STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
5350 Master's thesis in economics
Academic year 2021-2022

The Silver Lining of Political Uncertainty: AI Innovation

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Abstract: Artificial intelligence (AI) is one of the most transformative technologies of our time. Therefore, analyzing the driving forces behind AI innovation is of interest to any researcher or policymaker who wants to understand the modern economy. Building on economic theories suggesting that uncertainties impact investments, we propose political uncertainty as a determinant of the level of AI innovation. To proxy for AI innovation, we use data on AI patents provided by the United States Patent Office (USPTO) between 2000-2018. To capture the existence and degree of political uncertainty, we use data on election dates and the victory margin between the two major political parties. We conduct a cross-country analysis with 32 democratic countries as well as a US case study including all the 50 states. Our empirical strategy tests to what extent political uncertainty has an effect on the level of AI innovation using a panel regression model with entity and time fixed effects. The results suggest a positive relationship between political uncertainty and AI innovation. In the cross-country analysis, we find an increase in AI patents a year before and during years of national elections, and in the US case study we find an increase in AI patents a year after close gubernatorial elections.

Keywords: Uncertainty, Innovation, Artificial Intelligence, Patents, Elections
JEL: D72, D81, O33

Supervisor: Maiting Zhuang
Date submitted: May 13, 2022
Date examined: May 23, 2022
Discussants: Valter Frankenberg
Examiner: Magnus Johannesson

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Acknowledgements

To begin with, we are grateful to our supervisor Maiting Zhuang at the Stockholm School of Economics for guidance and feedback throughout the entire process of writing this thesis. We are also indebted to Jonathan Rebane, AI expert at anch.AI, for conversations in the idea generation process which laid the foundation of our research question. Finally, we would like to thank Nicholas Pairolero, Economist in the Office of the Chief Economist at the United States Patent Trademark Office and co-author behind the Artificial Intelligence Patent Dataset, for helpful guidance regarding the patent data.

1 Introduction

The Dartmouth Summer Research Project on Artificial Intelligence, organized by John McCarty in 1956, is widely considered the birth of artificial intelligence (AI). The conference brought together a group of scientists to clarify and develop ideas about "thinking machines" (McCarthy et al., 2006; Nilsson, Nils J., 2009). Since then, AI has grown fast and diffused widely across organizations, industries and geographies. In essence, AI has become one of the most transformative technologies of our time. By changing the ways firms operate and society at large, the development of AI is closely related to economic growth. As explained by Agrawal et al. (2018), much of the interest in the relationship between AI and the economy comes from the potential of AI being a general purpose technology (GPT).[1] Analyzing the driving forces behind technological innovation related to AI is therefore of interest to any researcher or policymaker who wants to understand the modern economy.

However, the deployment of AI has also raised controversies involving privacy, discrimination, and manipulation of decision making (Felländer & Gambelin, 2021; Purdy, 2020). In light of this, AI governance has become a debated political topic, giving rise to uncertainties around the future regulatory and policy landscape of AI (Acemoglu, 2021; Agrawal et al., 2018). Overall, the regulatory responses to AI have emerged during the last decade for most democracies and generally operate on a national level, but some cross-national organizations such as the EU and the OECD have recently started to develop common policies as well.[2] Given that AI has a huge potential for both businesses and society, but at the same time constitutes a new and relatively unregulated industry, it is particularly interesting to examine how AI innovation goes together with politics.

At the same time, globalization, financial crises, and political instability are increasing the degree of uncertainty in economies across the world. Particularly, political polarization is shaking many countries. In the US, Baker et al. (2014) document a strong upward drift in policy-related uncertainty and political polarization since the 1960s. Similarly, Boxell et al. (2020) show that affective polarization, defined as the degree of distrust and feeling negative about other political parties than their own, has risen substantially in many democracies over the past four decades. Economic theories suggest that uncertainties in the economy impact investments. The theory of irreversible investments suggests that uncertainty will delay the current rate of investments if investments are associated with sunk costs and if more relevant information arrives over time (Bernanke, 1983; Dixit & Pindyck, 1994). Building on this, the real options theory suggests

[1] GPT:s are characterized by the potential for pervasive use in a wide range of sectors and by their technological dynamism (Bresnahan & Trajtenberg, 1995). GPT:s not solely affect productivity directly, but also boost other complementary innovations.

[2] The OECD has developed a database named the AI Policy Observatory that provides data of over 700 AI policies and initiatives from 60 countries (OECD, 2021a). The EU started to work on their approach to AI in 2018, and published their capstone proposal for regulation called the "White Paper on Artificial Intelligence" in July 2020 (European Commission, n.d.). Another multi-stakeholder initiative is the Global Partnership on Artificial Intelligence (GPAI), built around the OECD recommendations on AI, that was launched in June 2020 and today has 25 members (GPAI, n.d.), all included in our analysis.

that patents can act as options because holding a patent gives its owner the possibility to delay investments while waiting for more information. As such, the value of patents are expected to increase under greater uncertainty (Bloom & Van Reenen, 2002; Pakes, 1986).

This study aims to understand how political uncertainties affect AI innovation. However, identifying AI innovation is challenging not solely because of the ambiguity of what should be defined as AI technology and the changes of these definitions over time, but also because of methodological issues such as limited availability of data and alternative measures of AI. To proxy for AI innovation, we use AI patent counts. Using this proxy, however, implies that we cannot distinguish between whether AI patent counts capture investments in AI innovation or the value of AI patents as real options, which rests on two economic theories suggesting different effects. As such, we cannot pre-determine whether the number of AI patents will increase or decrease. Therefore, we set up two rival hypotheses that we empirically test in order to determine whether AI patent counts capture the effects of actual investments in innovation or as patent real options in this context. The first hypothesis [H1] suggests that AI patents act as the output of irreversible investments in innovation, and therefore decrease under political uncertainty following Bernanke (1983). The second hypothesis [H2] suggests, conversely, that AI patents act as real options and because the value of real options increases under uncertainty accordance with Bloom and Van Reenen (2002) and Pakes (1986), the quantity also increases. Altogether, testing these hypotheses allows us to establish the direction as well as the potential underlying mechanism of the relationship between political uncertainty and AI innovation.

We use a novel dataset on AI patents filed by the United States Patent Office (USPTO) together with data on national elections in established democracies. The data on patents was provided by the Artificial Intelligence Patent Dataset (AIPD), and contains the number of AI patents per year and country, which we exploit as our dependent variable.[3] This function as a proxy for the level of AI innovation. The data on national elections was provided by the Parliaments and governments database (ParlGov) and the American Presidency Project (APP). We use data on national election dates and the victory margin between the major political parties to capture the existence and degree of political uncertainty. The two independent variables of interest are the year of a national election and the occurrence of a close election, where we define an election as close if the victory margin lies within the first quartile of the sample distribution of all victory margins. In addition, we conduct a case study on the US using state-level data on filed AI patents together with data on gubernatorial elections provided by the CQ Press Library.

Our empirical strategy tests whether political uncertainty has an effect on the level of AI innovation. This is done using a panel regression model with entity and time fixed effects. We first present a cross-country analysis spanning 32 countries over the years 2000-2018, which allows us

[3]A patent is a type of intellectual property protection for an invention. A granted patent gives its owner "the right to exclude others from making, using, offering for sale, or selling" the invention in the country where the patent is issued (USPTO, 2021). Typically, the patent protection lasts for 20 years from the filing date (WIPO, 2015). While offering recognition for the inventor and protection against free-riders, a patent also facilitates mutual knowledge since the technical information is made publicly accessible. This gives incentives for competitors to search for other solutions, meanwhile building on the knowledge from existing patented inventions (WIPO, n.d.-a).

to draw broad conclusions about the effect of political uncertainty on AI. We complement this analysis with a US case study spanning the 50 states over the years 2000-2018, which allows for more convincing causal identification as we can isolate our effect of interest from potentially confounding country-level trends. The US is particularly interesting since it has experienced a high and rising degree of affective polarization over the past decades, and has been one of the front runners when it comes to AI innovation and patenting. Furthermore, we hypothesize that the effect could also arise in the pre- or post-election period, and address this by extending our model to investigate the year before and after an election. Finally, a major challenge in our model is to establish causality due to potential omitted variable bias. We tackle this issue by including country-specific or state-specific time trends. Following previous literature, we consider economic growth to be the main confounder and include it as a control variable.

The results suggest a positive relationship between political uncertainty and AI innovation. In the cross-country analysis, AI patents increase by 7% in the year before a national election, significant at the 5 % level, and by 9% during the actual election year, significant at the 1 % level, as compared to non-election years. In the US case study, AI patents increase by 12% a year after a close gubernatorial election, significant on the 0.1 % level, as compared to non-election years. The positive relationship confirms [H2], and we reason that the underlying mechanism is explained by the theory of patents as real options. Moreover, these results suggest that political uncertainty is reflected in different ways in different settings and may be explained by institutional differences such as polarization.

We pursue the following five robustness checks: use an inverse hyperbolic sine which can handle zero-values, restrict our sample to 23 countries by excluding countries with few AI patents for a log-normal distribution, use a poisson regression as it more properly addresses the patent count data, define a close election by the first quintile of the distribution of victory margins in order to alter the cut-off level, and use the share of AI patents in a levels-levels regression. The robustness checks reveal that the poisson regression yields different results than the log-normal transformed regression for the cross-country analysis. As such, we rely more on the results from the US case study since the data is log-normally distributed.

We contribute to the current state of knowledge in two main ways. To begin with, as economic theory suggests two different paths for how innovation may be affected by uncertainty, our first contribution is to empirically test this relationship. We follow a large strand of literature that uses patent statistics as a proxy for innovation (Acemoglu et al., 2020; Bloom et al., 2011; Griliches, 1998; Schmookler, 1966). Our findings support that our proxy for AI innovation captures AI patents as real options, since we find an increase in AI patents. For this to happen, there must be an incentive to delay investments in AI, although not captured by our proxy. In a broader context, this suggests that because incentives to delay investments in AI increase, the value of patent real option increases and contributes to an overall increase in the level of AI innovation.

Our second area of contribution relates to the investigation of AI innovation in particular, as we propose political uncertainty as a macro-level determinant of the level of AI innovation. A large body of literature documents a negative relationship between political uncertainty and investments, utilizing election data (Besley & Case, 1993; Canes-Wrone & Park, 2012; Jens, 2017; Julio & Yook, 2016). However, few have looked into the effects of uncertainty and investments in innovation in particular (Czarnitzki & Toole, 2011; Goel & Ram, 2001). Building on these studies, we use data on the year of national and gubernatorial elections and compute a definition of a close election but we focus on the effects on AI innovation. We propose that AI is of particular interest because investments in AI are considered to be notably irreversible and we posit that AI is more reactive to political uncertainty. To the best of our knowledge, our study is the first to empirically investigate the relationship between political uncertainty and AI innovation.

The remainder of this paper is structured as follows. Section 2 presents the economic theories that underlies our research question, reviews empirical literature relevant for the purpose of our study, and ends with our contribution. Section 3 describes the data. In Section 4, we develop our research design, discuss the challenges of causal inference and provide our empirical strategy. Section 5 presents the results and Section 6 the robustness checks. Section 7 discusses the findings and potential limitations while Section 8 concludes.

2 Literature Review

We begin this literature review by presenting two economic theories on the impacts of uncertainty that underlies our research question. Next, we give an overview of the empirical research that tests this relationship, with emphasis on studies examining political uncertainty using election data. Finally, as we are interested in what drives AI innovation, we survey the literature measuring technological innovation in general and AI innovation in particular. We briefly go over the limited but growing literature on the determinants of AI innovation. Recognizing the importance of understanding the dynamics of AI innovation, we propose political uncertainty as a source of macro-determinant and develop our arguments for this relationship. As such, we contribute to the previous literature in two main ways. First, we empirically test whether the effects of political uncertainty on AI innovation, proxied by patent counts, can be explained by the theory of irreversible investments or patents as real options. Second, we investigate whether AI innovation in particular is responsive to political uncertainty.

2.1 Economic Theories of Uncertainty

2.1.1 Irreversible Investments

Building on the economics literature of business cycles, Bernanke (1983) develops the theory of irreversible choice under uncertainty and provides an explanation for investment fluctuations.

The theory relies on two assumptions: (1) investment projects are irreversible - the investment cannot be undone without sunk costs (2) more relevant information arrives over time - there is a benefit of waiting in order to make better and more reliable decisions. That is, the dynamics of investments are sensitive to the timing of valuable information and this becomes substantially important when investments are irreversible. Moreover, in times of uncertainties, the expected value of the investment also becomes uncertain, therefore the value of waiting for more information increases. Hence, uncertainties delay the current rate of investments in order to benefit from more information about the future.[4]

In much the same way, Dixit and Pindyck (1994) argue that there are three characteristics that determine the optimal decisions of investors: (1) investment is partially or completely irreversible, (2) there is uncertainty over future rewards of investment, and (3) there is flexibility about the timing of investment, making it possible to postpone and wait for more information. Further, they provide a real options approach of the theory of irreversible choice under uncertainty. They describe the concept of firms holding the opportunity to invest analogically to holding a financial call option, with the term real option distinguishing it from a financial asset. That is, a real option gives the economic actors the right to make a future investment, but they are not obligated to do so. When one decides to exercise the option, one gives up the opportunity to make the investment in the future. This may result in a lost option value that counts as an opportunity cost and must be included as a part of the investment costs. Moreover, they mention that many previous studies have shown that the opportunity cost often can be very large, in particular during times of uncertainties. Dixit and Pindyck (1994) brings up important considerations regarding the possibilities of choosing the timing of investments, one such circumstance is the fact that some investments require strategic considerations which constrains quick decisions. Moreover, considering that the market is competitive, there may be a cost of delaying due to the risk of entry by other firms which ultimately increases the barriers of entry and puts oneself in a disadvantageous position (Dixit, 1992; Dixit & Pindyck, 1994; Pindyck, 1991).

2.1.2 Patents as Real Options

In this study, we are interested in the effects of uncertainty on AI innovation as proxied by patents. As such, it is important to highlight the real options theory in a framework of investments in innovation and the role of patents (Bloom & Van Reenen, 2002). The theory is based on Pakes (1986) that values patents as options. In brief, patents provide exclusive rights to develop new innovations, thereby giving its owner the possibility to delay investments while waiting for more

[4]There are also theories that find that uncertainties can lead to increased investments. However, these rely on different assumptions. Oi (1961) looks at price uncertainty and firms' total returns and concludes that the expected profit is higher with higher variability in future prices. Hartman (1972) suggests that uncertainties in future output prices, wages and investment costs do not decrease a firm's investment levels. Moreover, Bar-Ilan and Strange (1996) propose that returns of investments are generally associated with a lag and extreme prices are more likely with longer lags. Hence, investments with longer lags may encourage investments because they want to avoid learning of high prices while investments with shorter lags may be delayed in accordance with Bernanke (1983).

information. Furthermore, building on Pakes (1986) and Dixit and Pindyck (1994), Bloom and Van Reenen (2002) develops the real options theory in a context of patents. They explain that new inventions covered by patents often need to be embodied by other sunk cost investments - such as new capital equipment, training, marketing, or further R&D - that are (at least partially) irreversible. The patent real option can be seen as the value its owner places on the flexibility to choose the timing of investment of their patented invention. This makes it possible for the owner to delay investments and wait for more information while at the same time protecting the idea from market entries by other firms. Altogether, according to this framework, high market uncertainty implies that firms will delay investments while at the same time increase the value of patents as real options.

2.2 Uncertainty in Empirical Studies

2.2.1 Uncertainty in General

Previous literature using volatility as a proxy for uncertainty has found ambiguous results regarding the effects on economic outcomes. Bloom et al. (2007) study the effects of uncertainty measured with stock-market volatility on companies' investments dynamics. They use a panel of UK manufacturing firms during the period 1972-1991 and apply a general method of moments model to find that during demand shocks that generate higher uncertainty, companies tend to be more cautious about investments in the short-run. This is because the option to wait and delay the investment is more valuable in times of high uncertainties. Their study is based on Leahy and Whited (1996) who use a panel of US firms to study the relationship between stock-market return based uncertainty and investments. The findings of these papers are consistent. Bloom (2009) uses a parameterized model to simulate macro uncertainty shocks and finds that this produces a drop and rebound in various outcomes such as output, employment and productivity growth. Fernández-Villaverde et al. (2011)) study volatility shocks in small open emerging economies using volatility in real interest rates and find a negative effect on a number of economic outcomes such as consumption and investment. Goel and Ram (2001) find a negative effect of uncertainty on R&D expenditures, which is not evident for non-R&D. They empirically test this for nine OECD countries over the period 1981-1992 using two inflation-based measures of uncertainty. Similarly, Czarnitzki and Toole (2011) refer to the real options theory and highlight that R&D investments are particularly irreversible since it is often related to salaries and cannot be revoked, even if a project fails. As such, they point out that investments in R&D should decline and that patent protection may mitigate the risks related to uncertainty as it protects the firm from market competition. They empirically test these two hypotheses using panel data of innovative firms that operate in the manufacturing sector in Germany. They generate two firm-specific proxies for uncertainty which measures the volatility in past sales revenue related to innovation and uncertainties related to established products. They employ a pooled cross-sectional approach and a random effects panel estimator and find support for both of their hypotheses.

Although many of the studies find a negative effect of uncertainties on economic outcomes, there is a limited strand of the literature finding little to no impact. Born and Pfeifer (2014) point out that the theoretical literature has acknowledged that there may be an opposing effect to the "wait-and-see" approach as proposed by Bernanke (1983) and others. This effect suggests that uncertainties increase investments through inducing economic actors to proactively build up a capital stock. As such, these two effects that work in opposite directions might reduce the aggregate economic impact of uncertainties. The results from their empirical model show that uncertainty about monetary and fiscal policy is unlikely to play a major role for business cycle fluctuations. Bachmann and Bayer (2013) show that the "wait-and-see" dynamics caused by shocks to firms' profitability risk is unlikely a major source of business cycle fluctuations. Bekaert et al. (2013) find that while shocks to uncertainty and risk aversion cause changes in monetary policy, these results are less robust and weaker statistically.

A more recent strand of literature uses news-based high frequency data to measure uncertainties around the world. Baker et al. (2016) develop the economic policy uncertainty (EPU) index for the US using text analysis based on newspaper data dating back until 1985. They use leading newspapers and identify the following terms in association with each other: "economic" or "economy"; "uncertain" or "uncertainty"; and one or more of "Congress," "deficit," "Federal Reserve," "legislation," "regulation," or "White House" (Baker et al., 2016, p.1599). The index is based on high frequency data and provides daily, monthly and yearly measures of policy uncertainty. Moreover, they use the EPU index and find negative impacts on micro outcomes such as stock price volatility, investment rates and employment growth as well as macro outcomes including aggregate investment, output and employment. The index has been extended over time, across countries and along policy categories and has been widely used by succeeding scholars. For instance, both Gulen and Ion (2015) and Kang et al. (2014) use the EPU index and find negative effects of policy uncertainty on firm-level investments.

2.2.2 Political Uncertainty

The literature within the field of economics that is mostly related to our topic are studies investigating how uncertainties associated with elections influence decisions about investments. The motivation for this stems from work suggesting that politics and uncertainties are closely related. For instance, Alesina and Perotti (1996) propose that income inequality and investment are inversely related through the channel of uncertainties in the politico-economic environment which reduces investments. Their hypothesis is confirmed empirically in a sample of 70 countries over the years 1960-1985, using a two-equation model with investment in physical capital and a measure of political instability as the endogenous variables. Similarly, Barro (1991) and Swagel et al. (1992) find an inverse relationship between political instability and economic growth.

One common way of measuring political uncertainty is to exploit election data. Building on the EPU index, Baker et al. (2020) show that presidential elections are associated with larger spikes in economic policy uncertainty. More specifically, they study the patterns of the EPU index around national elections using monthly country-level data with 23 countries to estimate a fixed effects model. Across all countries in their sample, they find EPU values to be 13% higher in the month of and the month prior to an election, as compared to the other months of the same election cycle. However, when they study the US in detail they find that not all elections are associated with greater uncertainty. The elections that led to uncertainty were close elections and more polarized elections, as illustrated with a EPU value rising by 28% in the month of such elections as compared to elections that are neither. They measure close elections using polling data from Jennings and Wlezien (2018) about anticipated closeness of elections, which is the average expected vote share for each political party in the period leading up to a national election. In the study by Baker et al. (2020), an election is classified as closed if the expected difference in vote shares between the major political parties in the three months before the election is less than 5%.

