sources of long-term growth. There exist various endogenous growth models with different focus areas (Greenhalgh and Rogers, 2010). For example, Lucas (1988) emphasizes the attention of human capital;

through education, specialized human capital accumulation is at the center of economic growth. In Romer (1990), the model is built on microeconomic foundations, where profit-maximizing firms undertake R&D. Developers of innovation have monopoly power over the development and can raise prices above the marginal costs; this provides incentives for innovation. The main conclusion is that the share of workers within R&D affects the growth rate. In turn, the share of R&D workers is affected by the patience of workers, population size, and the substitutability and productivity within the R&D sector.

Subsequent models have relaxed some of the strong assumptions imposed by the endogenous growth models. Evolutionary growth models relax the assumption of optimizing agents. Instead of firms knowing all the potential production methods, evolutionary growth models argue that firms explore production through continuous learning and imitation (Greenhalgh and Rogers, 2010). The hybridizing growth model developed by Weitzman (1996) argues that innovation follows a combinatorial process. The combinatorial process relaxes the assumption of diminishing return to capital. The idea is that a previously untried combination of existing ideas grows faster than anything else in the economy; in addition, some innovation is so dominant that it creates a whole new range of innovation opportunities.

2.1.2 Innovation and Microeconomics

Tohidi and Jabbari (2012) identify innovation as one of the most critical factors for firms, as it is fundamental for the success of an organization. Innovation can attract new customers; by implementing efficient and innovative processes, the firms enable the prospect of keeping up with competition and remain in the market. Cefis and Marsili (2005) defines an innovation premium that extends the life expectancy of innovative firms. The survival time is documented to be 11% higher, and for high-intensity technology sectors, the effect is even more prominent. Innovation may affect the prices and the costs within an industry but can also affect the market structure in which the firms operate. However, the causality between market structure and innovation runs both ways. In the extreme case of perfect competition, all knowledge is assumed to be known by all firms; this will remove the incentives to innovate. A process innovation might reduce the marginal cost of production, but as soon as the innovation occurs, all firms will react to the new information, implement the innovation, and effectively reduce their marginal cost. As a result, the innovative firm will make zero economic gain (Greenhalgh and Rogers, 2010).

In a monopolistic market, the reduced marginal cost would lead to lower prices, higher quantity, higher consumer surplus, and higher profits. However, without the threat of new entrants, the incentives to innovate remain limited (Swann, 2009). Gilbert and Newbery (1982) study incumbent monopolist's innovation for patentable substitute technologies to avoid potential entrants. To withhold the monopoly power, the incumbent tends to have higher incentives to innovate than the entrant. The intuition for this is that the entrant's profit would be lower than the monopolistic profits, due to increased competition and divided market share. The monopolist may opt to patent the innovation and thereby deter potential entrants from using it. After protecting the innovation, the monopolist need not use it, which results in a "sleeping patent" that solely allows the monopolist to maintain its monopoly power. In an oligopolistic market, threats of new entry and rivalry between oligopolists provide incentives for innovation (Swann, 2009).

Furthermore, the protection of firms' innovation might affect the incentives to innovate. Reinganum (1982) evaluates firms' decisions connected to R&D, such as the possibility that a rival firm might innovate first, uncertainty regarding possible profits of capturing market shares in a new market, and protections of a patent. The developed theory is based on a dynamic game analysis that determines the *Nash equilibrium* of *n* identical firms. Development and innovation increase with patent protection; this effect accelerates increased rivalry. However, if imitation is possible, innovation might accelerate or decrease with an increasing number of Nash rivals depending on the changes in the payoff structure.

2.1.2.1 Creative Destruction

Innovation often distinguishes between incremental and drastic. Incremental innovations are minor changes to existing processes or products, while drastic innovations introduce an entirely new type of production process or product. Drastic innovations often give rise to a new genre or range of innovative products or applications. The classification of an innovation as incremental or drastic has an effect on the interactions between competition and innovation, as new entrants can exploit the disruptive nature of drastic innovations to unseat incumbents (Greenhalgh and Rogers, 2010).

In *Theory of Economic Development* (published 1911), Schumpeter places entrepreneurs at the center of innovation. However, in contrast, Schumpeter states in *Capitalism, Socialism and Democracy* (published 1942) the hypothesis that larger firms with market power accelerate the rate of innovation (Nicholas, 2003). Schumpeter (1942) states that larger firms with market power will revolutionize the economic structure from within the firm and destroy aging processes by creating new ones. This process is defined as *creative destruction*. However, as market power is not endogenous to Schumpeterian growth, new firms may enter and dominate an industry through creative destruction. Hence the two arguments are not entirely separated. The common conclusion is that the ability to maintain or gain market shares provides incentives for innovation (Nicholas, 2003).

2.1.3 Innovation and International Trade

An implication of Romer (1990) is that a larger economy will experience faster growth due to a higher fraction of workers within the R&D sector. An extension of this insight is that free international trade can act to speed up growth. One of the traditional theories within international trade developed by Ricardo (1817) states that competitive advantages across countries provide welfare gains from trade. Countries should specialize and export according to comparative advantages and import where the country has comparative disadvantages. Bernard, Eaton, Jensen and Kortum (2003) study plant-level export behavior and report that only the most productive firms will expand to enter export markets. The increased competition in the international market imply that only the most productive will enter and less productive firms will exit; this provides welfare gains as the average industry productivity increases. Aghion, Blundell, Griffith, Howitt, and Prantl (2004) find that increased foreign competition increases the innovation activities by domestic incumbents, leading to faster aggregate productivity growth.

Foreign R&D has beneficial effects on domestic productivity, and the effect increases with how open an economy is to foreign trade. International trade may also lead to international knowledge spillovers, which directly affect the rates of innovation and growth. Due to knowledge spillovers, a country's productivity depends on the domestic R&D stock and the R&D of its trade partners. Furthermore, the estimated rate of return on R&D is central to domestic output and international spillovers (Coe and Helpman, 1995). Buera and Oberfield (2020) separate benefits from trade into static and dynamic components. The static component implies gains from increased specialization and comparative advantages, whereas the dynamic component implies any benefits that operate through the flow of ideas and technology. A tractable theory on the diffusion of technology across countries is provided to quantitatively assess the role of trade in the transmission of knowledge. Calibrated results indicate that the benefit of trade on the total factor productivity growth is more than double when technology diffusion is introduced in the model.

2.2 The Nature of Innovation

Innovation can be seen as an investment for a firm, however, innovation differentiates itself from regular investments in tangible assets such as capital expenditures due to the intangible nature and the long-time horizon and high tail risk. In addition, the economic factors that affect innovation differ compared to those which affect tangible assets investments (Bhattacharya et al., 2017).

The Organization for Economic Co-operation and Development (OECD) defines innovation and R&D in the *Frascati Manual 2015: Guidelines for Collecting and Reporting Data on Research and Experimental Development*. The Frascati Manual has been an international standard for more than fifty years for how to collect and report statistics associated with R&D. In order to understand how innovation contributes to economic growth and welfare, a sound evidence foundation is required. The objective of the Frascati Manual is to provide a common language regarding the definitions of R&D and, by that, support evidence and allow for comparable international statistics. The first Frascati Manual was developed in 1963 after the OECD met with national experts on R&D statistics. The continued relevance is motivated by an increasing interest in understanding the features and drivers of R&D as well as comparing efforts across national borders. Compared to the previous edition of the Frascati Manual the current version has an increased focus on linking dynamics from a micro level to the aggregate macro level (OECD, 2015).

According to the Frascati Manual, R&D comprises creative and systematic work that increases the knowledge stock and devises new applications for existing knowledge. Standard features exist that identify R&D activities even as procedures are carried out in different ways and can be undertaken both on a continuous or occasional basis. For an activity to be defined as an R&D activity, five core criteria must jointly be satisfied:

1) *Novel*: within the business enterprise sector, the potential novelty is assessed by comparing the activity to the existing stock of knowledge in the industry. The result of the R&D activity must lead to findings that are new to the business and not already used in the industry. New products, procedures, or applications are all considered to be novel.
2) *Creative*: the objective of an R&D activity must imply new concepts or ideas of improvements. Therefore, any changes to routine work are excluded, while new methods with originality could be defined as an R&D activity.
3) *Uncertain*: any R&D involves multidimensional uncertainty. There is general uncertainty regarding the costs and time needed to achieve the desired outcome. In addition, the extent to which the outcome is feasible is also unknown.

4) *Systematic*: records of the process and its outcomes must be conducted, and the purpose of the project must be verified.
5) *Transferable and/or reproducible*: as the purpose of R&D is to increase the existing stock of knowledge, any results need to be transferable, ensuring that other researchers can reproduce the result as a part of further research (OECD, 2015).

Furthermore, the Frascati Manual identified three types of activities that are covered in the term R&D:

- *Basic research*: is defined as experimental or theoretical work undertaken to acquire new knowledge of an underlying phenomenon or observable facts. The objective is to analyze properties, structures, and relationships with some freedom regarding the goal and implication. This type of research is usually performed by the higher education sector or within the government sector. Firms may undertake this type of research without any specific short-term commercial application in mind. However, only a small share of R&D by firms is assumed to be basic, as firms often innovate for commercial use. Basic research is often directed to a broad field of general interest or with the explicit goal of a range of future applications.
- *Applied research*: distinguished from basic research due to specified predetermined objectives. Applied research can either be undertaken to determine applications for basic research findings or to determine new methods and applications to products, operations, or systems.
- *Experimental development*: the largest component of firms R&D, refers to systematic work that draws from existing knowledge. These additions to existing knowledge are used to produce new products and processes or improve on existing ones.

The relationship between the three types of R&D activities can be seen as dynamic, and a clear separation rarely exists within one organization. The time until a project is likely to provide results and the range of potential fields for which the results can be applied can help to distinguish between the different types of R&D activities. In order to provide intuition and help distinguish between R&D activities, the following example is provided. Basic research is the review of theories that identify variables for economic growth. Applied research is the analysis of a specific theory with the purpose of developing government policies. Lastly, experimental development is the development of operational models based on statistical evidence and the design of economic policy tools that foster economic growth (OECD, 2015).

2.2.1 Measuring Innovation

A widely covered topic in the innovation literature is that of measuring and accurately capturing the true level of innovation within a firm (Griliches, 1990, Kleinacht, 1996, Trajtenberg, Henderson, and Jaffe, 1997, Lanjouw, Pakes, and Putnam, 1998, Hall, Jaffe, and Trajtenberg, 2001, Hall, Jaffe, and Trajtenberg, 2005, Bernstein, 2015). The breadth of measures strive to indicate the level of innovation output and span from scientific citations databases and innovation surveys to R&D expenses and patents. Scientific citations databases and innovation surveys are limited in coverage and therefore difficult to use in economic analysis (Kleinknecht, 1996). R&D expenses is a convenient measure of innovation, as it is publicly available firm level data. However, while the data is public and readily available, it may be argued that R&D expenses best capture the innovative inputs into an innovative process, as these are associated with much uncertainty that may not effectively result in successful innovation (Lanjouw, Pakes, and Putnam, 1998). Moreover, using R&D expenditure as a measure of innovation presents difficulties with respect to ensuring consistency across time and firms. As accounting practices evolve dynamically over time, it may impact the way in which R&D expenditure is recorded both within a single firm, but also across firms. Furthermore, a firm may engage in some form of innovative activities without having a specification of standalone R&D expenditure in its financial statements, hence making it a measure for a subset of firms (Lanjouw, Pakes, and Putnam, 1998).

In effect, patents are usually preferred in the studies of innovation, as they posit a combination of consistent detail at a firm level and the inclusion of all firms that generate innovation output worthy of protection. While patents are a good measure of innovation for the reasons that R&D expenditure is not, it introduces another set of challenges that may question its appropriateness. Griliches (1990) proposed two major issues with using patents for economic analysis: *classification* and *intrinsic variability*. Classification refers to the search for a meaningful mapping of patent data to standardized industries like the North American Industry Classification System (NAICS). While patents are filed at a firm level, they do not necessarily pertain to the industry of the assignee (the patent filer). Patents are filed under a specific technology class, where they are deemed to make a contribution to the existing innovation, however, there is not a direct link between such technology class and official industry classification. Intrinsic variability refers to the variability in the true value, importance, and contribution of the underlying innovation protected by a patent, with respect to both technical and economic significance. In dealing with the industry classification of a patent, it is inherently important to understand the possible biases associated with a mapping approach that involves a degree of subjectivity. There are no strictly defined rules that require the patent to be assigned to the industry in which it was made, the industry in which it is likely to produce, or the industry that will directly benefit from the innovation (Griliches, 1990). Patents from the United States Patents and Trademark Office (USPTO) have information on the Standard Industrial Classification (SIC) or World Intellectual Property Organization (WIPO), which then allows for translation into NAICS industry codes through public concordance tables, however, while the industry classifications may be straightforward to deduce, it is important to be cognizant of its application value.

Extensive literature exists on the economics of technological change, which suggests that patenting activity reflects the quality and extent of firm innovation. Historically, the raw patent counts have been used as a measure of innovation, which can be considered its most basic form. However, the patent count does not distinguish between incremental and drastic innovation and thus disregards the innovation quality (Griliches, 1990). To account for the inability of the patent count to distinguish between the quality of innovation, patent citations denote the number of citations that a patent receives after its approval and thereby reflects the impact of a patent on subsequent innovation. Moreover, the number of patent citations also captures economic importance as it correlates with the market value (Hall, Jaffe, and Trajtenberg, 2005). Both the patent count and the patent citations vary over time and across technology classes. The variation across time may be a direct effect of increasing availability and accessibility of research with more individuals having access to computers in the 90s as opposed to the 20s. Moreover, the variation could stem from changes in the relative importance of technologies or from actual changes in the patent system (Bernstein, 2015). Previous literature has highlighted the phenomenon called the *truncation problem*. This refers to the tendency of patent data to become distorted towards the end of a sample period in the event that the sample extends to a few years within the research year. This occurs due to natural lag between the application date (day of filing) and grant date (day of approval) coming from the application processing time of the USPTO. As an example, if patent data is extracted between 1985 and 2019 based on application date, then the final year of the sample would only include patents that have been granted sometime between 2019 and 2022. Effectively, this would truncate both the patent counts and number of citations. For the patent count, this would be severely distorted in the final years, since the approval process can last for many years. The citations are also distorted, as patents in 2019 only receive citations from subsequent patents that are granted by 2022 (Hall, Jaffe, and Trajtenberg, 2001). To combat this issue, Hall, Jaffe, and Trajtenberg (2001) proposed a fixed effects approach, where the purpose would be to create scaled versions of the patent count and patent citation.

The scaled patent measure is the scaling of a single patent by the average number of matched patents. In the work of Hall, Jaffe, and Trajtenberg (2001), matched patents refer to those granted to firms in the same year, technology class or both year and technology class depending on the intent of the scaling. There may be systematic differences across citations within the various fields, which must be normalized in the measure. While the scaling purges data of truncation effects and changes in the propensity to cite, it also eliminates the possibility of capturing systematic changes in the impact of matched patent. When scaling by year and technology class, patents granted in a technology class that collectively had many patents granted in that same year would not receive as big of a weighting as if it had been a technology class with few other patents granted that year. The scaled number of patents for a firm would be the sum of all the individual scaled patents in that year. The scaled citation is given by scaling the patent citations that a single patent receives by the average number of citations for matched patents (Hall, Jaffe, and Trajtenberg, 2001).

$$Scaled\ citations = \frac{x}{y/d}$$

$$Scaled\ patents = \frac{x}{d/z}$$

Where x denotes the number of citations a patent has received, y is the total citations received by matched patents, z is the number of firms with matched patents, and d is the number of matched patents.

Furthermore, a wide variety of innovation measures exist in order to capture different aspects of innovation. Two such measures were introduced by Trajtenberg, Henderson, and Jaffe (1997), and are given by the formulas below:

$$Generality_i = 1 - \sum_j^{n_i} s_{ij}^2$$

$$Originality_i = 1 - \sum_j^{n_i} c_{ij}^2$$

where s_{ij} denotes the percentage of citations received by patent i that belong to patent class j, out of n_i patent classes (Herfindahl concentration index) and c_{ij} denotes the percentage of citations made by patent i that belong to patent class j, out of n_i patent classes. The *generality* measure ranges from zero to one and will be closer to one if it is cited by subsequent patents that reference and belong to a wide range of technology classes. On the contrary, the measure is closer to zero if the subsequent patents belong to a more narrow range of technology classes. Generality may be interpreted as an innovation's range of influence on future innovations and thereby a measure of its impact in the field of innovation.

The interpretation of the *originality* measure is similar to that of generality except that it refers to citations made. If a patent cites previous patents that belong to a narrow set of technology classes, then this has a score closer to zero, whereas citing patents belonging to a wide range of technology classes would result in a higher score. Historically, both measures have shown a high degree of correlation with the number of citations made (originality) and received (generality), which indicate that patents with a higher level of citations tend to have a higher generality score and patents that cite a lot of other innovations is more likely to have a higher level of originality. Hence, more citations are likely to equate to a wider coverage of technology classes. While these measures of innovation may be considered more refined than the more basic patent count, they also, just like patent counts, come with a built-in truncation bias. Originality and generality tend to display a downward bias towards the end of the sample, if the sample period extends to recent years. Generality suffers from the truncation associated with a lack of observed citations, as other patents that may have cited the innovation have yet to be granted and thereby are not recorded in the data. The effect that drives originality downward towards the end of the sample period is perhaps less obvious, but may be due to the fact that patents granted in a relatively short time frame are suggestive of the patent's complexity and thereby is more likely to make fewer citations which, in turn, increases the likelihood of a lower originality score. It is possible to correct for this bias by scaling the measures using the same approach as explained in the case of patent counts and patent citations (Trajtenberg, Henderson, and Jaffe, 1997).

2.3 Measuring Policy Uncertainty

The *Economic Uncertainty Index*, also commonly referred to as the Policy Uncertainty Index (PUI), was developed by Baker, Bloom and Davis (2016) in effort to measure the level of economic uncertainty that stemmed directly from uncertainty regarding policy. More specifically, the authors strived to measure uncertainty about when and what economic policy action would be undertaken, and economic repercussions of political action or inaction, which also includes ripple effects of decisions that are not directly linked to economics i.e. military action. The index dates back to 1985, where the authors began to study its evolution in the United States. The authors have extended this to many other countries. In talking about economic uncertainty associated with policy uncertainty, it is important to make the distinction between the effects to economic conditions that come from the actual uncertainty regarding policy in contrast to general concerns about such future economic conditions.

The PUI is comprised of three different components, where each has a different weighting in the construction of the index. The first component is considered to be the core of the index, as it is also a common denominator with the PUI measures for other countries. It is characterized by its flexibility, as it is a text-based measure that involves the newspaper coverage of policy-related economic uncertainty. Specifically, it is an index of search results from the top 10 largest newspapers in the United States and from these papers the authors construct a normalized index of the volume of news articles pertaining to economic policy uncertainty. The search results had to include a triple of "*economic*" or "*economy*"; "*uncertain*" or "*uncertainty*"; and one or more of "*congress*", "*deficit*", "*Federal Reserve*", "*legislation*", "*regulation*" or "*White House*". This first component of the PUI has a weighting of 0.5, making it the most influential in capturing economic policy uncertainty. The second component pertains to uncertainty regarding taxation stemming from the number of federal tax code provisions that are set to expire . This is based on reports from the Congressional Budget Office, which has a record of temporary federal tax code provisions. The authors create annual dollar-weighted numbers of tax code provisions that are scheduled to expire throughout the following 10 years. The authors intend for this to capture the level of uncertainty about the future trajectory of tax policy. The third component relates to the disagreement among economic forecasters. The authors exploit the variation in the forecasts of individual forecasters at The Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The forecast measures of interest are the Consumer Price Index, Federal Expenditures, and State and Local Expenditures, where the dispersion in the forecasts is used to generate indices on uncertainty pertaining to policy-related macroeconomic variables. The two final components of the PUI are weighted equally with 0.25 in the overall index (Baker, Bloom, and Davis, 2016).

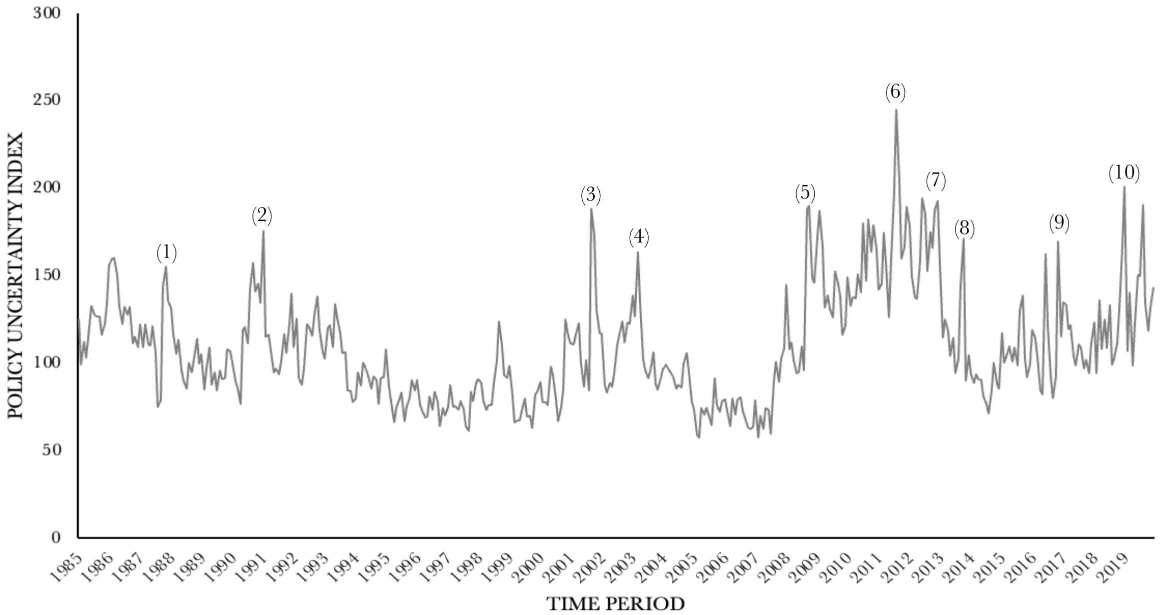
As can be observed from Figure 1 below, the PUI effectively captures times of elevated uncertainty around historical events. Examples of these events are:

1) *Black Monday:* the big stock market crash on October 19, 1987, when the Dow Jones Industrial Average dropped by 22.6% (Bernhardt and Eckblad, 2013).
2) *Persian Gulf War:* the Authorization for using Military Force against the Iraq Resolution passed the Congress on January 12, 1991 (Persian Gulf War, 2022).
3) *9/11 Attacks:* the deadliest terrorist attacks in US history. Series of airline hijackings committed by militants associated with al-Qaeda (September 11 attacks, 2021).
4) *The Iraq War:* on March 20, 2003, the US and allied forces launched an attack on the Iraqi government, marking the beginning of the Iraq war, also called the Second Persian Gulf War (Iraq War, 2021).

Figure 1:Policy Uncertainty Index

The development of the Policy Uncertainty Index over time.

The figure provides a timeline of the PUI based on monthly data for the time period January 1985 to December 2019. Events generating spikes in the index have been identified and numbered 1 to 10.



5) *Lehman Brothers:* in September 2008, the 168-year-old investment bank filed for the largest bankruptcy in US history. The bankruptcy created lasting disorder in financial markets worldwide and increased the distrust among banks (Financial crisis, 2019).

6) *Credit rating:* in August 2011, S&P lowered the AAA long-term US sovereign credit rating to AA+. The downgrade reflects the view of weakened stability and effectiveness of political institutions and policymakers as a result of prolonged controversy over raising debt ceilings and related issues (Jacob, 2011). S&P had previously ranked the US AAA since 1941 (Detrixhe, 2011).

7) *United States Presidential Election in 2012:* the incumbent president Barack Obama is reelected as president. A struggling economy is still recovering from the financial crisis, and the high unemployment rate had a prominent focus during the political campaigns (Election 2012, 2012).

8) *US government shutdown 2013:* beginning October 1, the US government shut down as the House and the Senate could not agree on a bill to fund the government. The shutdown was connected to the House passing a funding bill to delay Obamacare, while the delay was rejected in the Senate (Plumer, 2013).

9) *United States Presidential Election in 2016:* the presidential election on November 8, in which the Republican Donald Trump was elected president (Election 2016, 2021).
10) *US government shutdown 2019:* on December 22, 2018, the government shut down after the White House and Congress failed to reach a spending deal connected to the wall to the Mexican border. The shutdown came to be the most prolonged government shutdown in US history and ended on January 25, 2019 (Douliery, 2019).

The authors perform a series of validity checks to ensure that PUI appropriately proxies for economic uncertainty. They compare the performance of the index against the implied volatility index of S&P 500 (VIX). Moreover, they perform human audits of newspaper articles to determine if these would be deemed to display a degree of policy uncertainty. The authors also investigated whether or not the political orientation of a newspaper would impact the policy related news and produce skewed results.

The PUI can be broken into its constituent parts in terms of the sources of policy uncertainty. The index may be broken into fiscal policy, monetary policy and others. In particular, fiscal policy has been of much interest throughout time in the context of policy uncertainty, and the topic has been covered by Rodrik (1991), Higgs (1997) and many others with a particular focus on the detrimental economic repercussions of fiscal and regulatory policy uncertainty. The Beige Books of The Federal Reserve Bank also indicate that fiscal policy has been the most important source of policy uncertainty over the past years, largely driven by tax policy (Baker, Bloom, and Davis, 2016).

2.4 The US Political Structure

In discussing policy uncertainty in the US, it is imperative to understand the political structure that governs the nation and ultimately serves as the source of economic uncertainty brought on by uncertainty pertaining to policy.

The US political structure is ideologically based on liberal republicanism. It was first codified within the articles of confederation and perpetual union and later made it into the constitution. After the Philadelphia Convention of 1787, the Federal Constitution established the framework for the operating structure of the central government, which is also in place today. This consists of three branches: the *legislative*, *executive*, and *judicial*. These are commonly known as Congress, the Presidency, and the Supreme Court, respectively. This was originally done to create a separation of power, which in England historically had resided with the monarch and British Parliament. The horizontal decentralization in the US is present at all levels of the political system. At state level (legislators, governors, and judiciaries), county level (commissioners, sheriff's, and courts), and municipality level (city council, mayor, and judges) (Pew Research Center, 2018).

2.4.1 The Senate

The Senate is technically elected every six years, but this is a staggered election, which means that every two years a third of the members run for re-election. The Senate consists of 100 members, with two representatives from each state, that are elected by the respective state at a public vote. In addition to the 100 members, the Vice President of the United States has a conditional vote in case of a tie. The Senate has two important functions: it runs impeachment trials and has the power to ratify or reject treaties and bills coming from the president. Ultimately, a law cannot be passed without making it through the Senate (Pew Research Center, 2018).

2.4.2 The House of Representatives

The 435 members of the House are elected every two years by the public and are based on proportional representation. *Proportional representation* refers to that each district has a representative in the House and that the number of districts depends on the size of the state in terms of population. For instance, the state of California has 53 districts and hence a corresponding amount of representatives in the House, whereas the state of Alaska has one district and therefore one representative. The House has two important functions: they write up articles of impeachment and all revenue bills must originate in the House due to its historical function as a "house of the people". There is always a midterm election during the four-year presidency of the president of the United States, where the outcome of this is used as an indicator of the people's satisfaction with the president after two years of being in power. If the people are not satisfied, they may opt to vote in more representatives from the opposite party to make it more difficult for the president to pass laws (Pew Research Center, 2018).

2.5 Innovation and Financial Constraint

The industry of firms may dictate their dependence on external finance, this variation may stem from cross-industry differences in the *gestation period of products*, which is the time lag between the development and first sale. Moreover, the variation could also be attributed to the natural difference in industry life-cycle. An example being the tobacco industry compared to biotech industry, as biotech is usually in a constant growth phase, whereas tobacco has been declining over the past decade (Rajan and Zingales, 1998). Further, the authors argue that firms in industries with a particular dependence on external financing develop disproportionally faster in perfect capital markets because they are able to raise external capital at a reasonable cost. In their paper on the role of public policy in furthering innovation and growth, Hyytinen and Toivanen (1998) found that small and medium enterprises are subject to an upward sloping capital supply curve and thereby the market for financing is imperfect due to the fact that these firms may experience a lack of supply of funds from the credit market, which results in an inefficient allocation of funds in the economy. In effect, they argue that the evidence is consistent with the view that financial constraints hold back growth and innovation at a firm level.

