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Patenting uncertainty and its impact on innovation: Evidence from the United States

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Abstract

This paper investigates the effect of patenting uncertainty on innovations. Although the patent system was established to provide incentive and certainty to innovators, the patenting process itself contains elements of uncertainty, including pendency and variation in grant ratios. We use time series data on patent applications and patent grants from the United States and measure patent uncertainty in terms of variation in the grant ratio, i.e., the difference in the number of patent grants and the number of patent applications. Findings show that increasing patent uncertainty has a depressing effect on innovation rates. Moreover, our findings reveal important differences between the short-run and long-run effects and between overall patents and utility patents. We also consider the effects of the America Invents Act and find that the Act led to more patent applications. Besides adding to the literature, these findings underscore the point that transaction costs of patenting might be undermining the intent of innovation policy by reducing innovation.

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1. Introduction

Uncertainty is an inherent attribute of innovation, and it manifests itself in many stages of the process of innovation. For instance, there is the uncertainty associated with whether a new product or process will be successfully invented, whether the inventor (firms or individuals) will beat its competitors in inventing first, whether the firm will succeed in gaining regulatory protections for the invention (patents, environmental/health clearances, etc.), and what share of the potential market will the invention capture (and how fast).¹

Innovators face different sources of uncertainty (Goel (2007)). One kind of uncertainty relates to the very nature of the innovation process. The results of R&D are inherently uncertain, and “the output (information obtained) can never be predicted perfectly from the inputs” (Arrow (1962, p. 616)). Hence R&D investments may fail or produce inventions which are not exactly the ones sought. Second, there is market uncertainty, i.e., it’s unclear how market demand for a newly created product will develop and how competitors will react. Moreover, the novelty of an invention may be contentious and its patentability insecure (Troy and Werle (2008)). This general uncertainty inherent in the patenting process may be aggravated by a high variability of patent grant ratios over time, which leads to a strong increase in patenting uncertainty.

The key contribution of the current paper is that it considers the effect of patenting uncertainty on innovations.² This is important because patenting uncertainty may have detrimental effects on innovation and turn the actual purpose of the patenting system – protecting and stimulating innovation – into its opposite. If it turns out that patenting uncertainty diminishes inventive activity, that would undermine the intent of the patent system in fostering innovation over time. Yet, due diligence in the patent award process is important to reward true inventors and to adequately determine the scope of a patent (Goel (2002)).

Not all patent applications are ultimately granted patents, with reasons for denials varying from a lack of originality, technical issues with filing paperwork (or the transaction cost of patenting), multiple, simultaneous filers of the same invention, etc. Consequently, some new inventors (nascent entrepreneurs or first-time inventors) might be dissuaded from filing patents or inventing by looking at the low success rate in patent grants. This possible effect has the potential to undermine the success of the patent process – whereas the intent of the patent process is to reward and encourage innovation by protecting the property rights of the inventors, the very process of due diligence to identify the true inventors and identify original contributions might have the opposite effect of dissuading innovation by some due to the uncertainty associated with patent grants.

A historical look at the USPTO data from 2001 shows the patent grant rate to be about 70 percent (<https://patentlyo.com/patent/2021/04/uspto-grant-rate.html>). Obviously, there would be

¹ Not all inventions are, however, patented. The potential imitation chances (Mansfield et al. (1981)) and litigation hassles (Amir et al. (2014)) might decrease, for instance, the lure of patents for some inventors. Also see, Boldrin and Levine (2013).

² Sampath (2018) provides a useful recent review of the empirical literature on patents and innovation.

significant variation in patent grant rates across innovation types, and types of patents applied for. We control for this somewhat in the analysis below by considering utility patents separately.