Empirical studies using election data to investigate the impacts of uncertainty have often considered the timing of elections as well as their closeness, measured either as the anticipated or actual victory margin between the major political parties or candidates. For instance, Julio and Yook (2016) exploit timing of elections to examine how political uncertainty affects FDI flows from the US to 43 other countries between 1994-2010. They propose that compared to domestic investments, cross-border investments are more reactive to the political environment because the investors lack protection from legal and political institutions in the country where the investments are placed. Using quarterly data, they find that FDI flows from the US drops in the quarter just prior to an election in the host country, and increases after the uncertainty is resolved. Their estimate suggests that FDI falls with approximately 13% relative to non-election years. The effect is short-term, only present the quarter before and after an election, with no effect using annual data. Further, they find a stronger effect for close elections, defined as having a victory margin in the lowest quartile of the sample distribution of victory margins which falls below 7.1%. Canes-Wrone and Park (2012) use quarterly data on 10 OECD countries between 1975-2006 and show that private actors postpone irreversible investments in the pre-election period, if the election is competitive or if the polarization between major parties is high. The data on costly-to-undo investments consists of non-government gross fixed capital formation, such as machinery, buildings, or equipment. They measure polarization between major coalitions based on the manifesto scaling of Lowe et al. (2011), and electoral competitiveness using the Mannheim Eurobarometer survey data which provide estimates of vote intentions in European countries. As such, their variable electoral competitiveness equals the absolute difference between the percentage of respondents who intend to support the incumbent party and those who would support another party, and is defined as competitive if less than 15 p.p. Redl (2020) finds that macroeconomic shocks matter for countries in the way that firms pause investments and reduce hours worked, contributing to a decline in GDP, and that the real effects are generally larger when conditioning on close elections.

Another factor contributing to the uncertainty associated with elections is the degree of political polarization. Boxell et al. (2020) study the affective polarization in several democracies since the 1980s and find that the US experienced the largest increase in polarization over this period while some Northern European democracies are becoming less polarized over time. Many other studies confirm that polarization in the US has risen sharply over the past decades, and much more compared to many other democracies (Baker et al., 2014; Iyengar et al., 2019). Altogether, this suggests that elections in the US might be associated with substantial uncertainty as voters are far apart, which makes the US a particularly interesting case study. To further highlight the relevance of conducting a more in-depth analysis of the US case, we rely on previous work studying gubernatorial elections in the US. The influential study by Besley and Case (1993) considers the differences in behavior of governors who faced term limits and those who were able to run again, found a significant effect of this variation on economic policy choices. The paper was one of the first to pave the way for establishing a link empirically between gubernatorial election impacts on policy in the US and emphasized the importance of studying state-level data. Gubernatorial elections have during recent years been widely used in previous literature as a source of variation for uncertainty. For instance, Canes-Wrone and Park (2014) use the variation in US gubernatorial elections cycles as a proxy for policy uncertainty together with data on housing investments to test the theory of irreversible investments. They reason that investments in housing is a sector of irreversible investments, and further that US state government policies affect individuals' incentives concerning housing purchases through for example taxes, job security or laws on real estates. Altogether, they find that housing sales and prices experience a pre-election decline because of the policy uncertainty, which in turn depend on the competitiveness of the race and the polarization between the major candidates. Electoral competitiveness is measured as a function of the winning candidate' share of the two-party vote, for home sales the median value of this share is 55%, and for house prices 56%, implying a victory margin of 10 or 12 p.p. respectively.

Jens (2017) studies gubernatorial elections in the US and importantly points out that two things must hold for political uncertainty to be able to affect investments in their analysis. First, changes to state-level policies must affect firm investments, which they argue is true by relying on Bernanke (1983) and presenting concrete examples from US history. Second, governors must have power over these policies such that gubernatorial elections indeed lead to uncertainty, which is strengthened by previous work that consistently finds that governors do matter to state-level policies. She uses firm-level investment data as measured by capital expenditure scaled by total assets from 1984-2008 on a quarterly level combined with data on timing of elections in a difference-in-difference framework. The findings suggest a 4.9% decline in investment rates a quarter before gubernatorial elections and points out the importance of politics on firm-level behavior in the US. Moreover, she proposes that closer elections should impose greater uncertainty and use term limits as an IV for close elections due to potential threat of reverse causality between investments and contested elections. Close elections is defined as the lowest tercile within the sample distribution of the vote differential between the winner and the runner-up. The cut-off level defining whether an election is close or not appears at 7.1%. The results suggest a 15.1% decline in investment rates two quarters before close gubernatorial elections.

2.3 Innovation

2.3.1 Measuring Innovation

The inherent challenge of studying technological change and innovative processes is the lack of appropriate and unambiguous measures, which forces scholars to rely on various residual measures and proxies. The most widely used proxies for innovation within the field of economics have been either research and development (R&D) expenditures or patents.[5]

First, R&D expenditures can be seen as a measure of the inputs into the innovation process. Previous research in economics uses R&D data in various ways when studying firms' innovative activities. Bound et al. (1982) utilize data on R&D expenditures together with financial variables, employment, and aggregate patent applications to study the relationship between R&D, inventive output and technological change for firms in the US manufacturing sector. Zoltan and Audretsch (1988) develop a model of innovative activity that suggests that R&D expenditures positively influence innovative output. Similarly, Griliches (1998) presents evidence that patents are highly correlated with R&D expenditures. A more recent study by Acemoglu et al. (2018) develops a model of firm-level innovation, productivity growth and reallocation. In their model, they define a firm as "innovative" if it is conducting R&D or patenting.

Secondly, patents can be seen as a measure of the outputs of the innovation process. As stated by the OECD (2021b), patent-based indicators are probably the most frequently used for proxying technology output and analyzing innovative activities. Apart from the obvious close link between patents and inventions, patents indicators have many other advantages such as being publicly available through patent offices and covering many technologies that are often not available through other sources. Patent documents also contain valuable information such as the applicant, inventors, assignees, technical description of the invention, citations, patent office, and publication date (OECD, 2021b). There is a voluminous previous literature on the use of patents as indicators for innovation, discussing both its theoretical motivation, empirical applications, and potential flaws. The influential survey by Griliches (1990) covers recent economic research using patents as a proxy for the underlying innovation and technological change, and concludes that patent statistics, although some drawbacks, are interesting to use. Among the key findings is a strong relationship between the count of patents and R&D expenditures across firms and

[5]This overview about measuring innovation leads us to the distinction between *invention* and *innovation*. The term invention is usually used to describe the creation of something entirely new and original while innovation refers to the act of making changes and improvements to an existing product or process. As such, innovation flows from invention. In this thesis, we take the approach of focusing on innovation since we are interested in the overall developments within AI technology, which could be proxied by patent data as further described in Section 3.1.

industries. This implies that when the desired R&D data is not available, detailed patent data can be used as a good indicator of differences in inventive activity - both inventive input and output. In order to capture the value of patents, Griliches suggests using patent counts together with patent renewal information and patent citations. Furthermore, Schmookler (1966) uses US patent statistics in his influential work investigating inventive activity. Acemoglu et al. (2020) study the determinants of radical innovations using different proxies based on USPTO patents and citations data. Bloom et al. (2011) examine the impact of Chinese import competition on firm-level technical change across European countries, and proxy for firm-level innovation by using either patenting, R&D spending, IT or TFP.

Like any other proxy, there are however several considerations to bear in mind when measuring innovation with patents. As pointed out by Pakes and Griliches (1980) p. 378, "patents are a flawed measure (of inventive output); particularly so since not all new innovations are patented and since patents differ greatly in their economic impact". While some patents have no industrial application at all, others have a large economic impact. Similarly, Hall and Harhoff (2012) argue that this leads to an interpretative problem when using patent counts. One common way to address this issue is to combine counts of patents with quality adjustments such as citations associated with the patent (Trajtenberg, 1990).

2.3.2 Identifying AI Patents

Particularly, identifying AI innovation is challenging not solely because of the ambiguity of what should be defined as AI technology and the changes of these definitions over time,[6] but also because of methodological issues such as limited availability of data and alternative measures of AI. Nevertheless, the most common method for identifying AI innovation in the economics literature is through utilizing patents or scientific research, which can be categorized based on their technological content.

The process of identifying patents related to a particular topic is called patent landscaping. Traditionally, patent landscaping has been a human-driven process that relies on queries such as keyword searches, patent classifications, and citations in order to categorize patents Trippe (2015). One influential paper using such a query-based approach for identifying AI innovation is Cockburn et al. (2018). They develop a novel database capturing AI scientific papers from the Thomson Reuters Web of Science, and AI patents issued by the USPTO. The patents are categorized based on keywords associated with robotics, symbolic systems, and deep learning. Using complementary datasets they relate the variables of interest to organization type, location, and application sector. The World Intellectual Property Organization (WIPO) published a report in 2019 where they also use a limited query for analyzing recent trends in AI technology based on

[6] Although it is sometimes hard to draw a clear cut-off of what qualifies as AI technology or not, modern dictionaries offer broad definitions that serve as a good starting point. Merriam-Webster (n.d.) defines AI as the following: (1) a branch of computer science dealing with the simulation of intelligent behavior in computers and (2) the capability of a machine to imitate intelligent human behavior.

patents and scientific publications (WIPO, 2019a). Their identification of AI patents are based on patent classification codes (IPC, CPC, FI and F-term), a classification scheme for categorization of AI technologies, and an extended list of carefully selected specific keywords. Samples of the results are manually checked and validated using a text-mining tool. Interestingly, their data analysis enables them to reveal trends in AI techniques, AI functional applications and AI fields. In short, they show that AI inventions have grown constantly and dramatically between 1960 and 2016. There was a significant boom in scientific publications starting around 2001, followed by a boom in patent applications 12 years later. The most heavily represented countries both over time and today are Japan, the US and China, which together account for 78% of total AI patent filings in their sample. Furthermore, they also show that the different technology components involved have experienced different trends over time and across industries.

Recently, scholars have increasingly used machine learning methods and natural language processing for patent landscaping. This was first done by Abood and Feltenberger (2018), who develop a novel automated approach for patent landscaping that jointly leverage human domain expertise, heuristics based on patent metadata, and machine learning. In short, they take human-selected patents that are representative of a topic (called the "seed" set), and then adapt a methodology using references and class codes from this data to identify patents that are probably unrelated to that group (called the "anti-seed" set). Next, they expand these two groups by developing a machine learning model that is trained on the seed and anti-seed patents. A. Toole et al. (2020) adapt the methodology developed by Abood and Feltenberger (2018) to categorize USPTO patents into eight AI categories, but add a manual validation step. Moreover, they recreate the AI landscapes from Cockburn et al. (2018) and WIPO (2019a) in order to benchmark their model, and show that machine learning methods are better at predicting AI documents than the narrowed traditional approach. Giczy et al. (2021) also build on the approach by Abood and Feltenberger (2018) for identifying AI in US patents using machine learning models that analyze patent text and citations, but add an analysis of patent claims in order to further improve the identification. The dataset, called the Artificial Intelligence Patent Dataset (AIPD), is utilized in this thesis and will therefore be described in depth in Section 3.1.

2.3.3 Determinants of Innovation

There is a scarce previous literature empirically investigating the driving forces behind AI innovation, particularly when it comes to macro-level determinants. This is somewhat surprising given the rapid growth and diffusion of AI and its potential as a GPT. Potential explanations could be the difficulties in defining and measuring AI innovation as well as the challenge of establishing causal inference since AI innovation is closely related to economic growth. Below, we survey existing research investigating the determinants of AI innovation.

Certain firm attributes could be beneficial for the deployment of a given technology, so firms possessing such characteristics might be more likely to adopt the technology (Cho et al., 2021;

DeStefano & Moussiegt, 2017; Hall & Lerner, 2010). Cho et al. (2021) identify firm size and use of intangible assets as being most important for firm-level AI use for their sample of businesses in South Korea. They also test the importance of technology complementarities, finding that AI is adopted together with other digital technologies that facilitate AI processes such as big data practices and cloud computing. Zolas et al. (2020) study the adoption and use of advanced technologies including AI through the 2018 Annual Business Survey. They find that advanced technology adoption is rare and generally most common among larger and older firms. Additionally, they find evidence of technology complementaires. Babina et al. (2021) study the determinants and consequences of AI investments by US firms, employing a novel measure of AI investments based on firms' AI-skilled human capital. They find a mutually reinforcing relationship between AI investments and firm size: AI investments are concentrated among the largest firms, and firms investing in AI also grow larger in terms of sales, employment and market valuation.

Moreover, the manner and rate of knowledge diffusion affects the overall level of innovation. Technological knowledge transfers may enable the adoption of existing innovative processes, or help sprung new innovations. While the diffusion of innovation has been a somewhat neglected research area in economics as argued by Hall (2004), there is some existing work of interest. Overall, the empirical evidence indicates that geographic distance is a barrier to the diffusion of innovation between patenting inventors (Henderson et al., 2005; Jaffe et al., 1993; Moretti, 2021; Peri, 2005). The empirical work on the diffusion of AI presents similar findings. Bloom et al. (2021) find that the introduction of US patents related to AI and other disruptive technologies are at first highly clustered geographically compared to overall patents. As time passes, the diffusion of these technologies increases through new related employment. Similarly, A. Toole et al. (2020) find that AI inventors in the US tend to be concentrated in Silicon Valley and California in general which are known to be technology hubs, however, since 2001 AI has been diffusing widely across US states. Bessen et al. (2021) find that job vacancies requiring AI skills grow more slowly in locations farther away from AI innovation hot-spots, indicating that geographical distance is a moderate barrier for the adoption and adaptation of AI. Baslandze (2016) analyzes the impact of the diffusion of ICT on innovation, and finds two opposing effects. Knowledge diffusion between firms and industries naturally stimulates the growth of innovation through learning opportunities, but it could also harm innovation incentives through commercializing others' ideas instead. They further argue that the former effect will dominate the latter for sectors that rely more on external knowledge, such as the high-tech sector. Aghion et al. (2018) suggest that the argument also applies to AI.

Studies looking at the macroeconomic determinants of innovation stems from the theory about the demand-pull effect by Schmookler (1966). Schmookler (1966) studies capital-goods inventions as measured with patents using time series and cross-sectional data to show that variation in demand in terms of the potential market size and profit-making opportunities outweigh the effect from changes in supply such as the state of scientific knowledge. Building on Schmookler (1966), many scholars such as Kleinknecht and Verspagen (1990) re-estimates his cross-section results and conducts a similar study using R&D instead of patents to measure innovation. Kleinknecht and Verspagen (1990) concludes weaker correlation between the demand effect and innovation and ambiguity regarding the direction of causality due to potential simultaneity between the variables. DeStefano and Moussiegt (2017) point out that policy environments in a country affect the digital technology adoption by firms across countries. However, they find that investments in hardware technologies are positively correlated with favorable policies for the business environments while investments in software technologies are negatively correlated. They posit that the negative relationship is explained by a greater incentive of adopting cost-saving technologies. Thus, they find that the effects of policy environments on innovation adoption are heterogeneous and moderated by the type of technology.

2.4 Contribution

This paper contributes to the current state of knowledge in two main ways. To begin with, given the challenges in measuring AI innovation, it is ambiguous whether the empirical results could be explained by the theory of irreversible investments, or the patent real options framework. By using patent counts we cannot directly capture irreversible investments in innovation, although they serve as a reasonable proxy for the output of investments. Neither can we measure the values of patents, however if patents become more attractive under uncertainty it might be reflected in an increase in the number of patent applications. Therefore, our first contribution is to empirically test the economic explanation behind the relationship between uncertainty and AI innovation when using patents as a proxy. On the one hand, given that investments in innovation are irreversible, they are expected to decrease under periods of uncertainty. On the other hand, if patents act as real options because they enable its owner to delay irreversible investments while waiting for more information, the value of patents is expected to increase under uncertainty which is also reflected in an increase in the number of patents.

Our second area of contribution relates to the investigation of AI innovation in particular. Given the importance of AI for economic growth, the literature on understanding the driving forces behind AI innovation is scarce. To the best of our knowledge, we are the first to propose political uncertainty as a macro-determinant for AI innovation. In essence, we argue that investments in AI innovation are particularly responsive to political uncertainty because of two main reasons. First, investments in AI innovation have a high degree of irreversibility. As explained by Pindyck (1991), page 1111, an expenditure is irreversible if the capital is firm or industry specific, or is subject to the "lemons problem". Since developed AI algorithms based on consumer data cannot be used productively by another firm, we consider it firm specific and hence irreversible. Developing AI also requires AI-skilled labor, which usually is an irreversible investment because of the costs of hiring and training new competence. Second, political uncertainty could imply changes in policies that specifically regulate the use of AI. The regulatory and policy landscape for AI is still emerging and the direction for which AI governance should evolve are much more ambiguous and subject to different perceptions as compared to other existing technologies. Hence, investments in AI are associated with particularly large sunk costs that arise because of the obligation to adapt to changing AI regulations. For example, firms might be forced to change their processes for managing data privacy and transparency or avoiding discriminatory algorithms. Furthermore, the possibility of changing AI regulations makes the expected return of investments in AI even more uncertain than investments in other more established technologies. Again following the reasoning of Bernanke (1983), this would make it particularly valuable to "wait and see" for AI investments during periods of political uncertainty. Importantly, existing AI regulations are primarily on a national level though some cross-national policies have recently been developed, which strengthens the argument that political uncertainty in a firm's home country may have implications for their investment in AI innovation.

3 Data

For the purpose of this study, three different datasets are needed. First, the count of AI patent applications per year and country, which function as a proxy for the level of AI innovation. Second, data on national election dates and the share of votes for each political party in order to capture the existence and degree of political uncertainty. Third, control variables to address omitted variable bias. The datasets are combined to a panel of 32 countries with patents filed over the years 2000-2018. In addition, a case study on the US is conducted which requires data on state-level resulting in a panel of 50 states with patents filed over the years 2000-2018. This section presents the data collection methods, some important data manipulations, summary of statistics, and ends with a section addressing potential data limitations.

3.1 Dependent Variable

The data on patents was provided by the Artificial Intelligence Patent Dataset (AIPD) and PatentsView (www.patentsview.org). The AIPD is initiated by the Office of the Chief Economist in the USPTO, and is described in a working paper by Giczy et al. (2021). The dataset identifies AI patents among 13,244,037 granted patents and pre-grant publications (PGPubs)[7] issued in the US between 1976-2020.[8] The AIPD contains information on each patent document, including the publication date, patent document id, assignee id, AI technology component, and dummy variables distinguishing between patents and PGPubs. For the purpose of finding the nationality of each assignee, we match the AIPD to data from PatentsView. Our final dependent variable is a measure of the number of AI patents for each country in each year.[9]

The AIPD is constructed using machine learning models that analyze text from patent document abstracts and claims as well as patent citations. More specifically, the AIPD identifies patent

[7]PGPubs are patent applications that have been published before being granted (A. Toole et al., 2020).
[8]A detailed description of the USPTO patent system is presented in Appendix B.
[9]A detailed description of how the final patent dataset was created is presented in Appendix C.

documents containing one or more of the following eight AI technology components: machine learning, natural language processing, computer vision, speech, knowledge processing, AI hardware, evolutionary computation, and planning and control. The queries used to generate the seed sets include classification codes from the CPC system, the IPC system, the USPC system as well as the Clarivate Derwent World Patent Index. From this process, the AIPD generated a so-called AI prediction score for each component technology as well as a consolidated dummy variable which indicates 1 if the patent document was predicted to be AI in any of the eight component technologies based on a 50% threshold of accuracy, and 0 otherwise. Altogether, the number of AI patent documents amounts to 1,517,174 (11.5% of all documents).