In theory, any firm may be subject to financial constraints. This arises when a firm starts to have liquidity problems that stem from an insufficient flow of funds. Lamont, Polk, and Saa-Requejo (2001) found that constrained firms are marginally younger than unconstrained counterparts and that there is no significant difference in size. Moreover, the constrained firms have more tangible assets on their balance sheet but simultaneously have less cash. These firms are also less often loss-making and have substantially higher leverage than unconstrained firms. Their market to book ratios are lower as well as their growth in sales, and while they spend more on fixed assets, they spend considerably less on R&D. Ultimately, the unconstrained firms are more likely to withstand adverse economic shocks and uncertainty about future states of nature. For this reason, raising external finance in order to fund innovation and future growth may not always be straightforward for the constrained firm.

2.5.1 Measuring Degree of Financial Constraint

The previous literature on how to best capture and measure financial constraint is vast (Kaplan and Zingales, 1997), (Lamont, Polk, and Saa-Requejo, 2001). In essence, the existing measures attempt to capture the level of liquidity in a firm, in order to assess its sensitivity to uncertainty about future states of nature and give an indication of its ability to raise external finance.

Kaplan and Zingales (1997) classify firms into discrete categories based on their level of financial constraint and relate these classifications to specific accounting variables using an ordered logit regression. Lamont, Polk and Saa-Requejo (2001) utilized these regression coefficients to construct the *KZ score*. This index is higher for more constrained firms, and the five accounting variables of interest (and the sign of the coefficients) are: cash flow to total capital (negative), the market to book ratio (positive), debt to total capital (positive), dividends to total capital (negative), and cash holdings to capital (negative). The formula is given by the following:

$$KZ\ score = -1.0001909 * \frac{Cash\ flows}{K} + 0.2826389 * Q + 3.139193 * \frac{Debt}{Total\ capital}$$
$$-39.3678 * \frac{Dividends}{K} - 1.3114759 * \frac{Cash}{K}$$

By construction, firms with a high KZ score have low dividends, low cash levels and high debt. *K* is given by capital expenditures, and *Q* refers to the long term debt and debt in current liabilities divided by the total of long term debt, debt in current liabilities and stockholders equity. The KZ score has been used in many different contexts, particularly in the corporate finance literature with Li (2011) and Rashid and Jabeen (2018), among others. There is not a common consensus in terms of how the authors decide to split their samples based on the score. There exist examples of splitting the sample below and above the median or mean KZ score, or splitting the sample into tertiles where the upper tertile is classified as constrained and the lower as unconstrained. There is however consensus around the fact that it is insensible to conclude that every observation in the group can be classified as constrained or unconstrained but that, as a group, one is inarguably more constrained than the other.

Another measure of financial constraint is that of *debt to asset ratio*. Arugaslan and Miller (2006) used this measure, which is given by the following formula:

$$Debt\ to\ asset\ ratio = \frac{Book\ value\ of\ debt}{Assets}$$

This measure of financial constraint belongs to the group of financial leverage ratios and indicates the share of a firm's assets that are financed with debt. In turn, this is an indicator of financial health and, in combination with other factors, acts as a signal to financial institutions about whether or not the firm has the capacity to take on more debt.

A third measure of financial constraint is the *interest coverage ratio*. This ratio indicates the ability of a firm to take on more debt in terms of its capacity to make higher interest payments. The formula is given by the following:

$$Interest\ coverage\ ratio = \frac{EBIT}{Interest\ expenses}$$

Hence, if a firm has a high coverage ratio, it is an indication that the firm is better able to make its interest payments at current debt levels. Therefore an interest coverage ratio above the sample median is considered to be a sign of an unconstrained firm.

2.6 Investment and Innovation under Uncertainty

Government policies will affect innovation differently depending on which industries that are influenced by the policy and if the policy impacts a firm's input or output within the supply chain. Uncertainty regarding government policies increases the complexity for business decision-makers to estimate the trade-off between risk, costs, and opportunities associated with a specific investment. Increased uncertainty and unclear interpretation of provisions in laws may delay innovation adoption. In addition, due to the lack of an established standard when reviewing industry performance, it is difficult to determine the cause-and-effect relationship between policy uncertainty and innovation (Marcus, 1981).

2.6.1 The Theory of Investment

The large body of theoretical literature has investigated the effect of policy uncertainty, however, the sign of the relationship remains discussed. The relationship between policy uncertainty and investment has been reported as negative and positive depending on which mechanisms and channels a theory emphasizes (Atanassov, Julio, and Leng, 2015).

The real option model states that increased uncertainty harms investment and emphasizes capital irreversibility. Uncertainty increases the option value of postponing investment and waiting for more information (Bernanke, 1983, McDonald and Siegel, 1986, Dixit and Pindyck, 1994). However, several mechanisms may restrict a firm's ability to wait for more information (Atanassov, Julio and Leng, 2015). Postponing investment in periods of heightened uncertainty can result in disappearing competitive advantages due to the loss of an early mover advantage. According to the strategic growth option argument, policy uncertainty may increase innovation and result in competitive advantage (William and Fengrong, 2021). The theories rely on different assumptions; the real option theory assumes that a firm has monopoly power over an investment opportunity, and that the investment does not affect prices or market structure. However, with potential competitors, early investment is associated with greater expansion and introduces the idea of strategic growth options. Furthermore, under imperfect competition, a commitment of an irreversible investment provides signals to the market and may insinuate strategic entry deterrence (Kulatilaka and Perotti, 1998).

2.6.1.1 The Net Present Value of Investment

The valuation principle states that current market prices can be used to determine the present value of the costs and benefits associated with an investment. From this principle, one can derive the net present value (NPV), which often is a foundation for many financial decisions. The NPV of a project or investment is simply the difference between the present value of its benefits and its costs. The NPV is expressed in present day cash value, meaning that all future cash flows have been discounted to present value. All projects or investments with a positive NPV increase firm and shareholder wealth; the higher the NPV, the more wealth is generated.

The calculation formula can be expressed as following:

$$NPV = \sum\nolimits_{t=1}^{T} \frac{C_t}{(1+r)^t} - C_0$$

The initial investment is denoted by C_0, C_t is the net cash flow for period *t* and *1+r* denotes the interest rate for the cash flows for period *t* (Berk and DeMarzo, 2020).

The discount rate used for NPV calculations is firm-specific and related to the firm's capital structure and the time horizon. Fundamentally, the interest rates are based on the willingness to borrow and lend funds. Inflation, government policy, and future growth expectations also impact the discount rate. The interest rate affects the incentive to raise capital and invest; the higher the interest rate, the heavier future cash flows are discounted, causing NVP to decrease (Berk and DeMarzo, 2020). The Federal Reserve uses the relationship between interest rates and investment by increasing the interest rate when inflation rises, and the economy expands and decreases the interest rate in a recession. As the discount rate will affect firms' decisions regarding investment, policy uncertainty makes this calculation difficult and can therefore have an adverse impact on investment (Marcus, 1981). In addition, future cash flow is often uncertain as both costs and benefits of a project are first realized in the future. Due to limited knowledge about possible future states of nature, the outcome of a project is also uncertain (Gaspars-Wieloch, 2017).

2.6.1.2 The Real Option Theory

To further develop the simple NPV rule, one can add risk adjustments, sensitivity analyses and provide guidelines of priority in the case of limited investment budgets or if some investment decisions have implications for other projects. However, the intuition and fundamental rule remain the same no matter the adjustment. The real option theory argues that the NPV rule is insufficient, and under uncertainty, it may be beneficial to delay a positive NPV investment (Ingersoll and Ross, 1992). The optimal timing for the investment is derived under the assumption that investment is irreversible and that new information about future returns is arriving over time. With the two assumptions, the investment decision becomes a stochastic dynamic optimization. In each period, the investor may choose between committing to the investment or deferring commitment. Each action is associated with a cost; early commitment might come with the cost that future information eventually reveals that the investment was unprofitable. Deferring the investment may imply increased costs of the project or forgone income. The irreversible project resembles an American call option with an increasing exercise price and will only be exercised when the expected exercise value exceeds the options holding value. The more uncertainty associated with an investment, the more likely it is that the investor will defer commitment as the value of waiting increases. The uncertainty may arise from cash flow prediction, investment rates, or which states of nature that materialize (Bernanke, 1983).

While traditional capital budgeting theory suggests that one should undertake an investment if the NPV is positive, the premise of the option theory implies the other extreme: the option to invest should never be exercised. The underlying asset, the investment opportunity, does not pay dividends while the option is alive. Within the finance derivative theory, it is derived that it will never be optimal to exercise a call option until it expires if the underlying pays no dividends. However, the finance derivative theory is not entirely applicable for an investment option. For example, compare the investment option to a zero-coupon bond option with the same maturity. The price of the bond changes with the interest rate and increases as its maturity shortens; in contrast, only the first effect is present for an investment. Without commitment, the time horizon remains constant for the investment payoff, and hence, the present value does not tend to increase. Consequently, the present value of the investment will lag behind the value of the zero-coupon bond. This lag has a similar impact as a continuous dividend stream and creates an incentive to exercise the investment option (Ingersoll and Ross, 1992). McDonald and Siegel (1986) study the optimal investment timing where the benefits and costs follow a continuous time stochastic process. By applying option-pricing techniques, simulations show that the option value is significant and optimal behavior is to wait until benefits are twice the investment costs. Calculations are based on risk-averse investors who are well diversified. Bloom, Bond and Van Reenen (2007) show that firms become more cautious with increased uncertainty before investing or disinvesting, leading to decreased responsiveness of investments to demand shocks. This further implies that the responsiveness to any given policy stimulus is weaker in times of high uncertainty.

Both Bernanke (1983) and McDonald and Siegel (1986) emphasize that the uncertainty around investments is resolved by waiting. Dixit and Pindyck (1994) define uncertainty as the downside risk that can be limited by waiting, and the discount rate is a measure of the relative importance of the future against the present, which can affect the investment timing. Ingersoll and Ross (1992) highlight that interest rate uncertainty is the fundamental mechanism behind the real option theory. Even with no uncertainty regarding the future cash flow, the interest rate uncertainty by itself has a significant effect on investment. While the uncertainty regarding costs and benefits associated with a specific investment may cause delays, the effect of interest rate uncertainty remains crucial in understanding the macroeconomic structures behind investments.

Dixit and Pindyck (1994) define that the investment delay does not imply a market failure and is an insufficient argument for a government to interfere in the market. However, in line with public policy debates, the government often intervenes and acts to provide investment incentives. Dixit and Pindyck (1994) further study common policy intervention and its implication on investment. Governments may try to reduce price volatility by imposing price controls. Economists tend to emphasize scarcity and poor quality products as potential harmful side effects, consistent with the standard supply-and-demand framework. However, incorporating investment decisions under uncertainty makes the analysis more nuanced. By implementing a price ceiling, investment is discouraged, and firms wait to observe a higher level of demand before they act, meaning that the entry threshold will increase. As the ceiling is lowered, the long-run average price might increase, resulting in the opposite effect as the policy intended. While the ceiling introduces an upper limit, the price will on average be higher, due to the reduction in investment and the long-run supply. In the presence of options to invest, antitrust policies might act on false signals. Within the industrial organization literature, monopoly power and high barriers to entry are signaled by abnormally high profits combined with the lack of new entrants. These assumptions could be incorrect, and the industry is competitive with standard long-run expected returns. Similarly, observing prices below minimum average variable cost does not necessarily need to imply predatory dumping, but an incumbent that under volatile conditions keeps an out of the money option in the hope of a more beneficial state of nature in the future. However, all government interference is not suboptimal and the effect depends on the situation and the specific policy. Various kinds of taxation are highlighted to provide indirect risk sharing. For instance, trade tax may change the risk allocation between a firm and its subsidy.

2.6.1.3 Strategic Growth Option

The real option literature does not incorporate that early investment is associated with an increased ability to expand in the future, an advantage that can be explained as a growth option. In the real option literature, the effect of market structure is minimal, and deferring investment does not lead to a lost investment opportunity that instead is utilized by competing firms. The strategic growth option theory acknowledges that the commitment to irreversible investment has strategic effects under imperfect competition. Depending on the nature of the competition and the investment, the commitment might discourage entrants, enhance market share or increase profits. The initial investment can be seen as an investment in a capability that allows the firms to take better advantage of future growth. For example, the initial investment in a growth option can be a capability that reduces production costs leading to a cheaper expansion relative to the competition. Within this model, uncertainty has an ambiguous effect on investment. If the strategic advantage is strong, increased uncertainty incentivizes investment in growth options. Higher uncertainty implies more opportunity, in contrast to simply more risk. However, if the strategic advantage is weak, the reverse relationship is true (Kulatilaka and Perotti, 1998). Aligned with the strategic growth option theory is the *good versus bad news principle*, which implies that a firm can expand and utilize good news and contract and hedge against bad news. This mechanism will make firms more risk-seeking in an uncertain environment (Atanassov, Julio and Leng, 2015).

2.6.1.4 Strategic Net Present Value

The trade-off between making a long-term commitment or deferring investment when faced with uncertainty is one of the most complex strategic choices a firm makes. Smit and Trigeoris (2017) combine the real option theory with game theory to develop a strategic net present value framework that integrates the interplay between NPV, real options and strategic games. The strategic NPV provides a more complete representation of various components:

$$Strategic\ Net\ Present\ Value = [Direct\ NPV + Strategic\ value] + Flexibility\ value$$

In addition to the expected discounted cash flows, the strategic NPV also reflects the strategic value and the flexibility value under uncertainty. The strategic and flexibility values are in dynamic conflict and must be balanced; their relevance and role are context-dependent and change with various conditions of uncertainty and different information structures.

2.6.2 The Impact of Policy Uncertainty

Recent literature has reported that political uncertainty has real adverse effects on the economy. Governments can not only decrease uncertainty facing potential investors through different policies, but also increase uncertainty through the prospect of changing policies (Dixit and Pindyck, 1994). Rodrik (1991) states that policy uncertainty can act as a tax on investment; even if a reform is sensible, it might become damaging if shareholders within the economy have doubts regarding permanence.

Julio and Yook (2012) study policy uncertainty connected to elections and its impact on investment across 48 countries. Election outcomes are relevant for firms' decisions as the outcome has significant implications on industry regulation, trade policy, and taxation. Due to the potential endogeneity between uncertainty and economic growth, a recession itself is arguably generated by increased political uncertainty, making the impact that uncertainty has on investment complex to measure. The use of elections works as a natural experiment and allows one to disentangle some of the endogeneity between economic growth and political uncertainty. Furthermore, elections take place at different points in time across nations, allowing one to net out any global trends in firm investment. The empirical result shows that firms tend to reduce investment expenditures by an average of 4.8% in election years relative to non-election years. Across countries, the decline in investment is more extensive in countries with a less stable government and a higher ratio of government spending to GDP. In close elections, measured by voting results, the adverse reaction in investment is more prominent. Furthermore, firms' cash holdings increase by 4.3% on average in election years; this is consistent with the precautionary motive studied by Opler, Pinkowitz, Stulz and Williamson (1999). Publicly traded US firms with solid growth opportunities and risker activities tend to hold more cash. Further, aligned with precautionary motives, management tends to accumulate excess cash if the opportunity to do so is feasible (Opler et al., 1999).

For the US, Baker, Bloom, and Davis (2016) use firm level data and report that policy uncertainty is associated with higher stock price volatility, especially for firms with greater exposure to government purchases. Policy uncertainty is also connected to reduced investment and employment rates. By utilizing the PUI developed by Baker, Bloom and Davis (2016), Kang, Lee and Ratti (2013) examine the effect of policy uncertainty and find that it decreases firm investments in interaction with firm level uncertainty. This effect is higher for firms with higher firm level uncertainty. Furthermore, for the top 20% largest firms, policy uncertainty does not affect firm investment. Overall, policy uncertainty has the most considerable depressing effect for small firms with high stock volatility. Jens (2017) examines the link between policy uncertainty and investment by utilizing US gubernatorial elections as an exogenous variation in uncertainty. By performing a difference-in-differences analysis, the result indicates a 4.9% decline in the investment of firms with headquarters in states that has a gubernatorial election in the next quarter, compared to the investment of firms in states without an upcoming gubernatorial election. The damping effect is greater for smaller firms that are more geographically concentrated, firms with more investment opportunities, politically sensitive firms, and firms with high disinvestment costs. These subsamples of firms tend to be more affected and exposed to state policy changes. If a governor is reelected, investment tends to increase post-election; the increase is of the same magnitude as the pre-election decline, indicating that firms wait for the policy uncertainty to decline. If a new governor is elected, the overall investment for the following year remains lower. Furthermore, firms tend to postpone the issuance of debt and equity to post-election, and the issuance that does occur is less likely to be associated with the initiation of a high-intensity investment period.

Bhattacharya et al. (2017) examines 43 countries and investigates whether policy or policy uncertainty affects technological innovation. Patent data is used to capture innovation activities, while national election data is used as an exogenous event that affects policy uncertainty. The primary motivation to study innovation separately from other investments is the intangible and long-term nature of innovation, characteristics that may separate innovation from other forms of investments. Moreover, the economic factors that affect innovation differ from those affecting regular investment. The effect of policy uncertainty on capital investment can easily be measured, however, it is unclear how to measure the quality of capital investments. One can capture the quantity of innovation by counting patents and the quality by the number of citations a patent subsequently receives. Based on the spread of citations made across technology classes, one can also calculate the originality and riskiness of the specific patent. A multivariate regression analysis indicates that, on average, innovation activities are unaffected by which policy is in place. For the analysis, a country-specific standard was adopted, where each political party was assigned a political position corresponding to right, center, or left.

Within the US, both Democratic and Republican administrations initiate policies that aim to foster innovation, however, the focus and goals of specific policies differ between the two parties. Democrats' emphasis on specific identifiable national goals is often connected to safe and clean energy. The Small Business Innovation Research Program, which provides grants to new small firms, and the Advanced Technology Program, which provided cost-sharing grants to firms developing pre-competitive technologies, are also launched by democratic administrations. Democrats tend to create new programs that provide targeted resources to the private sector and subsidize early-stage innovation. On the other hand, republicans tend to focus on incentives with a general application, such as low corporate tax, tax incentives for R&D expenditures, and free trade regimes. The party lines are not completely strict, but the partisan differences make programs and policies for innovation fragile and subject to change, depending on political party control (Kahin and Hill, 2010). Atanassov, Julio, and Leng (2015) find little evidence that political regimes affect the R&D sensitivity to political uncertainty around the election cycle. However, the incumbent republican regime is on average associated with higher R&D over the entire sample.

In contrast to the real option theory, Vo and Le (2017) find a positive relationship between R&D and uncertainty, measured by idiosyncratic volatility of returns. The effect is greater for firms in competitive industries and where the product has less market power. The result is consistent with the strategic growth theory, where firms innovate more under uncertainty due to preemptive strategy motives. Directly connected to policy uncertainty, Atanassov, Julio, and Leng (2015) reports a positive relationship between firm level R&D and policy uncertainty. Firms tend to increase their R&D investment, defined by R&D expenditure to total assets, by an average of 4.6% in the year of US gubernatorial elections relative to non-election years. The effect is more prominent in politically sensitive industries as firms are more likely to face regulatory changes that affect firm operations. Consistent with the theoretical literature predicting increased R&D under uncertainty, the positive effect is more pronounced for hard-to-innovate industries, firms with higher growth options, and industries with high product market completion. Hard-to-innovate industries tend to have long R&D processes with high technical uncertainty; these mechanisms create competitive pressure to invest earlier. In addition, technical uncertainty cannot be eliminated by postponing the investment. The findings suggest that the effect of policy uncertainty depends on the properties of an investment and the market competition; the total effect of policy uncertainty on long-run economic growth is ambiguous.

In contrast, Bhattacharya et al. (2017) report that policy uncertainty harms innovation regarding the number of patents, citations, and originality. On average, innovation drops by 1.8% to 3.5% in the year following an election across all 43 countries. The negative effect is more extensive for patents with more citations, suggesting an adverse effect of policy uncertainty on innovation quality. The standard deviation of citations also decreases with elections which implies that elections dampen risk-taking in innovation. Furthermore, the negative effect is greater in more innovation-intensive industries. Overall, the result suggests that firms can adapt to different policies but postpone investment when unsure about the permanence of policies. Political compromise is hence seen as an essential factor for innovation.

By examining the relationship between policy uncertainty and innovation using cross-country industry data from 17 countries William and Fengrong (2022) find that policy uncertainty impedes innovation; patent counts, patenting entities, citations per patent, patent originality, and patent generality all decrease. High-tech intensive industries have high R&D expenditures and naturally higher risk associations. Periods of high policy uncertainty impedes innovation in these industries to a higher degree, suggesting that policy uncertainty reduces firms' risk tolerance. The effect is also more distinct in non-transparent industries with asymmetric information. Policy uncertainty amplifies information frictions leading to more severe problems connected to moral hazard, adverse selection, and misallocation of resources. The negative impact is also more pronounced in industries heavily dependent on external finance. Xu (2020) reports for a US sample that policy uncertainty decreases innovation due to increased cost of capital. The cost of capital channel is more prominent for firms with a higher exposure to policy uncertainty, financial constraints, or high dependence on external finance.

2.6.2.1 Uncertainty within Fiscal Policy

The stability of tax credits and budget adjustments acts as an implicit subsidy and incentivizes the investment of firms. In contrast, fiscal volatility shocks have significant disadvantageous effects on economic activity (Kang, Lee, and Ratti, 2013). Furthermore, the feature of policy processes is especially relevant within the US, where tax policy is frequently changed and discussed. Even after a tax legislation passes in Congress, months or even years of debate and modification will still follow. Shifting expectations and policy uncertainty do not only raise the real option threshold before committing to an investment, but lower the level of undertaken investment (Dixit and Pindyck, 1994).

Fernandez-Villaverde, Guerron-Quintana, Kuester and Rubio-Ramirez (2015) find a significant amount of time-varying volatility in the US taxes and government spending processes. Estimates of a vector autoregression of the US economy indicate that increased fiscal volatility results in lower capital income tax, output, consumption, household investment, working hours, and the price level falls for subsequent quarters. When the economy hits the lower bound of zero for the nominal interest rate, the effect on output is 15 times more prominent. Hassett and Metcalf (1999) identify tax policy as a significant source of uncertainty in the cost of capital for US firms, the tax policy for investment tax credits is especially underlined. Firms will delay or accelerate investment depending on perceptions regarding the probability and magnitude of tax changes. Models for the impact of tax policy uncertainty on investment results in the opposite effect depending on the nature of the stochastic process. Using a model where the uncertainty follows a Geometric Brownian Motion, increased tax policy uncertainty diminishes investments. In contrast, increased uncertainty can have the opposite effect if the tax policy is modeled as a stationary discrete jump process. The difference between the two models arises from the bounded and discrete nature of the jump process model, which affects the value of waiting.

2.6.2.2 Uncertainty within Monetary Policy

Monetary instability has a slowing effect on growth, which works by reducing investment efforts and lowering return to capital (Kormendi and Meguire, 1985). Historically, the Federal Reserve has not had any explicit inflation targets, which meant that the regulatory direction was somehow less defined. However, in 2012, the Federal Reserve released a statement detailing that the Federal Open Market Committee (FOMC), which is the Federal Reserve's decision-making body, had committed to an inflation target of 2%. The FOMC had expressed that they would be concerned if the inflation were to run persistently above or below its target (Board of Governors of the Federal Reserve System, 2012). Monetary policy has not been a big source of policy uncertainty in recent years. This may be due to the adoption of a fixed target in 2012, or alternatively, largely attributed to persistently low and negative interest rates (Baker, Bloom, and Davis, 2016).

The Federal Reserve has been below the inflation target for a number of years, which is partly attributed to the anchoring of the inflation expectations that may change with economic development, as well as current and past monetary policy. Anchoring refers to the insensitivity to incoming data. For instance, inflation expectations are said to be well-anchored if there is a shock to inflation that makes it spike above the public's long-run expectation, but the long-run expectations remain unchanged. On the contrary, expectations are poorly anchored if the long-run expectation changes considerably. With persistent inflation, the expectations have historically become unanchored, as seen in the inflation runs of the 1970s and 1980s, where the expectations rose with actual inflation, giving rise to the wage-price spiral (Bernanke, 2007). Arguably, the anchoring is dynamic and, to some extent, it changes with the uncertainty about the future economic situation. Gürkaynak, Sack, and Swanson (2005) found that long-run inflation expectations move in response to news about the economy, thus giving rise to the imperfectly anchored inflation expectations.

3 DATA

The final data sample consists of an unbalanced panel dataset consisting of 2 085 unique firms from January 1985 to December 2019. In total, the sample consists of 54 876 observations. The variable of interest is monthly patent applications by public firms, as patents are considered a representative indicator of innovation output coming from resource input (Hall, Jaffe, and Trajtenberg, 2001). We use the log of scaled patents as the dependent variable in this study, where this is given by patents applied for, scaled by the average number of patent applications by firms in the same month and technology class. This approach is similar to that of Hall, Jaffe, and Trajtenberg (2001), however, they use the patents granted as opposed to patent applications and consider patents to be matched if they are within the same year and technology class as opposed to month and technology class. We use patent applications to minimize the impact of the patent approval process, which otherwise introduces a lag. Moreover, we match patents by month and technology class in order to account for the time fixed effects in the sample with monthly observations.

3.1 Policy Uncertainty Index

We use the Policy Uncertainty Index (PUI), developed by Baker, Bloom and Davis (2016). The PUI has two appealing features: it is recorded on a monthly basis, and it may be decomposed into its constituent sources of uncertainty. The monthly data allows for the study of its impact on innovation at narrow time intervals, and thus opens up to the study of dynamic variation in innovation brought on by resource planning and a firm's effort to time the market (Baker and Wurgler, 2002). The decomposed index consists of economic, trade, fiscal and monetary policy, government spending, healthcare, national security, entitlement programs, regulation, financial regulation, and sovereign debt. Taxes are also a part of the decomposed index, but this may be considered a subgroup of fiscal policy. The reason for this additional decomposition is that fiscal policy has been a driving factor in the PUI in recent years, and that this has been largely attributed to policy related to tax (Baker, Bloom, and Davis, 2016).

3.2 Innovation Data

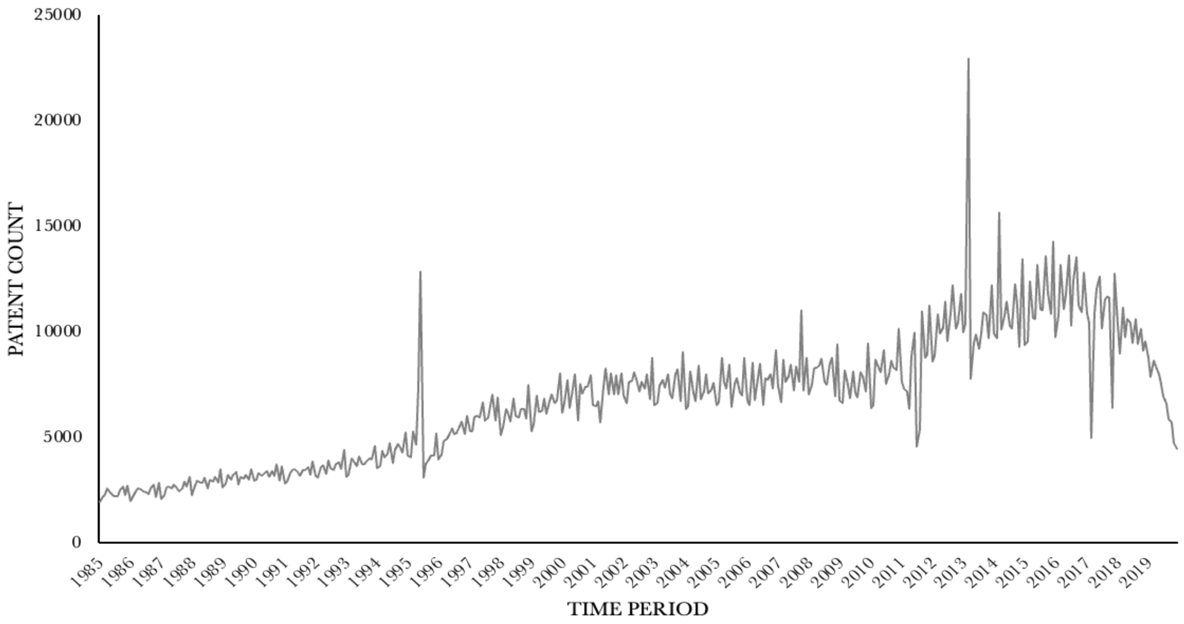
The patent data comes from the *USPTO Patentsview* database. The unique feature about this database is that it does not limit the data to that contained in their bulk-download options. It is possible to build and tailor a specific query that extracts exactly the variables of interest. Notably, these non-standard variables include inventor country, WIPO field and sector title, CPC category and data on the number of citations in which the patent has both received and made. Moreover, it is possible to only extract patent applications filed by public firms (that were public at the time their application was submitted), which is a feature we exploit to filter the data output. Importantly, although acquisitions occurred throughout the sample period, the patents were still assigned to the acquired rather than the acquiring firm and thus it was possible to consistently track innovation across firms despite of M&A activities during the period (Bernstein, 2015).