A significant institutional development during the time period under consideration was the Leahy-Smith America Invents Act (AIA) of 2011 (<https://www.congress.gov/bill/112th-congress/house-bill/1249>; https://en.wikipedia.org/wiki/Leahy%E2%80%93Smith_America_Invents_Act) that, among other changes, switched the patenting criterion from the “first-to-invent” to the “first-to-file”. This change could have impacted patent applications and we test for this effect in Section 5.4.³

To operationalize the analysis, we use time series data on patent applications and patent grants from the United States. The focus on the United States is due to the availability of a relatively long time period of data and the relatively good comparability of the data (although foreign inventors could be some of those applying for patents in the United States). We will also determine if the effect of uncertainty on utility patents is different than that on overall patents. Finally, we are able to compare the short-run and long-run effects of patenting uncertainty on innovation.

To quantify the presence of uncertainty in patenting, we assess the variation in the difference between patent applications and patent grants. This helps us gauge the extent to which patent applications fail to materialize into actual patents. Subsequently, we compute the five-year moving standard deviation of this difference. The results, based on this measure of patenting uncertainty, show that our main hypothesis of greater patenting uncertainty leading to lower innovation rates is supported. Furthermore, we find some differences between the short-run and long-run effects and between overall patents and utility patents. Besides adding to the literature, these insights have useful implications for technology policy. Are the efforts to reward true inventive activity having adverse outcomes of innovation? Are the effects of patenting uncertainty alike in the short term and the long term?

The large body of (mostly theoretical) economics and business research has recognized and modeled various dimensions of the innovation process and their effects on research spending, the pace of technological change, economic growth, etc. (see Kamien and Schwartz (1982) and Reinganum (1989) for overviews of the related literature and Goel (2007) for specific application). However, quantifying different aspects of uncertainty is a challenge, resulting in relatively few empirical studies accounting for innovation uncertainty (see Czarnitzki and Toole (2011) and Goel and Nelson (2021) for notable exceptions).

The structure of the rest of the paper includes a short review of the related literature in Section 2 and an exposition of the econometric model and the hypotheses in Section 3. This is followed by data and estimation (Section 4), results (Section 5), and conclusions (Section 6).

2. Related literature

³ We thank Al Link for bringing this to our attention.

In this section, we provide a brief review of the related literature to set up the contribution of this work. Following the seminal work by Kenneth Arrow (1971), the role of uncertainty in economic decision-making has received widespread attention. According to the real options literature, investment decisions are negatively affected by uncertainty because the value of waiting to invest increases with uncertainty (Dixit and Pindyck (1994)). Firms are facing various uncertainties, including economic, political, and regulatory uncertainties (Goel (2007)).⁴ Empirical studies investigating the effect of economic uncertainty on investment decisions include Binding and Dibiasi (2017), Czarnitzki and Toole (2011), and Goel and Ram (2001), whereas An et al. (2016), Goel and Nelson (2021), Jens (2017), and Kang et al. (2014), focus on the effects of political uncertainty. Bloom (2007) provides a theoretical model of R&D dynamics under uncertainty, showing that greater uncertainty reduces the responsiveness of R&D spending to changes in demand conditions.

Uncertainty is important with respect to innovation as it alters the expected costs and benefits of projects, and an increase in uncertainty might lead to a delay or even the abandonment of innovation projects (Goel and Nelson (2021)). Different responses to uncertainty across individuals and firms might occur according to different risk attitudes (Goel and Göktepe-Hultén (2019)).⁵

A special and clearly under-researched area of regulatory uncertainty is patent uncertainty. Patenting practices may cause uncertainty with respect to pendency, granting, and changes of scope (Goel (2002), Yang (2008), Yang and Sonmez (2018)). Pendency is the time span from filing a patent application to receiving the respective patent grant. Granting is usually measured as the grant ratio, i.e. the ratio of the number of grants against the number of applications. Changes of scope can lead to an unexpected reduction in the breadth of a patent, e.g. when applicants are asked to change their applications from invention to utility patents.