In order to assist researchers and policymakers, the AIPD has been made publicly available and formatted to be compatible with PatentsView. The PatentsView enables us to identify the nationality of the assignees of a patent. We identify assignees from a total number of 61 countries. PatentsView is an open analysis platform with US patent data, supported by the USPTO (PatentsView, n.d.). Each published USPTO patent document contains information on its inventors and assignees. The ownership of a USPTO patent initially belongs to the inventors or the applicant (USPTO, 2020). The inventors of a patent are individuals who have contributed to the concept of an invention, and the applicant of a patent is the inventor or joint inventors who apply for a patent on their invention. Moreover, the ownership of a patent can later be transferred from its owner to another entity, called an assignee. There may be several assignees of a patent (USPTO, 2022a). The assignees of a patent are often the company or organization employing the inventor. We choose to use data on assignees as we are interested in the entity that has been assigned ownership of the patent, rather than the inventor that has contributed to the concept of the invention. The assignee's country of origin thus reflects where the individual, company or organization that has been given the legal rights of the patent is located. Note that some patent documents have several assignees from different countries. In order to deal with this, we follow the approach taken by OECD Statistics in their dataset "Patents by technology" (OECD, 2021a) and give each country a count of 0-1 for each patent weighted by the number of assignees originated from that country.

We utilize patents published between 2000-2020, where 2020 is the latest year available in the dataset.[10] The decision to restrict the data from 2000 onwards is partly because of the development of AI - the number of AI patents before 2000 were scarce and generally uninformative, and AI regulations has not been introduced in most countries until the very recent years - and partly because of the changes caused by the American Inventors Protection Act (AIPA) in 1999. AIPA mandated that USPTO publish patent applications (and not just patent grants) 18 months after the filing date (Dzenitis, 2021). Before the AIPA, the USPTO kept patent applications confidential until they were granted. The act increased the volume of publicly available patents as it thereafter included not only granted patents, but also PGPubs. Accordingly, PGPubs are always published 18 months after their filing date, with the exception that applicants can pay a fee

[10]The publication of a patent refers to the date at which the patent application is made publicly available by the USPTO.

(called a non-publication fee) so that their applications are not published. Patents are generally published after the application has been granted, which could occur either before 18 months, in which case the application would not have a PGPub, or after 18 months. As such, looking at a sample after the regulation was introduced makes the analysis more coherent. Using data after the AIPA also allows for a larger sample as the publicly available data consist of both granted patents and PGPubs.

Since AIPD includes patent publication dates but not patent filing dates, we approximate patent filing dates by subtracting 18 months from each patent publication date, and use this data for the rest of our analysis. This is done in order to trace back to the timing of applying for a patent and relate it to the year of elections as it otherwise would imply a lag of 18 months. Notably, since patents could be published earlier than 18 months if they are granted earlier, the approximation may incorrectly assign patents to the wrong year. However, we argue that this is not a major threat to our model as it seems unlikely that patents are granted long before 18 months since the traditional total pendency was around 23 months between 2020-2021 (USPTO, 2022b).[11] Moreover, the approximation could also be incorrect if patents are published later than 18 months after filing date, which could happen if a non-publication fee has been paid. However, we believe that the share of people who have paid a non-publication fee is unlikely to be very high. Importantly, this implies that if we deduct 18 months from all publication dates with data limited to patents published in 2020, the latest approximated filing date occurs at mid 2019. Including data from 2019 will therefore not be representative, hence the final dataset for the analysis is limited to patents applied between the years 2000-2018.[12] Summary statistics of the initial AIPD cross-country sample is presented in Appendix C Table 26, including 61 countries over 19 years.[13]

Following the same steps as described above, we are able to create longitudinal data on US state-level. For this sample, AIPD identifies 654,441 (15.8%) AI patents among a total of 4,149,662 granted patents and PGPubs between the years 1979-2020 with assignees from any of the 50 states in the US and the District of Columbia. Summary statistics of the US case study sample constructed from AIPD is presented in Appendix C Table 27, including 50 states and the District of Columbia with patents filed between 2000-2018.

[11] The average total pendency is measured as the average number of months from filing date to the date the patent application has reached final disposition, i.e. being either granted or abandoned (USPTO, 2022b).

[12] 19,486 documents of reissued patents are removed from the dataset since reissued patents are filed to correct errors in the patents and hence do not represent new patents.

[13] A list of all 61 countries included is presented in Appendix A, Table 20.

3.2 Independent Variables

3.2.1 National Elections

The data on election dates and results was provided by the Parliaments and governments database (ParlGov). The database includes elections and cabinets in established democracies. More specifically, they include democratic national lower house elections and European Parliament elections for all EU and most OECD members after 1945 or after full democratization, reporting election results for all parties that won 1.0% vote share. Importantly, the ParlGov dataset does not contain data on the US due to the fact that they exclude OECD countries with presidential systems (Döring & Manow, 2020). For this reason, data on election results and election dates for the US were instead retrieved separately from The American Presidency Project (APP).

The two independent variables of interest are the year of an election and whether an election resulted in a small victory margin between the winning party and the runner-up. The ParlGov and the APP dataset consist of the years where a national election occurred. Hence, we created a binary variable indicating 1 for years where an election was held, and assigned a 0 to the years in between elections. The resulting dataset contains 722 observations for 33 countries between 2000-2018 with 194 elections and 528 non-election years. In order to create the variable for a close election, we used data on the political parties' vote share. For each country, in each year for which a national election took place, the actual victory margin was calculated as the percentage point difference in share of votes between the winning party and the runner-up. We follow Julio and Yook (2016) and define an election as close if the victory margin lies within the first quartile of the sample distribution of all victory margins. The cutoff-level appears at 2.8 p.p., in contrast to their 7.1 p.p., which is more competitive than most previous literature that lies within 5-15 p.p. (Baker et al., 2020; Canes-Wrone & Park, 2012; Jens, 2017). The binary variable takes the value 0 if it is a non-close election year or a non-election year. In total, this resulted in 48 close elections. Furthermore, for the purpose of robustness check we defined a close election as the first quintile of the victory margin. The cutoff level for this variable appears at 2.32 p.p. and consists of 38 close elections. The average victory margin for close elections is 1.57 p.p. and the corresponding value for non-close elections is 10.37. p.p. Finally, we created two binary variables which indicate 1 if it is a year before or a year after an election or a close election, respectively, to capture the variations around the politically uncertain events.

Notably, we exclusively investigate democratic countries with parliamentary systems, as well as the US with a presidential system. The reason for this is that established democracies have similar electoral systems and institutions in general, which enables us to create a general election-based independent variable for all countries in the sample. More specifically, these countries are all characterized by regular national elections, universal suffrage, more than one political party, and one or several incumbent parties that have de facto power over future policies. In addition, the vast majority of countries that have been most prominent in AI innovation during the last decade, and hence also the ones that have implemented national or cross-national AI policies, are in fact democracies. The exceptions are China, standing for a large share of the world's AI patents, which together with Russia have been excluded from the analysis on the basis of their dictatorship and different electoral systems.

3.2.2 Gubernatorial Elections

The data on the US gubernatorial elections was provided by the CQ Press Library. The CQ Press Library is operated by CQ Press which is a division of SAGE Publishing. The purpose of CQ Press Library is to provide resources for research in American government, politics, history, public policy, and current affairs. A dataset within the period 2000-2018 which contained information on gubernatorial elections and voting results was retrieved from CQ Press Library. We followed the same steps as for the data from ParlGov and APP when constructing the variables for year of an election and close election. The dataset contains 259 elections and 692 non-election years. For the same reasons as in the cross-country analysis, a close election is defined as the first quartile for the sample distribution of victory margins where the cutoff level appears at 5.73 p.p. which corresponds to 65 close elections and 886 of either non-election years or elections not defined as close. The final dataset from CQ contains 950 observations for 50 states between 2000-2018.[14]

3.3 Control Variables

The data used for the control variables was provided by the USPTO, the World Bank, and the US Bureau of Economic Analysis (BEA). Similarly to the dependent and independent variables, the control variables are given at country (or state) level per year. We control for the total number of patents since it makes it possible to capture the dynamics of the number of AI patents while holding the total number of patents constant. This variable is retrieved from the AIPD, following the same procedure as done for the AI patents. For the cross-country analysis, we used data on annual real GDP growth (%) per country from the World Bank. The annual GDP growth was given at market prices based on constant local currency 2015. For the US case study, we used the dataset SAGDP1 from the BEA on annual real GDP growth (%) per state. Real GDP is in millions of chained 2012 dollars.

[14]The dataset initially consisted of 951 observations, indicating one observation per state and year as well as one additional observation. This additional data point has been removed since it comes from the fact that Louisiana had two gubernatorial elections in 2015, where the former was a general election and the latter a so-called general election run-off. As explained by the CQ Press Library, Louisiana has a unique two-tier electoral system for House seats that implies that if no candidate wins a majority in the first round, the top two candidates participate in an additional run-off. We keep solely the observation for the general election run-off.

3.4 Summary Statistics

3.4.1 Cross-Country

The countries included in the final cross-country data are the following (32): Australia, Austria, Belgium, Canada, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States. They are the intersection between the AIPD, ParlGov, and APP. The dataset contains 608 observations for 32 countries over 19 years, with a total of 164 elections and 41 close elections. For the purpose of a robustness check, a close election is defined as the first quintile of victory margin which decreases the number of close elections to 32. See Table 1 and 2 for summary statistics.

Table 1: Descriptive Statistics, Cross-Country

Statistic	Mean	St. Dev.	Min	Max	N
Patent Variables:					
Number of AI Patents	1,311.37	6,057.81	0	54,947	608
ln(AI Patents + 1)	3.88	2.59	0.00	10.91	608
asinh(AI Patents)	4.43	2.78	0.00	11.61	608
Number of Total Patents	9,405.44	31,879.14	1	251,184	608
ln(Total Patents)	6.27	2.63	0.00	12.43	608
ln(Total Patents + 1)	6.29	2.60	0.69	12.43	608
asinh(Total Patents)	6.96	2.63	0.88	13.13	608
Share of AI Patents (%)	0.09	0.08	0.00	0.57	608
Election Variables:					
Election Now	0.27	0.44	0	1	608
Close Election	0.07	0.25	0	1	608
Close Election Quintile	0.05	0.22	0	1	608
Victory Margin (p.p.)	0.08	0.06	0.002	0.36	160
Annual Real GDP growth (%)	0.02	0.03	−0.10	0.25	608

Notes: Descriptive statistics for all variables in the cross-country dataset. *Number of AI Patents* and *Number of Total Patents* are the total count of (AI) patents published by the USPTO for the 32 countries in our sample during the period 2000-2018. *Share of AI Patents* is the share of AI patents out of all patents. *Election Now* is a dummy variable which takes the value 1 if there has been a national election, and 0 otherwise. *Close Election* is a dummy variable which takes the value 1 if there has been a close national election defined as a victory margin lying within the first quartile of the sample distribution of all victory margins, and 0 otherwise. The cut-off level appears at 2.8 percentage points. *Annual Real GDP Growth* is the annual real GDP growth PPP per capita. Sources: USPTO, AIPD, ParlGov, APP, World Bank.

Table 2: Close Election, Cross-Country

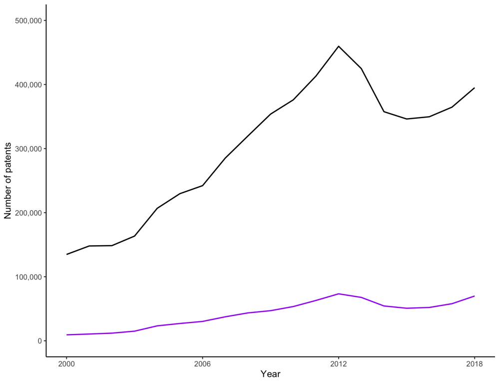
	Close Election	Close Election Quintile
Share of all elections (%)	25	20
Cut-off level (p.p.)	2.8	2.32
Number of Close Elections	41	32
Average Victory Margin Close Elections (p.p.)	1.57	1.30
Number of Non-close Elections	123	132
Average Victory Margin Non-close Elections (p.p.)	10.37	9.82

Notes: Additional descriptive statistics for the close election variables in the cross-country dataset. *Close Election* is a dummy variable which takes the value 1 if there has been a close national election defined as a victory margin lying within the first quartile of the sample distribution of all victory margins, and 0 otherwise. The cut-off level appears at 2.8 percentage points. *Close Election Quintile* is a similar dummy variable which utilizes the first quintile of the sample distribution of all victory margins, and is used for an robustness check. The cut-off level appears at 2.32 percentage points. Sources: ParlGov and APP.

Figure 1 displays the number of AI patents and total patents, respectively, summarized over all countries in the sample during the period 2000-2018. There is a sharp drop in both AI patents and total patents around 2014. One contributing factor is likely the US Supreme court decision named Alice Corp. v. CLS Bank International in 2014. Alice, which has received considerable attention, reduced the patent eligibility for certain inventions that contain “abstract ideas” (A. Toole & Pairolero, 2020). This is relevant as such inventions could often involve AI technology. As such, Alice has had a differential effect on some technologies that are no longer qualifying for patent protection. Also, the ambiguous definition of the scope of technologies involving “abstract ideas” has made it difficult to predict which inventions will be affected, thereby creating uncertainty for inventors. Because of this, the effect of Alice will probably be larger for AI patents than total patents. This is partly evident in the data in the way that the share of AI patents out of all patents (Figure 2) have consistently increased up until 2014, but after this year the share of AI patents drops sharply for the first time.

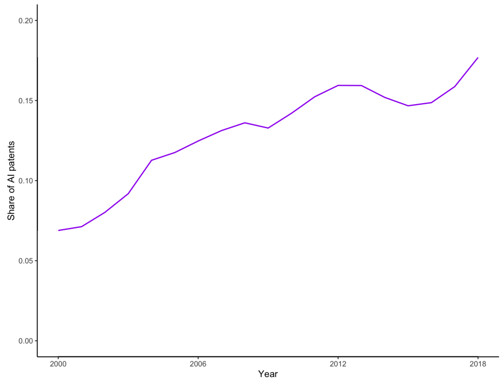
Figure 3 displays a world map over AI patents by assignee-patentee location during the period 2000-2018. Figure 4 and 5 displays the total number of national elections and close national elections, respectively, during the period 2000-2018.

Figure 1: AI Patents and Total Patents, 2000-2018, Cross-Country



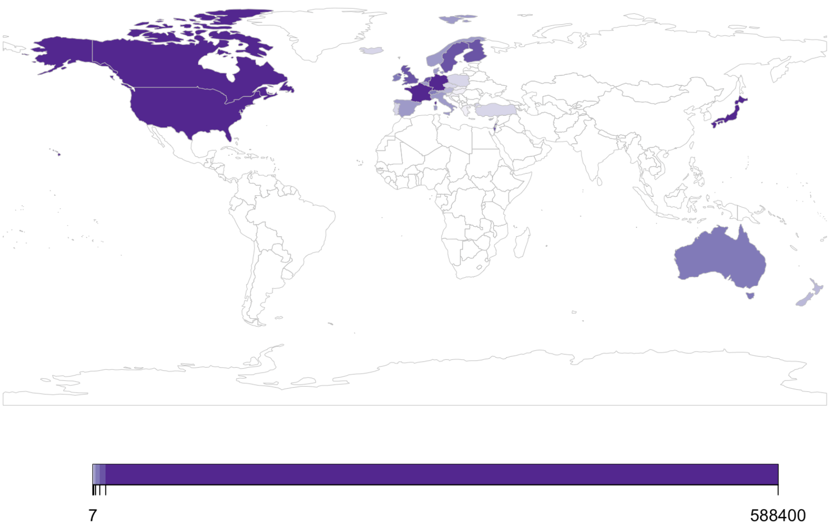
Notes: Figure 1 displays the count of all patents (black line) and AI patents (colored line) published by the USPTO for the 32 countries in our sample during the period 2000-2018. Sources: USPTO and AIPD.

Figure 2: Share of AI Patents, 2000-2018, Cross-Country



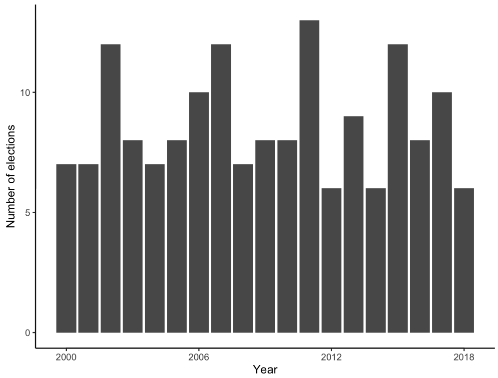
Notes: Figure 2 displays the share of AI patents out of all patents published by the USPTO for the 32 countries in our sample during the period 2000-2018. Sources: USPTO and AIPD.

Figure 3: AI Patents by Assignee-Patentee Location, 2000-2018, Cross-Country



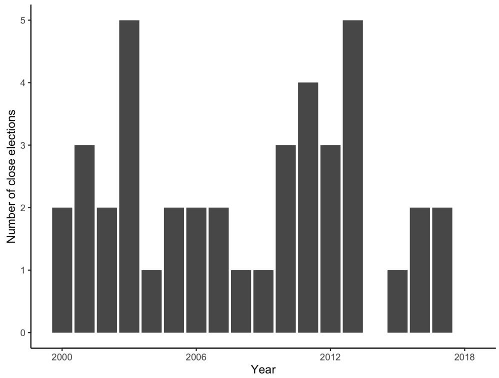
Notes: Figure 3 displays a world map over the aggregated count of AI patents published by the USPTO during the period 2000-2018 for the 32 countries in our sample. The intensity of the color represents the number of AI patents, going from 7 (Croatia) to 588,400 (US) AI patents. White-colored countries are not part of the sample. Sources: USPTO and AIPD.

Figure 4: National Elections, 2000-2018, Cross-Country



Notes: Figure 4 displays the total number of national elections held each year during the period 2000-2018 for the 32 countries in our sample. Sources: ParlGov and APP.

Figure 5: Close National Elections, 2000-2018, Cross-Country



Notes: Figure 5 displays the total number of close national elections each year during the period 2000-2018 for the 32 countries in our sample. An election is defined as close if the victory margin lies within the first quartile of the sample distribution of all victory margins. The cut-off level appears at 2.8 percentage points. Sources: ParlGov and APP.

3.4.2 US Case Study

The final US case study panel dataset is a merge between AIPD and the dataset retrieved from CQ Press Library. The dataset contains 950 observations for 50 states over 19 years. In total, there are 258 gubernatorial elections in the dataset and the number of close elections amounts to 65. For the purpose of a robustness check, a close election is defined as the first quintile of victory margin which decreases the number of close elections to 52. See Table 3 and 4 for a summary statistics.

Table 3: Descriptive Statistics, US Case Study

Statistic	Mean	St. Dev.	Min	Max	N
Patent Variables:					
Number of AI Patents	615.89	1,870.62	0	19,142	950
ln(AI Patents + 1)	4.52	2.05	0.00	9.86	950
Number of Total Patents	3,136.11	6,872.38	4	67,960	950
ln(Total Patents)	6.75	1.77	1.39	11.13	950
ln(Total Patents + 1)	6.75	1.76	1.61	11.13	950
Share of AI Patents (%)	0.12	0.09	0.00	0.54	950
Election Variables:					
Election Now	0.27	0.45	0	1	950
Close Election	0.07	0.25	0	1	950
Close Election Quintile	0.05	0.23	0	1	950
Victory Margin (p.p.)	0.23	0.24	0.0000	0.99	258
Annual Real GDP growth (%)	0.02	0.03	−0.09	0.22	950

Notes: Descriptive statistics for all variables in the US case study dataset. *Number of AI Patents* and *Number of Total Patents* are the total count of (AI) patents published by the USPTO for the 50 states of the US during the period 2000-2018. *Share of AI Patents* is the share of AI patents out of all patents. *Election Now* is a dummy variable which takes the value 1 if there has been a gubernatorial election, and 0 otherwise. *Close Election* is a dummy variable which takes the value 1 if there has been a close gubernatorial election defined as a victory margin lying within the first quartile of the sample distribution of all victory margins, and 0 otherwise. The cut-off level appears at 5.73 percentage points. *Annual Real GDP Growth* is the annual real GDP growth PPP per capita. Sources: USPTO, AIPD, CQ Press Library, BEA.