The application entries in the database were of varying quality and some contained entry errors. These errors could be a missing application date, missing inventor country, or missing data on the amount of citations made and the amount of citations received. As these would inhibit significant and meaningful calculations and inference, we removed observations where at least one of these were missing. Measures of scaled patents and scaled citations were calculated following the method of Hall, Jaffe, and Trajtenberg (2001). The scaled patent is calculated by scaling a single patent by the average patents of firms in the same month and technology class. The scaled citation is calculated by dividing the number of citations that a patent has received by the average number of citations of matched patents, which is a patent within the same month and technology class. The scaled originality and scaled generality measures were calculated following the method of Trajtenberg, Henderson, and Jaffe (1997) the measurements are scaled using the same approach as for the scaled patent and citations. Figure 2 shows the development of patent counts from 1985 to 2019. The patent count has generally increased over time, however, in 2001 it dropped and stagnated for a period until 2008. The financial crisis was hard on both private individuals and firms, and it is therefore not unlikely that firms opted to remove focus from R&D activities around this time to concentrate their resources elsewhere. There is a gradual uptrend after the turning point in 2009, where the patent count increases until the last few years of the sample. The decrease around 2019 indicates that the data is subject to truncation bias. Following Hall, Jaffe, and Trajtenberg (2001) we account for this bias by employing the log of scaled patents as the primary dependent variable as opposed to patent count.

Figure 2: Patent Count Over Time

The development of the patent count over time.

The figure provides a timeline of the monthly aggregated patent count for the time period January 1985 to December 2019.



After aggregating the measures of innovation monthly at the firm level, the resulting panel data is unbalanced. There are two sources of the imbalance in the dataset: firstly, the sample is categorized as a *rotating panel*, where some firms may drop in and later out of the sample due to incorporations or bankruptcies over the course of the sample period. Secondly, the firms may periodically leave and reenter the sample if they have periods in which they do not file any patent applications. Working with unbalanced data is common in the economics literature and is often a natural feature in different datasets. A rebalance of this would introduce a risk of *survivorship bias,* which arises when restricting the sample to firms that have been present for the entire sample period and leaving out the ones that have filed for bankruptcy. In turn, this would cause a skewness in the data in terms of the change in innovation in response to policy uncertainty and effectively create a bias in the result. The second source of imbalance may resemble that of *general attrition*, which occurs if the decision to exit and later reenter is based on factors that are systematically related to the dependent variable, even after conditioning on explanatory variables (Wooldridge, 2010). However, the second source of imbalance can be considered random in nature. According to the Leahy-Smith America Invents Act (2011), a patent application must be filed within one year of the first offer to sell an invention or within one year of first public use or disclosure. Hence, the application may be filed across a timeline that is contingent on various factors pertaining to individual firm choices. A random source of the fluctuation in the patent filing dates may be that of project duration. Assuming that a firm chooses to apply for its patents at project completion when its value materializes, the timeline of the project dictates this. If a project is completed earlier or later than the estimated time, this may cause the patent to be filed accordingly. Overall, we deem that it is sensible to use the naturally unbalanced dataset in this particular study, as the act of rebalancing would introduce undesired side effects.

3.3 Control Variables

The independent variables originate from miscellaneous sources. There are two main categories of controls in this paper, namely firm and macroeconomic controls. The firm-related controls are selected based on prevalent arguments and findings in the corporate finance theory, following Kaviani et al. (2020) and Matray (2020). The macroeconomic controls are carefully selected to capture and reflect the full extent of the macroeconomic development in the US from 1985 to 2019. The following section consists of source reference, description of the included variables, and, where applicable, an outline of the calculations involved.

As a general note on macroeconomic controls, we have reported these at the most detailed level possible. Since the innovation data is monthly, we opted for monthly controls whenever available. Moreover, the patents are filed by companies in different states, which also highlights the need to control at a state level, since local factors could drive innovation. Hence, we have used state-level data whenever relevant and possible.

3.3.1 Variable Description

Table 1: Variable Description

	Source	Description	Calculation
Dependent variable			
Scaled patent (l.s_pat)	USPTO Patentsview Database	The primary innovation measure, which captures time and technology class fixed effects on a monthly basis.	A patent is divided by average patents per firm in the same month and technology class and is aggregated at firm level. The variable is then logged.
Patent count (patent_count)	USPTO Patentsview Database	The secondary innovation measure used as robustness in main regression.	Raw patents are counted and aggregated at firm level.

Table 1: Variable Description (continued)

	Source	Description	Calculation
Variable of interest			
Log of PUI (l.PUI_US)	BBD webpage	The Policy Uncertainty Index reflects the level of economic uncertainty brought on by political uncertainty and is provided monthly at a federal level.	Log transformation of the Policy Uncertainty Index.
Decomposition of Policy Uncertainty			
Log of Fiscal PUI (l.Fis_PUI_US)	BBD webpage	Decomposed part of the Policy Uncertainty Index pertaining to fiscal policy uncertainty. This is provided monthly and at a federal level.	Precalculated value that is a part of the general PUI, but also separately specified.
Log of Monetary PUI (l.Mon_PUI_US)	BBD webpage	Decomposed part of the Policy Uncertainty Index pertaining to monetary policy uncertainty. This is provided monthly and at a federal level.	Precalculated value that is a part of the general PUI, but also separately specified.
Firm controls			
Log of total assets (l.at)	COMPUSTAT	The total assets of a firm reflects its relative size and is provided on an annual basis.	Log transformation of total assets.
Book to market (bm)	COMPUSTAT	The book value compared to the market value reflects a firm's value and is provided on an annual basis.	Common shareholder's equity divided by the market capitalization.
Cash to assets (ch_at)	COMPUSTAT	Cash to asset ratio reflects how much of a firm's cash is tied up in assets and is provided on an annual basis.	Cash and cash equivalents divided by total assets.
Debt to equity (de_ratio)	COMPUSTAT	Debt to equity ratio is an indicator of a firm's gearing and overall financial health and is provided on an annual basis.	Total debt including fixed payment obligations divided by shareholder's equity.
Standard deviation (sdev)	CRSP	The standard deviation indicates the level of risk in a firm and is provided on a monthly basis.	A pre-calculated measure of the deviation of current share price from its mean.
Log of R&D expenses to assets (l.r&d _at)	COMPUSTAT	R&D expenses is an indicator of the funds that a firm puts towards innovation.	Log transformation of R&D expenditure scaled by total assets.
Macroeconomic controls			
Change in trade balance (Δt_balance)	Census database	The US trade balance indicates the net difference between imports and exports, which results in either a surplus or deficit. The data is yearly until 1992, and monthly thereafter, and is reported at a federal level.	The change in the country's imports subtracted from its exports.

Table 1: Variable Description (continued)

	Source	Description	Calculation
Macroeconomic controls			
Change in college enrollment (Δenroll)	Census database	College enrollment is composed of 14 years olds or above enrolled in either undergraduate programs, graduate programs or community college. The data is yearly at a federal level.	The change in the total college enrollment.
Change in federal R&D (Δfed r&d)	American Association for the Advancement of Science	The federal R&D expenditure indicates the total amount of funds in which the government allocates to furthering R&D in society. The data is yearly at a federal level.	The first difference of total R&D expenditure.
Change in federal deficit/surplus (Δfed sur_def)	Federal reserve banks FRED database	The federal deficit or surplus indicates the profitability of the US and in conjunction with the GDP this reflects its overall financial health. The data is yearly at a federal level.	The change in a pre-calculated measure composed of US revenues minus total spending.
Change in gross domestic product (Δgdp)	Federal reserve banks FRED database	Gross domestic product indicates a country's growth rate and the size of its economy. The data is quarterly at a federal level.	The change in a pre-calculated measure composed of US revenues minus total spending.
Change in higher education spending per capita (Δhigh_edu)	Urban Institute (Census database)	The spending on higher education per capita reflects the amount of money that the government invests in furthering the education system. The data is yearly at a state level.	Change in the total spending on education divided by the population at the time.
Change in long term interest rates (Δltint)	OECD data	The long term interest is implied by the prices at which bonds are traded on the financial market and reflects investment incentive. The data is monthly at a federal level.	The change in price of a bond with a 10-year maturity.
Recession (rec)	NBER website	A recession is a state of nature characterized by a significant decline in economic activity that is spread across the economy and lasts more than a few months. The data is monthly at a federal level.	This is a dummy variable equalling one in the historical periods that have been classified as contractionary and zero otherwise.
Change in revenue per capita (Δrev)	Urban Institute (Census database)	The revenue per capita reflects the ability to generate money through taxes, fees and other charges. The data is yearly at a state level.	The change in revenue divided by the population at the time.
Unemployment (unemp)	BLS Beta Labs for the United States Department of Labor	The level of unemployment indicates the ability of the US workers to find jobs and reflects the amount of human resources that are put to use. The data is monthly at a state level.	The number of workers as a percentage of the total working population that are able and willing to work while being unemployed.

3.3.1.1 Sign Predictions for the Effect on Innovation

Policy Uncertainty Index: the coefficient is expected to be *negative*. The main hypothesis of this study is that an increase in policy uncertainty will cause a decrease in innovation. As the policy-related economic uncertainty in society increases, we believe that firms may opt to redirect their resources elsewhere due to a tougher economic climate, or that they will attempt to time the market and hold back their innovation until a more stable period.

Fiscal Policy Uncertainty Index: the coefficient is expected to be *negative*. Fiscal policy has been a main driver of policy uncertainty in recent years, primarily due to the effect of tax policy (Baker, Bloom, and Davis, 2016). The stability of tax credits, as a component of fiscal policy, incentivizes continuous investment in the firm, however, the volatility shocks to fiscal policy have significant adverse effects on economic activity (Kang, Lee, and Ratti, 2013). Changing expectations of the future and policy uncertainty itself, raise the real option threshold before committing to an investment and lower the amount of investment undertaken (Dixit and Pindyck, 1994). Moreover, Hassett and Metcalf (1999) identify tax policy as a significant source of uncertainty in the cost of capital for US firms, and therefore it is expected that firms delay investment as fiscal policy uncertainty increases, resulting in a lower level of innovation.

Monetary Policy Uncertainty Index: the coefficient is expected to be *ambiguous*. According to Baker, Bloom, and Davis (2016), monetary policy has not been a big source of policy uncertainty in recent years. This may be due to the changing strategy of the Federal Reserve, as they set a target inflation rate. An explicit target rate allows the public to develop an expectation of the long-run inflation rate, which ultimately is an important determinant of the actual inflation. Hence, one can argue that monetary policy uncertainty will not affect innovation, as the direction and long-run goal of the policy is clear. However, the monetary policy might have different implications on innovation depending on the anchoring of inflation expectations. If inflation expectations are poorly anchored, the expectations change considerably with the monetary policy shocks and may introduce a spiraling effect that causes persistence in inflation. Gürkaynak, Sack, and Swanson (2005) found that long-run inflation expectations move in response to news about the economy, which implies that inflation expectations are imperfectly anchored. Effectively, this implies that the anchoring of inflation expectations is reflected in the monetary policy uncertainty, as the decomposed index is based on newspaper content. In addition, Kormendi and Meguire (1985) found that monetary instability causes reduced investment efforts and lower return to capital. Hence, the overall effect is ambiguous and difficult to determine.

Assets: the sign of the coefficient is *ambiguous*. A high level of assets indicates that a firm has built up a lot of value in the form of either tangible or intangible assets and is therefore a direct measure of size. Referring to the arguments of Schumpeter from 1911 and 1942, the author argued that new firms have an incentive to innovate in order to disrupt a market and gain market share through creative destruction, but also that established firms have an equally strong incentive to innovate and thereby maintain their current market power. Due to this, it is indeed ambiguous whether large and established firms or small firms would produce a higher level of innovation output.

Standard deviation and book to market: the coefficients are expected to be *positive*. Standard deviation is a measure of the volatility of a firm's stock return and thus an indicator of risk. The book to market ratio reflects a firm's book value in relation to its market value and thereby indicates that investors are willing to invest in the firm at a premium. This is the case when there is a high potential for future growth and therefore a low book to market ratio is associated with growth firms (Fama and French, 1992). Growth firms are characterized by having high volatility, as the relative uncertainty about their future performance and profitability is greater than it is for a more established firm. Moreover, there may also be a higher level of volatility in particular industries. For instance, Gharbi, Sahut, and Teulon (2014) found that the tech industry is characterized by having high volatility compared to other industries. According to the authors, the tech industry is also an important driver of innovation, and therefore it is hypothesized that a higher standard deviation results in more innovation.

Cash to assets: the coefficient is expected to be *ambiguous*. Jensen and Meckling (1976) developed a theory of agency problems associated with free cash flow, which arises from the separation of ownership and control between the shareholders and manager. Managers have an incentive to engage in value destroying behavior by taking on risky and potentially unprofitable investments in order to achieve power and prestige associated with diversification and effectively engage in empire building (Jensen 1986, Stulz 1990). This undertaking of "pet" projects for the manager is likely to result in an unorganized effort towards innovation that may not produce any real or tangible results. Effectively, when a firm has a higher cash to asset ratio, it is more likely to be exposed to the agency problem of free cash flow. Thus, it is likely that having a higher cash to asset ratio would cause the managers to decrease the innovation output of the firm due to the inefficiencies of the free cash flow problem. Alternatively, Keynes (1936) introduced a series of motives for holding cash, which has since been widely covered in the literature. Opler et al. (1999) focused on this in their paper on the determinants and implications of corporate cash holdings. The authors propose two primary reasons for holding cash. The first is the *transaction cost motive*, which arises when a firm holds cash in order to avoid inefficient liquidation of assets in order to make payments. The second is the *precautionary motive*, which refers to the action of holding more cash in order to prevent cash shortfalls that would cause a firm to turn away an otherwise profitable investment in the event that other sources of funding are unavailable or excessively costly. This would indicate that a higher level of cash to assets is associated with more innovation.

R&D expenditure to assets: the coefficient is expected to be *positive*. When a firm discloses its R&D expenditure, this may be an indication of the resources that are put towards innovation. It is expected that firms with a higher R&D expenditure in relation to their assets have a higher level of innovation.

Debt to equity: the coefficient is expected to be *negative*. Debt to equity is a measure of a firm's gearing and thereby their current debt capacity. Financial institutions look to this indicator of a firm's financial health and therefore, if the debt to equity ratio is too high, it may put a firm at risk of not being able to finance its innovative activity through external sources of financing. Hence, it is expected that a higher debt to equity implies lower levels of innovation.

Trade balance: the coefficient is expected to be *ambiguous*. The trade balance denotes whether the US has a trade deficit or trade surplus. It is difficult to define a deficit in the trade balance as strictly negative or positive. Generally, it is more insightful to consider the trade balance contemporaneously with other measures, or study its development over time. For instance, if the US has higher exports than imports (surplus) this may be positive, as the country is producing domestically and then selling it off. For the reverse argument, if the import is higher than the export, this implies that the country imports in order to consume something domestically and thus may be considered a negative thing. However, it is also possible that these imported goods are vital to further growth and production domestically, and thus, one may argue that the perception of a deficit depends on the use and application of the imported goods. Thus, the effect of a change in the trade balance on innovation depends on the context.

GDP: the coefficient is expected to be *positive*. The GDP is a measure of the economic growth and performance of the US. A positive increase in GDP indicates higher growth than in the previous period. With respect to Solow (1956), growth is largely dependent on technological advancement and innovation and therefore it is expected that a higher level of growth and productivity results in a higher level of innovation.

College enrollment and higher education spending: the coefficients are expected to be *positive*. College enrollment indicates the number of individuals that are enrolled in a college program at a US institution and the higher education spending per capita reflects the amount of resources put towards higher education. Both variables provide an indication of the resources devoted to innovation and the flow of labor to the R&D sector. Hence, it is expected that a higher college enrollment and higher education spending is associated with a higher level of innovation.

Federal R&D expenditure: the coefficient is expected to be *positive*. The federal expenditure on R&D in society is partly reflected at a firm level. The funds allocated towards R&D at a federal level dictate the policies that may be implemented. For instance, this spending funds initiatives like investment tax credits or direct subsidies for particular types of innovation. Effectively, it is expected that a greater positive change in R&D expenditure at a federal level leads to a higher degree of innovation.

Federal surplus/deficit: the coefficient is expected to be *negative*. Historically, the US mostly reports a deficit at the end of a fiscal year. Having less of a deficit may imply that there is more room to invest in growth and innovation, which a sustained high deficit may eventually put a stop to. Due to this, it is expected that a higher change in the deficit (deficit becoming larger) is associated with less innovation.

Long term interest rates: the coefficient is expected to be *negative*. The long term interest rate reflects the cost of financing and is considered the leading indicator that dictates the overall investment incentive in society. If financing is cheaper, this will incentivize investment and therefore a positive change in the long term interest rate implies a lower level of innovation.

Recession: the coefficient is expected to be *negative*. A recession is characterized by a significant decline in economic activity that is spread across the economy and lasts more than a few months. By definition, it is expected that there will be less activity in these periods and therefore a recessionary period would be associated with less innovation.

Revenue per capita: the coefficient is expected to be *positive*. The revenue per capita in a state, provides an indication about the general economic condition in that state. An increase in revenue per capita implies better economic conditions, and provides the state with a better opportunity to increase the living standards of the population. Koo, Choi, and Park (2020) find that welfare spending has a strong impact on marginal effects of R&D investment, implying that welfare spending can influence the level of innovation. Although the revenue per capita is not directly reflective of the level of welfare spending, it may provide an indication of the ability to spend on welfare relative to other states. Hence, it is expected that a higher level of revenue per capita is associated with more innovation.

Unemployment: the coefficient is expected to be *negative*. Unemployment rate reflects how much of the able population at a working age are actually working. Unemployment has a direct and an indirect effect on innovation, which operates in the same direction. Unemployment directly indicates the amount of human resources that are not employed and thereby cannot contribute to the productivity in the economy. Moreover, unemployment is expensive for a country, as the unemployed may be eligible for costly government benefits and social security that imposes extra costs in a society. In turn, it is expected that a higher level of unemployment results in lower innovation.

3.3.2 Merging Databases

A significant challenge of the data process has been the merge between the innovation data and the *Compustat* and *CRSP databases*. The merge involved a two step process: first, merging the Compustat and CRSP data, and second, merging that data into the USPTO Patentsview data. The initial merge of Compustat and CRSP required the use of the pre-merged Compustat and CRSP database. Obtaining the Compustat data from the linked database allowed the bridging of that data to the CRSP data through a unique identifier for historical observations.

The merge between the firm controls coming from the Compustat and CRSP data and the innovation data from USPTO was a limiting factor in terms of retaining observations. Existing literature has accentuated and highlighted the challenges associated with merging patent data with information from other databases. We follow the approach of Hall, Jaffe, and Trajtenberg (2001) by merging via the assignee organization names. The difficulty of performing a merge via the names is that these are subjective and considered a free-text field on the patent applications. Thus, these are not necessarily consistent even though it may be the same firm that exists in the firm control data. To increase the likelihood of a successful merge, Hall, Jaffe, and Trajtenberg (2001) performed a series of transformations on the assignee organization name, which included removing special characters, spaces, commas, periods and making everything lowercase. The resulting string would then be the link between the two datasets. Implementing this partial solution matched the most obvious and correctly spelled firms, however, it left the misspelled firm names unmatched. We were inspired by the approach of the data project by Liu and Mei (2019) to add an additional step in the matching procedure. The unique contribution of this paper is a new matching approach that uses machine learning to match companies based on top 50 Bing searches resulting in a particular firm. Unfortunately, the data is not publically available and therefore it is not possible to follow their exact approach. However, since the authors' method was based on identification and matching based on similarity, this led to the approach of using fuzzy matching to match the unmatched firms in the patent data with the firms in Compustat. The initial number of unmatched firms in the patent data was approximately 172 000, however, after using fuzzy matching and setting the similarity score to 93% around another 7 000 companies were matched. Since the similarity score was 93%, not all the matched firms were actual matches, and therefore this required a manual look-through in order to separate out the actual matches. In the end, this resulted in approximately another 1 000 firms entering the final sample.

3.4 Supplemental Data

The supplemental data section outlines the variables and databases used for the supplemental tests and investigations in this paper. The supplemental analyses pertain to the following topics: the quality of innovation, cross-sectional firm and industry characteristics, sensitivity of innovation, and causality of policy uncertainty. Firstly, the measures of innovation quality aim to investigate if some types of innovation are more exposed to policy uncertainty than others. This is investigated through three types of innovation measures, that indicate the relative impact and novelty of innovation. Secondly, the sample is split into a series of subsamples depending on firm and industry characteristics in order to dissect the main result and understand its drivers, and hence, investigate the characteristics of firms and industries whose innovation is impacted more by increasing policy uncertainty. The analyses are conducted based on measures of firm size, financial constraint, cash holdings, lobbying activity, and industry regulation. The measures of financial constraint aim to establish whether constrained firms are more exposed to policy uncertainty through the use of three different measures. The other firm and industry characteristics under investigation are outlined and covered in detail in Table 2. Thirdly, the sensitivity of innovation refers to the study of the relationship between innovation and the change in policy uncertainty, where this change is interacted with a dummy variable indicating if there is a relatively high level of policy uncertainty at the time of change. Lastly, there is a need to establish causality between innovation and policy uncertainty. The PUI measure may indeed be contaminated by economic uncertainty that is unrelated to policy and thereby the PUI may not be the most appropriate measure. We attempt to establish causality through the use of a series of alternative measures to capture policy uncertainty.

3.4.1 Additional Variable Description

Table 2: Additional Variable Description

	Source	Description	Calculation
Measures of innovation quality			
Scaled citations	USPTO Patentsview Database	Scaled citations reflect the number of citations that a patent received following its approval, scaled by the average citations received by patents in the same month and technology class, thus reflecting the relative impact.	Sample is split by the median scaled citation score, where a scaled citation score above the median corresponds to a relatively higher level of impact.
Scaled generality	USPTO Patentsview Database	Scaled originality reflects how many different technology classes a patent cites relative to patents in the same month and technology class, thus reflecting the relative novelty.	Sample is split by the median scaled originality score, where a scaled originality score above the median corresponds to a relatively higher level of novelty.
Scaled originality	USPTO Patentsview Database	Scaled generality reflects how many different technology classes a patent is cited by relative to patents in the same month and technology class. It indicates an innovation's influence on future innovation, thus reflecting the relative impact.	Sample is split by the median scaled generality score, where a scaled generality score above the median corresponds to a relatively higher level of impact.
Financial constraint			
KZ score	COMPUSTAT	This measure was developed by Lamont, Polk, and Saa-Requejo (2001) as an extension of the work of Kaplan and Zingales (1997). It captures a firm's level of constraint through a score generated from its combined performance in five different accounting measures.	Sample is split by the median KZ score, where a KZ score above the median corresponds to a relatively higher level of financial constraint.
Debt to asset ratio	COMPUSTAT	Debt to asset ratio captures the leverage of a firm by denoting how much of a firm's assets are financed with debt	Sample is split by the median debt to asset ratio, where a debt to asset ratio above the median corresponds to a relatively higher level of financial constraint.
Interest coverage ratio	COMPUSTAT	Interest coverage ratio reflects how many times a firm would be able to pay its current level of interest.	Sample is split by the median interest coverage ratio, where interest coverage ratio above the median corresponds to a relatively lower level of financial constraint.
Cash holding motives			
Cash to assets ratio	COMPUSTAT	Cash to asset ratio reflects the level of cash relative to the assets in a firm and is provided on an annual basis.	Sample is split by the median cash to asset ratio, where a cash to asset ratio above the median corresponds to a relatively higher level of precautionary motives.

Table 2: Additional Variable Description (continued)

	Source	Description	Calculation
Other firm and industry characteristics			
Firm size	COMPUSTAT	The asset value is a reflection of the relative size of a firm, as this indicates the total value in a firm as generated by equity and liabilities.	Sample is split by the median asset value, where an asset value above the median corresponds to a relatively larger firm.
Lobbying	Open Secrets database	Indicates if a firm attempts to influence the voting decision of legislators or the government.	Sample is split by firms that have made a monetary contribution at any point in time during the sample period and firms that have not made a contribution.
Regulation intensity	QuantGov database	Text based measure that captures the restrictiveness in the Code of Federal Regulation for specific industries.	Sample is split by the median regulation intensity, where regulation intensity above the median corresponds to a relatively higher level of restrictiveness at the industry level.
Sensitivity of Innovation			
Change in log PUI x high PUI dummy (Δl.PUI_US x PUI_high)	Webpage BBD	Used to reflect the state of the nature in terms of policy uncertainty in order to test the sensitivity to changes in policy uncertainty at higher levels of the PUI.	A dummy equalling one if the PUI is above the median for the sample period and zero otherwise, which is interacted with the change in the PUI.
Alternative measures of Policy Uncertainty			
Canadian PUI (PUI_CA)	Webpage BBD	Used to filter out the part of the US PUI that is associated with general concerns about economic conditions and thereby resulting in residuals that aim to reflect a more representative measure for economic policy uncertainty.	Pre-calculated value of the Canadian PUI.
Relative legislative power	Web Pages of the Senate and the History, Art & Archives, United States House of Representatives	The legislative power indicates the voting power that the Democratic and Republican Parties have in terms of the number of seats in the House and Senate. This reflects the level of opposition that may be expected in a law-making process. The legislative power is used as an IV estimator for the US PUI.	Calculated as the absolute value of the percentage difference in the share of republican and democratic combined seats in the House and Senate, respectively. The value is multiplied by -1 since we expect lower values to lead to higher uncertainty.
Polarization	Voteview: Congressional Roll-Call Votes Database	The level of polarization indicates how different the political views of the Democratic and Republican Parties are. The polarization variable is used as an IV estimator for the US PUI.	Calculated as the average polarization in the House and Senate based on the party mean difference.

Table 2: Additional Variable Description (continued)

	Source	Description	Calculation
Alternative measures of Policy Uncertainty			
Election (3 months)	US Election Atlas	Elections occur every four years and are associated with increased uncertainty regarding future economic policy.	A dummy equalling one for the month of an election and up to three months prior to an election and zero otherwise.
Election (5 months)	US Election Atlas	Elections occur every four years and are associated with increased uncertainty regarding future economic policy.	A dummy equalling one for the month of an election and up to five months prior to an election and zero otherwise.

3.4.1.1 Sign Predictions for the Relation between Policy Uncertainty and Innovation

3.4.1.1.1 Measures of Innovation Quality

Scaled citations and scaled generality: the coefficient is expected to be *more negative* for firms with a higher level of scaled citations or scaled generality. Scaled citations measure of how many citations a patent has received relative to patents in the same month and technology class. Scaled generality refers to the extent to which a patent is cited by distinct technology classes relative to patents in the same month and technology class. Both the scaled citations and the scaled generality measure the relative impact of a patent. According to Trajtenberg, Henderson, Jaffe (1997) more citations is likely to equate to a wider coverage of technology classes, hence we expect similar results for scaled citations and scaled generality. In times of uncertainty, it may not merely be the quantity of innovation that is impacted, but also the nature of the innovation itself. According to Bhattacharya et al. (2017) firms under political uncertainty undertake less risky innovations, resulting in fewer influential patents. Hence, it is expected that the innovation of firms with scaled citations or scaled generality above the median is more affected by policy uncertainty.