A study of US patenting practices performed by Popp et al. (2003) showed that pendency depends, inter alia, on technology type, claim width, complexity and the length of the reference list. A similar study for Europe found complexity, originality, and backward citations to be the main determinants of pendency at the European Patent Office (Harhoff and Wagner (2006))

Several studies have analyzed national differences in patenting practices and whether national patent offices discriminate against foreigners in terms of grant ratios and pending duration. The pioneering work by Kotabe (1992) suggests that discrimination against foreigners exists but takes different forms in different national patenting systems. While the US, the UK, and the German systems discriminated against foreign applications in terms of lower grant ratios, the Japanese system discriminated in terms of longer pendency for foreign applications (Kotabe (1992)). A more recent study comparing pendency and grant ratios of foreign and domestic

⁴ There may be other dimensions of regulatory approvals, not directly related to patents (e.g., in medical technologies (Stern (2017))).

⁵ Another aspect might be credit market or borrowing uncertainty that could affect the innovation via financing constraints (Capasso and Mavrotas (2010)).

patent applications in the US and China does not confirm these results: It finds that the US in the period 1985 to 2002 provided equal treatment to residents and non-resident applicants in terms of pendency and grant ratios, whereas China in the same period provided equal (and shorter) pendency, but unequal grant ratios in favor of domestic applicants (Yang (2008)). While the above-mentioned studies have made important contributions to measuring patent uncertainty and to comparing it across countries there is – to the best of our knowledge – no study investigating the effects of patent uncertainty on innovation outcomes. This paper intends to fill this gap.

3. The model

Based on the above discussion, we formulate our main hypothesis:

Hypothesis H1: Greater uncertainty of patent grants lowers innovation, *ceteris paribus*.

Theoretically speaking, greater patenting uncertainty undermines the expected rewards from innovation, and this might dissuade some inventors from either not pursuing new inventions (or not bringing them to light via the patent process).

The basic empirical model has the following general form:

$$\text{Innovation}_j = f(\text{Patenting uncertainty}_M, Z) \quad (1)$$

$j = \text{Total patents, Utility patents}$

$M = 5\text{-year moving standard deviation between patent applications and patent grants for total patents (LnPatentUncertain)}; 5\text{-year moving standard deviation between patent applications and patent grants for utility patents (LnPatentUncertain (Utility))}$

$Z = \text{GDP, R\&D, GovtSize, Inflation, and Education.}$

The dependent variable is an indication of innovation, measured alternately via total patents granted and utility patents. Whereas total patents might include a range of innovations, the subclass of utility patents protects innovations related to the way an innovation is used or works.

The main explanatory variable of interest is patenting uncertainty, measured as the 5-year moving standard deviation between patent applications and patent grants, for total and utility patents, respectively.⁶ As not all patent applications result in patent grants, the discrepancy represents the number of applications that do not materialize into actual grants. To capture the variability in this discrepancy between patent applications and grants, we calculate the 5-year standard deviation, effectively measuring the volatility in this relationship.

Among the vector of Z controls, GDP denotes economic prosperity, $R\&D$ measures research spending as a percentage of GDP, the size of government proxies for the scale of institutions, and in some cases the government might be directly participating in research (Leyden and Link

⁶ We also had information on design patents. However, due to their qualitatively different nature (e.g., many design patents are not resulting from R&D, and their overlap with trademarks) and their relatively few numbers, we do not include them in the analysis.

(2012)), inflation would proxy for economic uncertainty (Goel and Ram (2001)), and education denotes human capital, measured as the share of population 25 years and older that completed at least four years of college education. Research spending is the main input in innovation (Cohen (2010), Goel et al. (2023), Kamien and Schwartz (1982)), while economic prosperity accounts for the affordability and future expectations about innovation profits.

Equation (2) below will describe in greater detail how the general equation (1) will be estimated to test Hypothesis H1 and to exploit the information in the underlying time series data.

4. Data and estimation

4.1 Data

With the well-known difficulties associated with measuring the true extent of innovative activity, we take patents granted as a readily available indicator of innovation our outcome variable. The data are time-series for the U.S. from 1971 to 2020. Table 1a includes the variable details and Table 1b reports the summary statistics.