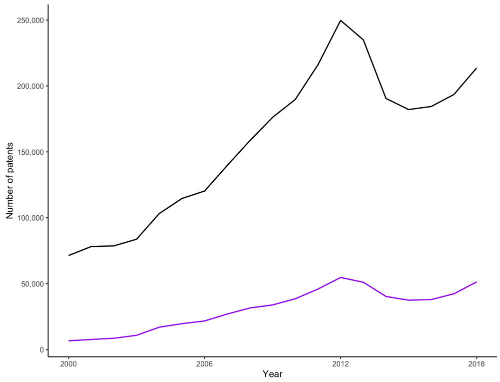
Table 4: Close Election, US Case Study

	Close Election	Close Election Quintile
Share of All Elections (%)	25	20
Cut-off level (p.p.)	5.73	4.53
Number of Close Elections	65	52
Average Victory Margin Close Elections (p.p.)	2.98	2.41
Number of Non-close Elections	193	206
Average Victory Margin Non-close Elections (p.p.)	29.60	28.06

Notes: Additional descriptive statistics for the close election variables in the US case study dataset. *Close Election* is a dummy variable which takes the value 1 if there has been a close gubernatorial election defined as a victory margin lying within the first quartile of the sample distribution of all victory margins, and 0 otherwise. The cut-off level appears at 5.73 percentage points. *Close Election Quintile* is a similar dummy variable which utilizes the first quintile of the sample distribution of all victory margins, and is used for an robustness check. The cut-off level appears at 4.53 percentage points. Sources: CQ Press Library.

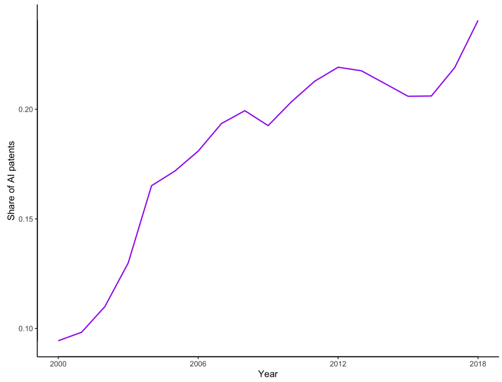
The yearly development of AI patents and total patents in the US alone follow the same positive trend for the aggregated countries with a sharp drop in 2014 as seen in Figure 6 and 7. Figure 8 displays a US map over AI patents by assignee-patentee location during the period 2000-2018. Each of the 50 states has at least 28 AI patents in total between 2000-2018. It is evident that the level of AI innovation in the US is concentrated in California, where the region Silicon Valley is located, which is the center for high technology and innovation. This suggests that innovation clusters exist within the US. Figure 9 and 10 displays the total number of gubernatorial elections and close gubernatorial elections, respectively, during the period 2000-2018.

Figure 6: AI Patents and Total Patents, 2000-2018, US Case Study



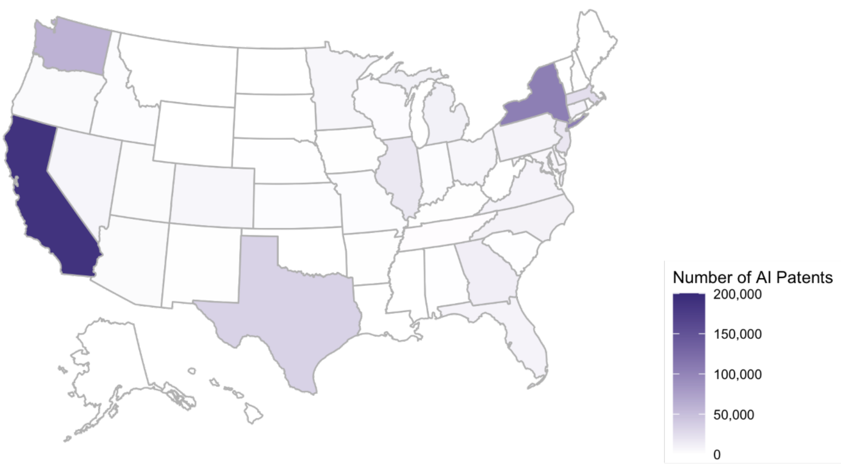
Notes: Figure 6 displays the count of all patents (black line) and AI patents (colored line) published by the USPTO for the 50 states of the US during the period 2000-2018. Sources: USPTO and AIPD.

Figure 7: Share of AI Patents, 2000-2018, US Case Study



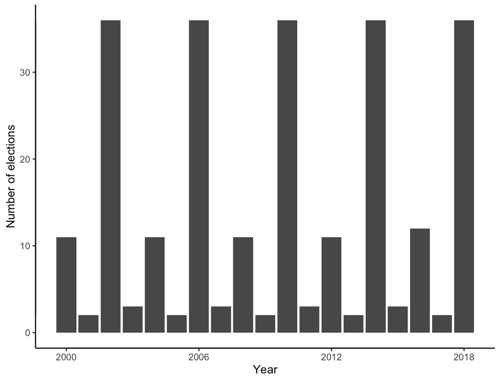
Notes: Figure 7 displays the share of AI patents out of all patents published by the USPTO for the 50 states of the US during the period 2000-2018. Sources: USPTO and AIPD.

Figure 8: AI Patents by Assignee-Patentee Location, 2000-2018, US Case Study



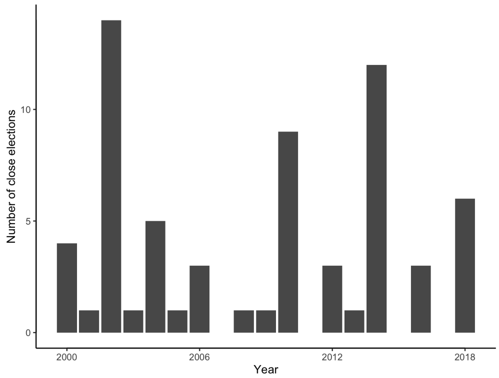
Notes: Figure 8 displays a map over the aggregated count of AI patents published by the USPTO during the period 2000-2018 for the 50 states of the US. The intensity of the color represents the number of AI patents. Sources: USPTO and AIPD.

Figure 9: Gubernatorial Elections, 2000-2018, US Case Study



Notes: Figure 9 displays the total number of gubernatorial elections held each year during the period 2000-2018 for the 50 states of the US. Source: CQ Press Library.

Figure 10: Close Gubernatorial Elections, 2000-2018, US Case Study



Notes: Figure 10 displays the total number of close gubernatorial elections each year during the period 2000-2018 for the 50 states of the US. An election is defined as close if the victory margin lies within the first quartile of the sample distribution of all victory margins. The cut-off level appears at 5.73 percentage points. Source: CQ Press Library.

3.5 Data Limitations

There are two main limitations associated with the datasets. First, using the USPTO dataset implies that the analysis is limited to examining innovations that have been granted patent protection on the US market. The optimal alternative would have been to use data from all patent offices worldwide, however, such data was not publicly available on the required level of detail (categorize patents by AI technology, and identify assignees' different countries of origin).[15] We argue that this still works as a reasonable proxy. The world's five largest patent offices together accounted for 85.1% of the world's total patent applications in 2020 (WIPO, 2021). This pattern has been similar for the last decade, with a gradual upward trend in their combined share (WIPO, 2019b). Between 2000 and 2020, the USPTO has been either the leading office for world patent filings or the second leading after the patent offices of China or Japan (WIPO, 2019b). Based on these statistics, we argue that a country's number of patents granted in the US is a reasonable proxy for the country's total number of granted patents. In addition, our empirical strategy enables us to include country fixed effects which accounts for the possibility that some countries are more likely to file patents in the US on average.

[15]The World Intellectual Property Organization (WIPO) collects data on patents applied for in all member countries. However, there was unfortunately no dataset available that had identified AI patents based on WIPO's database. It was neither possible to ourselves identify AI patents based on IPC codes because there were only 4-digit IPC codes available from WIPO. Following the approach by Giczy et al. (2021) and other similar patent landscaping studies, 8-digit IPC codes are required to reach the needed level of detail for identifying AI technologies.

Second, like for any other patent landscaping model, the AIPD's prediction of AI patents is not completely true to reality. The AIPD was developed using machine learning models that predict whether each patent document contained the AI component technologies, producing a probability between 0-1 of being in that particular technology, and then a 50% threshold was used to determine whether a given document was in the AI technology or not. As the definitions of AI technologies are unclear and changeable, and because of the lack of data on AI, there will probably always be some error margin. Nevertheless, using machine learning for patent landscaping seems to be the most accurate method for identifying certain patents, Giczy et al. (2021) pursue a detailed model evaluation where the predictions from their algorithm was compared to decisions made by several patent examiners experienced in AI. Additionally, they compared their model results to AI classifications from Cockburn et al. (2018) and WIPO (2019a). Altogether, their algorithm compared favorably both to the manual validation made by human raters and these existing approaches in the literature.

4 Empirical Model

The aim of this study is to test whether political uncertainty has an effect on the level of AI innovation. We begin by presenting the issues with identifying causality and go on with our research design. We first demonstrate our main empirical model in a cross-country framework, which broadens the external validity and is advantageous in the sense that regulations often operate on a national level. We continue to introduce some model extensions and important considerations. Moreover, we make an effort to address issues regarding omitted variable bias. In order to further address the threat of unobserved heterogeneity, we pursue a case study on the US since it removes country-specific omitted variable bias. At last, we set up two rival hypotheses in order to evaluate whether AI patent counts captures the effects of investments in AI or patents as real options.

4.1 Research Design

In our attempt to investigate the effect of political uncertainty on AI innovation, we utilize two proxies: elections for political uncertainty and AI patents for AI innovation. As such, we test this relationship by looking at how AI patents evolve around elections. However, the major challenge is to establish causality. Ideally, we would like to randomly assign political uncertainty across countries and years. This would allow us to compare treated with untreated countries and hence isolate the effect that stem from political uncertainty from other confounding factors. More specifically, the random assignment would rule out the possibility that there are other factors, for example an economic downturn, that could drive both political uncertainty and innovation. Accordingly, we would be able to establish causal inference because the treatment will be completely exogenous. However, this type of experiment does not exist, particularly because randomly assigning a treatment of this kind to countries is unrealistic.

Instead, using election data, we make an attempt to mimic this setting by constructing proxies for political uncertainty. We construct two different variables that measure political uncertainty to varying extents. First, we utilize the year of national elections. The idea is that there will be uncertainties around elections since the election outcome is unpredictable and may lead to a change in the ruling government and thus future policy changes. Given that political parties have different views about what policies they want to pursue, the government's future policies are largely determined by the elections. The time period around an election is therefore often associated with uncertainties about what to expect policywise, as the election outcomes are unforeseen. At the same time, the year of elections provides a quasi-natural experiment because they are fixed by constitutional rules and are not in control or determined by individuals or economic actors. Thus, we are able to solve some of the endogeneity problems that we face.

Second, we exploit the occurrence of national elections where the victory margin was small. This rests on the argument that using the year of national elections may not necessarily imply uncertainty in itself, although the outcome is unexpected, the timing is indeed expected. The idea is that elections when the winning party defeats the other with only a few votes might reinforce even greater uncertainty, as such election outcomes could imply a shock to citizens and financial markets. Highly competitive elections could also reflect strong disagreements among voters and hence greater ambiguity about future government policy. Particularly, Baker et al. (2020) find evidence of greater uncertainty around future elections in countries that have recently experienced increasing political polarization. Moreover, the variable close election could be seen as a quasi-random assignment since it allows us to compare elections where the results could have gone either way and indicates an unexpected election outcome. Hence, this proxy is considered to represent a year with higher degree of political uncertainty.[16]

4.2 Main Empirical Model

The following baseline regression estimates the effect of political uncertainty on AI innovation:

$$\ln(AI\_patents_{c,t} + 1) = \beta_1 PU_{c,t} + \beta_2 \ln(total\_patents_{c,t} + 1) + \gamma_c + \lambda_t + u_{c,t} \qquad (1)$$

where the dependent variable $AI\_innovation_{c,t}$ denotes the number of AI patents by country c in year t. The independent variable of interest $PU_{c,t}$, for political uncertainty, is proxied by either the year of an election or a close election. It takes the value of 1 if there has been an election or a close election, respectively, in country c in year t and 0 otherwise. Next, $total\_patents_{c,t}$

[16]We also thought to exploit the occurrence of a change in leadership, as a consequence of a national election. This could be seen as a source of political uncertainty since individuals' leaderships and policy decisions might be different both across or within political parties. However, when exploring the data, a change in leader almost perfectly correlates with the year of an election, since almost all national elections (99%) in our cross-country dataset result in a leadership change. Therefore, using this variable would contribute little to our existing analysis.

denotes the number of total patents in country c in year t. It is included in the model in order to capture the effects of AI innovation while holding the total innovation in a country constant, thus being able to evaluate whether AI innovation is more reactive to political uncertainty than overall innovation. By controlling for total patents, we also eliminate the bias coming from potential outside events that affects a country's total degree of innovation. When we use the variation from close elections, we are treating non-close election years the same as non-election years, thereby suggesting that political uncertainty arises solely around elections associated with a small victory margin.

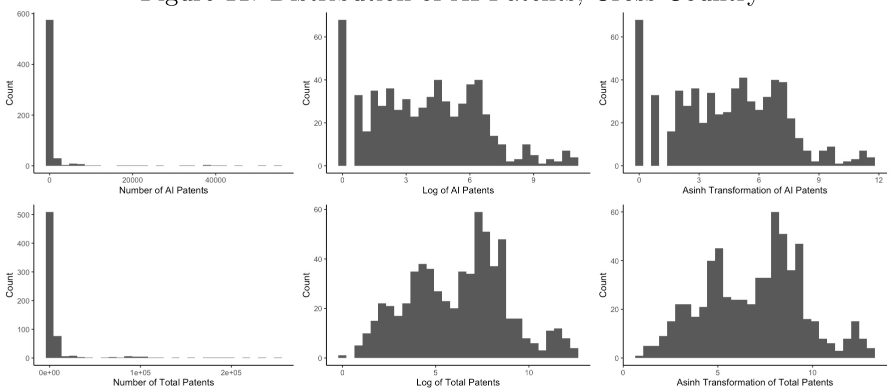
Although our proxies for political uncertainty provide quasi-exogenous variation, there is most likely some unobserved heterogeneity confounding the relationship between political uncertainty and AI innovation. Fortunately, because of the nature of our panel data, we are able to account for these types of unobserved heterogeneity by including country and year fixed effects denoted by c and t in Equation 1. The country fixed effects in our model take away the potential bias of, for instance, the probably disproportionate large number of patents from assignees coming from the US. It also accounts for countries' different quality of government such as corruption levels and rule of law that affect both electoral systems and the degree of innovation. The year fixed effects account for the bias coming from events affecting all firms seeking patents on the US market, such as the global financial crisis in 2008 or changes in US patent laws such as Alice in 2014. Changes in patent laws are naturally correlated with the number of patents being granted, and it might also create uncertainties around which inventions will be eligible for patent protection, thereby contributing to overall political uncertainty.

In addition, we utilize the US patent data as a proxy for a country's total patents worldwide. For the underlying data, this practically implies that we assume that uncertainties in an assignee's country of origin will affect his or her decision to apply for patent protection on the US market. It is important to note that uncertainties happening in the US may affect countries differently, fortunately, the country and year fixed effects also eliminates the potential bias from this. However, if any country has a changing relationship with the US that is connected to political uncertainty, this would not be accounted for by the fixed effects. We reason that this is not a major concern since we study a short time period, and the political relationship to the US is unlikely to have changed dramatically given the countries in our sample.

Lastly, we use the natural logarithm of patents. Patent data follows a Poisson distribution since the number of patents is a type of count data which can only take values that are non-negative and discrete (Bound et al., 1982). One of the assumptions for a linear regression model is for the standard errors to be normally distributed in order to conduct reliable inference, which is violated in this case. Hence, we use the natural logarithm to approximate the patents into a log-normal distribution. However, as seen in Figure 11, the log transformation of AI patents is still not normally distributed. This is due to the fact that the sample consists of several countries with zero to very few AI patents and a few countries such as the US and Japan with several thousands of AI patents each year. As such, we will deal with this issue by conducting a robustness check where we restrict the sample by excluding countries with few AI patents. We make another robustness check using a poisson regression, a type of av generalized linear model (GLM), in order to appropriately account for the patent data following Bound et al. (1982) who finds that the poisson model gives different results from the logarithmic OLS when analyzing patent data. In addition, to account for the logarithm of zero values, we take the logarithm of AI patents and add 1 since the zeros have an economic impact we would like to capture. For consistency, the same is done for total patents. Although this is not the ideal solution, we will again show in a robustness check that using an inverse hyperbolic sinh transformation will yield similar results.

All standard errors are clustered at the country level. We suspect a positive serial correlation since the level of AI innovation depends on the level the years before as we can see a general positive trend for AI innovation (See Figure 1). That is, there exist innovation spillovers across time as there is a positive development of acquired knowledge. As such, the homoscedasticity assumption is violated. Furthermore, as Angrist and Pischke (2008) point out, with clusters fewer than 42, using robust standard errors will most likely induce bias. Therefore, we follow Cameron et al. (2008) and use wild bootstrap standard errors which resamples the sample repeatedly in order to approximate the distribution of the true population.

Figure 11: Distribution of AI Patents, Cross-Country



Notes: Figure 11 displays the distribution of AI patents published by the USPTO during the period 2000-2018 for the 32 countries in our sample. The first row presents, respectively, the number, the logarithm, and the asinh transformation of AI patents. The second row presents the same for all patents. Sources: USPTO and AIPD.

4.3 Model Extensions

We hypothesize that the effect does not necessarily have to arise the same year. First, one may reason that elections in general and close elections in particular are preceded by uncertain political times, where citizens and firms are aware of the large discrepancies in society. Accordingly, firms may expect that the upcoming election would involve great uncertainty concerning policy outcomes, and hence they make their current investment decisions based on these expectations.

This effect is evident in previous literature that has found an effect during pre-election periods the months prior to an election (Baker et al., 2020; Canes-Wrone & Park, 2012; Jens, 2017; Julio & Yook, 2016). Second, it is intuitive to believe that it takes some time for political leaders to roll-out new policies and for firms to adjust their investment decisions after learning about election outcomes.

We address this issue by regressing the dependent variable on a lag and a lead of the independent variable, named $year\_after_{c,t}$ and $year\_before_{c,t}$ respectively in Equation 2, where the rest of the elements are the same as in Equation 1. These are binary variables indicating that a country was one period away from the event of interest. We choose to only investigate the effects one year before and one year after the election year, thus covering a total of three years. Otherwise the periods may overlap with the year before or after the adjacent election since most countries in our sample tend to have an election cycle of four years. Hence, if we would include the effects two years before and two years after the election, we would not be able to disentangle the effects from the subsequent election periods.

$$\begin{aligned} \ln(AI\_patents_{c,t} + 1) = \beta_1 PU_{c,t} + \beta_2 year\_before_{c,t} + \beta_3 year\_after_{c,t} \\ + \beta_4 \ln(total\_patents_{c,t} + 1) + \gamma_c + \lambda_t + u_{c,t} \end{aligned} \tag{2}$$

4.4 Omitted Variable Bias

Unfortunately, although the two-way fixed effects model control for the time-invariant and country-invariant characteristics, the model may still suffer from bias caused by omitted variables that vary over time within countries.