Scaled originality: the coefficient is expected to be *more negative* for firms with a higher level of scaled originality. Scaled originality refers to the extent to which a patent cites distinct technology classes relative to matched patents in the same month and technology class. Thus, this indicates the novelty of a patent, as a highly original patent incorporates various innovative elements from across different fields in order to create something entirely new. As reported by Bhattacharya et al. (2017), firms tend to produce fewer, and less original, patents in case of policy uncertainty. Hence, it is expected that the innovation of firms with scaled originality above the median is more affected by policy uncertainty.

3.4.1.1.2 Measures of Financial Constraint

KZ score: the coefficient is expected to be *more negative* for firms with a higher KZ score. The KZ score captures the level of financial constraint of a firm through a specific combination of five different accounting variables that provide an indication of its ability to finance projects and make interest payments. A higher KZ score indicates that a firm is more constrained. A central part of growth and innovation is the ability to finance investments when the opportunities arise. A constrained firm may be more vulnerable to political uncertainty, as they do not have the same financial stability as unconstrained counterparts. Hence, it is expected that the innovation of firms with a KZ score above the median in the sample are more impacted by policy uncertainty (Lamont, Polk, and Saa-Requejo, 2001).

Debt to asset ratio: the coefficient is expected to be *more negative* for firms with a higher debt to asset ratio. A firm with a high debt to asset ratio is considered constrained. The debt to asset ratio is a measure that financial institutions look at when evaluating if a firm is eligible for a loan. It is not necessarily an indicator that these institutions view in isolation, however, it provides an indication of its current debt level relative to its assets and thereby also the amount of collateral that the firm may be able to provide. As for the KZ score, the intuition here is that the innovation of a firm with a debt to asset ratio above the median is expected to be more impacted to policy uncertainty (Arugaslan and Miller, 2006).

Interest coverage ratio: the coefficient is expected to be *less negative* for firms with higher interest coverage ratio. The interest coverage ratio reflects a firm's capacity to take on more debt in terms of being able to repay its interest. Firms with a higher interest coverage ratio are considered unconstrained. With policy uncertainty, a firm with a higher interest coverage ratio may be more adaptive and flexible, and effectively able to withstand economic shocks coming from policy uncertainty. Thus, it is expected that the innovation of firms with an interest coverage ratio above the median are less impacted by policy uncertainty (Kaplan and Zingales, 1997)

3.4.1.1.3 Cash Holding Motives

Cash to assets: the coefficient is expected to be *less negative* for firms with a higher cash to assets ratio, according to Keynes (1936) and Opler et al. (1999) due to the transaction cost and the precautionary motive. However, the coefficient is expected to be *more negative* for firms with a higher cash to assets ratio, according to Jensen and Meckling (1976) due to agency problems associated with free cash flow. Overall, the difference between the coefficients is *ambiguous*.[1]

3.4.1.1.4 Other Industry and Firm Characteristics

Firm size: splitting the sample by firm size is expected to have an *ambiguous* effect on the coefficient. According to Schumpeter (1911, 1942), new firms have an incentive to innovate in order to become larger and more established. Aside from the value creation that occurs when becoming a more established firm, this also implies that the firm has better access to funds and resources that can support the business. Conversely, the small firm does not yet have these tools to support itself in difficult times, and thus, one might expect that the innovation of small firms is impacted more by increased policy uncertainty, consistent with Kang, Lee and Ratti (2013) and Jens (2017) findings that policy uncertainty has the most damping effect on small firms' investment. On the other hand, large and established firms also have a strong incentive to innovate in order to maintain market power (Schumpeter, 1911, 1942). As implied earlier, large firms tend to have better access to funds and resources, which allow for selective behavior and provide the ability to time the market. This is consistent with Bhattacharya et al. (2017), arguing that firms postpone investment in case of increased policy uncertainty. Furthermore, as William and Fengrong (2022) reported, policy uncertainty amplifies information frictions that enlarge problems connected to moral hazard, adverse selection, and misallocation of resources which are more prominent in larger firms. Effectively, this may indicate that the innovation of large firms is more impacted by increased policy uncertainty.

Lobbying: the coefficient is expected to be *more negative* for lobbying firms. As reported by, Akey and Lewallen (2017), firms that are sensitive to policy uncertainty have higher incentives to make political contributions. Firms that engage in lobbying activities motivate this because they have a special interest in favoring a particular outcome. It may be an indication that there are certain states of nature where a firm is unfavored and that it therefore attempts to avoid this situation. Having more certainty regarding future states of nature may be important from an investment and innovation perspective. For example, a firm within the renewable energy industry may be dependent on particular subsidies in order to develop new technology that can make the freight and installation of wind turbines more

[1] We refer to the cash to assets paragraph in section 3.3.1.1 Sign Predictions for the effect on innovation, for a more detailed description of the theories.

environmentally friendly. In effect, the signaling value of engaging in lobbying activities implies that lobbying firms are more exposed to policy uncertainty.

Regulation intensity: the coefficient is expected to be *more negative* for highly regulated firms. Government regulations affect almost all industries, but to a different extent, both across industries and time. Davis (2017) reports that the US economic policies have become less predictable, and that the regulatory system has increased in scale, scope, and complexity over recent decades. The Code of Federal Regulations (CFR) compiles all federal regulations effective each year. Over the past 56 years, the CFR expanded by a factor of eight. With nearly 180 000 pages, the CFR contains about one million commandments in the form of "*shall*", "*must*". "*may not*", "*prohibited*", and "*required*". However, some legislation may only impose restrictions on specific industries. A firm in a regulated industry may need to find alternative and costly ways of achieving its objectives. If the regulation intensifies as a direct effect of economic shocks coming from policy uncertainty, this type of firm is more susceptible to the consequences and thus is likely more exposed to policy uncertainty.

3.4.1.1.5 Sensitivity of Innovation

Change in log PUI x high PUI dummy: when combining the interaction term change in log PUI x high PUI dummy with the change in log PUI the effect is generally expected to be *negative*. Furthermore, the effect is expected to be *more negative* for large compared to small firms. The effect indicates the sensitivity of innovation to changes in policy uncertainty at times of high policy uncertainty. In their annual High Growth Study (2021), Hinge Research Institute found that high growth firms are thriving under uncertainty. While growth firms are not synonymous with large firms, a vast amount of literature finds that there is a tendency for firms that experience the most growth to be smaller in size and younger than firms with less growth due to diminishing returns to scale (Evans, 1987, Hart, 2000, Klette and Griliches, 2000, Klette and Kortum, 2004, Lotti, 2007, Coad, Segarra, and Teruel, 2016). Previous literature has found that young firms are likely to have better failure-resilience capability (Audia and Greve, 2006, Desai 2008, Coad, Segarra, and Teruel, 2016), which may allow them to thrive relatively more under uncertainty. Hence, it is expected that small firms are less sensitive to changes in policy uncertainty at high levels of the PUI compare to large firms. Moreover, in environments characterized by low policy uncertainty, it is expected that small firms are also less sensitive to changes in policy uncertainty, as the level of innovation tends to stay at a consistently high level regardless of policy uncertainty (Hinge Research Institute, 2021).

3.4.1.1.6 Alternative Measures of Policy Uncertainty

Canadian PUI: the policy uncertainty estimated with residuals, relationship between innovation and policy uncertainty is still expected to be *negative*. The Canadian and American economies are inherently connected in terms of trade, as they have one of the largest trade relationships in the world. Due to this, many of the economic shocks that affect one country should also affect the other. On the contrary, shocks to policy uncertainty are expected to be more contained within the borders of a country (Kaviani et al., 2020). Thus, it is expected that the residual of regressing the US PUI on the Canadian PUI captures pure economic policy uncertainty and effectively that this robust measure will result in a lower level of innovation.

Relative legislative power: the policy uncertainty estimated with a relative legislative power instrument, relationship between policy uncertainty and innovation is expected to be *negative*. The US has a political system with an important interplay between having the power in the Senate and the House. If one party has the ultimate legislative power in both the House and the Senate, then one may expect there to be less policy uncertainty. The intuition is that if the president of the United States proposes a new bill, then this has to pass through the House and the Senate that may opt to vote against the bill if they are not favoring the president. Ultimately, less legislative power results in relatively more friction and resistance, and therefore it is expected that this results in less innovation (Gulen and Ion, 2016, Kaviani et al., 2020)

Polarization: the policy uncertainty estimated with a polarization instrument, relationship between policy uncertainty and innovation is expected to be *negative*. The relative polarization between the Democratic and Republican Parties may dictate the parties' ability to split the difference through mutual understanding of political views. A highly polarized political climate may result in more policy uncertainty, since the parties may find it harder to reach consensus. Due to this, it is expected that a higher level of polarization leads to less innovation.

Election: the coefficient is expected to be *negative*. Uncertainty regarding economic policy tends to be elevated around elections, as the future leader and decision-maker is to be elected, which consequently is important for the trajectory of the political climate and stability for the next four years. The timing of elections is exogenous, since they are predetermined every four years, and this makes it a suitable measure of policy uncertainty. Due to the uncertainty leading up to these events, it is expected that the innovation will be lower in the period before and on the election date.

3.4.2 Measuring Regulation Intensity

Government regulations impact most industries to some extent, but the relative influence varies greatly both across industries and time. McLaughlin, Nelson, Powers and Warlick (2021) define a measure of regulation intensity called *RegData*, which is publicly available. RegData is a text-based measure that attempts to quantify the regulatory laws that affect particular industries by performing a content analysis. The authors construct the measure by counting the number of binding constraints in the *Code of Federal Regulations*, where these binding constraints are defined as restrictions including the binding words "*shall*", "*must*", "*may not*", "*required*", and "*prohibited*". Here, the actual volume of text is not of importance, but rather the determining factor becomes the actual restrictiveness expressed in the text, based on the definitions of the authors. The authors then proceed to estimate the probability that a given industry is targeted by regulation in a given year, effectively resulting in an annual and industry specific index of regulation intensity. The index covers a subset of NAICS industries, based on two, three, four or five-digit codes. Since the index has time variation on an annual basis across industries, this allows for exploiting the cross-sectional variation in our test.

Due to our sample distribution, we primarily rely on four-digit NAICS codes. When calculating the dummy variable based on whether an industry is above or below the median within a given year, it is inevitable that certain industries dominate. Our sample is heavily skewed towards industry code 31 and, if using two-digit NAICS codes, then most of the sample would be made up of the regulation intensity in that particular industry. When using the four-digit codes, the distribution improved and introduced a greater degree of variation across industries.

4 METHOD

In order to test if policy uncertainty has an effect on innovation, we specify a series of econometric models. Patents are used to capture innovation. In its most generic form, a raw patent count is a naturally discrete variable. However, we use the log of scaled patents as our primary dependent variable, which transforms the otherwise discrete variable of patent count into a continuous one. Policy uncertainty is captured by the log of the US PUI and is used as the primary independent variable of interest to estimate the relationship between policy uncertainty and innovation. We use a *fixed effect* model to estimate the effect of policy uncertainty on innovation. Furthermore, we report robust and clustered standard errors at firm level. The baseline specification can be defined as:

$$l.s\_pat_{it} = \alpha_i + \beta_2 l.PUI\_US_{it} + \beta_3 Firm_{it} + \beta_4 Macro_{it} + \varepsilon_{it}$$

Where $l.s\_pat_{it}$ represents the innovation output, α_i is the firm fixed effects, $l.PUI\_US_{it}$ represents policy uncertainty, $Firm_{it}$ is a vector of firm controls and, $Macro_{it}$ is a vector of macroeconomic controls. See Table 1 for a full variable description.

4.1 Pooled OLS

One of the most fundamental regression models for a cross-sectional dataset is the *Ordinary Least Squares* (OLS) model. The OLS estimator results in regression coefficients that estimate a linear regression line as close as possible to the observed data. How close the regression line is to the observed data is measured by the sum of the squared residuals. When working with panel data a similar model can be applied, defined as the pooled OLS model (Stock and Watson, 2015). The regression specification can be denoted as the following:

$$y_{it} = \beta_1 + \beta_2 x_{2_{it}} + \beta_3 x_{3_{it}} + \dots + \beta_k x_{k_{it}} + \varepsilon_{it}$$

The subscript i denote the i^{th} entity and t denote the t^{th} time period. In total the sample consists of N entities such that $i=1, 2, \dots, N$. In case of an unbalanced panel data, T is different for each entity, and one define $t=1, 2, \dots, T_i$. The total number of observations is denoted $\sum_{i=1}^{N} T_i$. Note that the coefficients (β_1, β_2, β_3, and β_k) do not have an entity nor time period subscript. The coefficients are assumed to be constant for all entities in all time periods; this implies that the model does not allow individual heterogeneity. This assumption characterizes the pooled OLS model, entities are pooled together with no provision for individual differences (Hill, Griffiths and Lim, 2011). The shortcoming of the pooled OLS model is that all observations are treated as one unique entity; the model does not account for the fact that the same entity is studied across time. One fundamental assumption for OLS estimation is that variables are independent and identically distributed; this assumption does not hold if there is a correlation between observations. However, observations of the same entity across time have a high likelihood of being correlated. This model therefore risks providing improper results and eliminates the time dimension of the panel data (Stock and Watson, 2015).

4.1.1 OLS Assumptions

Under the following least squares assumptions, the OLS model will generate unbiased and consistent estimators:

1) The conditional distribution of the error term ε_i is zero, given dependent variables $x_1, x_2, \dots, x_T$: $\mathbb{E}(\varepsilon_i|x_{1i}, x_{2i}, \dots, x_{ki},) = 0$. Implies that on average the estimated independent variable falls on the population regression line. If the assumption is true, the independent variables are said to be exogenous.
2) $(x_{1i}, x_{2i}, \dots, x_{ki}, y_i)$, *i=1, 2,…,N* are independently and identically distributed random variables. This assumption is automatically fulfilled if data is collected by random sampling.
3) Large outliers are unlikely, (x_i, ε_i) have nonzero finite fourth moments. Large outliers can lead to misleading OLS regression results, as the statistical inferences will be dominated by a few observations.
4) There is no perfect multicollinearity. Perfect multicollinearity implies that one of the regressors is a perfect linear function of the other regressor. The OLS coefficient for one regressor is the effect of a change in that regressor, holding the other regressors constant. This partial effect cannot be estimated in case of perfect multicollinearity.

Further, one can add two additional assumptions: homoscedasticity, and normally distributed errors:

5) The error term ε_i is homoscedastic if the variance of the conditional distribution of the error term and the explanatory variables is constant for all *i=1, 2,…,N*: $var(\varepsilon_i|x_{1i}, x_{2i}, \dots, x_{ki}) = \sigma_\varepsilon^2$.

If assumption 1 to 5 holds, the Gauss-Markov conditions for multiple regression state that the OLS estimator of beta is efficient among all linear conditionally unbiased estimators, meaning that the OLS estimator is BLUE.

6) The conditional distribution of ε_i given $x_{1i}, x_{2i}, \dots, x_{ki}$ is normal.

The sixth assumption implies that the OLS estimators have a normal sampling distribution, and homoskedasticity only t-statistics has an exact Student t distribution (Stock and Watson, 2015).

4.1.1.1 Asymptotic properties OLS

In the context of large sample sizes, it is imperative to be cognizant of asymptotic sample properties when gauging the validity of estimators. Asymptotic behavior reflects what happens to estimators as the sample size tends to infinity. An important property of asymptotic behavior is that of consistency. For each *n*, $\hat{\beta}_k$ has a probability distribution, and assuming that $\hat{\beta}_k$ is unbiased under OLS assumption one through four, then the distribution has mean value β_k. For a consistent estimator, the distribution of $\hat{\beta}_k$ converges to that of β_k as the sample size increases. As the sample size tends to infinity, the distribution of $\hat{\beta}_k$ collapses to the true population mean β_k. Effectively, this suggests that the estimator can get arbitrarily close to the true population mean by collecting an infinite amount of data. However, if the use of more data does not cause the estimator to approach the true population parameter, then this is an indication of a poor estimation procedure. Just as assumption one through four imply unbiasedness of an OLS estimator, these also imply consistency (Wooldridge, 2012).

By referring to these OLS assumptions, an estimator can either be biased and inconsistent or unbiased and consistent. However, for consistency, a weaker zero conditional mean assumption suffices. Where assumption four for unbiasedness implies that any function of the explanatory variables is uncorrelated with the error term, the weaker assumption for consistency requires only that each explanatory variable is uncorrelated with the error term. The existence of the weaker zero conditional mean assumption for consistency implies that it is indeed possible to have biased estimators that are consistent for large sample sizes. Moreover, another practically important finding is that even without assumption six of normality, the t and F statistics have approximately t and F distributions for large sample sizes (Wooldridge, 2012).

4.2 Fixed Effects Estimation

One way to recognize the existence of heterogeneity in entity characteristics in a panel data model is to allow for individual errors in different time periods to be correlated by introducing cluster-robust standard errors. However, a second way to relax the assumption that all entities have the same coefficient is to apply the *fixed effects model* (FE), where behavioral differences between entities are captured in individual intercepts (Hill, Griffiths and Lim, 2011).

The fixed effects regression is a model estimation where one controls for omitted variables in the panel data that vary across entities but that do not change over time. Consider the following regression specification:

$$y_{it} = \beta_1 + \beta_2 x_{2_{it}} + \beta_3 x_{3_{it}} + \dots + \beta_k x_{k_{it}} + \beta_{k+1} Z_i + \varepsilon_{it}$$

y_{it} define the dependent variable, x_{it} define observed regressors and Z_i is an unobserved variable that varies across entities but remains constant over time. The objective is to estimate, the effect of x on y while holding the unobserved entity characteristics Z constant. As Z_i varies across entities but remains constant over time the population regression model can be interpreted as having *N* intercepts; one for each entity. The fixed effects regression model can therefore be specified as:

$$y_{it} = \alpha_i + \beta_2 x_{2_{it}} + \beta_3 x_{3_{it}} + \dots + \beta_k x_{k_{it}} + \varepsilon_{it}$$

where α_i,…,N are estimated intercepts for each entity. The slope coefficient of the population regression line, , is the same for all entities while the intercept varies across entities. The intercept can be interpreted as the effect of being entity i and is defined as the entity fixed effects. Equivalently, the fixed effects regression model can be written in terms of binary variables. One cannot include *N* binary variables and a common intercept due to the dummy variable trap leading to multicollinearity. Hence, arbitrarily omit one binary variable. Accordingly, the fixed effects regression model can be specified with a common intercept, the observed regressors and *N-1* binary variables representing all but one entity:

$$y_{it} = \beta_1 + \beta_2 x_{2_{it}} + \beta_3 x_{3_{it}} + \dots + \beta_k x_{k_{it}} + \gamma_2 D2_i + \gamma_3 D3_i + \dots + \gamma_n Dn_i + \varepsilon_{it}$$

where *D2i=1* if *i=2* and *D2i=0* otherwise, and so forth (Stock and Watson, 2015).

Just as fixed effects can control for unobserved variables that are constant over time but differ across entities, they may also control for unobserved variables that are constant across entities but differ across time. This is defined as time fixed effects (Stock and Watson, 2015).

4.2.1 The Fixed Effects Regression Assumptions

The fixed effect regression is built upon four main assumptions:

1) ε_{it} has a zero conditional mean given all *T* values of *x* for that entity $\mathbb{E}(\varepsilon_{it} | x_{i1}, x_{i2}, \dots, x_{iT}, \alpha_i) = 0$. Similar to the first least squares assumption for cross-sectional data this assumption does imply that there is no omitted variable bias. For a panel data, note

however, that the assumption is violated if current ε_{it} is correlated with any past, present, or future value of x.

2) $(x_{i1}, x_{i2}, \dots, x_{iT}, \varepsilon_{i1}, \varepsilon_{i2}, \dots, \varepsilon_{iT})$, $i=1, 2, \dots, N$ are all i.i.d. draws from the joint distribution. This implies that the variables from one entity are distributed identically and independently of the variables from another entity. This assumption holds if entities are selected by simple random sampling from the population.
3) Large outliers are unlikely: $(x_{iT}, \varepsilon_{iT})$ have nonzero finite fourth moments.
4) There is no perfect multicollinearity.

Note that in the case of multiple regressors, x_{iT} should be replaced with the full list of regressors, $x_{1,it}$, $x_{2,it}$, …, $x_{k,iT}$.

The third and the fourth assumption for the fixed effects regression are analogous to the corresponding assumption in the least squares assumptions for cross-sectional data. Consistent with the second assumption, the regression errors can be correlated over time within an entity. Correlation in the errors does not introduce bias into the fixed effects estimator, but it affects the variance of the fixed effects estimator and therefore affects the standard errors. Clustered standard errors, which are robust both to heteroskedasticity and to correlation over time within an entity, should be applied (Stock and Watson, 2015).

4.2.2 The Hausman Test

As an alternative to the fixed effect model could the random effect model be applied. Like the fixed effect model, the random effect model assumes that differences between entities are captured by individual intercepts. However, the random effect acknowledges that the sample is randomly selected and treats all entity differences as random rather than fixed. The random effects for each entity are denoted u_{it} and are assumed to have zero mean, be uncorrelated across entities and have a constant variance (Hill, Griffiths and Lim, 2011).

The random effect estimator permits one to estimate the effects of variables that are individually time-invariant. For a fixed effect model there must be variation across time to avoid multicollinearity. In addition, the random effect model has a greater precision than the fixed effect model for large samples, as the random effect model is a generalized least square estimation procedure while the fixed effect model is a least square estimator (Hill, Griffiths and Lim, 2011).

To determine whether a random effect model or a fixed effect model is to be preferred, one can conduct a Hausman test, which compares the coefficient estimates from the random effect and the fixed effect model. The underlying idea of the Hausman test is that both the random and the fixed effects estimators are consistent. Both estimators are consistent if there is no correlation between u_{it} and the explanatory variables x_{kit}. Hence, both estimators should converge to the true parameter values in large samples and the estimators for the two model specifications should be similar. On the other hand, if u_{it} and x_{kit} are correlated; the random effect estimator will be inconsistent and only the fixed effect estimator will converge towards the true parameter, implying that one expects a difference between the fixed and random effects estimates. The Hausman test jointly checks how close the difference in a pair of coefficients in the two model specifications are to zero and reports the chi-square statistic as well as the corresponding p-value. By construction, the null hypothesis of the Hausman test is that the difference between the estimators is zero and one rejects the null in favor of the fixed effects model if the p-value is less than a specified significance level (Hill, Griffiths and Lim, 2011).

4.3 Instrumental Variables Regression

Omitted variables, measurement errors in variables and simultaneous causality can all be sources to why the error term is correlated with explanatory variables. Endogenous variables, variables correlated with the error term, make least squares estimators biased and inconsistent. The estimators may therefore be far away from the true value of the regression coefficient even with a large sample. Instrumental variables (IV) regression is a commonly used method to obtain consistent estimator of the population regression function when independent variables, x, are correlated with the error term, ε. Instrumental variables, Z, are variables that isolate the part of x that are uncorrelated with the error term. A valid instrument must satisfy two conditions:

1) The instrument relevance condition: $corr(Z_{it}, x_{it}) \neq 0$
2) The instrument exogeneity condition: $corr(Z_{it}, \varepsilon_{it}) = 0$

A relevant instrument implies that the variation in the instrument is related to the variation is the explanatory variable. In addition, as the instrument is exogenous, the part of the variation in the explanatory variable captured by the instrument will also be exogenous (Stock and Watson, 2015).

4.3.1 The Two Stage Least Squares Estimator

Relevant and exogenous instruments can be used in a two stage least squares (TSLS) estimator. The first stage decomposes the endogenous explanatory variable into two components: one endogenous and

one exogenous. The second stage then uses the exogenous component of the explanatory variable to estimate consistent coefficients (Stock and Watson, 2015).
For the general IV regression model, the equation of interest is defined as:

$$y_{it} = \beta_1 + \beta_2 x_{2_{it}} + \dots + \beta_k x_{k_{it}} + \beta_{k+1} w_{1_{it}} + \dots + \beta_{k+r} w_{r_{it}} + \varepsilon_{it}$$

Where y_{it} is the dependent variable, $x_{2it},\dots,x_{kit}$ are the k endogenous regressors, , $x_{1it},\dots,x_{rit}$ are r included exogenous regressors which are uncorrelated with the error term, ε_{it}. The w variables are either exogenous regressors or control variables that do not need to have a casual interpretation but that are included to avoid the instrumental variable to be correlated with the error term (Stock and Watson, 2020).

The first-stage population regression of the TSLS relate the endogenous x to the exogenous variables. Given a single endogenous regressor the first-stage regression, often named the reduced form equation, can be defined as:

$$x_{it} = \pi_0 + \pi_1 Z_{1_{it}} + \dots + \pi_m Z_{m_{it}} + \pi_{m+1} w_{1_{it}} + \dots + \pi_{m+r} w_{r_{it}} + v_{it}$$

Where $Z_{1it},\dots,Z_{mit}$ are instruments, $\pi_0, \pi_1,\dots, \pi_{m+r}$ are unknown regression coefficients and v_{it} is the error term. Estimation of IV regression requires exact identification or overidentification, meaning that the number of instruments must be equal or greater than the number of endogenous regressors. In the second stage of the TSLS the x_{it} is replaced by the estimated value from the first stage. Meaning that the y_{it} is regressed on $\hat{x}_{it}$, $w_{1it},\dots,w_{rit}$ (Stock and Watson, 2015).

4.3.1.1 Weak Instruments

An instrument is defined as weak if the partial correlation between the instruments and the included endogenous variable is low. In the case of a weak instrument, the normal distribution provides poor approximation to the sampling distribution of the TSLS estimator. Weak instruments can produce biased instrumental variable estimators and the constructed confidence intervals can be misfitted. The instruments are in general unreliable even for large sample sizes (Stock and Watson, 2015).

A way to check for weak instruments is based on the F-statistic of testing the hypothesis that the coefficients on the instrument are zero in the first-stage regression of TSLS. The first-stage F-statistic provides a measure for the information contained within an instrument. The higher the F-statistic, the more information is contained within the instrument and thus deemed more relevant. As a rule of thumb in the case of a single endogenous regressor, a first-stage F-statistic less than 10 indicates a weak instrument (Stock and Watson, 2015). Stock and Yogo (2005) formally test for weak instruments, based on the F-statistic. The critical value will depend on the number of instruments, number of endogenous regressors and the maximal bias of the IV estimator relative to the OLS. Given one instrument and one endogenous regressors, the null hypothesis that the bias of the TSLS is greater than 10% of the bias in the OLS is rejected at a five percent level if F>9.08. The critical value is reported to be 13.91 if the maximal bias is five instead of ten percent.

4.4 Addressing Outliers

Cook (1977) developed a way to determine whether outliers are influential. According to Cook (1977), the confidence ellipsoids may be used in order to determine the specific contribution of each data point to the outcome of the least square estimate of a parameter vector. Namely, he shows that it is not necessary to remove all outliers, but instead identify influential outliers that significantly affect the estimators. Cook's D is given by the following formula:

$$D_i = \frac{\sum_{j=1}^{n} \left(\hat{y}_j - \hat{y}_{j(i)} \right)^2}{pMSE}$$

Where $\hat{y}_j$ is the *j*th fitted response value, $\hat{y}_{j(i)}$ is the *j*th fitted response value excluding observation i, *MSE* is the mean squared error, and *p* is the number of coefficients in the model.

4.5 Negative Binomial Model

When dealing with discrete dependent variables, the poisson regression model has convenient properties, as it represents the rate of incidence of some event. For instance, this may be applied to the case of innovation. This belongs to the class of generalized linear models, where one of the assumptions of the poisson model is that the mean equals the variance. When one is greater than the other, this violates the assumption and may cause the standard errors to be severely understated or overstated. The most common violation of this assumption is that the variance is greater than the mean, leading to overdispersion. The negative binomial model is a general case of the poisson model, as it does not require this assumption to hold. Poisson and the negative binomial have the same sample space, however, the negative binomial has an additional parameter that is used to model variance, which is referred to as a dispersion parameter.