The average number of patent grants (applications) per 100,000 population in our sample is 54.89 (102.73), with a high of 119.05 (203.77) and a low of 23.28 (47.81). Utility patent grants (applications) per 100,000 population show an average of 49.98 (96.01) with a high of 107.88 (189.16) and a low of 21.70 (44.25).

Figures 1 and 2 show the time series of (total and utility) patent grants, patent applications, and patenting uncertainty. These figures reveal steady innovation from the beginning of the sample period until the mid-1990's innovation shows an increasing trend. Interestingly, patenting uncertainty was heightened during the period of the Great Recession (2007-2009).

4.2 Estimation

To examine the long-run relationship and short-run dynamics between patents (grants and applications) and patenting uncertainty we estimate a conditional error correction model using an autoregressive distributed lag model (ARDL)—see Natsiopoulos and Tzeremes (2020). Because of the challenges related to identifying the order of integration of the variables that are potentially integrated to different orders, we employ the Bounds testing procedure originally developed by Pesaran et al. (2001), to test for the cointegration of variables with potentially different orders of integration. For this approach, no pre-testing of the variables is necessary except to ensure that the variables are not integrated to order 2 or higher. Therefore, we use the Phillips-Perron unit root test to test for stationarity of the variables (Phillips and Perron (1988)). The results reported in Table 2 confirm that the dependent variables are integrated of order 1 and that the explanatory variables are not integrated of order 2.

To start, we estimate the following error correction model for each dependent variable y_t ($LnPatGrant$, $LnPatApp$, $LnPatGrant$ (Utility), or $LnPatApp$ (Utility)):

$\Delta y_t = \alpha_0 + \alpha_1 t + \pi_y y_{t-1} + \pi_x x_{t-1} + \sum_{i=1}^{p-1} \psi y_{t-i} + \sum_{i=0}^{q-1} \gamma x_{t-i} + \varepsilon_t$	(2)
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x is a vector of explanatory variables and includes the following variables: patenting uncertainty (*LnPatentUncertain (Total, SD)* when y is *LnPatGrant* or *LnPatApp*; *LnPatentUncertain (Utility, SD)* when y is *LnPatGrant (Utility)* or *LnPatApp (Utility)*), *LnGDP*, *LnR&D*, *LnGovtSize*, *Inflation*, and *LnEducation*. This equation is estimated using OLS where the long-run parameters are π_y and π_x and the short-run parameters are ψ and γ .

The optimal lag lengths p and q are determined by the Akaike Information Criterion (AIC) with a maximum of 3 lags to conserve the degrees of freedom. The Bounds tests for cointegration is a two-step process (Pesaran et al. (2001)). The first step is an F test of the null hypothesis of no cointegration ($H_0: \pi_y = \pi_x = 0$) against the alternative of cointegration ($H_1: \pi_y \neq 0, \pi_x \neq 0$). If the F statistic exceeds the I(1) critical value we reject the null hypothesis in favor of cointegration; if the F statistic is below the I(0) critical value we fail to reject the null hypothesis, and if the F statistic falls between the two critical values, the test is inconclusive. If the F test favors cointegration, then to rule out degenerate cases we conduct a t-test under the null $H_0: \pi_y = 0$ against the alternative $H_1: \pi_y < 0$. Like the F test, if the t statistic exceeds the I(1) critical value we reject the null in favor of cointegration; if the t statistic is below the I(0) critical values we fail to reject the null, and if the t statistic falls between the two critical values, the test is inconclusive.

Because the asymptotic distribution of the F and t statistics are non-standard, we report critical values from Kripfganz and Schneider (2020) based on if all the variables are I(0) or I(1) for the case of unrestricted constant and restricted time trend.

5. Results

5.1 Testing for cointegration

First, we test for the presence of cointegration, using four different models (two each for total patents and utility patents, respectively). The Bounds test results are reported in Table 3. The results show that the F test rejects no cointegration in all models except Model 3 and the F statistic is marginally insignificant. According to the t-test, cointegration is confirmed in Model 1 given by the statistically significant t-statistic, while it is marginally insignificant for Models 2 and 4. Consequently, evidence of cointegration is confirmed for Model 1 and is inconclusive for Models 2-4.