First, in order to mitigate the omitted variable bias, we include a country-specific time trend, $\delta_c t$, in the baseline regression since there is evidently a positive trend in AI innovation as seen in Figure 1 which, however, differs from country to country. This helps us mitigate some of the country-specific omitted variables. Equation 3 includes the same elements as in Equation 2 but with the additional country-specific time trend $\delta_c t$.

$$\begin{aligned} \ln(AI\_patents_{c,t} + 1) = \beta_1 PU_{c,t} + \beta_2 year\_before_{c,t} + \beta_3 year\_after_{c,t} \\ + \beta_4 \ln(total\_patents_{c,t} + 1) + \gamma_c + \lambda_t + \delta_c t + u_{c,t} \end{aligned} \tag{3}$$

Second, common to most previous literature is to control for GDP as they point out that the key challenge in establishing causality is due to endogeneity between political uncertainty and economic outcomes (Jens, 2017; Julio & Yook, 2016; Redl, 2020). Hence, we consider GDP to be the main confounder and will go on by discussing GDP as the only relevant omitted variable and how we will deal with it.

In the long-run, per capita economic growth stimulates innovation through, for instance, increasing the quality of education and research, and providing access to capital. In the short-run, economic growth would drive an increased demand for new products as well as firms being more likely to invest as they have more liquidity and/or expect better sales in the future. Hence, we expect GDP to be positively correlated with our dependent variable.[17] Furthermore, a period characterized by slow economic growth might lead to political instability as citizens are less satisfied with the incumbent party's politics, which implies that GDP is expected to be negatively correlated with our independent variable. Excluding this control would thus bring negative bias to our model.

However, the issue with GDP as a confounding variable is that political uncertainty will likely also affect GDP. Large political uncertainties are often reflected on financial markets which in turn affects households to consume less and save more while economic actors delay their investments, resulting in a slowdown in economic activities. As such, GDP can also be seen as an outcome variable of political uncertainty. Following Angrist and Pischke (2008), a confounding variable that is also an outcome variable is considered to be a bad control. Addressing bad controls is a challenging task because including the variable would hamper the causal interpretation of our model. We make an effort to tackle this issue by testing our main specification with and without the control in order to see whether including it would significantly affect the results.

Furthermore, in a separate specification, we include the controls GDP and total patents as lagged variables. This is done in a further attempt to address the issue that GDP can be the outcome of political uncertainty as well as because we are concerned that the number of total patents also might be affected by political uncertainty as AI patents are. The intuition behind the lagged variables is that GDP and total patents last year is most likely not impacted by political uncertainty this year. However, it makes sense that GDP and total patents last year can affect political uncertainty this year. Since we posit that GDP and political uncertainty is negatively correlated, omitting this variable should again result in a negative bias.

4.5 US Case Study

While the cross-country analysis broadens the external validity and provides results in a more general setting, a potential downside of conducting an analysis based on cross-country data is that there are a lot of events happening across countries at different time points which may conflate different trends in both AI patents and political uncertainty. This increases the likelihood of

[17] One may suggest that the causal relationship between AI innovation and GDP might also go in the opposite direction as technical innovation is widely considered one of the most important components of long-term economic growth. However, since we are looking at the effects of a short time period (a year before and after an election), we argue that this will not be an issue since one does not expect AI patents filings to cause economic growth immediately.

unobserved heterogeneity that varies within countries over time. Hence, we complement our cross-country analysis with a case study of the US, using panel data across states and years. This gives us a larger sample and a more convincing causal identification since it allows us to isolate our effect of interest from potentially confounding country-level variables. For this, we use gubernatorial elections as a source of political uncertainty together with USPTO patents on state-level.

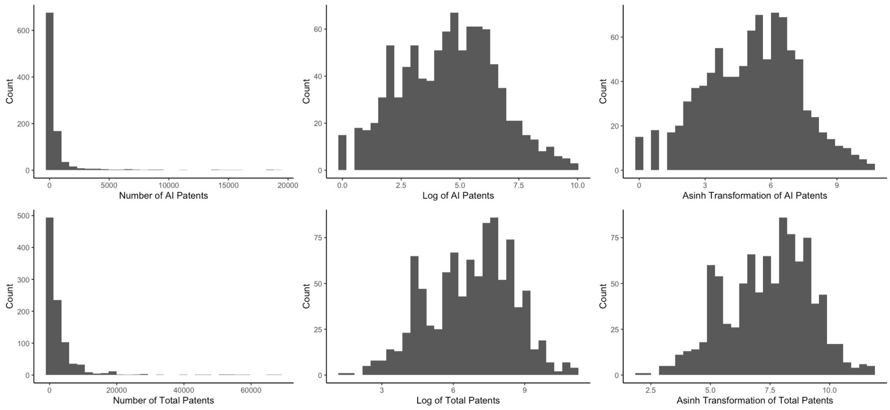
Every fourth year, governors of each state are popularly elected through gubernatorial elections except in New Hampshire and Vermont where the election occurs every two years. The election cycles differ between states, although some states' election cycles coincide. Historically, the majority of the winning candidates have either been Democratic or Republican governors. Governors are both state leaders and managers and their responsibilities include implementing, advancing and pursuing state laws, policies and programs as well as managing the operation of the state executive branch. However, the scope of power which the governors possess varies between states and depends on traditions and legislations (National Governors Association, 2022). As such, gubernatorial elections impose substantial political uncertainties since governors are highly influential when it comes to policy-making on state-level and the ideologies of the candidates are often conflicted. Gubernatorial elections always occur on a Tuesday after the first Monday in November (Cunningham, n.d.). The timing of the elections can be considered to be quasi-random since it is not determined by economic factors. Hence, using gubernatorial elections provide the same quasi-random experience as with national elections.

The empirical strategy follows the same steps and reasonings above.

$$\begin{aligned} \ln(AI\_patents_{s,t}+1) = \beta_1 PU_{s,t} + \beta_2 year\_before_{s,t} + \beta_3 year\_after_{s,t} \\ +\beta_4 \ln(total\_patents_{s,t}+1) + \gamma_s + \lambda_t + \delta_s t + u_{s,t} \end{aligned} \tag{4}$$

In Equation 4, $AI\_patents_{s,t}$ and $total\_patent_{s,t}$ denotes the number of AI patents and total patents in state s, during year t, respectively. $PU_{s,t}$ takes the value 1 if there has been a gubernatorial election in state s, during year t or if there has been a close gubernatorial election in state s, during year t, and 0 otherwise. $year\_before_{s,t}$ and $year\_after_{s,t}$ are binary variables indicating 1 if state s in year t, is one period away from a year of political uncertainty. Finally, $\gamma_{s,t}$, $\lambda_{s,t}$ and $\delta_s t$ are state fixed effects, year fixed effects and state-specific time trends respectively. The US case study data produces log-normal distribution (see Figure 12), hence, avoiding the non-normality issue that arose with the cross-country data. However, since we now have 50 states and therefore 50 clusters, we will rely on cluster robust standard errors instead of the wild bootstrap standard errors.

Figure 12: Distribution of AI Patents, US Case Study



Notes: Figure 13 displays the distribution of AI patents published by the USPTO during the period 2000-2018 for the 50 states of the US. The first row presents, respectively, the number, the logarithm, and the asinh transformation of AI patents. The second row presents the same for all patents. Sources: USPTO and AIPD.

4.6 Research Question and Hypotheses

This thesis aims to answer the following research question: *To what extent does political uncertainty affect innovation related to artificial intelligence technology as measured by patent counts?* In order to answer our research question, we empirically test two rival hypotheses which each rely on an economic theory. The theories are related to each other but suggest different mechanisms. The empirical analysis enables us to establish in what direction political uncertainty affects AI innovation, and which potential mechanism can explain the relationship when using patent count as a proxy for innovation. In addition, this relationship is analyzed in two separate but relevant settings, in a cross-country analysis and a US case study. The following hypotheses are tested:

[H1]: Because patents can be seen as the output of irreversible investments, political uncertainty will be associated with a lower level of aggregate AI innovation as measured by a decrease in the number of AI patents while holding the total number of patents constant.

[H2]: Because patents can be seen as real options, political uncertainty will be associated with a higher level of aggregate AI innovation as measured by an increase in the number of AI patents while holding the total number of patents constant.

5 Results

This section tests, each in turn for the cross-country analysis and US case study, our underlying research question. We start by estimating the effect of a year of election on the number of AI patents, and go on to estimate the effect of a year of a close election on the number of AI patents.

Altogether, the cross-country results suggest an increase in AI patents before and during years of national elections, and the US results suggest an increase in AI innovation a year after close gubernatorial elections.

5.1 Cross-Country

5.1.1 Election Year

Table 5 presents the results from estimating the effect of a year of a national election on the natural logarithm of AI patents for the cross-country analysis. In addition to country and year fixed effects, column (5) gives estimates when also including the country-specific time trend to mitigate potential country-specific omitted variables. The estimate suggests that the number of AI patents increases by 9% on average as compared to non-election years, holding total patents fixed. This is statistically significant on the 1% level.

The positive relationship suggests that political uncertainty associated with elections causes an increase in AI patent applications, hence, we find support for [H2]. As such, the results suggest that the mechanism for the relationship is explained by the theory of patents as real options that propose that the value of patents increase under greater uncertainty. We reason that a higher value of AI patents induce firms to file more such patents. Comparing this to previous literature investigating the economic impacts of uncertainty around elections, the magnitude of our estimates is similar, however our estimates point in the other direction. For example, Jens (2017) suggests a 4.9% decline in investments a quarter before elections, and Julio and Yook (2016) suggest that FDI flows fell by 13% relative to non-election years. Importantly, given that the previous literature empirically test the irreversible investment theory with actual data on investments, the magnitudes are not entirely comparable since our study of patents does not capture the actual investments in AI innovation.

Furthermore, column (5) includes independent variables indicating a year before and after an election. The results suggest that AI patents increase by 7%, on average, one year before an election, which is significant on the 5% level. In contrast, the results of AI patents one year after an election are insignificant, implying that we cannot rule out a zero effect. Altogether, this is consistent with the reasoning that political uncertainty affects innovation decisions in the pre-election period when it is yet unknown what the election outcome would be, but not in the post-election period.

As discussed above, we are concerned about potential endogeneity between political uncertainty and economic growth. To address this, in column (6), we control for the annual real GDP growth (%), and a lagged version in column (7). When adding the control GDP and when including the lagged variables, the significant effect remains and the magnitude for year before and year after becomes slightly larger which suggests that omitting GDP underestimates the effect in line with our reasoning that omitting GDP would yield a negative bias. However, overall the magnitude does not change remarkably which suggests that the omitted variable bias is not severe. Moreover, with the lagged controls, the results for a year after an election also becomes significant on a 5% level.

We also note that GDP is negatively correlated with our dependent variable, which is against the reasoning in Section 4.4. that GDP and innovation are positively correlated. We suggest that this could possibly be explained by the real options framework. Similarly to political uncertainties, an economic downturn will create uncertainty which in turn is hypothesized to increase the value of patents, hence the patent counts might also increase. Another potential explanation could be that while innovation in general is positively correlated with GDP, AI innovation in particular may be negatively correlated with GDP. As proposed by DeStefano and Moussiegt (2017) firms tend to adopt software technologies when business environments are poor in order to adopt cost-saving strategies. AI can primarily be categorized as a software technology and therefore, when there is an economic downturn, firms may increase their adoption of AI innovation as compared to innovation in general. Furthermore, we observe that the estimates for total patents and lagged total patents suggest a positive correlation with AI patents which is reasonable because if AI patents increase, it is implied that total patents increase.

Importantly, if omitting GDP yields a negative bias and GDP seems to be negatively correlated with AI patents, it follows that political uncertainty must be positively correlated with GDP. We propose that this might be explained by political business cycles, referring to the stimulation of the economy prior to an election by the incumbent government to increase the chances of being re-elected (Nordhaus, 1975), which might be particularly common if the election is expected to be highly competitive. However, this relationship is beyond the scope of this thesis and we leave it to future research. It could also simply be because including lagged GDP does not entirely resolve the bias induced by being a bad control.

Table 5: Results, Election Year, Cross-Country

	Dependent variable:						
	AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Election Now	0.03	0.04	0.04	0.05	0.09**	0.09**	0.09**
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Year Before		0.01		0.03	0.07*	0.08*	0.10*
		(0.03)		(0.04)	(0.04)	(0.03)	(0.04)
Year After			0.02	0.03	0.07	0.07	0.08*
			(0.04)	(0.05)	(0.04)	(0.04)	(0.03)
Total Patents	0.62***	0.62***	0.62***	0.62***	0.43**	0.42**	
	(0.10)	(0.10)	(0.10)	(0.10)	(0.15)	(0.16)	
Lagged Total Patents							0.08*
							(0.03)
GDP						−1.18	
						(1.05)	
Lagged GDP							−2.74*
							(1.21)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	608	607	607	606	606	606	606
R^2	0.97	0.97	0.97	0.97	0.99	0.99	0.98
Adjusted R^2	0.97	0.97	0.97	0.97	0.98	0.98	0.98

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The dependent variable is the natural logarithm of AI patents + 1 and Election Now is the year of a national election. Year Before and Year After are binary variables that indicate a year before and after the year of a national election. Total Patents is the natural logarithm of total patents + 1 and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

5.1.2 Close Election

Table 6 presents the results from the occurrence of a close election as the independent variable, which is defined as a national election with a victory margin less than 2.8 p.p. Similar to the previous results, this shows the effect of a close national election on the natural logarithm of AI patents for the cross-country analysis. In contrast to the results in Table 5, the effects are statistically insignificant and the results are therefore inconclusive.

The insignificant estimates imply that we find no effect of close elections on AI patent applications, hence, we find no support for any of our specified hypotheses. We highlight two potential explanations for this finding. First, it could be that highly contested national elections are not at all a factor of uncertainty that firms take into account when deciding about AI patent applications. Given that we find a significantly positive effect of overall elections but not of close elections, it might be that the election in itself is what creates uncertainty rather than the aspect of competitiveness between the major political parties or candidates. This would suggest elections to be a better proxy for political uncertainty. Second, it could be the case that our definition of a close election is too strict, which leads us to fail capturing many elections that are indeed associated with great uncertainty. We followed the strategy of previous literature and defined the cut-off for close elections to be at the first quartile of the sample distribution of all victory margins so that we reached the same variation in the variable, however, our cut-off appeared to be much smaller than theirs. As such, there is a trade-off between the cut-off level and the variation.

Table 6: Results, Close Election, Cross-Country

	Dependent variable:						
	AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Close Election	0.02	0.01	0.01	0.01	0.02	0.02	0.01
	(0.07)	(0.06)	(0.05)	(0.06)	(0.08)	(0.08)	(0.08)
Year Before		0.01		0.03	0.04	0.04	0.04
		(0.06)		(0.06)	(0.08)	(0.08)	(0.08)
Year After			−0.03	−0.03	−0.01	−0.02	−0.01
			(0.08)	(0.07)	(0.07)	(0.07)	(0.06)
Total Patents	0.44^{**}	0.62^{***}	0.62^{***}	0.62^{***}	0.43^{**}	0.43^{**}	
	(0.16)	(0.10)	(0.09)	(0.09)	(0.17)	(0.16)	
Lagged Total Patents							0.07^{**}
							(0.03)
GDP						−1.22	
						(1.08)	
Lagged GDP							-2.71^{*}
							(1.18)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	608	607	607	606	606	606	606
R^2	0.98	0.97	0.97	0.97	0.98	0.98	0.98
Adjusted R^2	0.98	0.97	0.97	0.97	0.98	0.98	0.98

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The dependent variable is the natural logarithm of AI patents + 1 and and Close Election is the year of national elections with small victory margins. Year Before and Year After are binary variables that indicate a year before and after the year of a close election. Total Patents is the natural logarithm of total patents + 1 and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. *p<0.05; **p<0.01; ***p<0.001

5.2 US Case Study

5.2.1 Election Year

Table 7 presents the results from estimating the effect of a year of a gubernatorial election on the natural logarithm of AI patents for the US case study. To begin with, while the cross-country analysis is of particular interest as it is more representative and broadens the external validity, we argue that the US case study is more reliable because the data is log-normally distributed as seen in Figure 12, and because it increases the sample size with 342 observations as compared to the cross-country analysis. Also, as discussed previously, state-level data enables us to reduce the risk of potential country-specific unobserved heterogeneity.

The effects are statistically insignificant, with standard errors equal or larger than the estimates in itself. This implies that we find no effect of gubernatorial elections on AI patent applications, and thus no support for any of our specified hypotheses. Relying on our reasoning in Section 4.1, this might indicate that an election in itself does not induce substantial uncertainty as elections are expected by the public. Alternatively, if highly contested gubernatorial elections are the ones that lead to uncertainty and most elections are instead rather harmonious, any existing effect may be overlooked if all elections are taken into account.

Table 7: Results, Election Year, US Case Study

	Dependent variable:						
	AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Election Now	−0.05	−0.06	−0.03	−0.04	−0.04	−0.04	−0.04
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
Year Before		−0.04		−0.01	−0.0004	−0.0001	0.02
		(0.03)		(0.04)	(0.04)	(0.04)	(0.04)
Year After			0.05	0.04	0.06	0.06	0.08
			(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Total Patents	1.19***	1.18***	1.19***	1.18***	1.06***	1.06***	
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	
Lagged Total Patents							0.09***
							(0.03)
GDP						−0.67*	
						(0.02)	
Lagged GDP							−1.04
							(0.02)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	950	949	949	948	948	948	948
R^2	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Adjusted R^2	0.97	0.97	0.97	0.97	0.98	0.98	0.98

Notes: Robust standard errors are clustered at the state-level in parentheses. The dependent variable is the natural logarithm of AI patents + 1 and Election Now is the year of a gubernatorial election. Year Before and Year After are binary variables that indicate a year before and after the year of a gubernatorial election. Total Patents is the natural logarithm of total patents + 1 and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a state-specific time trend to account for state-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. *p<0.05; **p<0.01; ***p<0.001

5.2.2 Close Election

Table 8 presents the results from exploiting the occurrence of a close election as the independent variable, defined as a gubernatorial election with a victory margin less than 5.73 p.p. As such, it estimates the effect of a close gubernatorial election on the natural logarithm of AI patents for the US case study. The results in column (5), including the state-specific time trend, indicates that the number of AI patents increases by 12% on average a year after a close gubernatorial election compared to other years, holding total patents fixed. This is significant on the 0.1% level and remains so even after adding the controls in column (6) and (7). Conversely, there are no significant effects neither for a year before nor during a close gubernatorial election on AI patents. This suggests that political uncertainty associated with close gubernatorial elections drives an increase in AI patent applications the year following the close election-year. Again, we find support for [H2]. However, while the effect for the cross-country analysis is present during years of elections, this effect for the US case study is present years after close elections.

We highlight two important contributing factors to this pattern. First, there might be institutional differences between the US and the other countries in our sample. Since the US has experienced a particular polarization in politics during recent years, there might be severe differences in policy depending on which political party wins, and close elections are therefore associated with much uncertainty. Conversely, as shown by Boxell et al. (2020), some democracies that are included in our cross-country sample have experienced a decrease in polarization over the recent decades. As such, the competing parties might not have widely different policies. Thus, closer elections are not necessarily associated with greater uncertainty. Altogether, close elections could matter more in the US and therefore explain the significant effect even though the close election cut-off is higher than in the cross-country analysis.

Second, US gubernatorial elections always occur in November. It is reasonable to assume that close elections influence firm behavior not only during the actual election month but also during the surrounding months, which is the reason for why we have pursued our event studies in the first place. This might be particularly evident in our study utilizing patents, if it takes some time between firms deciding to increase their R&D spendings and then patenting the resulting inventions. The patent behavior responding to uncertainty induced by a close election in November is hence likely to spill over also to the beginning of next year. Accordingly, as we aggregate patents on a yearly basis, this makes it natural that we observe changes in patent applications during the year after. Contrasting this to the cross-country study, there is no clear pattern of national elections in different countries occurring in the same month, and evidently the positive and significant effects occur both before, during and after the election year in the main results. Given these two explanations, the different results in the cross-country analysis and US case study propose that political uncertainty is reflected differently in different settings.