This is given by the following relationship:

$k = 1 + \alpha * \mu$ where $\mu = e^{x_j \beta + offsett_j}$

k denotes the dispersion parameter, α the overdispersion parameter, and μ indicates the mean. When $\alpha=0$ then there is no overdispersion, which effectively results in $k=1$. This results in the poisson case, which may be verified by the variance formula:

$$var = \mu + \alpha * \mu^2$$

If there is no overdispersion ($\alpha=0$), then the variance equals the mean. Thus, it is evident that the poisson model is indeed a special case of the negative binomial model. Effectively, the aim of the poisson and the negative binomial model is the same: modeling the relationship between the predictors and the likelihood of the dependent variable.

The model is considered a log-linear model as it assumes the logarithmic of the expected value is modelled by a linear combination of parameters. Using a log link function, the negative binomial model specification is given by the following:

$$ln\,(\mu) = \beta_1 + \beta_2 x_{2_{it}} + \beta_3 x_{3_{it}} + _{\dots} + \beta_k x_{k_{it}}$$

The effect on the dependent variable is given by the beta coefficient after a one unit increase in the respective independent variable. Specifically, the interpretation would be the following: if x_2 increases by one unit, the difference in the log of expected dependent variable outcome is expected to increase by β_2 units, holding the other variables constant (Hilbe, 2011).

5 RESULT

Table 3 reports the descriptive statistics of the PUI index and the different control variables. We refer to the Appendix D for more detailed information regarding the distribution of data throughout the sample period.

Table 3: Descriptive Statistics

This table reports the descriptive statistics for the variables used in further analysis.

Both scaled patents (s_pat) and the patent count (patent_count) will be used as the dependent variable in further regressions, while the PUI_US is the independent variable of interest. Firm controls are at, bm, ch_at, de_ratio, and sdev. Macroeconomic controls are r&d_at, t_balance, enroll, fed r&d, fed sur_def, gdp, high_edu, ltint, rec, rev, and unemp. A description of the variables is reported in Table 1.

Number of observations: 54 876

	mean	std. dev.	min	max
s_pat	4.119	9.972	0.052	303.959
patent_count	5.104	13.293	1	537
PUI_US	109.191	33.295	57.203	245.127
at	4 704	16 693	0.463	751 216
bm	0.414	0.352	0.0003	7.171
ch_at	0.333	0.259	0.00001	0.997
de_ratio	1.098	3.828	-120.110	124.055
sdev	0.033	0.019	0	0.287
r&d_at	0.147	0.192	0	7.825
t_balance	-42 302	25 211	-151 683	-831
enroll	14.900	2.625	9.507	18.600
fed r&d	0.116	0.109	0.091	0.132
fed sur_def	-3.084	2.763	-9.789	2.335
gdp	14 502	2 864	7 829	19 202
high_edu	649.232	186.460	186	1 621
ltint	4.297	1.980	1.500	11.860
rec	0.091	0.287	0	1
rev	7 473	1 200	1 791	24 715
unemp	5.780	1.601	3.5	10

The descriptive statistics of the PUI provide initial evidence that the level of policy uncertainty differs across time and could potentially affect the environment in which firms operate. The mean of the PUI is 109.191 with a standard deviation of 33.295. This indicates a large variation of the index and significant fluctuations from one period to another. Large variation is also reported within both the firm and the macroeconomic controls, although the variation within the firm controls may be more prominent.

Firm characteristics like assets, cash to assets, book to market, debt to equity ratio, R&D expenditure to assets and standard deviation all report a significant variation. The lowest observation of firm assets is reported to be $0.463 million, while the high observation is reported to be $751 216 million. The R&D expenditure to assets has a mean of 0.192, the lowest observation is zero and the highest 7.825, indicating that the reported R&D resources vary heavily across observations. The mean of the debt to equity ratio is 3.828, which indicates that the average observation has close to four times the amount of debt relative to equity. The highest debt to equity ratio is reported to be 124.055, and the lowest is reported to be negative 120.110. Thornblad, Zeitzman, and Carlson (2018) state that negative equity implies that a firm has more liabilities than assets. This can occur when a firm experiences loss, depreciation of assets, or takes on debt for non-assets expenditures. Furthermore, 7.95 percent of Compustat firms have reported negative equity. As a result of the negative value, the ratio loses its ordinal properties and is hard to interpret. We keep observations with negative debt to equity to preserve observations and avoid omitted bias. Since the debt to equity ratio acts as a control variable, we deem that the variable's interpretation is not the main focus.

Regarding the macroeconomic controls, one can identify by the negative mean of the federal budget balance variable that the US is in a deficit rather than a surplus on average. The net export is negative for all observations, but the level differs substantially. The mean of the recession dummy indicates that the US economy is in an expansion for a majority of the period, where approximately 9.1 percent of the observations are during a recession.

Figure 3 reports the share of foreign inventors across the period. The graph indicates an upward trend for the share of foreign inventors. The lowest observation was reported in December 1992 with a foreign share of approximately 5.7 percent, and the highest value was reported in July 2011 with approximately 17.4 percent of foreign inventors. The trend is consistent with the development and growth of globalization and international trade.

Figure 3: Share of Foreign Inventors

The development of the share of foreign inventors over time.

The share of foreign inventors is based on a monthly aggregation for the time period January 1985 to December 2019. The percentage of foreign inventors is determined by the number of patents filed by inventors located outside the US divided by the total patent count for a specific month.

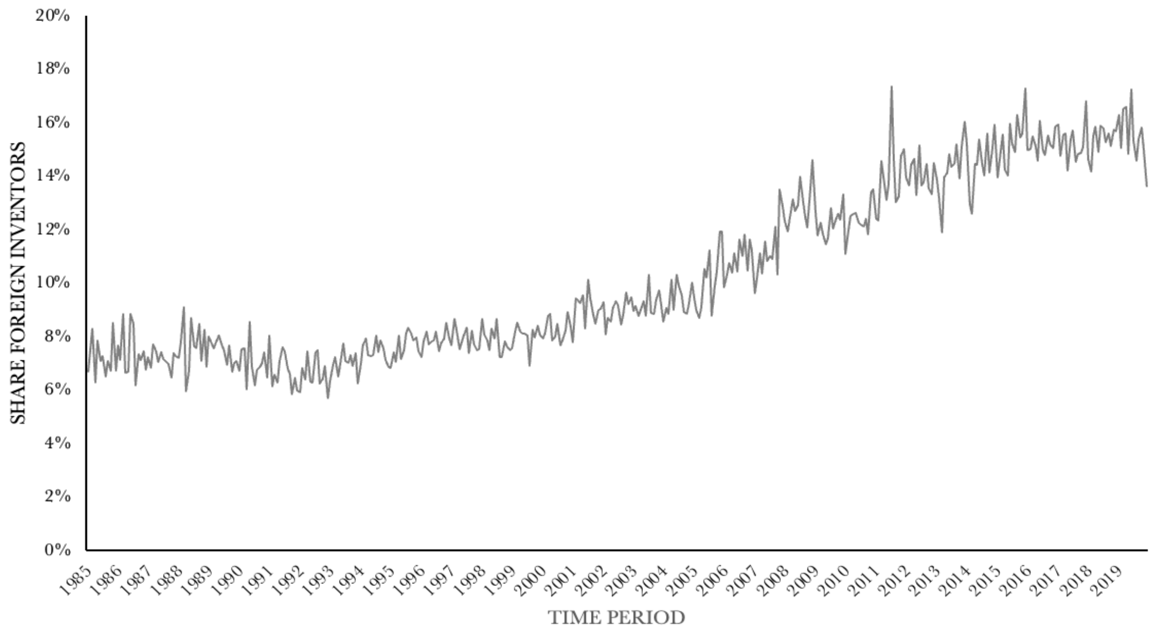


Figure 4 reports the share of patents categorized as inventional rather than additional by the *Cooperative Patent Classification* (CPC). A slight negative trend can be identified, but it is unclear whether this pattern is obtained by changing requirements regarding the categorization or an actual decline in the share of inventional innovations. The lowest share of inventional patents was reported in February 2019, with a value of approximately 60.7 percent. In contrast, the highest value of 79.5 percent was reported in April 1985.

Figure 4: Share of International CPC Patents

The development of the share of patents defined as inventional according to the Cooperative Patent Classification (CPC). The share of inventional CPC patents is based on a monthly aggregation for the time period January 1985 to December 2019. The percentage of inventional CPC patents is determined by the number of patents defined as inventional divided by the total patent count for a specific month.

5.1 Innovation and Policy Uncertainty

The main specification is reported in Table 4 and reports the effect of policy uncertainty on innovation. The first model specification (1), is a univariate pooled OLS model, while the second model specification (2), is a univariate fixed effects model. Note that the fixed effects model controls for firm fixed effects and not time fixed effects. As the scaled patent measurement is constructed for each month, the time fixed effects is not considered. Both the pooled OLS and the fixed effects specifications report a significant and negative relationship between innovation and policy uncertainty. The fixed effects model reports that a one percent increase in policy uncertainty is associated with a 0.113 percent decrease in innovation. This result indicates a negative and inelastic relationship; the inelasticity is consistent with the standard deviation of the two variables. As reported in the descriptive statistics, the standard deviation is higher for the policy uncertainty variable relative to the innovation as measured by scaled patents. This provides an initial indication that policy uncertainty has a higher variation than scaled patents.

We add firm controls to the univariate model, with a pooled OLS (3) and the fixed effects (4) specification. The relationship between policy uncertainty and innovation output remains negative and inelastic. For the fixed effects specification; assets, book to market, and cash to assets are all insignificant, meaning that these firm characteristics are estimated to have an insignificant impact on innovation. The debt to equity ratio reports a significant negative ratio, meaning that a higher debt to equity ratio decreases the innovation of firms. However, due to negative values reported for the debt to equity ratio, one should be careful with the interpretation of this variable. The standard deviation and the R&D expenditure to assets report a positive and significant relationship but at different significance levels.

We also add macroeconomic controls to the univariate model, again with a pooled OLS (5) and a fixed effects specification (6). With the fixed effects specification is a one percent increase in policy uncertainty associated with a 0.361 percent decrease in innovation. The variable of interest still reports a significant and inelastic relationship, however, the coefficient is more negative compared to the previous specification. All macroeconomic controls are significant for the pooled OLS specification, while the change in the trade balance is insignificant in the fixed effects specification. The direction of the relationship is consistent with theory for most of the variables, however, the recession and unemployment variables report a relationship inconsistent with the prediction. However, a positive relationship between recession and innovation may be consistent with the strategic growth option. Strategic advantages might incentivize firms to undertake investments in times of an economic contraction due to future growth advantages relative to competing firms. In addition, one could argue that the dynamics behind the general unemployment rate are not the same as the unemployment rate for workers within R&D; requirements for education and experience might affect these dynamics. Therefore, the general unemployment rate might not provide an indication of the number of workers within R&D but rather provide information on the general economic condition.

We add all control variables for the pooled OLS (7) and the fixed effects (8) specifications. Consistent for all the model specifications, the relationship between policy uncertainty and innovation is negative and inelastic, although the coefficient value changes throughout the specifications. The pooled OLS specification consistently reports a more negative coefficient than the fixed effects specification. The pooled OLS reports a higher adjusted R^2 than the fixed effects specification for the full model. However, as the pooled OLS does not consider the time dimension of the panel data, the fixed effect model is considered the main model specification.

The main speciation reports that a one percent increase in policy uncertainty is associated with a 0.411 percent decrease in innovation. All macroeconomic control variables are significant at a one percent significance level, and the direction of the relationship remains consistent with previous model specifications. In this specification, assets and cash to assets are significant compared to the fixed effects specification (4). The adjusted R^2 is estimated to be 0.194, meaning that the model can explain 19.4 percent of the variation in the dependent variable. The reported R^2 is similar to that reported in other model specifications within the literature. For example, Kaviani et al. (2020) reported an R^2 of 0.13 for the primary model estimating the relationship between the change in the PUI and credit spreads. Jens (2017) reports an R^2 of 0.096 when estimating policy uncertainty by gubernatorial elections on investment, and Julio and Yook (2012) report an R^2 of 0.13 when estimating the effect of policy uncertainty measured by election data on firm investment. This comparison provides evidence for the expected level of reported R^2 within this research area.

Table 4: Model Specification for Policy Uncertainty and Innovation

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents, and the independent variable of interest is the log of the PUI. A detailed description of the variables is given in Table 1. Regressions (1) and (2) report a univariate model estimated with a pooled OLS and an FE specification. Regressions (3) and (4) include firm controls in the pooled OLS and FE specifications, while (5) and (6) instead add macroeconomic controls. The full model is reported in (7) and (8). The FE model, reported in (8), is considered the main model specification. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1.
Number of observations are 54 876.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l.PUI_US	-0.332***	-0.113***	-0.457***	-0.134***	-0.600***	-0.361***	-0.763***	-0.411***
	(0.043)	(0.035)	(0.046)	(0.036)	(0.043)	(0.036)	(0.044)	(0.037)
l.at			0.233***	0.032			0.271***	0.082***
			(0.030)	(0.031)			(0.029)	(0.031)
bm			0.060	0.038			-0.047	-0.030
			(0.067)	(0.035)			(0.065)	(0.035)
ch_at			-0.801***	-0.170			-0.526***	-0.229**
			(0.115)	(0.119)			(0.097)	(0.116)
de_ratio			-0.009***	-0.003***			-0.008***	-0.003**
			(0.003)	(0.001)			(0.003)	(0.001)
sdev			3.390***	3.502***			2.826**	3.063***
			(1.191)	(0.736)			(1.137)	(0.712)
l.r&d_at			0.132***	0.083*			0.183***	0.103**
			(0.036)	(0.045)			(0.033)	(0.042)

Table 4: Model Specification for Policy Uncertainty and Innovation (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δt_balance					1.490***	0.273	1.891***	0.449***
					(0.271)	(0.178)	(0.244)	(0.146)
Δenroll					4.259***	2.541***	4.859***	2.573***
					(0.327)	(0.286)	(0.300)	(0.262)
Δfed r&d					1.149***	0.249**	1.679***	0.457***
					(0.182)	(0.127)	(0.177)	(0.112)
Δfed sur_def					-0.068***	-0.046***	-0.090***	-0.048***
					(0.006)	(0.006)	(0.006)	(0.006)
Δgdp					9.368***	3.141***	14.534***	3.838***
					(1.596)	(1.160)	(1.493)	(1.046)
Δhigh_edu					0.568***	0.625***	0.606***	0.536***
					(0.216)	(0.129)	(0.175)	(0.124)
Δltint					-0.628***	-0.303***	-0.789***	-0.328***
					(0.082)	(0.065)	(0.008)	(0.064)
rec					0.336***	0.189***	0.394***	0.186***
					(0.027)	(0.022)	(0.025)	(0.020)
Δrev					0.111***	0.087***	0.127***	0.103***
					(0.024)	(0.018)	(0.021)	(0.019)
unemp					0.108***	0.075***	0.129***	0.085***
					(0.008)	(0.007)	(0.008)	(0.007)
constant	2.078***	1.059***	1.019***	1.082***	2.527***	1.684***	1.918***	1.566***
	(0.221)	(0.164)	(0.224)	(0.243)	(0.196)	(0.151)	(0.188)	(0.228)
Adjusted R^2	0.006	0.007	0.167	0.029	0.051	0.053	0.247	0.194
Hausman p-value		0.000		0.000		0.000		0.000

5.2 Innovation and Decomposed Policy Uncertainty

Previous estimations indicate that increased policy uncertainty has a negative effect on innovation. Estimating the same model specification on different subcategories of policy uncertainty might provide more nuanced insight into the variation coming from distinct areas of policy and their specific impact on innovation. The descriptive statistics in Table 5 indicate that the fiscal and monetary policy uncertainty indices have a broader and more volatile distribution relative to the general PUI.

Table 5: Descriptive Statistics of Fiscal and Monetary Policy Uncertainty

This table reports the descriptive statistics for the fiscal and monetary policy uncertainty indices.
Both Fis_PUI_US and Mon_PUI_US are used as the independent variable of interest in the following analysis. A detailed description of the variables is reported in Table 1.
Number of observations is 54 876.

	mean	std. dev.	min	max
Fis_PUI_US	100.732	62.272	23.052	374.307
Mon_PUI_US	86.246	56.302	16.575	407.941

Figure 5 and 6 provide a graphical representation of the fiscal and the monetary policy uncertainty indices across time. Consistent with the reported standard deviation in Table 5, both indices have large up- and downswings. However, graphically, the two indices follow different patterns. Local trends are noticeable in the fiscal PUI, where a trend of heightened or decreased policy uncertainty is observed for an extended period. For instance, a downward trend is noticeable between 2003 and 2007, while an upward trend occurs between 2008 and 2013. Similar patterns of local trends are reported in the general PUI.

In contrast, similar local trends are not apparent in the monetary PUI, where shocks to the index instead seem to return to a constant mean. Furthermore, the volatility of the monetary PUI appears to have decreased over the sample period. The reduced volatility is consistent with Baker, Bloom, and Davis (2016), who report that monetary policy has not been a big source of policy uncertainty in recent years.

Figure 5: Fiscal Policy Uncertainty

The development of the Fiscal Policy Uncertainty Index over time.

The figure provides a timeline of the Fis_PUI based on monthly data for the time period January 1985 to December 2019.

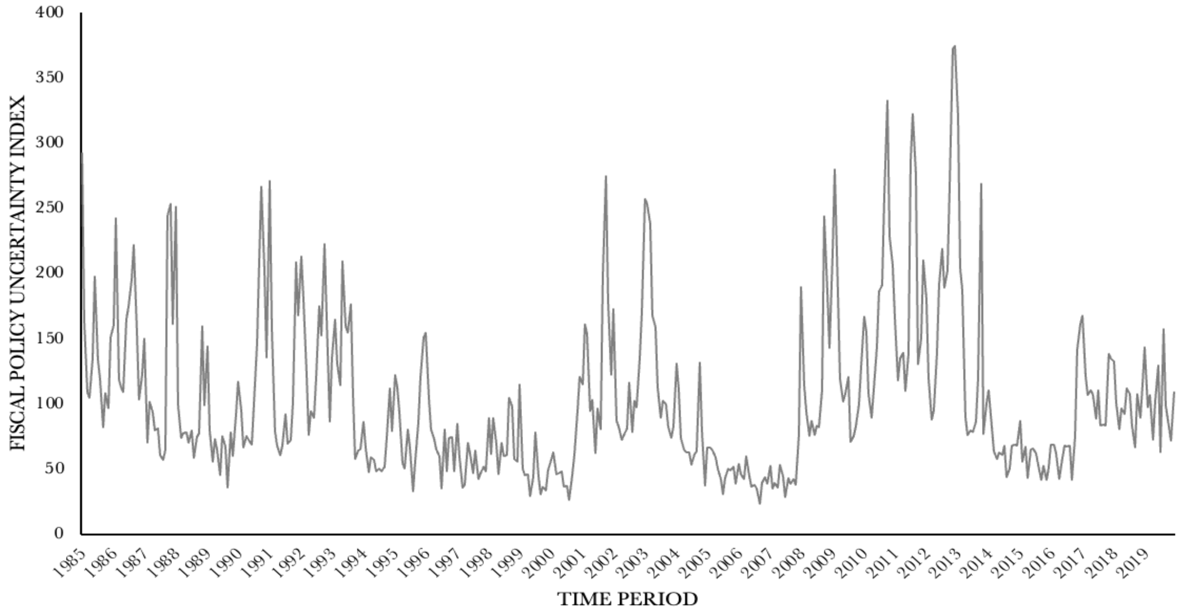
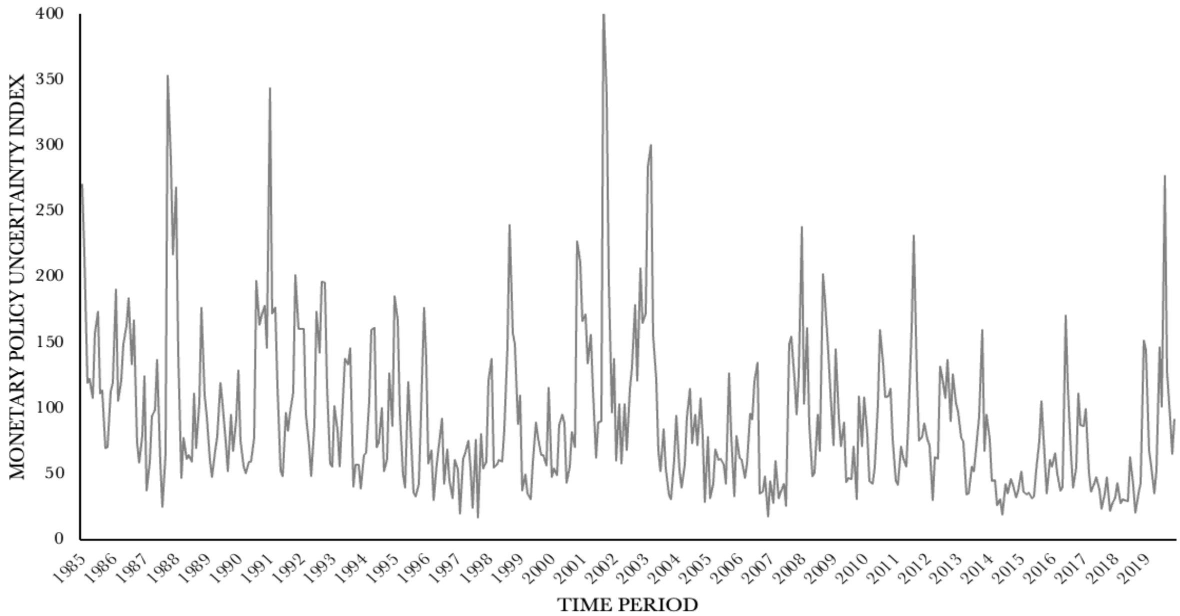


Figure 6: Monetary Policy Uncertainty

The development of the Monetary Policy Uncertainty Index over time.

The figure provides a timeline of the Mon_PUI based on monthly data for the time period January 1985 to December 2019.



Kang, Lee, and Ratti (2013), Fernandez-Villaverde et al. (2015), and Hassett and Metcalf (1999) all identify fiscal policy and tax regulation as significant sources of policy uncertainty. Regression (1) in Table 6 provides a univariate pooled OLS regression between fiscal policy uncertainty and innovation. The coefficient is significant at a five percent significance level and implies that a one percent increase in fiscal policy uncertainty is associated with a 0.028 percent decrease in innovation. The relationship is insignificant for the fixed effects specification. Overall, the negative effect is lower and less significant compared to the main specification in Table 4, where the general PUI is used as the independent variable. The direction of all the firm and macroeconomic controls is consistent with the general policy uncertainty model, although the magnitude and significance level differ. For instance, the change in higher education expenditure per capita is insignificant in the pooled OLS specification (5).

The fiscal policy uncertainty variable is insignificant in two fixed effects specifications (2) and (4). Nevertheless, the variable is significant at a one percent significance level for the main model specification (8). The estimated relationship implies that a one percent increase in the fiscal policy uncertainty is associated with a 0.111 percent decrease in innovation. The result indicate a less prominent for fiscal policy uncertainty compared to general policy uncertainty.

Table 6: Model Specification for Fiscal Policy Uncertainty and Innovation

The table reports the results of panel data regressions where the dependent variable is the scaled patents, and the independent variable of interest is the log of the fiscal PUI. A detailed description of the variable is given in Table 1. Regressions (1) and (2) report a univariate model estimated with pooled OLS and FE. Regressions (3) and (4) add firm controls to the pooled OLS and FE specifications, while (5) and (6) instead add macroeconomic controls. The full model is reported in (7) and (8). The FE model, reported in (8), is considered the main model specification. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1.
Number of observations is 54 876.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l.Fis_PUI_US	-0.028**	-0.005	-0.059***	-0.011	-0.132***	-0.103***	-0.155***	-0.111***
	(0.014)	(0.012)	(0.015)	(0.013)	(0.015)	(0.013)	(0.014)	(0.014)
l.at			0.242***	0.024			0.262***	0.062**
			(0.029)	(0.031)			(0.029)	(0.031)
bm			0.030	0.021			-0.055	-0.035
			(0.069)	(0.036)			(0.066)	(0.035)
ch_at			-0.720***	-0.171			-0.569***	-0.229**
			(0.116)	(0.119)			(0.100)	(0.116)
de_ratio			-0.009***	-0.004***			-0.008***	-0.003**
			(0.003)	(0.001)			(0.003)	(0.001)

Table 6: Model Specification for Fiscal Policy Uncertainty and Innovation (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
sdev			3.511***	3.341***			2.505**	2.774***
			(1.191)	(0.726)			(1.160)	(0.710)
l.r&d _at			0.168***	0.081*			0.183***	0.096**
			(0.036)	(0.045)			(0.033)	(0.043)
Δt_balance					1.434***	0.211	1.785***	0.336**
					(0.270)	(0.179)	(0.242)	(0.148)
Δenroll					4.940***	2.758***	5.723***	2.778***
					(0.360)	(0.306)	(0.331)	(0.280)
Δfed r&d					1.300***	0.264**	1.835***	0.433***
					(0.193)	(0.130)	(0.188)	(0.115)
Δfed sur_def					-0.077***	-0.050***	-0.100***	-0.051***
					(0.007)	(0.006)	(0.007)	(0.006)
Δgdp					14.419***	5.051***	20.791***	5.690***
					(1.854)	(1.307)	(1.735)	(1.152)
Δhigh_edu					0.355	0.512***	0.345*	0.420***
					(0.217)	(0.127)	(0.187)	(0.125)
Δltint					-0.363***	-0.145**	-0.439***	-0.139**
					(0.073)	(0.059)	(0.069)	(0.058)
rec					0.314***	0.176***	0.361***	0.166***
					(0.026)	(0.021)	(0.025)	(0.020)
Δrev					0.132***	0.101***	0.151***	0.116***
					(0.024)	(0.019)	(0.022)	(0.019)
unemp					0.075***	0.059***	0.085***	0.065***
					(0.008)	(0.008)	(0.008)	(0.007)
constant	0.659***	0.558***	-0.233	0.569***	0.474***	0.544***	-0.648***	0.374*
	(0.091)	(0.056)	(0.164)	(0.202)	(0.087)	(0.053)	(0.161)	(0.120)
Adjusted R^2	0.0002	0.0002	0.171	0.010	0.040	0.041	0.230	0.150
Hausman p-value		0.017		0.000		0.000		0.000

Furthermore, we investigate the relationship between the monetary policy uncertainty and innovation, which is reported in Table 7. The estimated relationship is positive and statistically significant for all model specifications. For example, the main specification (8) reports that a one percent increase in monetary policy uncertainty is associated with a 0.054 percent increase in innovation.

Book to market change direction for three out of four model specifications compared to the specification in Table 4. However, the variable remains insignificant when changing the independent variable from general policy uncertainty to monetary policy uncertainty. Also, the change in the long-term interest rate changes direction in the final model specification of Table 7 relative to Table 4. Otherwise, the direction of the control variables remains consistent, although the magnitude and the significance level might vary.

The positive relationship between innovation and the monetary PUI is inconsistent with Kormendi and Meguire (1985) who report that monetary instability causes reduced investment efforts and lower return to capital. The opposing sign of the monetary PUI compared to that of the general and fiscal PUI is to some extent consistent with Baker, Bloom, and Davis (2016), who state that monetary policy has not been a big source of policy uncertainty in recent years. The Federal Reserve's implementation of a target inflation rate allows firms to develop an expectation of the long-run inflation rate, which in turn has important implications for the actual inflation. Effectively, the target inflation brings clarity about the long-run goals of any monetary policy. Hence, one can argue that the nature of monetary policy uncertainty is fundamentally different from that of general policy uncertainty, as it does not have a clear goal and can change depending on the current administration and external factors. However, this argument only provides intuition for the decreased impact of monetary policy in recent years. The monetary policy has always been separated from the political system and therefore it is possible that firms have treated this source of uncertainty differently throughout time.