5.2 Long-run effects of patenting uncertainty

Table 4 reports the long-run coefficients for all four models.⁷ Based on these results, we find that patenting uncertainty has a negative and statistically significant effect on patent grants (total and utility), but no statistical impact on patent applications. These findings support Hypothesis H1, especially for patent grants. It makes sense that patenting uncertainty would have a pronounced impact on patent grants and not applications. Many patent applications might either be spurious, not serious, or underdeveloped. Some new inventors might be naïve or firms might just be filing patent applications for strategic reasons. In such cases, heightened patenting uncertainty is unlikely to impact their patent applications. The coefficients suggest that a 10 percent increase in patenting uncertainty, on average, reduces total (utility) patent grants by 1.3 (1.4) percent.

Turning to the control variables, we find that R&D spending (as a percent of GDP) promotes patents grants, but not patent applications, in the long run with the coefficient representing a 1 (1.2) percent increase in total (utility) patent grants following a 10 percent increase in R&D. R&D is a prime input in the innovation process and our findings bear this out with regard to innovation as measured by patent grants. The insignificant impact on patent applications is consistent with the discussion in the previous paragraph.

In contrast, a larger government has a deleterious effect on innovation with unitary elasticity for both total and utility patent grants. This may be due to bureaucratic delays associated with larger governments. In contrast, we find that both GDP and inflation have positive effects on (total and utility) patent applications, but no statistical effect on patent grants. Specifically, we find that the effect of GDP on total and utility patent applications is economically significant with elasticities equal to 2.4 and 3.0, respectively. Greater economic prosperity makes the potential payoffs from innovation more attractive (also see Cohen (2010)). On the other hand, inflation, although statistically significant, has a rather negligible effect on total and utility patent applications with elasticities equal to roughly only 0.04. Interestingly, the effect of education on patent grants and applications is negative and statistically significant across all models, with an elasticity of approximately 2.⁸ Finally, the coefficient on the time trend is positive and statistically significant across all models showing that patent grants and applications are increasing over time.

5.3 Short-run effects of patenting uncertainty

Table 5 reports the results for the underlying short-run dynamics in the error correction model. The diagnostics tests at the bottom of Table 5 show that overall, the models satisfy the conditions for ARDL modeling. In particular, we fail to reject no ARCH effects (ARCH LM test), homoskedasticity (Breusch-Pagan test), no serial correlation (Breusch-Godfrey LM test; with the exception of Model 4 the null is rejected at lag 3), no model misspecification (RESET test), and normality (Cameron & Trivedi (1990) IM test). In addition, we fail to reject model instability given by the CUSUM recursive and OLS residuals.

⁷ The coefficients in Models 2-4 should be interpreted with caution given that the evidence for cointegration is inconclusive.

⁸ Some caution is advised here. Some R&D expenditures might include spending on research personnel, who would already be included in the educated labor force.

The coefficient on the error correction term representing the (negative) speed of adjustment is negative, less than the absolute value of one revealing partial adjustment, and statistically significant across all models. The magnitude of the error correction term is greater (in absolute value) for patent grants relative to patent applications suggesting that following a shock, patent grants return to equilibrium faster. In particular, a shock to the long-run equilibrium is corrected by approximately 60% (55%) within a year for total (utility) patent grants, while for patent applications the long-run equilibrium is restored by 35% (45%) within a year.

Interestingly, the short-run dynamics show that greater patenting uncertainty reduces patent grants contemporaneously, while it reduces patent applications with a lag. This difference may be due to inventors viewing patent applications as having relatively longer-term payoffs. Numerically speaking, a ten percent increase in patenting uncertainty reduces patent grants (applications) by roughly 2 (1) percent, *ceteris paribus*.