Table 8: Results, Close Election, US Case Study

	Dependent variable:						
	AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Close Election	−0.05	−0.05	−0.04	−0.04	0.003	0.001	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Year Before		−0.02		−0.004	0.05	0.04	0.05
		(0.03)		(0.03)	(0.03)	(0.03)	(0.05)
Year After			0.09**	0.09*	0.12***	0.12***	0.13**
			(0.03)	(0.04)	(0.04)	(0.04)	(0.05)
Total Patents	1.19***	1.19***	1.19***	1.18***	1.06***	1.06***	
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	
Lagged Total Patents							0.08**
							(0.03)
GDP						−0.56**	
						(0.02)	
Lagged GDP							−1.07
							(0.02)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	950	949	949	948	948	948	948
R^2	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Adjusted R^2	0.97	0.97	0.97	0.97	0.98	0.98	0.98

Notes: Robust standard errors are clustered at the state-level in parentheses. The dependent variable is the natural logarithm of AI patents + 1 and Close Election is the year of a gubernatorial election with small victory margin. Year Before and Year After are binary variables that indicate a year before and after the year of a close gubernatorial election. Total Patents is the natural logarithm of total patents + 1 and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a state-specific time trend to account for state-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. *p<0.05; **p<0.01; ***p<0.001

6 Robustness Checks

We conduct five robustness checks. All robustness checks are made on the cross-country analysis, except for varying the close election cut-off which is done both for the cross-country analysis and the US case study. The robustness checks reveal that the poisson regression yields different results than the log-normal transformed regression for the cross-country analysis. As such, we rely more on the results from the US case study since the data is log-normally distributed.

6.1 Inverse Hyperbolic Sine

First, we conduct a robustness check where an inverse hyperbolic sine has been used to transform the patent variables instead of the natural logarithm since the natural logarithm cannot deal with zero-values as ln(0) is undefined. In our main results, we have thus added a count of 1 to the patent variables in order to transform the zero-values into zero. However, adding a count of

1 is not ideal as it changes the ratio between AI patents and total patents. Hence, an inverse hyperbolic sine is sometimes preferred since it is able to transform zero-values into zero while at the same time have the characteristics of approximating the natural logarithm for large enough values (Burbidge et al., 1988). The results can therefore be interpreted in the same way as for log transformations. However, since the term large enough values is arbitrary and one could argue that the variable AI patents unfortunately contain too small values, the asinh transformation is neither a perfect solution. Nevertheless, Table 9 and 10 suggest that the results are robust to the inverse hyperbolic sine transformation of the dependent variable.

Table 9: Robustness Check, Election Year, Inverse Hyperbolic Sine

	Dependent variable:						
	AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Election Now	0.04	0.05	0.05	0.07	0.10**	0.10**	0.11**
	(0.03)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)
Year Before		0.02		0.04	0.09*	0.09*	0.11*
		(0.03)		(0.05)	(0.04)	(0.04)	(0.04)
Year After			0.03	0.04	0.08	0.07	0.08*
			(0.04)	(0.06)	(0.05)	(0.04)	(0.04)
Total Patents	0.70***	0.70***	0.70***	0.70***	0.41*	0.40*	
	(0.09)	(0.09)	(0.09)	(0.09)	(0.17)	(0.16)	
Lagged Total Patents							0.07*
							(0.03)
GDP						−1.57	
						(1.09)	
Lagged GDP							−3.40*
							(1.45)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	608	607	607	606	606	606	606
R^2	0.97	0.97	0.97	0.97	0.98	0.98	0.98
Adjusted R^2	0.97	0.97	0.97	0.97	0.98	0.98	0.98

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The dependent variable is the asinh transformation of AI patents and Election Now is the year of a national election. Year Before and Year After are binary variables that indicate a year before and after the year of a national election. Total Patents is the asinh transformation of total patents and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. *p<0.05; **p<0.01; ***p<0.001

Table 10: Robustness Check, Close Election, Inverse Hyperbolic Sine

	Dependent variable:						
	AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Close Election	0.03	0.01	0.001	0.004	0.03	0.03	0.03
	(0.08)	(0.07)	(0.06)	(0.07)	(0.09)	(0.09)	(0.10)
Year Before		0.01		0.02	0.05	0.06	0.05
		(0.07)		(0.06)	(0.09)	(0.08)	(0.10)
Year After			−0.05	−0.05	−0.02	−0.02	−0.02
			(0.09)	(0.09)	(0.07)	(0.07)	(0.06)
Total Patents	0.42*	0.70***	0.70***	0.70***	0.41*	0.40*	
	(0.17)	(0.09)	(0.10)	(0.09)	(0.17)	(0.16)	
Lagged Total Patents							0.07*
							(0.03)
GDP						−1.61	
						(1.13)	
Lagged GDP							−3.36*
							(1.49)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	608	607	607	606	606	606	606
R^2	0.98	0.97	0.97	0.97	0.98	0.98	0.98
Adjusted R^2	0.98	0.97	0.97	0.97	0.98	0.98	0.98

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The dependent variable is the asinh transformation of AI patents and Close Election is the year of a national election with small victory margin. Year Before and Year After are binary variables that indicate a year before and after the year of a close election. Total Patents is the asinh transformation of total patents and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. *p<0.05; **p<0.01; ***p<0.001

6.2 Restricted Sample

In the second robustness check we have restricted our sample to only 23 countries which decreases the sample size to 418.[18] The goal of the log transformation is to obtain a log-normal distribution of the data. However, as Figure 11 shows, the data does not seem entirely normally distributed and this is most likely due to the fact that our sample consists of several countries with zero to few AI patents and few countries with thousands of AI patents each year. Therefore, we conduct an analysis where we exclude the countries with very few AI patents since we are most interested in countries who are highly engaged in AI innovation rather than countries that are barely engaged as their level of AI innovation might not vary significantly. We exclude countries with less than 200 AI patents in total over the time period. In Figure 13 below, we show that restricting the sample does indeed enable a log-normal distribution.

The estimates in column (5) in Table 12 suggest that the immediate effect is insignificant and

[18] A list of all 23 countries included is presented in Appendix A, Table 20.

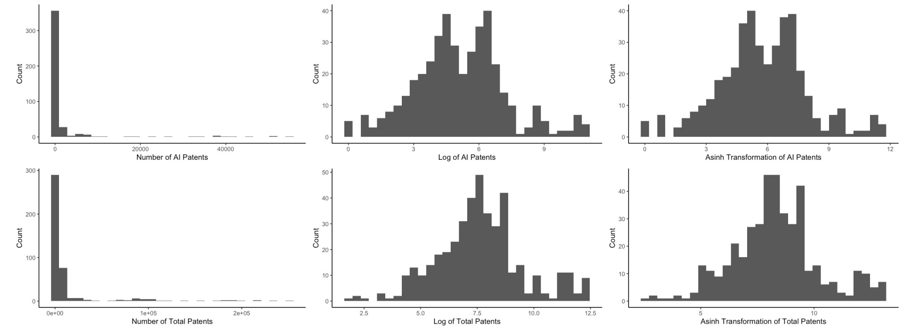
suggest a zero effect while the effect a year before and after election years is significant and positive at a 5% level and suggest significant results a year before election years as compared to non-election years. When adding the GDP and lagged GDP as a control in column (6) and (7) the immediate effect becomes significant at a 5% level and suggests a 6% and 8% increase in AI patents respectively. Although, the estimates a year before an election remain significant the magnitudes become larger. The effect a year after an election becomes insignificant when the lagged control variables are added. Hence, the main results for a year of election are not entirely robust to the sample restriction. On the other hand, the estimates for close election in Table 13 are insignificant which suggest that the main results are robust to the sample restriction in this case. However, it is important to note that there is a trade-off between only including countries most prominent in AI innovation and the sample size. The sample size in the restricted sample has been reduced by 190 observations and should therefore be interpreted with caution.

Table 11: Descriptive Statistics, Restricted Sample

Statistic	Mean	St. Dev.	Min	Max	N
Patent Variables:					
Number of AI Patents	1,905.52	7,230.85	0	54,947	418
ln(AI Patents + 1)	5.12	2.10	0.00	10.91	418
asinh(AI Patents)	5.77	2.17	0.00	11.61	418
Number of Total Patents	13,657.80	37,700.51	7	251,184	418
ln(Total Patents)	7.61	1.91	1.95	12.43	418
ln(Total Patents + 1)	7.61	1.91	2.08	12.43	418
asinh(Total Patents)	8.30	1.91	2.64	13.13	418
Share of AI Patents (%)	0.10	0.08	0.00	0.57	418
Election Variables:					
Election Now	0.26	0.44	0	1	418
Close Election	0.07	0.26	0	1	418
Victory Margin (p.p.)	0.07	0.05	0.002	0.25	110
Annual Real GDP growth (%)	0.02	0.03	−0.08	0.25	418

Notes: Descriptive statistics for all variables in the restricted sample. *Number of AI Patents* and *Number of Total Patents* are the total count of (AI) patents published by the USPTO for the 23 countries in the restricted sample during the period 2000-2018. *Share of AI Patents* is the share of AI patents out of all patents. *Election Now* is a dummy variable which takes the value 1 if there has been a national election, and 0 otherwise. *Close Election* is a dummy variable which takes the value 1 if there has been a close national election defined as a victory margin lying within the first quartile of the sample distribution of all victory margins, and 0 otherwise. The cut-off level appears at 2.8 percentage points. *Annual Real GDP Growth* is the annual real GDP growth PPP per capita. Sources: USPTO, AIPD, ParlGov, APP, World Bank.

Figure 13: Distribution of AI Patents, Restricted Sample



Notes: Figure 13 displays the distribution of AI patents published by the USPTO during the period 2000-2018 for the 23 countries in the restricted sample sample. The first row presents, respectively, the number, the logarithm, and the asinh transformation of AI patents. The second row presents the same for all patents. Sources: USPTO and AIPD.

Table 12: Robustness Check, Election Year, Restricted Sample

	Dependent variable:						
	AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Election Now	0.03	0.05	0.03	0.06	0.06	0.06*	0.08*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Year Before		0.05*		0.06**	0.06*	0.07**	0.09*
		(0.02)		(0.02)	(0.03)	(0.03)	(0.04)
Year After			0.0001	0.02	0.03*	0.03*	0.05
			(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
Total Patents	1.38***	1.38***	1.38***	1.38***	1.12***	1.09***	
	(0.08)	(0.08)	(0.09)	(0.09)	(0.22)	(0.22)	
Lagged Total Patents							0.04
							(0.04)
GDP						−2.46***	
						(0.43)	
Lagged GDP							−1.81
							(0.93)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	418	417	417	416	416	416	416
R^2	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Adjusted R^2	0.99	0.98	0.99	0.98	0.99	0.99	0.98

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The sample used to generate the results are restricted to 23 countries instead of 32 based on countries with more than 200 AI patents in total between 2000-2018. The dependent variable is the natural logarithm of AI patents + 1 and Election Now is the year of a national election. Year Before and Year After are binary variables that indicate a year before and after the year of a national election. Total Patents is the natural logarithm of total patents and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 13: Robustness Check, Close Election, Restricted Sample

	Dependent variable:						
	AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Close Election	0.03	0.04	0.03	0.03	0.03	0.03	0.01
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
Year Before		0.05		0.06	0.06	0.08	0.08
		(0.04)		(0.04)	(0.05)	(0.05)	(0.07)
Year After			−0.06	−0.05	−0.05	−0.05	−0.06
			(0.06)	(0.06)	(0.05)	(0.06)	(0.07)
Total Patents	1.14***	1.38***	1.38***	1.38***	1.12***	1.10***	
	(0.20)	(0.09)	(0.08)	(0.09)	(0.22)	(0.20)	
Lagged Total Patents							0.04
							(0.04)
GDP						−2.55***	
						(0.43)	
Lagged GDP							−1.80*
							(0.90)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	418	417	417	416	416	416	416
R^2	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Adjusted R^2	0.99	0.98	0.99	0.98	0.99	0.99	0.98

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The sample used to generate the results are restricted to 23 countries instead of 32 based on countries with more than 200 AI patents in total between 2000-2018. The dependent variable is the natural logarithm of AI patents + 1 and Close Election is the year of a national election with small victory margin. Year Before and Year After are binary variables that indicate a year before and after the year of a close election. Total Patents is the natural logarithm of total patents and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. *p<0.05; **p<0.01; ***p<0.001

6.3 Poisson Regression

The patent data is a type of count data and is therefore poisson distributed, hence, a poisson regression may be more efficient to use instead of estimating a transformed normal distribution with OLS. A poisson regression is a type of GLM with a log-link function which is particularly useful for modeling count data. In short, the parameters are fitted using a maximum likelihood approach which implies to find the optimal values of the parameters such that the likelihood of the observed data for the model is maximized, given the model assumptions. Moreover, the log-link function implies that the estimates should be interpreted as the exponential of the coefficients, e^{β}, and is a multiplicative indicator rather than an additive. For instance, column (5) in Table 14 proposes that during an election year, the number of patents is on average 1.001 times the number of patents during non-election years, suggesting a slight increase in the number of patents. The results in Table 14 and 15 are statistically insignificant and suggest that there is no effect between political uncertainty and AI innovation. As such, the results are not robust to a GLM estimation.

Importantly, this suggests that the results of the cross-country analysis should be interpreted with caution. Since the log-transformation was unable to produce normally distributed data, it might be more appropriate to use a GLM. As also pointed out by Bound et al. (1982), using a log-normal OLS and poisson regression yield very different results. Since the GLM results show that all results are insignificant, we suggest future research to investigate this further using a more elaborated GLM approach.

Table 14: Robustness Check, Election Year, Poisson Regression

	Dependent variable:						
	AI Patents						
	Poisson						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Election Now	−0.0003	−0.01	0.01	0.002	0.001	0.001	0.01
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Year Before		−0.02		−0.01	−0.01	−0.01	−0.01
		(0.01)		(0.02)	(0.02)	(0.02)	(0.02)
Year After			0.02	0.01	0.02	0.02	0.02
			(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Total Patents	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Lagged Total Patents							0.0000
							(0.0000)
GDP						−1.31	
						(0.93)	
Lagged GDP							−0.50
							(0.94)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	608	607	607	606	606	606	606
Log Likelihood	−4,806.68	−4,793.48	−4,787.98	−4,778.76	−3,351.78	−3,316.61	−3,342.69
Akaike Inf. Crit.	9,717.36	9,692.97	9,681.96	9,665.52	6,873.57	6,805.21	6,857.37

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The results are generated in a GLM framework with a log-link function. The estimates should be interpreted as the exponential of the coefficients e^{β}. The dependent variable is the number of AI patents and Election Now is the year of a national election. Year Before and Year After are binary variables that indicate a year before and after the year of a national election. Total Patents is the number of total patents and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. *p<0.05; **p<0.01; ***p<0.001

Table 15: Robustness Check, Close Election, Poisson Regression

	Dependent variable:						
	AI Patents						
	Poisson						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Close Election	0.001	0.01	0.02	0.02	0.01	0.01	0.02
	(0.04)	(0.05)	(0.05)	(0.06)	(0.07)	(0.07)	(0.06)
Year Before		0.02		0.03	0.01	0.02	0.02
		(0.05)		(0.05)	(0.06)	(0.05)	(0.05)
Year After			0.03	0.03	0.02	0.02	0.03
			(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
Total Patents	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Lagged Total Patents							0.0000
							(0.0000)
GDP						−1.22	
						(1.04)	
Lagged GDP							−0.68
							(0.92)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	608	607	607	606	606	606	606
Log Likelihood	−3,386.79	−4,792.79	−4,783.94	−4,770.01	−3,361.90	−3,330.87	−3,347.20
Akaike Inf. Crit.	6,939.58	9,691.58	9,673.87	9,648.03	6,893.80	6,833.75	6,866.39

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The results are generated in a GLM framework with a log-link function. The estimates should be interpreted as the exponential of the coefficients e^{β}. The dependent variable is the number of AI patents and Close Election is the year of a close election. Year Before and Year After are binary variables that indicate a year before and after the year of a close election. Total Patents is the number of total patents and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. *p<0.05; **p<0.01; ***p<0.001

6.4 Close Election Cutoff Quintile

In the main results, the definition of a close election is determined by the first quartile of the victory margins. Since the cutoff appears at 2.8 p.p for the cross-country analysis and 5.73 p.p. for the US case study, one may argue that uncertainties may not be induced until even narrower victory margins. However, as there are trade-offs between choosing a lower cutoff level and losing variation, as a robustness check, we therefore alter the cutoff level for the cross-country analysis to 2.32 p.p. and the US case study to 4.53 p.p. and define a close election by the first quintile of the distribution of victory margins. The results are broadly robust to the quintile definition of close election. Although, the estimate for Table 17 in column (7) suggests a significant and positive increase in AI patents a year before close elections which was not evident in the main results for the US. This might suggest that elections with narrower victory margins between the winner and the runner-up may induce more uncertainties, although this was only evident when adding the lagged variables.

Table 16: Robustness Check, Quintile, Cross-Country

	Dependent variable:						
	AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Close Election Quintile	−0.06	−0.06	−0.07	−0.08	−0.01	−0.01	−0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.08)	(0.10)	(0.11)
Year Before		−0.05		−0.04	0.04	0.05	0.05
		(0.07)		(0.06)	(0.08)	(0.10)	(0.10)
Year After			−0.10	−0.10	−0.04	−0.04	−0.04
			(0.10)	(0.08)	(0.06)	(0.07)	(0.07)
Total Patents	0.62***	0.62***	0.62***	0.62***	0.43**	0.42**	
	(0.09)	(0.08)	(0.09)	(0.09)	(0.16)	(0.16)	
Lagged Total Patents							0.07*
							(0.03)
GDP						−1.23	
						(1.09)	
Lagged GDP							−2.68*
							(1.29)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	608	607	607	606	606	606	606
R^2	0.97	0.97	0.97	0.97	0.98	0.98	0.98
Adjusted R^2	0.97	0.97	0.97	0.97	0.98	0.98	0.98

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The results are based on a close election which is defined by the first quintile of the distribution of victory margins with a cutoff level at 2.32 p.p as compared to 2.8 p.p. in the main results. The dependent variable is the natural logarithm of AI patents + 1 and Close Election is the year of a close election. Year Before and Year After are binary variables that indicate a year before and after the year of a close election. Total Patents is the natural logarithm of total patents + 1 and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. *p<0.05; **p<0.01; ***p<0.001

Table 17: Robustness Check, Quintile, US Case Study

	Dependent variable:						
	AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Close Election Quintile	−0.04	−0.04	−0.03	−0.03	0.01	0.01	0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Year Before		−0.02		−0.01	0.05	0.05	0.08*
		(0.04)		(0.04)	(0.03)	(0.03)	(0.04)
Year After			0.09**	0.09*	0.12***	0.12***	0.14**
			(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Total Patents	1.19***	1.19***	1.19***	1.18***	1.05***	1.06***	
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	
Lagged Total Patents							0.08**
							(0.03)
GDP						−0.56**	
						(0.02)	
Lagged GDP							−1.07
							(0.02)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	950	949	949	948	948	948	948
R^2	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Adjusted R^2	0.97	0.97	0.97	0.97	0.98	0.98	0.98

Notes: Robust standard errors are clustered at the state-level in parentheses. The results are based on a close election which is defined by the first quintile of the distribution of victory margins with a cutoff level at 4.53 p.p as compared to 5.73 p.p. in the main results. The dependent variable is the natural logarithm of AI patents + 1 and Close Election is the year of a gubernatorial election with small victory margin. Year Before and Year After are binary variables that indicate a year before and after the year of a close election. Total Patents is the natural logarithm of total patents +1 and GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a state-specific time trend to account for state-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of total patents and GDP. *p<0.05; **p<0.01; ***p<0.001

6.5 Share of AI Patents

Another way of measuring how AI patents change while holding total patents constant is to use the share of AI patents as a dependent variable. The share of AI patents is simply the number of AI patents divided by the total number of patents. As such, we use a levels-levels regression and do not need to control for the number of total patents. The results in Table 18 suggest a positive and significant effect during election years on AI patents and remain the same when adding GDP and the lagged variables, although the level of significance increases from 5% to 1%. However, as opposed to the results in Table 5, the year before and the year after an election are statistically insignificant suggesting that there is only an effect during the actual year of an election. As such, the main results in the cross-country analysis are not entirely robust to using the share of AI patents as the dependent variable in a levels-levels regression. The results in Table 19 are insignificant and suggest no effect on political uncertainty as measured with close elections on the share of AI patents as evident in the main cross-country results.