Table 7: Model Specification for Monetary Policy Uncertainty and Innovation

The table reports the results of panel data regressions where the dependent variable is the scaled patents, and the independent variable of interest is the log of the monetary PUI. A detailed description of the variable is given in Table 1. Regressions (1) and (2) report a univariate model estimated with pooled OLS and FE. Regressions (3) and (4) add firm controls to the pooled OLS and FE specifications, while (5) and (6) instead add macroeconomic controls. The full model is reported in (7) and (8). The FE model, reported in (8), is considered the main model specification. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1.
Number of observations is 54 876.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
l.Mon_PUI_US	0.214***	0.086***	0.243***	0.078***	0.141***	0.050***	0.180***	0.054***
	(0.016)	(0.011)	(0.013)	(0.009)	(0.016)	(0.012)	(0.013)	(0.010)
l.at			0.242***	0.030			0.261***	0.063**
			(0.029)	(0.031)			(0.029)	(0.030)
bm			-0.015	0.005			-0.073	-0.048
			(0.065)	(0.036)			(0.065)	(0.035)

Table 7: Model Specification for Monetary Policy Uncertainty and Innovation (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ch_at			-0.665***	-0.164			-0.533***	-0.196*
			(0.111)	(0.118)			(0.098)	(0.115)
de_ratio			-0.009***	-0.003*			-0.008***	-0.003**
			(0.003)	(0.001)			(0.003)	(0.001)
sdev			2.301**	2.853***			1.709	2.361***
			(1.159)	(0.706)			(1.146)	(0.696)
l.r&d _at			0.171***	0.086*			0.181***	0.100**
			(0.029)	(0.045)			(0.034)	(0.043)
Δt_balance					1.441***	0.261	1.809***	0.397***
					(0.257)	(0.178)	(0.227)	(0.146)
Δenroll					5.009***	2.870***	5.872***	2.928***
					(0.360)	(0.309)	(0.334)	(0.289)
Δfed r&d					1.130***	0.249**	1.604***	0.407***
					(0.174)	(0.122)	(0.174)	(0.110)
Δfed sur_def					-0.055***	-0.038***	-0.074***	-0.039***
					(0.006)	(0.006)	(0.006)	(0.006)
Δgdp					17.780***	7.266***	25.104***	8.113***
					(1.897)	(1.376)	(1.807)	(1.217)
Δhigh_edu					0.210	0.452***	0.183	0.368***
					(0.221)	(0.129)	(0.193)	(0.127)
Δltint					-0.022	-0.004	-0.021	0.019
					(0.066)	(0.056)	(0.064)	(0.056)
rec					0.196***	0.114***	0.226***	0.105***
					(0.022)	(0.018)	(0.022)	(0.018)
Δrev					0.086***	0.076***	0.091***	0.087***
					(0.024)	(0.018)	(0.020)	(0.018)
unemp					0.045***	0.037***	0.048***	0.042***
					(0.007)	(0.007)	(0.007)	(0.007)
constant	-0.380***	0.168***	-1.490***	0.175	-0.545***	-0.009	-1.875***	-0.208
	(0.082)	(0.049)	(0.179)	(0.194)	(0.091)	(0.062)	(0.183)	(0.195)
Adjusted R^2	0.011	0.011	0.184	0.037	0.042	0.043	0.239	0.157
Hausman p-value		0.000		0.000		0.000		0.000

5.3 Policy Uncertainty and the Quality of Innovation

In order to investigate the impact that policy uncertainty has on the quality of innovation, we construct two subsamples depending on if the observation is below or above the median of a given innovation quality measure. The quality of innovation is captured either by the relative novelty of a patent or its impact on subsequent innovation, where *scaled citations* and *scaled generality* are measures of impact and *scaled originality* is a measure of novelty.

Table 8 reports the result for the innovation quality measures. The regression with scaled citations that are below the median of the sample (1) reports a negative relationship with a coefficient of 0.197. The interpretation is that a one percent increase in policy uncertainty is associated with a 0.197 percent decrease in the innovation of firms with a low level of scaled citations. For the regression with scaled citations above the median (2) a one percent increase in policy uncertainty led to a 0.381 percent decrease in innovation. These results indicate that the innovation of firms with a relatively high level of scaled citations has a more adverse reaction to increased policy uncertainty. The difference is statistically significant at a one percent level according to the recorded z-score. However, note that the adjusted R^2 is smaller for the subsample with a low level of scaled citations relative to that of the subsample with a high level of scaled citations. This is important to be aware of when interpreting the result. Consistently, the same relationship is reported for the scaled generality. We report a negative relationship between innovation and policy uncertainty for the subsample with a scaled generality score below the median (3). The analysis implies that an increase in policy uncertainty is associated with a 0.240 percent decrease in innovation. For the subsample with a scaled generality score above the median (4), a one percent increase in policy uncertainty is associated with a 0.499 percent decrease in innovation. The difference is statistically significant at a one percent level according to the recorded z-score. The observed results are consistent with Bhattacharya et al. (2017), who reports that the negative effect of increased policy uncertainty on innovation is more prominent for influential and impactful patents.

The subsample of scaled originality scores below the median of the sample (5) reports a negative relationship between innovation and policy uncertainty with a coefficient of negative 0.386. The coefficient is estimated to be negative 0.255 for the subsample with above the median scaled originality (6). The difference is statistically significant at a five percent level according to the z-score. The result is inconsistent with Bhattacharya et al. (2017), who reports that original patents are more affected by increased policy uncertainty. A high scaled originality score could be obtained if the innovation has a more complex or novel nature; this type of innovation could relate to more uncertainty and risk. From this point of view, one would predict that the innovation of firms with more original patents would be more negatively affected by policy uncertainty. However, a high scaled originality score could also be an indication of the size of the project, which yields the specific patent. Citations made to a wide range of technology classes indicate that the patent is the output of a time-demanding project. A long development phase and a significant project could be seen as more inelastic to fluctuations in policy uncertainty as this effect will have a lower impact across the life span of a project. From this point of view, the innovation of firms with less original patens would have a more adverse reaction to increased policy uncertainty, as the project is of smaller scope. This argument is consistent with the generated estimations.

Table 8: The Quality of Innovation and Policy Uncertainty

The relationship between innovation and policy uncertainty depending on the quality of innovation.

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents, and the independent variable of interest is the log of the PUI. Scaled citations, scaled generality, and scaled originality are used to measure the quality of the innovation. A detailed description of the measurements is given in Table 2. The sample is divided by the median for each of three different measurements of innovation quality. The regressions estimations are performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. Regression (1), (3), and (5) report the result for the subsample with low scores of innovation quality, while regression (2), (4), and (6) report the results for the subsample with high quality scores. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1. The estimated z-scores and p-value for each quality measure are: scaled citations, z-score 3.814 and p-value of 0.000, scaled generality, z-score 4.469 and p-value of 0.000 and scaled originality, z-score -2.362 and p-value of 0.018.

	(1) Low Scaled Citations	(2) High Scaled Citations	(3) Low Scaled Generality	(4) High Scaled Generality	(5) Low Scaled Originality	(6) High Scaled Originality
l.PUI_US	-0.197***	-0.381***	-0.240***	-0.499***	-0.386***	-0.255***
	(0.025)	(0.041)	(0.033)	(0.048)	(0.038)	(0.040)
Adjusted R^2	0.051	0.307	0.232	0.106	0.228	0.209
Observations	27 438	27 438	27 438	27 438	33 691	21 182

5.4 Policy Uncertainty and Firm and Industry Characteristics

Policy uncertainty may affect firms to a varying degree depending on specific firm and industry characteristics. In order to provide a more nuanced investigation regarding the relationship between policy uncertainty and innovation in the cross-section, we construct subsamples depending on specific firm and industry characteristics.

5.4.1 Firm Size

We construct two subsamples based on the reported asset value. If an observation corresponds to an asset value below the median, the observation is defined as a small firm and reported in regression (1) in Table 9. The regression estimation reports that a one percent increase in policy uncertainty is associated with a 0.226 percent decrease in innovation for small firms. In contrast, the second subsample consists of large firms, where the asset value is above the median. The regression for large firms (2) estimates that a one percent increase in policy uncertainty results in a 0.503 percent decrease in innovation. One might expect that the effect would be more prominent for small firms, consistent with the findings of Kang, Lee and Ratti (2013) and Jens (2017), suggesting that policy uncertainty has the most dampening effect on the innovation of small firms. However, the estimation that the effect is more prominent for large firms may be consistent with Bhattacharya et al. (2017), where firms postpone investment in case of increased policy uncertainty. Large firms may have a better ability to time the market and postpone innovation. Furthermore, as William and Fengrong (2022) reported, policy uncertainty amplifies information frictions that enlarge problems connected to moral hazard, adverse selection, and misallocation of resources which are more prominent in larger firms. This mechanism can explain why the adverse effect is more prominent for large firms relative to small firms. However, note that the adjusted R^2 is smaller for the subsample of small firms relative to that of the subsample of large firms. This is important to be aware of when interpreting the result.

Table 9: Policy Uncertainty and Firm Size

The relationship between innovation and policy uncertainty depending on firm size.

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents, and the independent variable of interest is the log of the PUI. The sample is divided by the median firm size, measured by assets, to distinguish between small and large firms. A detailed description of the measurement is given in Table 2. The regression estimations are performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. Regression (1) reports the FE estimation for small firms, while regression (2) reports for large firms. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1. The z-score is estimated to 4.270 with a corresponding p-value of 0.000.

Number of observations in each regression is 27 438.

	(1) Small Firm Size	(2) Large Firm Size
l.PUI_US	-0.226***	-0.503***
	(0.028)	(0.058)
Adjusted R^2	0.061	0.220

5.4.2 Financial Constraint

The KZ score, debt to asset ratio, and interest coverage ratio are measurements that describe the perceived degree of financial constraint within a firm. We divide firms into two subsamples for each measurement depending on if the observations report a value above or below the median for the specific financial constraint measurement, the results are reported in Table 10. Regressions (1), (3), and (6) report the result for the subsamples with low financial constraint observations, while regressions (2), (4), and (5) report the results for the high financial constraint subsamples. Note that variation in the number of observations arises due to varying availability of the financial constraint measurements.

The relationship varies across the three measurements. Reported by the two first measures, the KZ score and debt to asset ratio, policy uncertainty has an adverse effect on innovation, and this effect is more prominent for firms with a higher degree of financial constraint than firms characterized by a lower degree of financial constraint. The debt to asset ratio reports that a one percent increase in policy uncertainty is associated with a 0.273 percent decrease in innovation for the subsample with a low degree of financial constraint and a 0.477 percent decrease in innovation for the subsample with a high degree of financial constraint. However, as reported by the second measure, interest coverage ratio, policy uncertainty has an adverse effect on innovation but the effect is more prominent for the subsample with a lower degree of financial constraint. The difference between the two subsamples is significantly different at a one percent level for the debt to asset ratio and at a five percent level for the interest coverage ratio. However, the difference is not significantly different when the KZ score is used as the measure of financial constraints. Overall, the result is dependent on which measurement is used for the analysis.

Table 10: Policy Uncertainty and Financial Constraint

The relationship between innovation and policy uncertainty depending on financial constraint.

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents, and the independent variable of interest is the log of the PUI. KZ score, debt to asset ratio, and the interest coverage ratio are used to measure financial constraint. A detailed description of the measurements is given in Table 2. The sample is divided by the median for each of the three measurements of financial constraint. The regression estimations are performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. Regression (1), (3), and (6) report the result for firms with a low level of financial constraint, while regression (2), (4), and (5) report the results for firms with a high level of financial constraint. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1. The estimated z-scores and p-value for each quality measure are: KZ score, z-score 0.699 and p-value 0.485, debt to asset ratio, z-score 3.077 and p-value 0.002, and interest coverage ratio, z-score 2.010 and p-value 0.044.

	(1) Low KZ score	(2) High KZ score	(3) Low debt to assets ratio	(4) High debt to assets ratio	(5) Low interest coverage ratio	(6) High interest coverage ratio
l.PUI_US	-0.352***	-0.406***	-0.273***	-0.477***	-0.329***	-0.482***
	(0.051)	(0.035)	(0.038)	(0.054)	(0.054)	(0.053)
Adjusted R^2	0.127	0.212	0.173	0.110	0.176	0.156
Observations	24 847	24 487	27 234	27 231	21 679	21 678

5.4.3 Cash Holdings

We further investigate the relationship between policy uncertainty and innovation depending on the level of cash that a firm holds. According to Jensen and Meckling (1976), high cash holding is connected to the agency problem of free cash flow, which is expected to have a negative effect on innovation. However, Opler et al. (1999) states that a high level of cash holdings can provide firms with the opportunity to smooth out investment and make them less sensitive to changes in the external environment, as investments can be funded with internal funding.

The reported results in Table 11 indicate that the relationship between innovation and policy uncertainty is negative for both subsamples, while the effect is less prominent for firms with high cash holdings. The low cash holdings subsample (1) reports a negative relationship between innovation and policy uncertainty with a coefficient of negative 0.464. The coefficient is estimated to be negative 0.333 for the subsample with cash holdings above the median. The result is aligned with the theory of precautionary motives. The difference is statistically significant at a ten percent level according to the z-score. However, one should be aware that other firm characteristics can account for differences in cash holdings, such as industry affiliation or firm age, and thus we cannot isolate the effect of precautionary motives.

Table 11: Policy Uncertainty and Cash Holdings

The relationship between innovation and policy uncertainty depending on cash holdings.

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents, and the independent variable of interest is the log of the PUI. The sample is divided by the median cash holdings, measured by cash to assets, to distinguish between firms with a relatively high and low level of cash holdings. A detailed description of the measurements is given in Table 2. The regression estimations are performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. Regression (1) reports the FE estimation for firms with low cash holdings, while regression (2) reports for firms with high cash holdings. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1. The z-score is estimated to -1.543 with a corresponding p-value of 0.061.

Number of observations is 27 440 in regression (1) and 27 436 in regression (2).

	(1) Low Cash Holdings	(2) High Cash Holdings
l.PUI_US	-0.464***	-0.333***
	(0.054)	(0.042)
Adjusted R^2	0.161	0.156

5.4.4 Industry Regulation

Government regulation has become less predictable and increased in scale, scope, and complexity over recent decades. However, the industry regulation intensity differs between industries (Davis, 2017). Following Kaviani et al. (2020) we expect policy uncertainty to have a more prominent effect on the innovation of firms subject to higher regulation intensity due to the increased likelihood of impactful regulatory policy changes.

The reported NAICS industry code determines the assumed regulation affecting a firm. We create subsamples depending on whether the strictness of regulations affecting a firm in a specific year is above or below the median regulation intensity. Regression (1) in Table 12 reports the estimation for the subsample below the median regulation; a one percent increase in policy uncertainty is associated with a 0.339 percent decrease in innovation. For the subsample with a regulation intensity above the median, reported in regression (2), a one percent increase in policy uncertainty implies a 0.398 percent decrease in innovation. However, the obtained z-score implies that the coefficients are not statistically significant from each other and therefore it is not possible to infer that innovation of firms in more regulated industries is impacted to a higher degree by increased policy uncertainty. These results are inconsistent with Atanassov, Julio, and Leng (2015) which reports a positive relationship between R&D and policy uncertainty, and where the positive effect is more prominent for politically sensitive industries. In addition, the adjusted R^2 is much lower for the subsample with high industry regulation than for the subsample with low industry regulation. The lower adjusted R^2 implies that the model cannot explain as much of the variation in innovation for the high industry regulation subsamples compared to the low industry regulation subsample. The large variation in the R^2 and the fact that the reported difference is not statistically significant is something to keep in mind when interpreting the results.

Table 12: Policy Uncertainty and Industry Regulation Intensity

The relationship between innovation and policy uncertainty depending on industry regulation intensity.

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents, and the independent variable of interest is the log of the PUI. The sample is divided by the median industry regulation intensity. A detailed description of the measurements is given in Table 2. The regression estimations are performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. Regression (1) reports the FE estimation for firms subjected to low regulation intensity, while regression (2) reports for firms subjected to high regulation intensity. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1. The z-score is estimated to 0.577 with a corresponding p-value of 0.564.

Number of observations is 14 266 in regression (1) and 13 195 in regression (2).

	(1) Low regulation intensity	(2) High regulation intensity
l.PUI_US	-0.339*** (0.068)	-0.398*** (0.078)
Adjusted R^2	0.254	0.010

Due to a skewed distribution between the number of observations in each industry, we create three individual samples for the industries with the most observations to further investigate industry variation. The industries with the highest number of observations are:

1. NAICS code *3 254*, which is *Pharmaceutical and Medicine Manufacturing*, with 10 359 observations, this industry is consistently above the median regulation intensity throughout the sample period. This industry thereby accounts for a dominant part of the sample in regression (2) from Table 14.
2. NAICS code *3 344*, which is *Semiconductor and Other Electronic Component Manufacturing*, with 6 459 observations. This industry is consistently defined as an industry with low regulation intensity throughout the sample period.
3. NAICS code *3 342*, *Communications Equipment Manufacturing*, with 3 440 observations. This industry is consistently defined as an industry with low regulation intensity throughout the sample period.

Table 13: Policy Uncertainty across the Top Three Industries

The relationship between innovation and policy uncertainty across the top three industries.

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents, and the independent variable of interest is the log of the PUI. The regressions report the estimated relationship between innovation and policy uncertainty for the three industries with the highest number of observations. Appendix G provides further details on the distribution of observations across industries. The regression estimations are performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. Regression (1) reports the FE estimation for firms within the pharmaceutical and medicine manufacturing industry (3 254), while regression (2) reports for firms within the semiconductor and other electronic component manufacturing industry (3 344), and (3) reports the estimated coefficient for the communication equipment manufacturing industry (3 342). Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1. The z-score is estimated to 0.577 with a corresponding p-value of 0.564. The z-score for a significant difference in coefficients and the corresponding p-value are: all three industries combined, z-score 1.258 and p-value 0.209. Industry 3 254 and 3 344, z-score -0.032 and p-value 0.957. Industry 3 254 and 3 342, z-score -1.546 and p-value 0.122. Industry 3 244 and 3 342, z-score -1.325 and p-value 0.185.

	(1) Pharmaceutical and Medicine Manufacturing	(2) Semiconductor and Other Electronic Component Manufacturing	(3) Communications Equipment Manufacturing
l.PUI_US	-0.426***	-0.412***	-0.315**
	(0.088)	(0.109)	(0.137)
Adjusted R^2	0.026	0.272	0.270
Observations	10 359	6 459	3 440

Regression (1) in Table 13 reports the estimation for industry 3 254, where a one percent increase in policy uncertainty is associated with a 0.426 percent decrease in innovation. Out of the three industries, this displays the most negative relationship between policy uncertainty and innovation, consistent with the reported relationship in Table 12. The adjusted R^2 in regression (1) is lower than the reported adjusted R^2 for regressions (2) and (3), implying that the model explains a lower percentage of the variation in innovation for the Pharmaceutical and Medicine Manufacturing relative to the other two industries. The low adjusted R^2 is consistent with the relatively low adjusted R^2 in regression (2) from Table 12, as the Pharmaceutical and Medicine Manufacturing industry accounts for a large share of the sample for the reported regression. Furthermore, the variation in R^2 indicates that variables impacting innovation differ across industries. The Pharmaceutical and Medicine Manufacturing industries have specific characteristics which separate them from other industries. A combination of high R&D intensity, complex and long development stages, high costs and risks, focus on patent protection and monopoly power separates the pharmaceutical industry from many others (Scherer, 2000).

Furthermore, the estimated result for industry 3 344 is reported in regression (2), where a one percent increase in policy uncertainty is associated with a 0.412 percent decrease in innovation. For industry 3 342, as reported in regression (3), a one percent increase in policy uncertainty leads to a 0.315 percent decrease in innovation. The difference in the coefficient between the three industries is not significant. Hence, the reported result cannot conclude that the effect of policy uncertainty on innovation differs across industries.

5.4.5 Lobbying

Akey and Lewallen (2017) report that firms which are more sensitive to policy uncertainty have more substantial incentives to make political contributions. Firms will devote resources to lobbying if policymakers and policy decisions greatly impact the firm. Establishing political connections can help firms benefit from policy outcomes and act as a hedging mechanism against policy uncertainty (Kaviani et al., 2020).

Table 14: Policy Uncertainty and Lobbying

The relationship between innovation and policy uncertainty depending on lobbying activity.

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents, and the independent variable of interest is the log of the PUI. The sample is divided into non-lobbying and lobbying firms. A more detailed description of the variable is given in Table 2. The regression estimations are performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. Regression (1) reports the FE estimation for non-lobbying firms, while regression (2) reports for lobbying firms. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1. The z-score is estimated to 0.671 with a corresponding p-value of 0.502.

Number of observations is 22 599 for non-lobbying firms and 4 862 for lobbying firms.

	(1) Non-lobbying Firms	(2) Lobbying Firms
l.PUI_US	-0.331***	-0.410***
	(0.055)	(0.125)
Adjusted R^2	0.210	0.137

Following Kaviani et al. (2020), we define a firm as a lobbying firm if a positive lobbying expense is reported in the Open Secrets Center for Responsible Politics database for the firm at any point in time from 1985 to 2019[2]. The subsample of lobbying firms is reported in regression (2) in Table 14, which states that a one percent increase in policy uncertainty results in a 0.410 percent decrease in innovation.

[2] Note two underlying assumptions for this method are that no name inconsistencies lead to an unmatched observation and that the database is exhaustive. These assumptions were not highlighted by Kaviani et al. (2020), and the credibility of these assumptions is undetermined.

Consistent with previous literature, the effect of policy uncertainty is more prominent for lobbying compared to non-lobbying firms (1). However, the difference is not statistically significant.

5.5 The Sensitivity of Innovation

One could argue that the initial level of policy uncertainty has implications for how innovation is affected by incremental changes in policy uncertainty. Table 15 investigates the sensitivity of innovation to changes in policy uncertainty, while acknowledging the initial level of policy uncertainty. We define the binary variable, *PUI_high*, which takes on the value one if the PUI is above the median and zero otherwise.

The following model specification is reported in regression (1) in Table 15:

$$l.s\_pat_{it} = \alpha_i + \beta_2 \Delta l.PUI_{US_{it}} + \beta_3 PUI_{high_t} + \beta_4 \Delta l.PUI_{US_{it}} x\ PUI_{high_t} + \varepsilon_{it}$$

Table 15: The Sensitivity of Innovation

The sensitivity of innovation depending on the change in policy uncertainty and its initial level.

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents, and the independent variable of interest is the change in the log of the PUI. Furthermore, a dummy variable, PUI_high, is defined by dividing the sample by the median policy uncertainty reported. The interaction between the change in the log of the PUI and the dummy variable aims to capture the sensitivity of innovation to changes in policy uncertainty depending on the initial level of uncertainty. Regression (1) reports a univariate regression, (2) and (3) add firm and macroeconomic controls, respectively, and (4) reports the full model specification. All model specifications are estimated with FE. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1.

Number of observations is 54 876.

	(1)	(2)	(3)	(4)
Δl.PUI_US	1.159***	1.203***	1.282***	1.373***
	(0.178)	(0.178)	(0.174)	(0.176)
PUI_high	-0.074***	-0.085***	-0.163***	-0.179***
	(0.019)	(0.020)	(0.018)	(0.019)
Δl.PUI_US x PUI_high	-1.845***	-1.904***	-1.799***	-1.813***
	(0.203)	(0.209)	(0.199)	(0.204)
l.at		0.033		0.074**
		(0.031)		(0.031)
bm		0.039		-0.026
		(0.036)		(0.035)
ch_at		-0.173		-0.221*
		(0.119)		(0.115)

Table 15: The Sensitivity of Innovation (continued)

	(1)	(2)	(3)	(4)
de_ratio		-0.003**		-0.003**
		(0.001)		(0.001)
sdev		3.501***		2.761***
		(0.729)		(0.703)
l.r&d _at		0.084*		0.101**
		(0.044)		(0.042)
Δt_balance			0.264	0.420***
			(0.179)	(0.147)
Δenroll			2.694***	2.747***
			(0.295)	(0.272)
Δfed r&d			0.146	0.324***
			(0.127)	(0.111)
Δfed sur_def			-0.047***	-0.050***
			(0.006)	(0.006)
Δgdp			4.234***	5.053***
			(1.180)	(1.049)
Δhigh_edu			0.595***	0.508***
			(0.130)	(0.125)
Δltint			-0.203***	-0.209***
			(0.062)	(0.061)
rec			0.170***	0.163***
			(0.021)	(0.019)
Δrev			0.083***	0.098***
			(0.178)	(0.019)
unemp			0.060***	0.067***
			(0.007)	(0.007)
constant	2.078***	0.501**	0.167***	1.082***
	(0.221)	(0.203)	(0.037)	(0.243)
Adjusted R^2	0.008	0.035	0.050	0.106

The result indicates that a one percent increase in policy uncertainty given a low PUI environment leads to a 1.159 percent increase in innovation. In addition, a one percent increase in the policy uncertainty given a high PUI environment leads to a 0.686 percent decrease in innovation[3]. In an environment characterized by low policy uncertainty, a change in the PUI is associated with increased innovation.

[3] Calculated by adding the Δl.PUI_US and the Δl.PUI_US x PUI_high coefficients together, 1.159-1.845= -0.686.

In contrast, a change in the PUI during a period of high policy uncertainty is associated with decreased innovation. Furthermore, aligned with Bloom, Bond and Van Reenen (2007) the responsiveness of investment to policy uncertainty is, in absolute terms, lower in times of high policy uncertainty. Consistent with Williams (2021) and Meyer (2018) a statistically significant interaction term between the dummy and the continuous variable implies that the slope, the rate of change, differ between the low and the high PUI environment. The difference between the two environments will hence depend on the magnitude of the change in the PUI. Given that there is no change in the PUI, innovation will decrease by 7.133[4] percent for the average high PUI environment compared to the average low PUI environment.

Regression (2) includes firm controls and (3) includes macroeconomic controls. The full model specification is reported in regression (4) and includes both firm and macroeconomic controls. In the full model specification, a change in policy uncertainty is again associated with an increase in innovation given a low PUI environment, where a one percent increase in policy uncertainty results in a 1.373 percent increase in innovation. For a high policy uncertainty environment, a one percent increase in policy uncertainty leads to a 0.44 percent decrease in innovation. Again, due to the difference in the slope, the difference between the two environments depends on the magnitude of the change. With zero change in the policy uncertainty the average high PUI environment is associated with a 16.389 percent decrease in innovation compared to the average low PUI environment. Overall, the reported relationship in the PUI sensitivity is consistent for all model specifications, although the magnitude differs.

Table 16 reports the policy uncertainty sensitivity depending on firm size. Regression (1) reports the policy uncertainty sensitivity for small firms. The result indicates that given a low PUI level, a one percent increase in policy uncertainty leads to a 0.765 percent increase in innovation. Furthermore, a one percent increase in the policy uncertainty given a high PUI environment leads to a 0.291 percent decrease in innovation. The significant interaction term again implies that the difference between the two environments changes with the magnitude of the change in the policy uncertainty. However, with zero change in policy uncertainty the difference in innovation between the average low PUI and the average high PUI environment is 9.244 percent. Regression (2) reports the policy uncertainty sensitivity for large firms. In a low PUI environment, a one percent increase in uncertainty is associated with a

[4] Calculated as $100x(e^{\beta_2} - 1)$ following Halvorsen and Palmquist (1980).

1.700 percent increase in innovation. In a high PUI environment a one percent increase in policy uncertainty has an adverse impact on innovation by 0.493 percent. Lastly, given no change in policy uncertainty, innovation will decrease by 19.668 percent for the average high PUI environment compared to the average low PUI environment.

Table 16: The Sensitivity of Innovation by Firm Size

The sensitivity of innovation by firm size depending on the change in policy uncertainty and its initial level.

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents, and the independent variable of interest is the change in the log of the PUI. A dummy variable, PUI_high, is defined by dividing the sample by the median policy uncertainty reported. The interaction between the change in the log of the PUI and the dummy variable aims to capture the sensitivity of innovation to changes in policy uncertainty depending on the initial level of uncertainty. The sample is divided by the median firm size, measured by assets, to capture the sensitivity of small relative to large firms. The regression estimations are performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. Regression (1) reports the FE estimation for small firms, while regression (2) reports for large firms. Robust and clustered standard errors at firm level are reported in the parenthesis for regression (1) and (2), significance level: ***p<0.01, **p<0.05 and *p<0.1. Column (3) reports the z-score for a significant difference in coefficients and the corresponding p-value is reported in the parenthesis.

Number of observations is 27 427 for the small firms and 27 420 for the large firms.