Turning to the control variables, GDP has a statistically significant effect on only total patent applications. Greater research and development spending has a negative and significant effect on (total and utility) patent applications in period $t-1$. Both government size and inflation are statistically insignificant across all models. Greater education has a negative and contemporaneous effect across all models except in Model 4 education has a positive and significant effect in period $t-1$. Thus, we see that there are some differences in the short-term and long-term effects, especially in comparison to the impacts on patent applications versus patent grants. This finding is potentially useful for policymaking – lawmakers need to be cognizant of the underlying measure of innovation (patent applications versus patent grants) and the time horizon in framing policies. Mitigation of patenting uncertainty will not necessarily promote innovation both in the short- and long term.

5.4 Robustness check: Accounting for the impact of the America Invents Act

In 2011, President Obama enacted the Leahy-Smith America Invents Act (AIA), introducing a noteworthy transformation to the patent system. This legislation replaced the traditional “first to invent” approach with a “first to file” system, where the individual who files a patent application first holds the right to the patent grant. The Act’s crucial provisions took effect on September 16, 2012, marking a significant change in patent law. To account for this transformation in the patent system, we generate a dummy variable for the years the major provisions of the AIA went to effect from 2012 through 2020.⁹ To check the robustness of the main results to this significant change in the patent system, we add the dummy variable AIA to the model and re-run the analysis.

The results for the long-run relationship are reported in Table 4A in the Appendix. The results show that patenting uncertainty maintains its negative and statistically significant impact on patent grants (total and utility); however, the effect is considerably larger. The effect of patenting uncertainty on patent application (total and utility) is now marginally statistically significant, though practically small. Interestingly, AIA has a positive (negative) and statistically significant

⁹ This period also avoids any possible structural issues from the Great Recession of 2007-2009.

effect on patent applications (grants). This makes sense since the AIA, through the “first to file” change, lowers the transaction costs to patent applications.

The control variables show some differences. GDP has a negative and statistically significant effect on total and utility grants, while inflation has a positive and highly statistically significant effect on total and utility grants.

Turning to the short-run dynamics reported in Table 5A in the Appendix, the effect of patenting uncertainty maintains its negative and statistically significant and contemporaneous effect on patent grants; however, the coefficient on the first lag is now positive and statistically significant. The effect of patenting uncertainty on patent applications is consistent with the baseline results. That is, patenting uncertainty shows no contemporaneous effect on patent applications, but the effect is negative and statistically significant for the first two lags.

The effect of AIA shows some interesting differential dynamics across patent grants and patent applications. In particular, AIA has a contemporaneous and positive effect on patent applications, whereas, for patent grants, AIA shows no contemporaneous effect, and its first lag is negative and statistically significant. The remaining control variables are mostly in line with the main findings, with the one exception being that inflation is no longer significant. The concluding section follows.

6. Conclusions

This paper investigates the effect of patenting uncertainty on innovation rates. While other forms of regulatory uncertainty and their effects on R&D investment and innovation have received some attention in the literature this is not the case for patent uncertainty, i.e., the uncertainty of whether a developed idea or concept receives intellectual property protection and enables the patent holder to earn a temporary monopoly rent.

Findings show that greater patenting uncertainty has a detrimental effect on innovation rates. This holds true for both overall and utility patents, and is consistent with the notion that greater patenting uncertainty would reduce the expected rewards from patenting. The long-run analysis reveals that increasing patent uncertainty is associated with a significant decrease in the number of patents granted, but not in the number of patent applications. Analysis of the short-run dynamics suggests that increasing patent uncertainty has an immediate effect on the number of patents granted, but affects the number of applications only with a time lag.

Whereas different types of innovation uncertainties have been recognized in the related (mainly theoretical) literature (e.g., Lemley and Shapiro (2005), Goel (2007)), this paper provides empirical evidence on the influence of patenting uncertainty. The focus on total versus utility patents and on the short-run and long-run dynamics is another contribution of this work. We also consider the effects of the America Invents Act and find that the Act led to more patent applications. This finding provides evidence on the intent of the Act in bringing more inventions to light.