Table 18: Robustness Check, Election Year, Share of AI Patents

	Dependent variable:						
	Share of AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Election Now	0.01*	0.01*	0.01	0.01	0.01*	0.01*	0.01**
	(0.004)	(0.003)	(0.003)	(0.005)	(0.01)	(0.01)	(0.01)
Year Before		0.004		0.005	0.01	0.01	0.01
		(0.005)		(0.01)	(0.01)	(0.01)	(0.01)
Year After			0.0004	0.002	0.01	0.01	0.01
			(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
GDP						−0.09	
						(0.20)	
Lagged GDP							−0.32
							(0.23)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	608	607	607	606	606	606	606
R^2	0.69	0.54	0.54	0.54	0.69	0.69	0.70
Adjusted R^2	0.65	0.50	0.50	0.50	0.65	0.64	0.65

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The dependent variable is the share of AI patents and Election Now is the year of a national election. Year Before and Year After are binary variables that indicate a year before and after the year of a national election. GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of GDP. *p<0.05; **p<0.01; ***p<0.001

Table 19: Robustness Check, Close Election, Share of AI Patents

	Dependent variable:						
	Share of AI Patents						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Close Election	0.005	0.003	−0.0003	0.001	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Year Before		0.01		0.01	0.02	0.02	0.02
		(0.01)		(0.01)	(0.02)	(0.02)	(0.02)
Year After			−0.01	−0.01	−0.01	−0.01	−0.005
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
GDP						−0.10	
						(0.20)	
Lagged GDP							−0.31
							(0.24)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	Yes	Yes	Yes
Observations	608	608	607	607	607	607	607
R^2	0.69	0.54	0.54	0.54	0.69	0.69	0.70
Adjusted R^2	0.64	0.50	0.50	0.50	0.65	0.65	0.65

Notes: Wild Bootstrap standard errors are clustered at the country-level in parentheses. The dependent variable is the share of AI patents and Close Election is the year of a national election with small victory margin. Year Before and Year After are binary variables that indicate a year before and after the year of a close election. GDP is the annual real gross domestic product growth (%). Specification (1-4) explores the Year Before and Year After changes and (5) includes a country-specific time trend to account for country-specific omitted variable bias. Specification (6) examines how the estimates changes with the control GDP and specification (7) explores this with a one year lagged variable of GDP. *p<0.05; **p<0.01; ***p<0.001

7 Discussion

This section begins by discussing the findings and potential mechanisms behind the results. The findings support the real options theory that the number of AI patents increases during greater political uncertainty and suggests that there seems to be institutional differences between the cross-country analysis and the US case study which affects the results. However, we also address the possibility of other explanations behind the outcomes. At last, we highlight two limitations that may hamper the results.

7.1 Findings

Our findings in the cross-country analysis and the US case study support our [H2] that political uncertainty suggests an increase in AI innovation. Importantly, political uncertainty seems to be reflected in different ways in different settings as shown by varying effects of using the timing or closeness of elections. First, this mechanism seems to be explained by the real options theory. Second, the findings also suggest that AI innovation is more reactive to political uncertainties as compared to innovation in general. Throughout this study, we propose that this is due to the nature of AI being sensitive to ethical issues and the emerging debates regarding AI governance.

We go on to elaborate on how our results of using patent counts might be explained by the real options theory. As argued by Bloom and Van Reenen (2002) and others, patents can act as real options through enabling firms to choose the timing of their related investments while at the same time protecting the firm from market competition, and the value of the patent real option is expected to increase under uncertainty. Our results suggest that an increase in the value of patents also implies that the number of patents applied increases. We propose that one explanation for this is that there is a tradeoff between patenting the invention and keeping the invention from the public. When the value of a patent increases during uncertainties, firms may consider the gains from patenting the invention to be larger than keeping it from the public. While this does not suggest an increase in investments in innovation, this does suggest that the number of patent applications increases. When inventions are patented, they become publicly available and may provoke innovation diffusion. Hence, contributing to an overall increase in the level of innovation. Another potential explanation for the positive relationship, is that a patent as an intellectual property right can be sold to another actor. As such, patenting an invention can potentially compensate for the investments, hence making the investments less irreversible. This explanation would further strengthen the reasoning of Bloom and Van Reenen (2002), that patents can be seen as an option to reverse the investment.

However, we do not rule out the possibility that there may be other theories that could potentially explain our findings. For instance, as argued by Born and Pfeifer (2014), firms proactively want to build up a capital stock in order to hedge against uncertainties. What this means in terms of our findings, is that the positive effect of firms building up a capital stock related to AI innovation would outweigh the effect of wanting to delay investments in AI. This may seem reasonable since proactively investing in AI innovation could result in productivity growth which increases revenue and may put one in a more advantageous position in times of uncertainties. However, the study has been conducted in a different setting, therefore this potential mechanism is only tentative in order to raise the possibility of other mechanisms. Furthermore, there might be other potential mechanisms that we were unable to look into in this study that might be driving the results. For instance, the possibility that different industries respond differently to political uncertainties might influence our results. As mentioned previously, different AI component technologies have experienced different trends over time and across industries. This may suggest that there is a heterogeneous effect of political uncertainties on AI innovation depending on the type of industry a firm operates in. Hence, we encourage future research to use firm-level data and take into account the potential different dynamics of different industries.

7.2 Limitations

7.2.1 Yearly Data

While we have chosen to use yearly data in our analysis, using monthly data would potentially provide a more detailed analysis if the effects around uncertain periods are contemporaneous and particularly high solely during the month at which the election takes place, instead of lasting during an entire year. For instance, as mentioned in previous literature, Baker et al. (2020) found that EPU values are substantially higher in the month of and the months prior to a national election, as compared to the other months of the same election cycle. In addition, Julio and Yook (2016) found that the effect is short-term, lasting only one quarter before and after an election respectively. This leads to further issues in our model if the election - and hence the uncertainty - takes place in the very beginning or end of a year. In such situations the uncertainty is greater only in the first (last) months of a given year as well as the last (first) months of the preceding (subsequent) year, but we incorrectly assign uncertainty to the entire election year which may average out the entire effect. We suggest future research to also investigate the effects using more detailed monthly data.

7.2.2 Measuring AI Innovation

Unfortunately, there is no perfect measure of AI innovation available, and all proxies are associated with several limitations. In this study, we have used the quantity of patents. However, since patents could have differential economic values, another way of interpreting the level of AI innovation could be to also account for the quality of patents. This issue has been given much attention in previous research, and many propose to address it by using the count of patents together with patent citations (Acemoglu et al., 2020; Bloom et al., 2011; Trajtenberg, 1990). In our study, if the quality of AI patents indeed differ widely across years but we treat all AI patents as being equally valuable, this could have implications for our results. For instance, even though the quantity may not have changed during periods of uncertainties, the quality of the patents may differ in either direction due to distress. Using yearly data on the new citations of each patent would enable us to capture their changing value over time. However, data on AI patent citations were not available in the AIPD so we were unable to look at these effects.

Moreover, it would also be interesting to follow the strategy of Bloom et al. (2011)and Acemoglu et al. (2018) and include data on R&D expenditures as an alternative proxy for innovation and investigate how it relates to patent statistics. However, at the time of writing, there is no publicly available data on R&D expenditures associated with AI technology. As evident in our study, we cannot distinguish between AI patents as a measure of the investment in innovation, or the output of innovation. Therefore, the main challenge in interpreting the results is to disentangle these effects. More importantly, since Bernanke's theory refers to actual investments while the theory regarding patents as a real option refers to actual patents, we cannot neglect any of the theories since they do not rule out each other. Rather, the effects may simply work in opposite directions depending on whether patents are seen as the input or output of innovation.

Altogether, even though our findings suggest that the count of AI patents works in the direction explained by the patent real option theory, we suggest future research to further investigate the effects using data on AI patents citations as well as R&D expenditures associated with AI to gain a more holistic view.

8 Conclusion

The potential of AI being a general purpose technology indicates its importance for economic growth. At the same time, ethical considerations have raised debates about regulating the use of AI in a way that is responsible while at the same time does not constrain innovation. Hence, it is of interest for economic actors and policymakers to understand the driving forces behind AI innovation. In this study, we propose political uncertainty as a macro-determinant of AI innovation. We empirically test this using panel data with entity and time fixed effects in two different settings: a cross-country analysis for 32 democratic countries and a US case study. Using data on elections and AI patent counts, the results suggest a positive relationship between political uncertainty and AI innovation which seem to be explained by the economic theory of patents as real options. The results for the cross-country analysis suggest a 7% increase in AI patents a year before elections and a 9% increase in AI patents during election years as compared to non-election years. The results for the US case study suggest a 12% increase in AI patents a year after a close gubernatorial election. Altogether, these results indicate that political uncertainty is reflected in different ways in different settings and may be explained by institutional differences such as the degree of polarization. However, we observe that the cross-country results are not entirely robust to changes in the methodology. This reveals that there may be some methodological limitations in our model, notably since we showed that the underlying cross-country data were not log-normally distributed and the robustness check with the poisson regression provided insignificant results. The US case study results rely on log-normally distributed data and mitigates some of the country-specific omitted variables bias. As such, we deem the results for the US more reliable. However, we do not rule out the possibility that other limitations may hamper the interpretations of the US results.

To the best of our knowledge, this is the first study to empirically investigate the relationship between political uncertainty and AI innovation. Although one should interpret our results with caution, our findings are suggestive and contribute to new directions for which future studies could look into, both theoretically and empirically. Theoretically, our findings point to a positive relation between political uncertainty and AI innovation as opposed to the conventional theory that uncertainties impacts the economy negatively. Empirically, our findings propose a significant effect that deserves more attention to look into. Altogether, this study contributes to new and important insights regarding the determinants of AI innovation.

Our suggestions for future research can be divided into two main areas. First, on a data-level, we propose future research to explore firm-level data on different industries to look at potential heterogeneous effects as well as data on patent citations to account for patent quality and data on R&D expenditures associated with AI if available. We also recommend considering the effects using monthly data in addition to trying to disentangle the effects between proxying AI innovation with data on investments and patents in order for a more holistic understanding of the impacts that political uncertainty has on AI innovation. Second, we acknowledge the challenge in establishing causal effects, particularly since the nature of our research question includes omitted variables that are bad controls. Therefore, we hope that future research can further account for bad controls in order to draw more credible conclusions. Considering that our treatment effect is temporary, we were unable to analyze the relationship in a Difference-in-Difference framework. Altogether, we hope that future researchers will continue investigating the relationship between political uncertainty and AI innovation.

$$E(u_{c,t}|PU_{c,t}, total\_patents_{c,t}, \gamma_c, \lambda_t, \delta_c t) = 0$$

References

Abood, A. & Feltenberger, D. (2018). Automated Patent Landscaping. *Artificial Intelligence and Law*, *26*(2), 103–125.

Acemoglu, D. (2021). Harms of AI. *NBER Working Paper Series*, no. 29247.

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N. & Kerr, W. (2018). Innovation, Reallocation, and Growth. *American Economic Review*, *108*(11), 3450–91.

Acemoglu, D., Akcigit, U. & Celik, M. A. (2020). Radical and Incremental Innovation: The Roles of Firms, Managers and Innovators. *American Economic Journal: Macroeconomics (Forthcoming).*

Aghion, P., Jones, B. F. & Jones, C. I. (2018). Artificial Intelligence and Economic Growth. *The Economics of Artificial Intelligence: An Agenda* (pp. 237–282). University of Chicago Press.

Agrawal, A., Gans, J. & Goldfarb, A. (2018). Introduction to 'The Economics of Artificial Intelligence: An Agenda'. *The Economics of Artificial Intelligence: An Agenda* (pp. 1–19). University of Chicago Press.

Alesina, A. & Perotti, R. (1996). Income distribution, political instability, and investment. *European Economic Review*, *40*(6), 1203–1228.

Angrist, J. D. & Pischke, J.-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion.*

Babina, T., Fedyk, A., He, A. X. & Hodson, J. (2021). Artificial Intelligence, Firm Growth, and Product Innovation. *Available at SSRN.* https://ssrn.com/abstract=3651052

Bachmann, R. & Bayer, C. (2013). 'Wait-and-See' business cycles? *Journal of Monetary Economics*, *60*(6), 704–719.

Baker, S. R., Baksy, A., Bloom, N., Davis, S. J. & Rodden, J. A. (2020). Elections, Political Polarization, and Economic Uncertainty. *NBER Working Paper Series*, no. 27961.

Baker, S. R., Bloom, N., Canes-Wrone, B., Davis, S. J. & Rodden, J. (2014). Why Has US Policy Uncertainty Risen since 1960? *American Economic Review*, *104*(5), 56–60.

Baker, S. R., Bloom, N. & Davis, S. J. (2016). Measuring Economic Policy Uncertainty*. *The Quarterly Journal of Economics*, *131*(4), 1593–1636.

Bar-Ilan, A. & Strange, W. C. (1996). Investment Lags. *The American Economic Review*, *86*(3), 610–622.

Barro, R. J. (1991). Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*, *106*(2), 407–443.

Baslandze, S. (2016). The Role of the IT Revolution in Knowledge Diffusion, Innovation and Reallocation. *Society for Economic Dynamics, 2016 Meeting Papers*, (1509).

Bekaert, G., Hoerova, M. & Lo Duca, M. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, *60*(7), 771–788.

Bernanke, B. S. (1983). Irreversibility, Uncertainty, and Cyclical Investment. *The Quarterly Journal of Economics*, *98*(1), 85–106.

Besley, T. & Case, A. (1993). Does Electoral Accountability Affect Economic Policy Choices? Evidence from Gubernatorial Term Limits. *NBER Working Paper Series*, no. 4575.

Bessen, J., Cockburn, I. & Hunt, J. (2021). Is Distance from Innovation a Barrier to the Adoption of Artificial Intelligence?, Presented at the Economics of Artificial Intelligence Conference, September 23, 2021.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, *77*(3), 623–685.

Bloom, N., Draca, M. & Van Reenen, J. (2011). Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. *NBER Working Paper Series*, no. 16717.

Bloom, N., Hassan, T. A., Kalyani, A., Lerner, J. & Tahoun, A. (2021). The Diffusion of Disruptive Technologies. *NBER Working Paper Series*, no. 28999.

Bloom, N. & Van Reenen, J. (2002). Patents, Real Options and Firm Performance. *The Economic Journal (London)*, *112*(478), C97–C116.

Bloom, N., Bond, S. & Van Reenen, J. (2007). Uncertainty and Investment Dynamics. *The Review of Economic Studies*, *74*(2), 391–415.

Born, B. & Pfeifer, J. (2014). Policy risk and the business cycle. *Journal of Monetary Economics*, *68*, 68–85.

Bound, J., Cummins, C., Griliches, Z., Hall, B. H. & Jaffe, A. B. (1982). Who Does R&D and Who Patents? *NBER Working Paper Series*, no. 908.

Boxell, L., Gentzkow, M. & Shapiro, J. M. (2020). Cross-Country Trends in Affective Polarization. *NBER Working Paper Series*, no. 26669.

Bresnahan, T. F. & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? *Journal of Econometrics*, *65*(1), 83–108.

Burbidge, J. B., Magee, L. & Robb, A. L. (1988). Alternative Transformations to Handle Extreme Values of the Dependent Variable. *Journal of the American Statistical Association*, *83*(401), 123–127.

Cameron, A. C., Gelbach, J. B. & Miller, D. L. (2008). Bootstrap-Based Improvements for Inference with Clustered Errors. *The Review of Economics and Statistics*, *90*(3), 414–427.

Canes-Wrone, B. & Park, J.-K. (2012). Electoral Business Cycles in OECD Countries. *The American Political Science Review*, *106*(1), 103–122.

Canes-Wrone, B. & Park, J.-K. (2014). Elections, Uncertainty and Irreversible Investment. *British Journal of Political Science*, *44*(1), 83–106.

Cho, J., DeStefano, T. J., Kim, H. & Paik, J. (2021). What Determines AI Adoption? *Economics of Artificial Intelligence Conference, Fall 2021*, Working Paper.

Cockburn, I. M., Henderson, R. & Stern, S. (2018). The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis. *The Economics of Artificial Intelligence: An Agenda* (pp. 115–146). University of Chicago Press.

Cunningham, J. M. (n.d.). *Why Are U.S. Elections Held on Tuesdays?* Retrieved March 9, 2022, from https://www.britannica.com/story/why-are-us-elections-held-on-tuesdays

Czarnitzki, D. & Toole, A. A. (2011). Patent Protection, Market Uncertainty, and R&D Investment. *The Review of Economics and Statistics*, *93*(1), 147–159.

DeStefano, K. D. B., T. & Moussiegt, L. (2017). Determinants of digital technology use by companies. *OECD Science, Technology and Industry Policy Papers*, no. 40.

Dixit, A. K. (1992). Investment and Hysteresis. *Journal of Economic Perspectives*, *6*(1), 107–132.

Dixit, A. K. & Pindyck, R. S. (1994). *Investment under Uncertainty.* Princeton University Press.

Döring, H. & Manow, P. (2020). Parlgov 2020 Release Codebook.

Dzenitis, T. (2021). *American Inventors Protection Act - Summary.* Retrieved March 9, 2022, from https://www.uspto.gov/patents/laws/american-inventors-protection-act-1999/american-inventors-protection-a-2

EPO. (2017). *Cooperative Patent Classification (CPC)*. Retrieved March 9, 2022, from https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/classification/cpc.html

European Commission. (n.d.). *A European approach to artificial intelligence*. Retrieved March 9, 2022, from https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence

Felländer, A. & Gambelin, O. (2021). Would you invest in a medical chatbot that advised a patient to kill themselves? *anch.AI*. https://anch.ai/uncategorized/would-you-invest-in-a-medical-chatbot-that-advised-a-patient-to-kill-themselves/

Fernández-Villaverde, J., Guerrón-Quintana, P., Rubio-Ramírez, J. F. & Uribe, M. (2011). Risk Matters: The Real Effects of Volatility Shocks. *American Economic Review*, *101*(6), 2530–61.

Five IP Offices. (n.d.). *About IP5 co-operation*. Retrieved March 9, 2022, from https://www.fiveipoffices.org/about

Giczy, A., Pairolero, N. & Toole, A. A. (2021). Identifying Artificial Intelligence (AI) Invention: A Novel AI Patent Dataset. *The Journal of Technology Transfer*, USPTO Economic Working Paper, no. 2021–2.

Goel, R. K. & Ram, R. (2001). Irreversibility of R&D investment and the adverse effect of uncertainty: Evidence from the OECD countries. *Economics Letters*, *71*(2), 287–291.

GPAI. (n.d.). Retrieved March 9, 2022, from https://gpai.ai/

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, *28*(4), 1661–1707.

Griliches, Z. (1998). Introduction to 'R&D and Productivity: The Econometric Evidence'. University of Chicago Press.

Gulen, H. & Ion, M. (2015). Policy Uncertainty and Corporate Investment. *The Review of Financial Studies*, *29*(3), 523–564.

Hall, B. H. (2004). Innovation and Diffusion. *NBER Working Paper Series*, no. 10212.

Hall, B. H. & Harhoff, D. (2012). Recent Research on the Economics of Patents. *Annual Review of Economics*, *4*(1), 541–565.

Hall, B. H. & Lerner, J. (2010). Chapter 14 - The Financing of RD and Innovation. *Handbook of the Economics of Innovation*, *1*, 609–639.

Hartman, R. (1972). The effects of price and cost uncertainty on investment. *Journal of Economic Theory*, *5*(2), 258–266.

Henderson, R., Jaffe, A. & Trajtenberg, M. (2005). Patent Citations and the Geography of Knowledge Spillovers: A Reassessment: Comment. *American Economic Review*, *95*(1), 461–464.

Iyengar, S., Lelkes, Y., Levendusky, M., Malhotra, N. & Westwood, S. J. (2019). The Origins and Consequences of Affective Polarization in the United States. *Annual Review of Political Science*, *22*(1), 129–146.