	(1) Small Firm Size	(2) Large Firm Size	(3) Z-score
Δl.PUI_US	0.765***	1.700***	-2.722
	(0.210)	(0.272)	(0.006)
PUI_high	-0.097***	-0.219***	3.763
	(0.015)	(0.029)	(0.000)
Δl.PUI_US x PUI_high	-1.056***	-2.193***	2.881
	(0.247)	(0.308)	(0.004)
Adjusted R^2	0.055	0.212	

Column (3) in Table 16 reports the z-score and the associated p-value for the test of the significant difference in the beta coefficients. The estimations indicate a significant difference on a one percent level between small and large firms for the respective coefficient. Compared to small firms, relatively large firms report a more positive relationship between innovation and change in policy uncertainty, given a low level of uncertainty. In addition, a one percent increase in policy uncertainty in a high PUI environment, has a more negative effect on innovation for large compared to small firms. Given zero change in policy uncertainty, the difference in innovation for the average low PUI and the average high PUI environments, are also bigger for large compared to small firms. Overall, the results indicate that large firms are more sensitive to policy uncertainty than small firms. This is consistent with the idea that young firms are likely to have better failure-resilience capabilities, thus allowing them to thrive relatively more under uncertainty (Audia and Greve, 2006, Desai 2008, Coad, Segarra, and Teruel, 2016) and thereby be less sensitive to incremental changes in in environments characterized by high uncertainty. Moreover, this is also consistent with the finding that innovation in small firms tends to stay at a constant level regardless of uncertainty (Hinge Research Institute, 2021), thus causing small firms to be less sensitive to changes in policy uncertainty at low levels of the PUI.

The relationship between the policy uncertainty sensitivity and innovation is consistent for all model specifications. A one percent increase in policy uncertainty positively impacts innovation given a low PUI environment and negatively impacts innovation given a high PUI environment. Furthermore, when studying the change given a high or low level of policy uncertainty, the innovation in large firms is more sensitive to policy uncertainty compared to that of small firms.

5.6 Establishing Causality

A principal concern is that omitted variables drive the main result and that the model can be subject to endogeneity problems. Although previous models include control variables for economic uncertainty, unobserved economic uncertainty dimensions are still plausible drivers of the observed results. Similarly, the PUI might be subject to a measurement error bias. The PUI aim to measure the policy uncertainty but may effectively also include other factors unrelated to policy uncertainty that drive economic uncertainty. In order to acknowledge these concerns and establish causality, we estimate four model specifications following Gulen and Ion (2016) and Kaviani et al. (2020).

5.6.1 Canada Residual Policy Uncertainty

The PUI is constructed only to reflect policy uncertainty, and the creators of the index, Baker, Bloom, and Davis (2016), performed several robustness checks in order to minimize any contamination. However, to further investigate any measurement error, one can exploit the similarities between the Canadian and US economies. Gulen and Ion (2016) argue that the extensive international trade between the US and Canada creates a tight link. Hence, a shock that affects the general economic uncertainty in the US should also affect the general economic uncertainty in Canada, although to a lower extent. In contrast, policy uncertainty is arguably more contained within a country's border. Hence, if the PUI is contaminated by economic uncertainty, this portion can be filtered out by exploiting the Canadian counterpart. By regressing the US PUI on the Canada PUI, while controlling for various macroeconomic variables, one can save these residuals and use them as an alternative measurement.

The following regression specification is used to obtain the policy uncertainty residuals:

$$l.PUI_{US_t} = \pi_0 + \pi_1 l.PUI_{CA_t} + \pi_2 MACROCTRL_t + \varepsilon_t$$

The obtained result in Table 17 indicates a negative relationship, where a one percent increase in the policy uncertainty, based on residuals, is associated with a 0.116 percent decrease in innovation. The magnitude is lower than the estimation in Table 4. This could imply that the PUI index captures general economic uncertainty and that using the alternative measurement provides a more dampened effect on innovation. However, it can also be the case that the residuals are not a better measurement for the policy uncertainty. As stated by Gulen and Ion (2016), the extent to which the PUI in Canada captures some of the variations in the US policy uncertainty and not only in Canada, dictates whether or not the coefficient will underestimate the strength of the genuine relationship between policy uncertainty and innovation.

Table 17: Innovation and the Residuals of the Policy Uncertainty Index

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents and the independent variable of interest is the residuals of the PUI after regressing the log of the US PUI on the log of the Canadian PUI. A more detailed description of the variables is given in Table 2. The regression estimation is performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1.
Number of observations is 54 876.

	(1)
l.PUI_US_resid	-0.116***
	(0.021)
Adjusted R^2	0.144

5.6.2 Relative Legislative Power and Polarization

Using instrumental variables is a standard method to address endogeneity concerns. Gulen and Ion (2016) propose partisan polarization as an instrument for studies connected to uncertainty and investment. A higher degree of partisan polarization will increase policy uncertainty as the outcomes will be more differentiated depending on which party has a majority. Polarization will increase the uncertainty regarding a policy's duration and permanence, increase the difficulty of building legislative coalitions, and increase the risk of policy gridlock. In addition to partisan polarization, Kaviani et al. (2020) also identifies relative legislative power as an instrument for policy uncertainty. High relative legislative power implies that one of the two parties has a higher percentage of the seats within the House of representatives and the Senate. Reducing the relative legislative power will increase the policy uncertainty as it will be harder to estimate and forecast which policies and subjects that will be processed. Both relative legislative power and polarization have been identified as sources of policy uncertainty. As Gulen and Ion (2016) stated, it is not apparent how the level of disagreement between politicians should impact investment in any other way than through the effect of policy uncertainty. Further, the first-stage F-statistic reports values higher than the threshold suggested by Stock and Yogo (2005) indicating that the instruments are relevant.

The second-stage estimation, where the relative legislative power is used as an instrument, is reported in regression (1) in Table 18. With the use of this instrument, a one percent increase in policy uncertainty is associated with a 3.189 percent decrease in innovation. Furthermore, when polarization is used as an instrument (2), a one percent increase in policy uncertainty is associated with a 6.190 percent decrease in innovation. These estimations are of a higher magnitude compared to previous results but provide further evidence of a negative relationship between policy uncertainty and innovation.

Table 18: Innovation and IV Regression for Policy Uncertainty

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents and the independent variable of interest is the log of the PUI. The relative legislative power and polarization are used as instruments for policy uncertainty. A more detailed description of the instrument is given in Table 2. The regression estimations are performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. Regression (1) reports the estimated coefficient when the relative legislative power is used as an instrument, while regression (2) reports the estimated coefficient when polarization is used as an instrument. Robust and clustered standard errors at firm level are reported in the parenthesis for regression (1) and (2), significance level: ***p<0.01, **p<0.05 and *p<0.1.
Number of observations is 54 876.

	(1) Relative legislative power	(2) Polarization
l.PUI_US	-3.189***	-6.190***
	(0.732)	(0.645)
Adjusted R^2	0.141	0.123
First-stage F-statistic	99.84	240.53

5.6.3 Presidential Election

Policy uncertainty is amplified during the period when policymakers are raising awareness about upcoming elections through various campaigns. Hence, elections are standard measurement for policy uncertainty within previous literature. Furthermore, as the election is predetermined, elections are exogenous to economic developments and can therefore be used to measure policy uncertainty while being distinct from general economic uncertainty. The low frequency of elections is a shortcoming, and periods where elections cannot reflect policy uncertainty variation remain a dominant fraction (Kaviani et al., 2020).

Following, Kaviani et al. (2020), the presidential election dummy variable in regression (1) in Table 19 equals one up to three months before, including the month of the election, and zero otherwise. The estimation reports a positive relationship between elections and innovation. In the three months leading up to an election, the innovation increases by 5.760 percent compared to non-election months. The estimation is sensitive to the assumption regarding the number of months before the election that are characterized by increased policy uncertainty. In regression (2), the election dummy equals one up to five months before, including the month of the election, and zero otherwise. The regression reports a positive relationship where the election is associated with a 4.081 percent increase in innovation compared to non-election months. Overall, the result is inconsistent with the previous result from Tables 4, 17, and 18, which all report a negative relationship between policy uncertainty and innovation.

Table 19: Innovation and Presidential Elections for Policy Uncertainty

The table reports the results of panel data regressions where the dependent variable is the log of scaled patents and the independent variable of interest is a dummy variable for presidential elections. A more detailed description of the variable is given in Table 2. The regression estimations are performed using FE. Firm and macroeconomic controls are included but not reported, a description of the control variables is given in Table 1. In regression (1), the election dummy equals one three months before the election, including the month of, and zero otherwise. In regression (2), the election dummy equals one five months before the election, including the month of, and zero otherwise. Robust and clustered standard errors at firm level are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1.
Number of observations is 54 876.

	(1) 3 months dummy	(2) 5 months dummy
Election	0.056***	0.040***
	(0.014)	(0.012)
Adjusted R^2	0.143	0.142

5.7 Robustness Check

The purpose of the following section is to investigate if the results are robust to other measures of innovation, namely that of patent counts. The discrete nature of the patent count makes the poisson model appropriate to use for modeling the relationship between innovation and policy uncertainty, however, due to the overdispersion coming from a significantly higher variance relative to the mean, an assumption of the poisson distribution is violated. Thus, the negative binomial model corrects for this by also modeling a variance parameter. The model is fitted with different regressors compared to those of table 4 in order to get the best fit, however, for consistency, the model is also fitted with the same set of regressors. The results are reported in Table 20, where column (1) is a univariate regression with the PUI, (2) is the model with the same regressors as the base specification, and (3) is the model with the best fit. Columns (4) to (6) report the same as (1) to (3), however, 2019 is removed in order to limit the truncation bias that arises with the raw patent count, which may also be observed in Figure 2.

Table 20: Robustness Check: Negative Binomial Model

The table reports the results of panel data regressions where the dependent variable is the aggregated monthly patent count on a firm level, and the independent variable of interest is the log of the PUI. A detailed description of the variables is given in Table 1. Regression (1) reports a univariate regression, (2) reports the estimated result when using the same control variables as the main model specification, and (3) reports the estimated result with the best fitted model specification for the negative binomial model. Regression (4) to (6) report the same specifications as (1) to (3), but observations from 2019 are excluded. Robust standard errors are reported in the parenthesis. The significance level is reported by: ***p<0.01, **p<0.05 and *p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
l.PUI_US	-0.184***	-0.342***	-0.191***	-0.177***	-0.256***	-0.164***
	(0.037)	(0.029)	(0.026)	(0.038)	(0.031)	(0.027)
l.at		0.465***	0.496***		0.469***	0.499***
		(0.004)	(0.004)		(0.004)	(0.004)
bm		0.068***	-0.032*		0.068***	-0.038**
		(0.019)	(0.018)		(0.019)	(0.018)
ch_at		-0.229***	-0.154***		-0.214***	-0.146***
		(0.027)	(0.026)		(0.027)	(0.027)
de_ratio		-0.014***	-0.014***		-0.014***	-0.014***
		(0.002)	(0.002)		(0.002)	(0.002)
sdev		-0.532			-0.597	
		(0.530)			(0.544)	
l. sdev			0.293***			0.296***
			(0.011)			(0.011)
l.r&d_at		0.343***	0.303***		0.344***	0.302***
		(0.007)	(0.007)		(0.007)	(0.007)
Δt_balance		0.323**			0.278**	
		(0.133)			(0.008)	
enroll			0.052***			0.036**
			(0.014)			(0.014)
Δenroll		1.076***			0.887***	
		(0.225)			(0.227)	

Table 20: Robustness Check: Negative Binomial Model (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Δfed r&d		0.274*			0.596***	
		(0.148)			(0.153)	
Δfed sur_def		-0.044***			-0.033***	
		(0.008)			(0.008)	
gdp			-0.0001***			-0.0001***
			(0.00001)			(0.00001)
Δgdp		3.756**			4.348***	
		(1.520)			(1.519)	
Δhigh_edu		-0.063			0.017	
		(0.113)			(0.128)	
ltint			-0.046***			-0.043***
			(0.008)			(0.008)
Δltint		-0.354***			-0.368***	
		(0.010)			(0.102)	
rec		0.100***	-0.087***		0.081**	-0.095***
		(0.032)	(0.020)		(0.032)	(0.021)
Δrev		0.008	0.040*		0.011	0.034*
		(0.022)	(0.020)		(0.022)	(0.020)
unemp		0.019***	-0.037***		0.0003	-0.032***
		(0.005)	(0.017)		(0.005)	(0.012)
constant	2.485***	0.537***	1.888***	2.453***	0.232***	1.718***
	(0.173)	(0.135)	(0.171)	(0.177)	(0.140)	(0.178)
Pseudo R^2	0.0004	0.128	0.140	0.0003	0.130	0.142
Observations	54 876	54 876	54 876	53 012	53 012	53 012

The univariate regression in column (1) on the full sample from 1985 to 2019 reports a coefficient of negative 0.184 on the PUI, which indicates that as the policy uncertainty increases by one percent, the expected value of innovation is expected to decrease by 0.184 percent, holding the other variables constant. Dropping 2019 to mitigate the truncation bias results in a slightly lower coefficient of negative 0.177, however, both are significant at the one percent level. Using the same regressors as in the main specification, the coefficients reported in both column (2) and (5) are higher than the alternative model for this specification, which provides a better fit based on the pseudo R^2. The pseudo R^2 is not the same as an adjusted R^2 as it is a different space. This means that it is not possible to compare the results produced by OLS and the negative binomial, however, the pseudo R^2 is a valid indicator when comparing multiple models that predict the same outcome on the same data.

6 DISCUSSION

6.1 The Measure of Policy Uncertainty

The study relies on the selected measures used to capture policy uncertainty. Throughout the study, we use different approaches to decrease the reliance on one specific measurement. The primary measurement of policy uncertainty is the PUI developed by Baker, Bloom, and Davis (2016). However, following previous literature by Gulen and Ion (2016) and Kaviani et al. (2020), we use polarization and relative legislative power as possible instrumental variables, the Canadian PUI as a way to remove possible uncertainty about general economic conditions distinct from economic uncertainty coming from policy, and lastly, election data as an alternative measurement. The alternative measurements and approaches give a more nuanced insight into the causality and robustness of the relationship between policy uncertainty and innovation.

Despite the different approaches, some aspects regarding the measurement of policy uncertainty are not captured and could alter the result of the study. The descriptive statistics report that the PUI has considerably higher volatility relative to the scaled patents, and consequently, we report an inelastic relationship between policy uncertainty and innovation. A monthly time frequency is used in the study for the PUI to capture more events and significant fluctuations and avoid infrequent data issues reported by previous literature working with election data. However, the data frequency decision can significantly affect the reported relationship as it is unlikely that firms will react to every policy uncertainty change. R&D is associated with high adjustment costs and is often financed with volatile sources, making it expensive for firms to adjust the flow of R&D (Brown and Petersen, 2011). In the sense that the costs of continuously updating any calculations and forecast analyses would exceed the costs of proceeding with an innovation project, periodic adjustments can be rational. This can be defined as costly rationality, as observations, communications, and computations imply extra costs. Bounded rationality can also give rise to infrequent adjustments, where the cognitive requirement on individual decision-makers can exceed the capabilities. Due to complexity and uncertainty, it will be cognitively impossible to account for all interconnected mechanisms in the internal and external environment (Radner, 1996). If one expects infrequent adjustments, one could change the time frequency of the data to investigate whether the relationship changes.

In addition, continuation bias, meaning that one provides follow-on investments to initial investments because of information fallacy and narcissistic fallacy, can lead to the continuation and commitment to projects regardless of profitability and external changes. Information fallacy implies the belief that today's activity will automatically generate knowledge advantages in a later stage, even if this is not necessarily true. The narcissistic fallacy means that decision-makers exaggerate the benefits of their own contribution; this fallacy further implies that decision-makers are more likely to fall for the information fallacy (Khanin and Mahto, 2013). Due to cognitive limitations and adjustment costs, one could expect that firms have a more significant reaction to large policy uncertainty events rather than the monthly changes. Hence, event studies associated with the most extensive levels of policy uncertainty could be a possible approach. However, if only large events were considered, it would change the study's objective. Examples of these events are the collapse of the Lehman brothers, the 9/11 attack, and the government shutdowns in 2016 and 2019. In addition, these events are likely interconnected with the overall business cycle or may have a direct and widespread societal impact, making it difficult to isolate the relationship between policy uncertainty and innovation.

As previously described, the PUI reflects the frequency of articles that contain a combination of specific words that are assumed to capture economic policy uncertainty in 10 leading US newspapers. Baker, Bloom, and Davis (2016) provide robustness to this method in the sense that the index matches important political developments and shocks. In addition, the index is evaluated in several ways to meet any potential concerns related to newspaper reliability, accuracy, bias, and consistency. A strong relationship between the index and measures of economic uncertainty, e.g., implied stock market volatility, is reported. A strong relationship between the index and other measures of policy uncertainty, e.g., the frequency at which policy uncertainty is mentioned in the Federal Reserve System's Beige Books, is also reported. Moreover, movements in the index remain consistent when based on both right-leaning and left-leaning newspapers. In addition, a manually generated index was performed in order to select the policy term set and evaluate the computer-automated method. After undergoing training, close supervision, and guidelines, teams of University of Chicago students assessed 12 000 randomly selected articles and deemed whether a given article discussed policy uncertainty based on the given criteria. The manually and computer generated indices had a 0.93 correlation in annual data from 1900 to 2010. The PUI has also received market-use validation; commercial data providers, including Bloomberg, FRED, Haver and Reuters, carry out indices to meet the demands of banks, hedge funds, corporations, and policymakers (Baker, Bloom and Davis, 2016).

Despite the deep analysis regarding the robustness of the index, it remains ambiguous whether policy uncertainty crosses national borders or to what extent international spillovers are present. Following

Gulen and Ion (2016) and Kaviani et al. (2020), we assume that policy uncertainty remains within a country and use the Canada PUI to filter out general economic uncertainty from the index. However, one could argue that this assumption is invalid, and that policy uncertainty has an international spillover. With the rise of globalization, the interdependence of economies worldwide has risen. The increased level of globalization has modified the landscape in which firms operate and altered the opportunities and threats that firms face (Greenhalgh and Roger, 2010). A major aspect of globalization is the increase in international trade relative to the world output. The rise in trade relative to world GDP is a common phenomenon across countries and regions, although the relative growth in trade and output varies (Dean and Sebastia-Barriel, 2004).

One could argue that policy uncertainty can have international spillovers through the channel of trade. The renegotiation of major trade agreements in Europe and North America and increasing trade disputes across countries alter global trade connections (Caldara, Iacoviello, Molligo, Prestipino, 2020). Trade policy has become more uncertain and more protectionist under the Trump presidency. Examples of this are the US withdrawal from the Trans Pacific Partnership Agreement (TPP) in January 2017, replacing the old North American Free Trade Agreement (NAFTA), and many tariff hikes, threats, and reversals. The average US tariff rate rose from less than 2% in December 2017 to 4% in May 2019, and the trade-weighted average US tariff on Chinese imports rose from 3.1% in 2017 to 12.4% in 2018 (Brown and Zhang, 2019). Caldara et al. (2020) study the effect of unexpected changes in trade policy uncertainty on the US economy and report that increased uncertainty reduces investment and activity both on a firm level and on an aggregated macroeconomic level. Both higher expected tariffs and increased uncertainty about future tariffs decrease investment. Alam and Istiak (2020) study the impact of US policy uncertainty on Mexico. More than 80% of Mexico's export is imported by the US, and the result shows that an increase in US policy uncertainty leads to a fall in Mexican production, price level, and interest rate. The contribution of the US uncertainty shock to Mexican output and interest rate is, in fact, more extensive than that of the Mexican uncertainty shock. Davis (2019) reviews the PUI and highlights the prominent role of trade policy as a source of uncertainty. However, to truly capture the international spillovers, it would be beneficial to analyze the PUI further to determine how well the policy term set captures these effects. Also, one could investigate the channels through which the international spillovers occur. Possible channels could be: pandemics, natural resource conflicts, natural disasters and wars. Moreover, one could investigate direct policy relationships across countries and their sensitivity. For instance, will an election or change of the leading party in one county automatically increase the policy uncertainty in a geographically close country, or alternatively, in a country with which it has close economic ties. Moreover, it may be that the international spillovers are more pronounced when the incumbent administration is not reelected, while the administration of the neighboring countries remains the same. However, we leave this for future research.

6.2 Other Measures of Innovation

This paper has focused on the measures of innovation, which were initially developed and further improved towards the end of the twentieth century. The traditional class of measures has historically been based on the number of citations made and received, and patent counts. These could be considered in their raw form or be scaled to remove time and technology class fixed effects and thus result in a more relative measure. In recent years, alternative measures have surfaced in effort to address perceived shortcomings of the traditional measures.

Kelly, Papanikolaou, Seru and Taddy (2018) believed that standard patent statistics are merely a useful starting point in the process of determining the degree of technological progress from patent data. The authors motivate their belief by noting that the class of measures which use this type of approach have the following shortcomings: (1) inconsistent records of patent citations, as these sometimes appeared within the text of a patent document prior to 1947, (2) citations tend to take discrete values and (3) citations mainly rely on the discretion of the assignee in the decision of which prior patents to cite and their particular awareness of closely associated patents. To address these shortcomings, the authors proposed a new text-based measure of innovation. This measure exploits the patent documents, which are available for the entire history of the US patent system. Moreover, since the text-based measure utilizes the official patent documents, there is limited discretion, as the text mainly contains and captures the technical description of the innovation itself. The measure leverages natural language processing techniques to create links between new patents and a set of existing and subsequent patents. Hence, the measures quantifies the level of commonality in the content of the patents through the use of measures capturing textual similarity. Kelly et al. (2018) identify an important patent as one where the content is distinct from that of previous patents and simultaneously similar to future patents. This is a unique combination of a patent being novel and impactful, where a novel patent is distinct from those of predecessors and an impactful patent is able to influence future innovation and scientific advances. The authors propose that an important patent is one that is both novel and impactful.

Arts, Hou, and Gomez (2021) created a similar measure based on natural language processing (NLP). They highlighted similar shortcomings of the old class of measures, and moreover, highlighted the shortcomings of the previous works pertaining to text-based measures. Primarily, these shortcomings pertained to the lack of testing of the text-based measures against the traditional measures. The authors employed two different methods to validate the text-based measures. Firstly, they used patents linked to famous awards and patent rejections. This consistently supported that text-based measures are valid in identifying new technologies and measure novelty, and moreover, that these are improvements to the traditional measures. Secondly, the authors exploited a consensus suggestion in related literature by Jaffe and Lerner (2006), Lemley and Shapiro (2005), Frakes and Wasserman (2017). They suggested that the USPTO is granting an increasing amount of "weak" patents that essentially fail to meet the novelty requirement. Moreover, they emphasize that the European (EPO) and Japanese (JPO) patent offices follow the same patent approval process and that, despite of this, these organizations have a more careful and time-consuming examination process. Using this information, Arts, Hou, and Gomez (2021) hypothesize that patents that are eventually granted in the US, EU and JPO are truly novel. Also here, the authors found that the results were consistent with the previous result and effectively that the text-based measures did a better job of indicating the true level of novelty.

Although the text-based measures address some of the central shortcomings of the traditional measures, these open up for yet another set of limitations that are imperative to acknowledge. The patent documents are written by the inventors or attorneys, who have a natural interest in glorifying the text in order to increase the apparent novelty, and effectively increase the likelihood of receiving the grant. Although the patent documents are required to be clear, concise and include exact terms, inventors may strategically opt for more unclear phrasing or invent new words to describe an otherwise innovel innovation, which might influence the text-based measures. In the same vein as the invention of new words that do not necessarily describe a new phenomenon, spelling errors, synonyms, and homonyms are not corrected for in the existing text-based measures. Hence, a particular patent may be labeled as pioneering in a field, although another innovation could have moved first without using the same definition of the most central words in the patent document.

It is difficult to infer whether it is best to use the traditional or the text-based measures. Both measures capture innovation to some extent, but particularly when looking at novelty and impact, the discretion of the inventor becomes important and influential. The text-based measures improve this by taking away the absolute reliance on the inventor's discretion in the citation of other patents, but introduces another set of issues, particularly with the potentially strategic phrasing of the patent document that could create a fundamental bias in the text-based measures. It is certainly more straightforward to use the traditional measures, where the use of sophisticated algorithms may be time-consuming. Ultimately, the choice of measure depends on the purpose of a particular study. If the primary purpose is to understand the relationship between something and the novelty and impact of innovation, then it may be beneficial to use the text-based measures, however, in the context of this paper, the primary objective is rather to understand what happens to the overall level of innovation, which the scaled patents and raw patent counts are able to capture.

6.3 The Time Lag of Innovation

The general consensus in the literature is that innovation is measured by the output, which is largely due to two things: first of all, it can be argued that the output itself is the true representation of the contributions of inventors, and secondly, it is indeed possible to measure due to the readily available patent data. In reality, the most truthful depiction of the undertaken innovation in any given firm starts with the generation of an idea and the subsequent decision to develop it by undertaking it as a project. In the context of policy uncertainty, and any other kind of uncertainty, this becomes particularly relevant.

When looking at the interplay between policy uncertainty and innovation, it may be argued that the decision to innovate is much more relevant than the manifestation of an idea that was generated back in time. This gives rise to the implications of the natural time lag between the decision to undertake a project and the resulting innovation output. With elevated levels of policy uncertainty, a firm may decide not to undertake a project at a particular time, however, once the project has been signed off on and the resources are allocated, the actual macroeconomic conditions may become less important. This could for instance be both due to earmarked resources for a specific project and a buildup of cash coming from the precautionary cash holdings motive. Looking at this from a different perspective, it may be the case that the relationship between innovation output and policy uncertainty depends on the particular characteristics of a project and the magnitude of a shock to policy uncertainty. Brown and Petersen (2011) argued that due to the high adjustment costs of R&D and the fact that it is financed with volatile sources of funds, it is expensive for firms to adjust the flow of R&D in response to transitory finance shocks. In other words, there should be no reaction to small changes in policy uncertainty due to the adjustment costs, but there could be in the case of a sufficiently high shock to the PUI. This indicates that after the commencement of a project, it is unlikely that the continuation of the project is compromised for small changes in policy uncertainty, however, this may be different at large changes. Moreover, in the context of large shocks to the PUI, the size of a project and the reason for innovating may have an impact on its relationship with policy uncertainty. The long and important projects may not be as sensitive to the policy uncertainty as the shorter projects, since a firm may choose to prioritize the relatively important projects. This would effectively allow a firm to optimally reallocate R&D resources to best support their core innovation activities whenever the macroeconomic climate requires this reprioritization.

6.4 Research Methodology

Reliability and validity are two central concepts to assess the chosen research methodology and its implication for the study. Reliability treats the consistency and the stability of the measure and method and has implications on the extent to which the result can be reproduced (Bryman and Bell, 2017). The study consists of data from 1985 to 2019 and has a large amount of observations in the cross-section, decreasing the likelihood that the results are dependent on the specific sample. The data is collected from different databases, which minimizes any subjectivity imposed by the authors in the data collection process. The fact that the study consists of quantitative data also increases the reliability of the study as it facilitates replications; the data will remain constant and can be reproduced at a later point in time. However, the fuzzy matching of databases decreases the reliability as it will make it harder to replicate the results. Lastly, we provide descriptions of all the variables used and any calculations associated with these variables to increase the reliability of the study.

The validity of the study implies the extent to which the result measures the true aim behind the measurement. As previously stated, this study relies on the PUI developed by Baker, Bloom, and Davis (2016) as a measure of policy uncertainty. However, this index is commonly used and has been proven robust. Hence, we deem that the study's validity remains high even with this dependency. Furthermore, we perform several additional analyses to establish the robustness and causality of the result, which is aligned with previous literature methods. One shortcoming of the study is the reliance on scaled patents as the measure of innovation, as this is a measure of innovation output and might not be the best measure to use. The innovation decision might be a better measurement to capture the effect of policy uncertainty on innovation, however, this data is more difficult to obtain and requires information on R&D processes, which are often classified information. Moreover, data is divided into subsamples for further analysis. The subsamples are created depending on if an observation is above or below the median of a specific characteristic. The method choice affects the validity and stability of the result. We cannot eliminate the possibility that the result would differ if the subsamples were created based on other criteria.

Lastly, observations drop out of the sample if we cannot match the data from different databases or if financial data is missing from the observation. Skewness or bias could therefore arise if omitted observations have any systematic pattern. The matching between databases is based on specific identification keys or the firm name, and the reason for dropout is often misspelling or inconsistent naming. We deem that there is no systematic pattern behind this inconsistent naming. One could argue that smaller firms are more likely to have missing financial observations. However, we use the well-established database, Compustat, for the financial data, and the descriptive statistic indicates a great spread in firm assets. Taken together, we believe that the implication of any systematic patterns in omitted observations due to missing financials has a low implication on the main result.

7 FURTHER RESEARCH

7.1 Foreign Inventors

From Figure 3 in the result, we report an increasing share of foreign inventors in the sample. The development is aligned with a general trend of increased globalization. An interesting aspect of globalization is the relocation of R&D across more countries. Multinational corporations aim to conduct innovation in countries with the most beneficial environment, where a given investment yields the highest reward. Competitive pressure also implies that firms seek out foreign research talent and lower costs. Modern communications allow firms to break up the research process and carry out different procedures across the globe, resulting in worldwide networks of R&D centers (Greenhalgh and Rogers,2010).

It would be interesting to investigate if policy uncertainty affects where a firm decides to conduct its innovation, given international innovation networks and an increasing share of foregin inventors. Where innovation is conducted may have important implications for the general economic growth within a country (Solow, 1956, Romer, 1990). A certain level of policy uncertainty could attract foreign firms to conduct innovation in the country and contribute to economic growth while other levels could demotivate domestic innovation.

7.2 Industry Analysis

The nature of innovation differs across industries. For instance, Sherer (2000) found that a series of characteristics separates the pharmaceutical industry from others. The innovation in this type of industry is central to ensure the longevity of human life and therefore the high R&D intensity, long development stages, and general complexity is justified and inevitably would be intervened with if development intentionally came to a halt. Another example is that of the tech industry, where the need to innovate comes from both a competition perspective in order to stay relevant, but also with a clear incentive to optimize processes and central technologies that are vital for the succession of the world. These industries have in common that they are fundamentally driven by more than merely commercial motives, which other industries may not share. The fashion industry may routinely come up with new collections, but developing new processes that redefine the industry itself may not be of utmost importance in the short or medium term and thus not create the same sense of urgency.

Based on this, one may conjecture that the innovation by industries with a sense of urgency are less likely to be impacted by policy uncertainty as opposed to the industries that lack this. As an extension of this, it would be interesting to look into the determinants of what makes certain industries more exposed to policy uncertainty than others. It could merely be the nature of the innovation as propositioned above, or it could relate to competitive nature in the industry, dependence on subsidies etc.

7.3 Competition

Lemley (2012) first introduced the concept of *patent racing*, which refers to the fact that the patent system naturally rallies competition in R&D and effectively incentivizes firms to innovate faster than their competitors in order to achieve the exclusive rights to the invention. Hence, patent racing, which is a reflection of competition, speaks to the increase in patents through time. Fundamentally, this idea comes from Grenadier (2002), where the author shows that, under the strategic growth option theory, the value of the option to invest converges to zero as the number of competing firms goes to infinity. Thus, confirming that an increase in competition will cause firms to invest earlier in order to act value maximizing and thereby engage in patent racing.

This raises natural questions regarding the impact of competition on the relationship between policy uncertainty and innovation. In an uncertain environment, the innovative approach of a firm may depend on the response of its competitors. For instance, in a competitive environment, a firm may be forced to consider the actions of its competitors and thereby incorporate strategic choices. This could involve the decision to innovate in order to get ahead of the competition or due to the fear of falling behind. Considering a monopolistic environment, a sole firm may need to innovate in order to increase the barriers to entry in the hopes of maintaining its position, commonly known as entry deterrence, or to lower its marginal cost and effectively make a bigger profit (De Bondt and Vandekerckhove, 2010).

8 CONCLUSION

This study shows that policy uncertainty negatively impacts innovation. The finding is robust to several econometric specifications, namely the use of raw patent counts as opposed to the log of scaled patents, and the treatment of the PUI as endogenous in the main specification.

Moreover, we find that the sensitivity of innovation to changes in policy uncertainty depends on the initial level of the PUI. For low levels of policy uncertainty, a change in the PUI is associated with an increased level of innovation, while the opposite relationship is reported for high levels of policy uncertainty. Furthermore, we find that the innovation of large firms, relative to small firms, is more sensitive to changes in policy uncertainty for both high and low levels of policy uncertainty. The finding is consistent with previous literature suggesting that young firms are likely to have better failure-resilience capabilities, and that innovation in small firms tends to remain at a constant level regardless of uncertainty.

After decomposing the PUI, we find that individual components of policy uncertainty, namely fiscal and monetary policy, do not have the same impact on innovation. Monetary policy uncertainty has a positive effect on innovation, while fiscal policy has a negative effect but of lower magnitude compared to the general PUI. The opposite sign of monetary policy uncertainty relative to that of the general PUI may be attributed to the fact that the Federal Reserve has opted to implement a target inflation rate, allowing the public to develop an expectation of the long-run inflation rate which has important implications for the actual inflation. Effectively, the target inflation brings clarity about the long-run goals and sense of direction for the economy.

We find that innovation is affected differently depending on the quality of innovation, where quality is denoted by impact and novelty measures. The impact measures, scaled citations and scaled generality, suggest that firms with more impactful innovations are affected more by increased policy uncertainty. This is consistent with previous findings that the negative effect of increased policy uncertainty on innovation is more prominent for influential and impactful patents. The novelty measure, scaled originality, indicates that firms with more novel innovation have a less adverse reaction to increased policy uncertainty. This is inconsistent with previous literature suggesting that original innovation is more affected by increased policy uncertainty. The finding may be attributed to a potential feature of original innovation, namely the size of the project. Citations made to a wide range of technology classes indicate that the innovation is an output of a time-demanding project. A long development phase and an important project could be seen as features that make a project more inelastic to fluctuations in policy uncertainty as this effect will have a lower impact across the life span of a project.

In the cross-section, we find that large firms tend to have a more adverse reaction to increased policy uncertainty. This is likely attributed to the fact that large firms have the ability to plan and allocate resources optimally and postpone projects in order to time their innovation. Moreover, policy uncertainty amplifies information frictions that enlarge problems connected to moral hazard, adverse selection, and misallocation of resources, where these are prevalent in large firms. We find the effect of the degree of financial constraint to be inconclusive, as it depends on the measure of financial constraint. Using the debt to asset ratio as a measure of financial constraint, we find that the innovation of financially constrained firms is impacted more by increased policy uncertainty. However, using the interest coverage ratio, we find evidence of the opposite relationship. The KZ score indicates that the innovation of financially constrained firms is impacted more by increased policy uncertainty, but it is not possible to conclude that there is a significant difference in the estimated coefficients. Furthermore, we find that the innovation of firms with a lower level of cash holdings has a more adverse ration to increased policy uncertainty. This is consistent with the argument that firms hold cash as a precautionary motive, whereby they are prepared for future uncertainty. Furthermore, we tested the idea that the innovation of lobbying firms is more impacted by increased policy uncertainty compared to that of lobbying firms, consistent with the argument that firms lobby to favor outcomes that effectively decrease their exposure to uncertainty. However, the coefficients are not significantly different from each other and therefore we cannot make this conclusion. Lastly, we test if regulation intensity impacts the relationship between policy uncertainty and innovation but find that there is no significant difference between the coefficients. We regress innovation on policy uncertainty for the top three industries but report no significant difference in the estimated coefficients. Differences in reported adjusted R^2 indicate that the variables impacting innovation differ across industries.

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APPENDIX

A. Scaled Patents

Figure A1: Scaled Patents Histogram

The figure provides a histogram over the density of scaled patents.

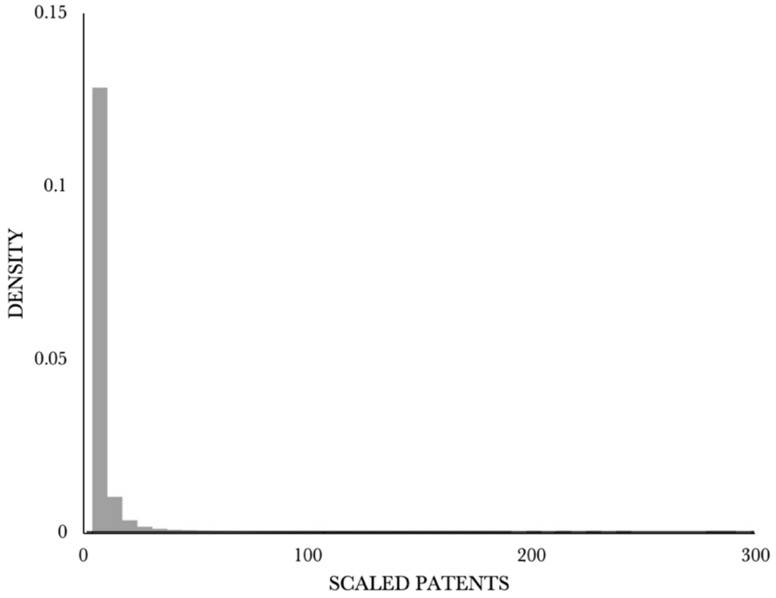
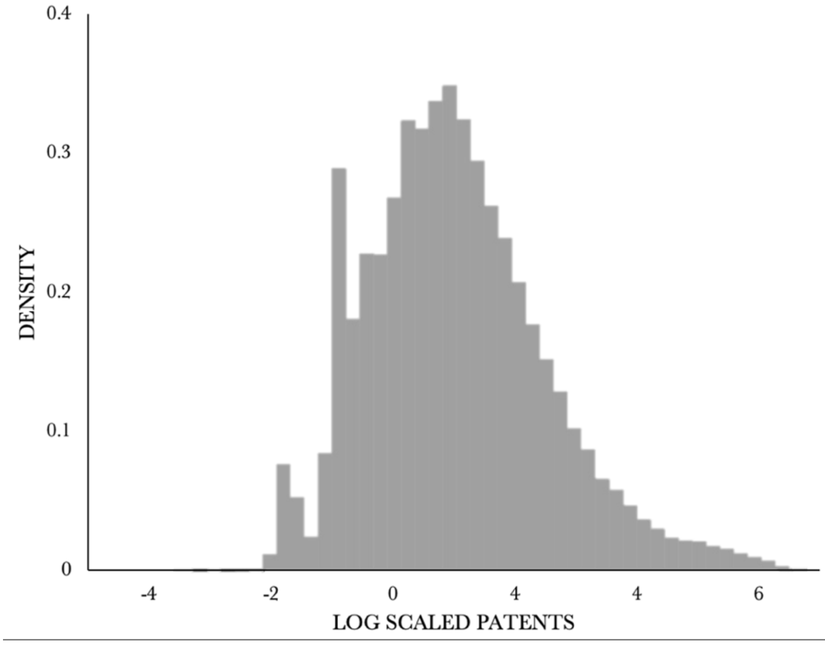


Figure A2: Log Scaled Patents Histogram

The figure provides a histogram over the density of logged scaled patents.



B. Residuals

Figure B1 indicates that large outliers are present in the sample, violating the third assumption for the pooled OLS and the FE specification. Following Cook (1977), we estimate influential outliers and proceed to remove the upper quartile of influential observations. A trade-off between keeping observations and removing large outliers where considered. Figure B2 provides the residual scatterplot corresponding to the residuals from the main model specification reported in regression (8) in Table 4. After outliers have been removed, the scaling on the x-axis is changed, and the residuals are more closely distributed. However, the residual scatter indicates heterogeneity in the error term. Hence, clustered standard errors, which are robust to heteroskedasticity and to correlation over time within a firm, are applied to the main specification. Furthermore, Figures B3 and B4 indicate that the obtained residuals are close to the normal distribution; hence we deem that the asymptotic properties of OLS make the application of confidence intervals and critical values associated with the student t distribution valid.

Figure B1: Residual Scatter before Outliers is Removed

The figure provides a scatterplot of the reported residuals against predicted value. The figure corresponds to estimated residuals of the main model specification reported in regression (8) in Table 4: Model Specification for Policy Uncertainty and Innovation, in the case that no outliers are removed.

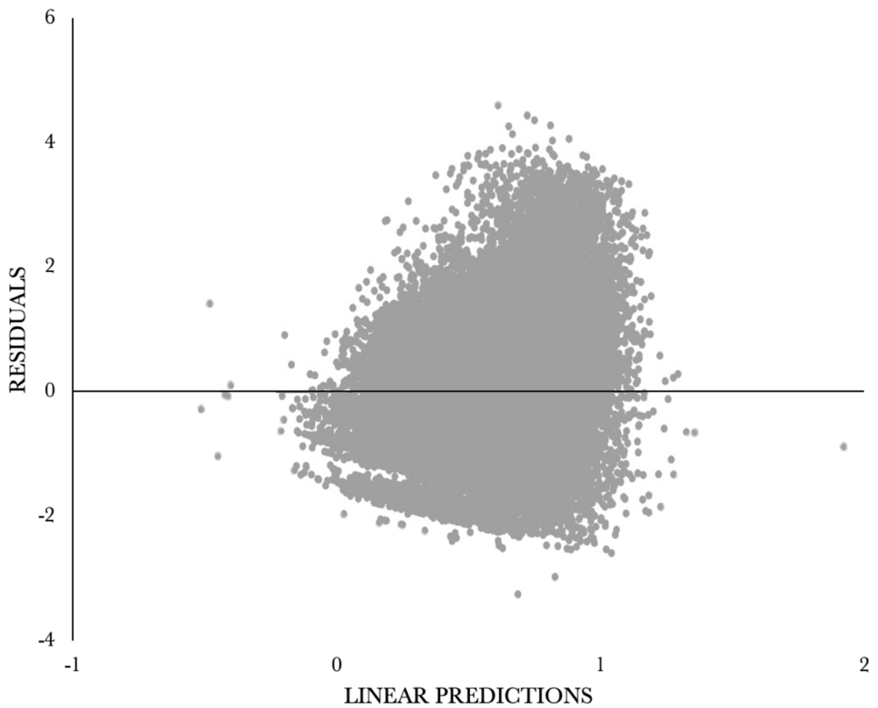


Figure B2: Residual Scatter after Outliers is Removed

The figure provides a scatterplot of the reported residuals against predicted value. The figure corresponds to the obtained residuals form the main model specification reported in regression (8) in Table 4: Model Specification for Policy Uncertainty and Innovation, where outliers are removed.

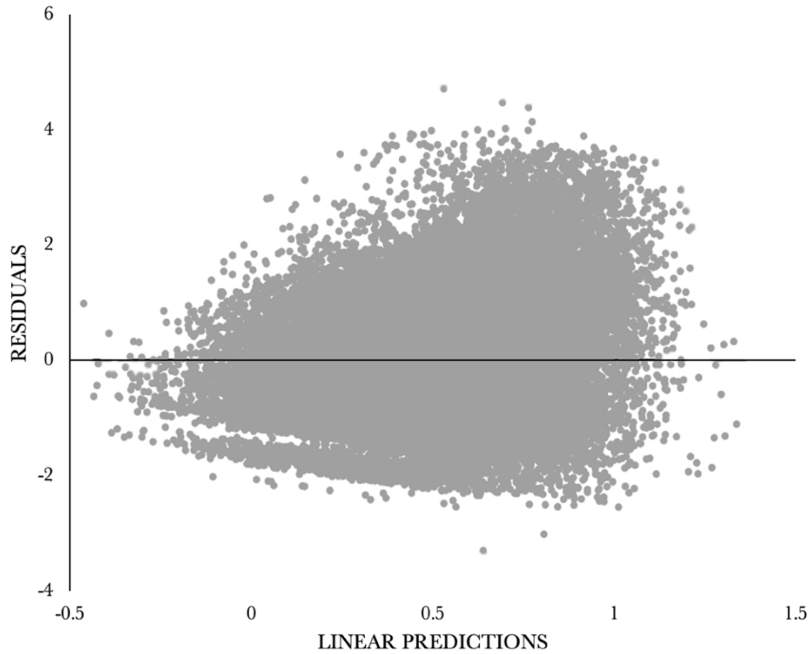


Figure B3: Residuals Histogram

The figure provides a histogram over the density of the obtained residuals form the main model specification reported in regression (8) in Table 4: Model Specification for Policy Uncertainty and Innovation.

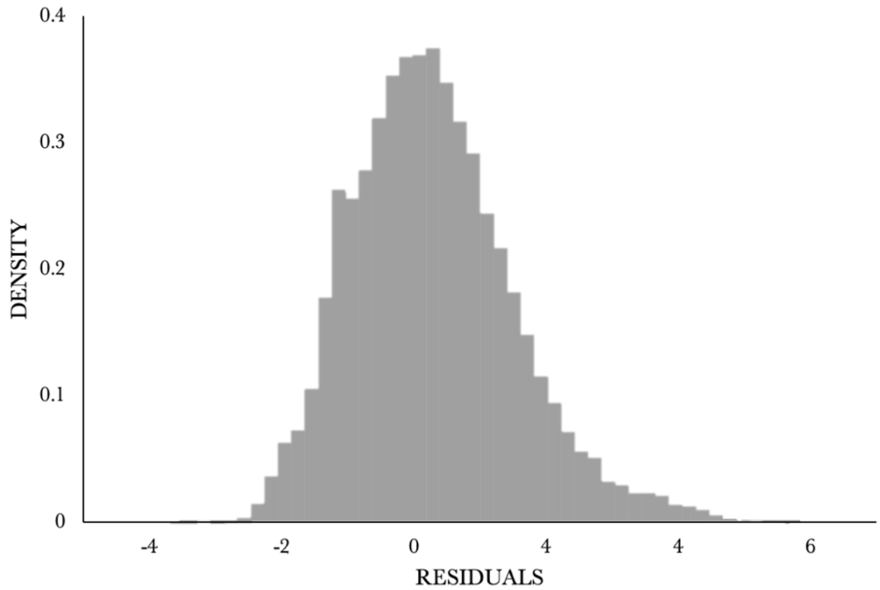
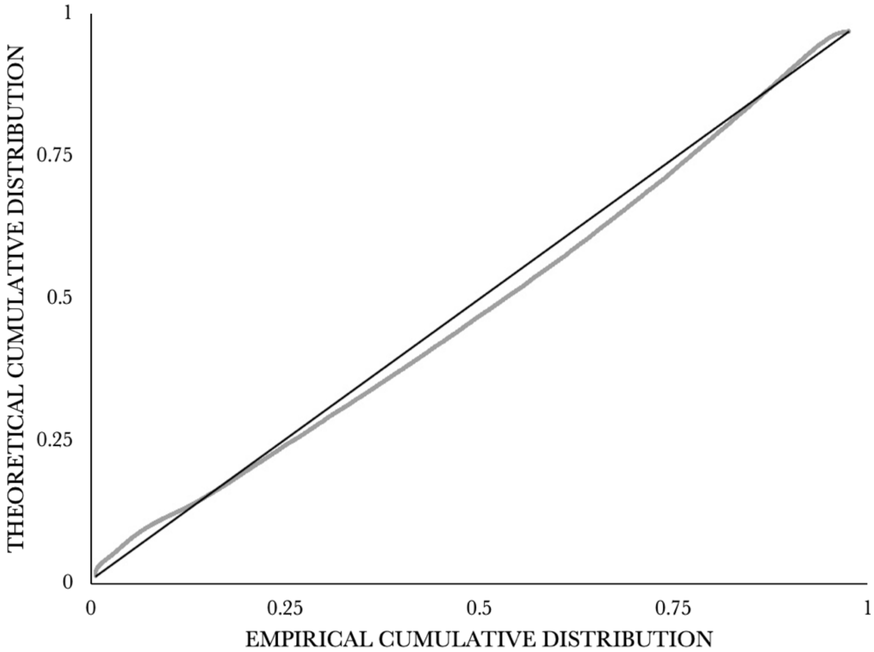


Figure B4: Residuals Cumulative Distribution

The figure provides the cumulative probability distribution to the obtained residuals form the main model specification reported in regression (8) in Table 4: Model Specification for Policy Uncertainty and Innovation.



C. Multicollinearity

The assumption of no perfect multicollinearity is necessary for both the OLS and the FE regression. However, even imperfect multicollinearity can be problematic in a model specification. (Stock and Watson, 2015). Table C1 reports the correlation matrix to investigate the linear relationships between the regressors used in the main model specification reported in Table 4. The general rule is that if a correlation coefficient between two regressors is greater than 0.8 in absolute value, then multicollinearity is a severe problem (Midi, Sarkar, and Sohel, 2010). Furthermore, we report the variance inflation factor in Table C2. The variance inflation factor is a commonly used measure to detect multicollinearity. The main rule of thumb is that a factor higher than 10 indicates a sign of server multicollinearity; however, the research is inconclusive regarding the specific threshold (O'Brien, 2007). From the reported values in Tables C1 and C2, we deem that multicollinearity is not an issue for the model specification.

Table C1: Correlation Matrix

The table provide a correlation matrix over the independent variable, the firm controls and the macroeconomic controls that are used in main model specification reported in Table 4: Model Specification for Policy Uncertainty and Innovation.

	l.PUI_US	*l.at*	*bm*	*ch_at*	*de_ratio*	*sdev*	*l. r&d _at*
l.PUI_US	1						
l.at	0.087	1					
bm	0.084	-0.077	1				
ch_at	0.032	-0.402	-0.202	1			
de_ratio	0.004	0.099	-0.069	-0.092	1		
sdev	-0.016	-0.552	0.079	0.358	-0.053	1	
l.r&d _at	0.001	-0.421	-0.208	0.570	-0.074	0.371	1
Δt_balance	-0.048	-0.031	0.046	-0.074	0.002	-0.039	-0.058
Δenroll	0.007	-0.055	0.107	-0.035	-0.020	0.159	-0.018
Δfed r&d	-0.064	-0.065	0.056	-0.072	-0.020	-0.044	-0.040
Δfed sur_def	0.228	0.066	-0.018	0.032	0.001	-0.031	-0.019
Δgdp	-0.362	-0.064	-0.053	-0.045	0.005	-0.058	-0.024
Δhigh_edu	0.073	-0.011	0.001	0.023	0.005	0.114	0.033
Δltint	-0.153	0.001	0.011	0.008	0.004	-0.023	0.002
rec	0.210	-0.004	0.086	0.001	-0.011	0.183	0.010
Δrev	0.056	0.014	-0.037	0.017	0.005	-0.101	-0.012
unemp	0.513	0.014	0.149	-0.028	-0.014	-0.088	-0.048

Table C1: Correlation Matrix (continued)

	Δt_balance	*Δenroll*	*Δfed r&d*	*Δfed sur_def*	*Δgdp*	*Δhigh_edu*	*Δltint*	*rec*	*Δrev*	*unemp*
l.PUI_US										
l.at										
bm										
ch_at										
de_ratio										
sdev										
l.r&d _at										
Δt_balance	1									
Δenroll	0.024	1								
Δfed r&d	0.033	0.061	1							
Δfed sur_def	-0.037	0.204	-0.228	1						
Δgdp	0.146	-0.210	0.105	-0.249	1					
Δhigh_edu	-0.035	0.065	-0.011	0.031	-0.079	1				
Δltint	0.019	-0.032	-0.033	-0.049	0.158	-0.052	1			
rec	-0.131	0.376	-0.063	0.200	-0.545	0.135	-0.016	1		
Δrev	0.047	-0.146	-0.154	0.105	0.222	-0.059	0.019	-0.273	1	
unemp	0.010	0.162	0.069	0.310	-0.148	-0.059	0.003	0.043	0.221	1

Table C2: Variance Inflation Factor

The table provide the variance inflation factor over the independent variable, the firm controls and the macroeconomic controls that are used in main model specification reported in Table 4: Model Specification for Policy Uncertainty and Innovation.

	VIF
l.PUI_US	1.67
l.at	1.72
bm	1.17
ch_at	1.66
de_ratio	1.02
sdev	1.67
l.r&d _at	1.67
Δt_balance	1.04
Δenroll	1.32
Δfed r&d	1.16
Δfed sur_def	1.29
Δgdp	1.69
Δhigh_edu	1.04
Δltint	1.07
rec	1.74
Δrev	1.25
unemp	1.73
Mean VIF	1.41

D. Frequency of Observations across Years

Table D1: Observations across Years

The table provide a frequency table over observations per year.

Year	Number of Observations	Percent of Total Observations
1985	497	0.91
1986	524	0.95
1987	535	0.97
1988	594	1.08
1989	570	1.04
1990	613	1.12
1991	666	1.21
1992	755	1.38
1993	959	1.75
1994	1 179	2.15
1995	1 245	2.27
1996	1 373	2.50
1997	1 613	2.94
1998	1 659	3.02
1999	1 644	3.00
2000	1 753	3.19
2001	2 088	3.80
2002	2 062	3.76
2003	1 983	3.61
2004	1 939	3.53
2005	2 025	3.69
2006	1 936	3.53
2007	1 949	3.55
2008	1 888	3.44
2009	1 799	3.28
2010	1 876	3.42
2011	1 873	3.41
2012	2 023	3.69
2013	2 082	3.79
2014	2 266	4.13
2015	2 346	4.28
2016	2 295	4.18
2017	2 202	4.01
2018	2 201	4.01
2019	1 864	3.40
Total	54 876	100

E. Z-score Estimation

In order to examine interactive effects in a regression context, a common method is to examine the difference between two regression coefficients across independent samples. A t- or z-test is commonly used to determine the significance of the difference between two regression coefficients, formally one test whether $\beta_1 = \beta_2$ or if $\beta_1 \neq \beta_2$. For example if β_1 reflects the effect of explanatory variable x within group 1 (ex. larger firms) and β_2 is the effect of that same variable within group 2 (ex. small firms), a test of explanatory invariance is based on the hypothesis test that the difference between β_1 and β_2 is zero (Paternoster, Brame, Mazerolle and Piquero, 1998).

Consider the case of an identical regression model which is estimated for two groups. The separate regressions can be retrieved from a regression model for both groups by combining the two subsamples and adding a dummy variable that denotes the groups variables as well as the interaction of the dummy with each of the predictors. Under the assumption that the residual variance is the same for each group, the difference of the regression coefficients can be examined by testing the interaction terms either singly or jointly. However, this method is not valid if the residual variance differs across the groups. For large samples, the significance of the difference between the coefficient can instead be estimated by the z-score:

$$z = \frac{\hat{\beta}_1 - \hat{\beta}_2}{\sqrt{s^2(\hat{\beta}_1) + s^2(\hat{\beta}_2)}}$$

The standard error of the difference is the square root of the sum of the two squared standard errors (Clogg, Petkova and Haritou, 1995).

F. Frequency of Observations across Industries

Table F1: Observations across Industries

The table provide a frequency table over observations across industries.

NAICS	Number of Observations	Percent of Total Observations
1111	87	0.32
1114	27	0.10
2111	1	0.00
2131	54	0.20
2211	2	0.01
3112	304	1.11
3114	20	0.07
3115	1	0.00
3119	83	0.30
3121	202	0.74
3221	70	0.25
3241	221	0.80
3251	73	0.27
3252	81	0.29
3253	44	0.16
3254	10 359	37.72
3255	116	0.42
3256	427	1.55
3259	469	1.71
3262	7	0.03
3272	2	0.01
3273	5	0.02
3311	55	0.20
3313	3	0.01
3333	548	2.00
3334	44	0.16
3342	3 440	12.53
3343	296	1.08
3344	6 459	23.52
3351	120	0.44
3352	39	0.14
3359	244	0.89

Table F1: Observations across Industries (continued)

NAICS	Number of Observations	Percent of Total Observations
3361	321	1.17
3362	134	0.49
3365	16	0.06
3366	1	0.00
4233	1	0.00
4234	63	0.23
4235	1	0.00
4236	5	0.02
4237	3	0.01
4239	18	0.07
4241	14	0.05
4242	49	0.18
4243	1	0.00
4244	1	0.00
4251	2	0.01
4483	3	0.01
5122	4	0.01
5171	22	0.08
5174	61	0.22
5179	132	0.48
5182	1 029	3.75
5191	1 409	5.13
5239	2	0.01
5241	4	0.01
5242	2	0.01
5311	10	0.04
5413	93	0.34
5419	31	0.11
5614	4	0.01
5622	24	0.09
6214	32	0.12
6219	66	0.24
Total	27 461	100