Jaffe, A. B., Trajtenberg, M. & Henderson, R. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics*, *108*(3), 577–598.

Jennings, W. & Wlezien, C. (2018). Election polling errors across time and space. *Nature Human Behaviour*, (2), 276–283.

Jens, C. E. (2017). Political uncertainty and investment: Causal evidence from U.S. gubernatorial elections. *Journal of Financial Economics*, *124*(3), 563–579.

Julio, B. & Yook, Y. (2016). Policy uncertainty, irreversibility, and cross-border flows of capital. *Journal of International Economics*, *103*, 13–26.

Kang, W., Lee, K. & Ratti, R. A. (2014). Economic policy uncertainty and firm-level investment. *Journal of Macroeconomics*, *39*, 42–53.

Kleinknecht, A. & Verspagen, B. (1990). Demand and innovation: Schmookler re-examined. *Research Policy*, *19*(4), 387–394.

Leahy, J. V. & Whited, T. M. (1996). The Effect of Uncertainty on Investment: Some Stylized Facts. *Journal of Money, Credit and Banking*, *28*(1), 64–83.

Lowe, W., Benoit, K., Mikhaylov, S. & Laver, M. (2011). Scaling Policy Preferences from Coded Political Texts. *Legislative Studies Quarterly*, *36*(1), 123–155.

McCarthy, J., Minsky, M. L., Rochester, N. & Shannon, C. E. (2006). A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. *AI Magazine*, *27*(4), 12.

Merriam-Webster. (n.d.). *Artificial Intelligence*. Retrieved March 9, 2022, from https://www.merriam-webster.com/dictionary/artificial%5C%20intelligence

Moretti, E. (2021). The Effect of High-Tech Clusters on the Productivity of Top Inventors. *American Economic Review*, *111*(10), 3328–75.

National Governors Association. (2022). *Governors' Powers Authority*. Retrieved March 9, 2022, from https://www.nga.org/governors/powers-and-authority/

Nilsson, Nils J. (2009). *The Quest for Artificial Intelligence*. Cambridge University Press. https://ai.stanford.edu/~nilsson/QAI/qai.pdf

Nordhaus, W. D. (1975). The Political Business Cycle. *The Review of Economic Studies*, *42*(2), 169–190.

OECD. (2021a). OECD.AI, powered by EC/OECD, database of national AI policies, Accessed on 9/03/2022. https://oecd.ai

OECD. (2021b). *Patents by technology - OECD Statistics*. Retrieved March 9, 2022, from https://stats.oecd.org/Index.aspx?DataSetCode=PATS_IPC

Oi, W. Y. (1961). The Desirability of Price Instability Under Perfect Competition. *Econometrica*, *29*(1), 58–64.

Pakes, A. (1986). Patents as Options: Some Estimates of the Value of Holding European Patent Stocks. *Econometrica*, *54*(4), 755–784.

Pakes, A. & Griliches, Z. (1980). Patents and RD at the firm level: A first report. *Economics Letters*, *5*(4), 377–381.

PatentsView. (n.d.). *What is PatentsView*. Retrieved March 9, 2022, from https://patentsview.org/what-is-patentsview

Peri, G. (2005). Determinants of Knowledge Flows and Their Effect on Innovation. *The Review of Economics and Statistics*, *87*(2), 308–322.

Pindyck, R. S. (1991). Irreversibility, Uncertainty, and Investment. *Journal of Economic Literature*, *29*(3), 1110–1148.

Purdy, M. (2020). Unlocking AI's Potential for Social Good. *Harvard Business Review*. https://hbr.org/2020/10/unlocking-ais-potential-for-social-good

Redl, C. (2020). Uncertainty matters: Evidence from close elections [NBER International Seminar on Macroeconomics 2019]. *Journal of International Economics*, *124*, 103296.

Schmookler, J. (1966). *Invention and Economic Growth*. Cambridge: Harvard University Press.

Swagel, P., Alesina, A. F., Roubini, N. & Ozler, S. (1992). Political Instability and Economic Growth. *NBER Working Paper Series*, no. 4173.

Toole, A., Pairolero, N., Giczy, A., Forman, J., Pulliam, C., Such, M., Chaki, K., Orange, D., Thomas Homescu, A., Frumkin, K., Chen, Y. Y., Gonzales, V., Hannon, C., Melnick, S., Nilsson, E. & Rifkin, B. (2020). Inventing AI: Tracing the diffusion of artificial intelligence with U.S. patents. *United States Patent and Trademark Office.*

Toole, A. & Pairolero, N. (2020). Adjusting to Alice: USPTO patent examination outcomes after Alice Corp. v. CLS Bank International. *IP Data Highlights.*

Trajtenberg, M. (1990). A Penny for Your Quotes: Patent Citations and the Value of Innovations. *The RAND Journal of Economics*, *21*(1), 172–187.

Trippe, A. (2015). Guidelines for Preparing Patent Landscape Reports. *World Intellectual Property Organization (WIPO).*

USPTO. (2020). *301 Ownership/Assignability of Patents and Applications [R-10.2019].* Retrieved March 9, 2022, from https://www.uspto.gov/web/offices/pac/mpep/s301.html

USPTO. (2021). *General information concerning patents.* Retrieved March 9, 2022, from https://www.uspto.gov/patents/basics/general-information-patents

USPTO. (2022a). *Glossary.* Retrieved March 9, 2022, from https://www.uspto.gov/learning-and-resources/glossary

USPTO. (2022b). *Patents Pendency Data January 2022.* Retrieved March 9, 2022, from https://www.uspto.gov/dashboard/patents/pendency.html

WIPO. (n.d.-a). *General information concerning patents.* Retrieved March 9, 2022, from https://www.wipo.int/patents/en/faq_patents.html

WIPO. (n.d.-b). *PCT – The International Patent System.* Retrieved March 9, 2022, from https://www.wipo.int/pct/en/

WIPO. (2015). WIPO Guide to Using PATENT INFORMATION. https://www.wipo.int/edocs/pubdocs/en/wipo_pub_l434_3.pdf

WIPO. (2019a). WIPO Technology Trends 2019: Artificial Intelligence. *World Intellectual Property Organization.* https://www.wipo.int/edocs/pubdocs/en/wipo_pub_1055.pdf

WIPO. (2019b). World Intellectual Property Indicators 2019: Patents. *World Intellectual Property Organization.* https://www.wipo.int/edocs/pubdocs/en/wipo_pub_941_2019-chapter1.pdf

WIPO. (2021). World Intellectual Property Indicators Report: Worldwide Trademark Filing Soars in 2020 Despite Global Pandemic. *World Intellectual Property Organization.* https://www.wipo.int/pressroom/en/articles/2021/article_0011.html

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D. N., Buffington, C., Goldschlag, N., Foster, L. & Dinlersoz, E. (2020). Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey. *NBER Working Paper Series*, no. 28290.

Zoltan, J. A. & Audretsch, D. B. (1988). Innovation in Large and Small Firms: An Empirical Analysis. *The American Economic Review*, *78*(4), 678–690.

A Appendix

Table 20: List of Countries

Countries included in the AIPD sample (61)
Australia, Austria, Bahamas, Barbados, Belgium, Bermuda, Brazil, British Virgin Islands, Canada, Cayman Islands, Chile, China, Colombia, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Gibraltar, Greece, Hong Kong SAR China, Hungary, Iceland, India, Iran, Ireland, Israel, Italy, Japan, Liechtenstein, Luxembourg, Malaysia, Mexico, Monaco, Netherlands,New Zealand, Norway, Panama, Philippines, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Thailand, Turkey, Ukraine, United Kingdom, United States
Countries included in Parlgov and APP (33)
Australia, Austria, Belgium, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States
Countries included in the main cross-country sample (32)
Australia, Austria, Belgium, Canada, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States
Countries included in the restricted sample (23)
Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, United Kingdom, United States

Table 21: List of Variables

Type of variable	**Name**	**Unit**	**Description**
Dependent variables	AI_patents	number	annual number of AI patents by entity
	share_AI	percentage	annual share of AI patents out of total patents by entity
Independent variables	election_now	binary	dummy variable which takes the value 1 if there has been an election, and 0 otherwise
	close_election	binary	dummy variable which takes the value 1 if there has been a close election defined as a victory margin lying within the first quartile of the sample distribution of all victory margins, and 0 otherwise
	close_election_quintile	binary	dummy variable which takes the value 1 if there has been a close election defined as a victory margin lying within the first quintile of the sample distribution of all victory margins, and zero otherwise
Control variables	GDP	percentage	annual real GDP growth PPP per capita by entity
	total_patents	number	annual number of total patents by entity

Notes: Entity represents country (for the cross-country analysis) or state (for the US case study).

Table 22: Data by Year, Cross-Country

Year	#AI Patents	#Total Patents	% AI Patents	#Elections	#Close Elections	% Close Elections
2000	9,278	134,734	6.89	7	2	28.57
2001	10,542	147,976	7.12	7	3	42.86
2002	11,904	148,475	8.02	12	2	16.67
2003	15,004	163,418	9.18	8	5	62.50
2004	23,303	206,777	11.27	7	1	14.29
2005	26,990	229,636	11.75	8	1	25.00
2006	30,201	242,136	12.47	10	2	20.00
2007	37,421	285,140	13.12	12	2	16.67
2008	43,505	319,678	13.61	7	1	14.29
2009	46,992	353,822	13.28	8	1	12.50
2010	53,414	376,055	14.20	8	3	37.50
2011	62,949	413,144	15.24	13	4	30.77
2012	73,288	459,653	15.94	6	3	50.00
2013	67,699	424,854	15.93	9	5	55.56
2014	54,330	357,569	15.19	6	0	0.00
2015	50,788	346,174	14.67	12	1	8.33
2016	51,984	349,638	14.87	8	2	25.00
2017	57,864	364,639	15.87	10	2	20.00
2018	69,858	394,992	17.69	6	0	0.00

Table 23: Data by Country, Cross-Country

Country	# AI Patents	# Total Patents	% AI Patents	# Elections	# Close Elections	% Close Elections
Australia	3,290	31,303	10.51	6	2	33.33
Austria	686	18,541	3.70	5	2	40.00
Belgium	1,170	22,938	5.10	4	1	25.00
Canada	14,602	99,221	14.72	6	0	0.00
Croatia	7	209	3.35	6	1	16.67
Cyprus	416	1,178	35.31	4	3	75.00
Czech Republic	94	1,383	6.80	5	2	40.00
Denmark	13,78	23,694	5.82	5	3	60.00
Finland	6,003	36,151	16.61	4	3	75.00
France	12,498	159,038	7.86	4	1	25.00
Germany	25,313	358,239	7.07	5	0	0.00
Greece	87	690	12.61	6	2	33.33
Hungary	73	1,131	6.45	5	1	20.00
Iceland	101	1,026	9.84	6	2	33.33
Ireland	4,191	14,356	29.19	4	1	25.00
Israel	8,649	44,008	19.65	5	1	20.00
Italy	1,925	46,517	4.14	5	1	20.00
Japan	93,063	1,479,940	6.29	7	1	14.29
Luxembourg	748	6,556	11.41	4	0	0.00
Netherlands	9,876	89,310	11.06	6	3	50.00
New Zealand	337	4,288	7.86	6	1	16.67
Norway	772	10,504	7.35	5	1	20.00
Poland	152	1,641	9.26	5	0	0.00
Portugal	106	1,050	10.10	5	1	20.00
Slovakia	14	210	6.67	5	0	0.00
Slovenia	25	680	3.68	6	2	33.33
Spain	928	12,420	7.47	6	0	0.00
Sweden	6,976	66,274	10.53	5	1	20.00
Switzerland	5,582	84,059	6.64	4	0	0.00
Turkey	149	1,528	9.75	5	0	0.00
United Kingdom	9,705	94,843	10.23	5	2	40.00
United States	588,398	3,005,584	19.58	5	3	60.00

Table 24: Data by Year, US Case Study

Year	# AI patents	# Total patents	% AI patents	# Elections	# Close Elections	% Close Elections
2000	6737	71381	9.44	11	4	36.36
2001	7685	78199	9.83	2	1	50.00
2002	8654	78684	11.00	36	14	38.89
2003	10881	83759	12.99	3	1	33.33
2004	17043	103215	16.51	11	5	45.45
2005	19695	114631	17.18	2	1	50.00
2006	21765	120308	18.09	36	3	8.33
2007	27032	139695	19.35	3	0	0.00
2008	31610	158559	19.94	11	1	9.09
2009	33926	176197	19.25	2	1	50.00
2010	38597	189724	20.34	36	9	25.00
2011	45979	216029	21.28	3	0	0.00
2012	54726	249680	21.92	11	3	27.27
2013	51126	234995	21.76	2	1	50.00
2014	40348	190522	21.18	36	12	33.33
2015	37501	182107	20.59	3	0	0.00
2016	38004	184422	20.61	12	3	25.00
2017	42392	193539	21.90	2	0	0.00
2018	51392	213656	24.05	36	6	16.67

Table 25: Data by State, US Case Study

State	# AI patents	# Total patents	% AI patents	# Elections	# Close Elections	% Close Elections
Alabama	542	6,362	8.52	5	1	20.00
Alaska	28	304	9.21	5	1	20.00
Arizona	3,084	26,398	11.68	5	1	20.00
Arkansas	1,307	4,463	29.29	5	0	0.00
California	188,939	777,447	24.30	5	1	20.00
Colorado	6,222	39,645	15.69	5	1	20.00
Connecticut	9,258	67,058	13.81	5	2	40.00
Delaware	5,674	51,768	10.96	5	1	20.00
Florida	8,145	55,106	14.78	5	3	60.00
Georgia	11,970	55,904	21.41	5	1	20.00
Hawaii	245	1,124	21.80	5	1	20.00
Idaho	2,341	32,529	7.20	5	0	0.00
Illinois	16,996	130,400	13.03	5	2	40.00
Indiana	2,181	37,991	5.74	5	1	20.00
Iowa	1,120	18,315	6.12	5	1	20.00
Kansas	2,266	13,057	17.35	5	0	0.00
Kentucky	1,152	11,507	10.11	4	0	0.00
Louisiana	247	5,059	4.88	4	1	25.00
Maine	217	2,550	8.51	5	2	40.00
Maryland	5,344	34,064	15.69	5	1	20.00
Massachusetts	24,246	150,508	16.11	5	2	40.00
Michigan	10,494	134,942	7.78	5	2	40.00
Minnesota	6,573	79,969	8.22	5	3	60.00
Mississippi	166	1,596	10.40	4	0	0.00
Missouri	2,083	26,377	7.90	5	3	60.00
Montana	124	1,660	7.47	5	3	60.00
Nebraska	647	4,890	13.23	5	0	0.00
Nevada	7,605	29,159	26.08	5	1	20.00
New Hampshire	1,310	11,481	11.41	10	2	20.00
New Jersey	18,551	119,650	15.50	5	1	20.00
New Mexico	1,037	7,157	14.49	5	0	0.00
New York	105,230	324,300	32.45	5	0	0.00
North Carolina	9,449	53,192	17.76	5	2	40.00
North Dakota	64	1,136	5.63	5	0	0.00
Ohio	6,315	75,360	9.38	5	2	40.00
Oklahoma	459	6,681	6.87	5	1	20.00
Oregon	3,891	25,904	15.02	6	2	33.33
Pennsylvania	8,425	74,280	11.34	5	0	0.00
Rhode Island	541	6,194	8.73	5	3	60.00
South Carolina	594	10,529	5.64	5	1	20.00
South Dakota	156	1,570	9.94	5	1	20.00
Tennessee	1,621	18,165	8.92	5	1	20.00
Texas	34,061	225,466	15.11	5	0	0.00
Utah	3,232	20,446	15.81	5	0	0.00
Vermont	300	2,409	12.45	10	3	30.00
Virginia	8,471	33,659	25.17	5	3	60.00
Washington	59,486	124,559	47.76	5	2	40.00
West Virginia	109	1,233	8.84	5	2	40.00
Wisconsin	2,462	34,398	7.15	5	3	60.00
Wyoming	113	1,381	8.18	5	1	20.00

B Appendix

Information About USPTO Patents

In order to apply for a patent, one must apply through a patent office. There are several patent offices in the world that cover the protection in the different regions. The five largest patent offices are the European Patent Office (EPO), the Japan Patent Office (JPO), the Korean Intellectual Property Office (KIPO), the National Intellectual Property Administration of the People's Republic of China (CNIPA) and the United States Patent and Trademark Office (USPTO). Together they form the IP5 co-operation and cover approximately 80% of the world's patent applications (Five IP Offices, n.d.). Moreover, the World Intellectual Property Organization (WIPO) administers the Patent Cooperation Treaty (PCT), an international treaty that allows applicants to file one application and receive protection in over 150 countries simultaneously (WIPO, n.d.-b).

The USPTO is the federal agency for granting US patents for the protection of inventions and registering trademarks. US granted patents are effective only within the US as well as its territories and possessions (USPTO, 2021). In 2013, the USPTO moved from using the United States Patent Classification (USPC) system to the Cooperative Patent Classification (CPC) system, which is developed jointly with the EPO (USPTO, 2022). The CPC is divided into nine sections, A-H and Y, which in turn is broken down by classes, sub-classes, groups, and sub-groups (EPO, 2017).

Foreign citizens who wish to apply for a patent in the US have the equivalent rights of protection as US citizens. However, there are some additional requirements for the eligibility of a granted patent. That is, the patents can only be granted if the application contains the signature of the inventor and an oath of inventorship and if the invention has not been patented in other countries 12 months prior to the application date in the US (or 6 months for design patents) (USPTO, 2021).

The design of the patent system has important implications for the development and commercialization of technological inventions in a country. There is a large previous literature, both theoretical and empirical, covering the impact of the design of patent systems on firm strategy, competition and innovation. For a review on this research, we refer to Hall and Harhoff (2012). Relevant to our thesis, the patent system design has consequences also for AI innovation, perhaps particularly so because of the difficulties in defining AI technology.

C Appendix

Construction of the AIPD Variables

The dependent variable is a measure of the number of AI patents for each country in each year. The variables are constructed in several steps. Using the AIPD dummy variable which indicates whether a document was predicted to be AI or not, we are able to construct a dataset which only contains documents that are predicted as an AI technology. As such, we have two datasets; one which contains all patent documents and one which only contains AI patents. We used the bulk download tables *location.tsv*, *publication_ assignee.tsv* and *patent_ assignee.tsv* from PatentsView and merged them with the patent datasets in order to identify the origin country of each assignee of each patent publication, using the variable "document id" as the unique identifier. Some missing values arise due to countries that could not be identified. The two datasets are merged with year and country as key identifiers. For years where countries' have total patents but missing AI patents, it is assumed that the number of AI patents issued are zero. As such we have created the variables number of AI patents, number of total patents and share of AI patents.

Descriptive Statistics, AIPD

Table 26: Descriptive Statistics, AIPD, Cross-Country

Statistic	Mean	St. Dev.	Min	Max	N
Number of AI Patents	750.14	4,435.12	0	54,947	1,159
Number of Total Patents	5,752.73	23,705.56	1	251,184	1,159
Share of AI Patents (%)	0.09	0.10	0	1	1,159

Notes: Descriptive statistics for the variables in the initial AIPD cross-country dataset. *Number of AI Patents* and *Number of Total Patents* are the total count of (AI) patents published by the USPTO for the 61 countries in the AIPD dataset during the period 2000-2018. *Share of AI Patents* is the share of AI patents out of all patents. Sources: USPTO, AIPD.

Table 27: Descriptive Statistics, AIPD, US Case Study

Statistic	Mean	St. Dev.	Min	Max	N
Number of AI Patents	606.91	1,853.28	0	19,142	969
Number of Total Patents	3,097.78	6,810.07	4	67,960	969
Share of AI Patents (%)	0.12	0.09	0	1	969

Notes: Descriptive statistics for the variables in the initial AIPD US case study dataset. *Number of AI Patents* and *Number of Total Patents* are the total count of (AI) patents published by the USPTO for the 50 states of the US and the District of Columbia during the period 2000-2018. *Share of AI Patents* is the share of AI patents out of all patents. Sources: USPTO, AIPD.