These findings have important implications for policy and for future research. The patent system is meant to create incentives for innovation by rewarding true innovative activity. However, a discretionary and volatile policy of the patent office leading to high patenting uncertainty may have the opposite effect. High patenting uncertainty imposes a negative externality on patenting firms and individuals and is associated with lower innovation rates. This implies that patent offices should be as consistent and reliable in their examination procedures and standards as possible, in order to not create unnecessary uncertainty that deters innovative activity,

Governments should also be cognizant of the possible innovation-crowding-out effects of additional government spending. Finally, technology policies may need to be fine-tuned depending upon the innovation type.

Possible extensions to this work might allow for other forms of patent uncertainty (e.g., increasing variance in pendency) and for different country and patenting system contexts. Moreover, it might be interesting to investigate which kinds of applicants (start-ups versus more established firms, frequent patentees versus first-time patentees) are most affected by increasing patenting uncertainty. Finally, future research could consider the impact of patenting uncertainty on entrepreneurship.

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Table 1a: Variable definitions and data sources

Variable	Description	Source
<i>LnPatentGrant</i>	The log of total patent grants per 100,000 population.	uspto.gov*
<i>LnPatentApp</i>	The log of total patent applications per 100,000 population.	uspto.gov*
<i>LnPatentGrant (Utility)</i>	The log of total utility patent grants per 100,000 population	uspto.gov*
<i>LnPatentApp (Utility)</i>	The log of total utility patent applications per 100,000 population.	uspto.gov*
<i>LnPatentUncertain</i>	Total patenting uncertainty: measured as the log of the 5-year moving standard deviation of the difference between total patent applications and total patent grants.	uspto.gov*
<i>LnPatentUncertain (Utility)</i>	Total utility patenting uncertainty: measured as the log of the 5-year moving standard deviation of the difference between utility patent applications and utility patent grants.	uspto.gov*
<i>LnGDP</i>	The log of real GDP per capita in constant 2012 dollars.	Johnston and Williamson (2023)
<i>LnGovtSize</i>	Government size measures as the log of government expenditures divided by nominal GDP.	Jordà et al. (2017)*
<i>LnR&D</i>	The log of total U.S. R&D expenditures (millions of current US dollars) divided by nominal GDP (millions of current US dollars).	National Science Foundation & Johnston and Williamson (2023)*
<i>Inflation</i>	Inflation rate: measured as the percentage change in the consumer price index.	Jordà et al. (2017)*
<i>LnEducation</i>	Percentage of the population 25 years and older that completed four or more years of college (in logs).	U.S. Census Bureau*
<i>AIA</i>	A dummy variable for the Leahy-Smith America Invents Act. The dummy variable equals one for years the AIA went into effect from 2012 through 2020 and zero otherwise.	https://www.uspto.gov/patents/laws/america-invents-act-aia/america-invents-act-aia-frequently-asked

Note: * denotes authors' calculations.

Table 1b: Summary statistics

Variables	mean	Std. Dev.	max	min
<i>LnPatentGrant</i>	3.903	0.446	4.780	3.148
<i>LnPatentApp</i>	4.487	0.541	5.317	3.867
<i>LnPatentGrant (Utility)</i>	3.813	0.435	4.681	3.077
<i>LnPatentApp (Utility)</i>	4.418	0.542	5.243	3.790
<i>LnPatentUncertain</i>	9.311	0.708	10.86	7.926
<i>LnPatentUncertain (Utility)</i>	9.281	0.726	10.86	7.943
<i>LnGDP</i>	10.56	0.278	10.96	10.08
<i>LnGovtSize</i>	-1.607	0.100	-1.160	-1.758
<i>LnR&D</i>	-3.683	0.101	-3.372	-3.877
<i>Inflation</i>	3.612	2.345	10.07	-0.349
<i>LnEducation</i>	3.077	0.348	3.625	2.351
<i>AIA</i>	0.170	0.379	0	1

Note: Data includes 50 observations from 1971 to 2020.

Table 2: Phillips-Perron unit root tests

Variables	Test statistic	P-value
<i>LnPatentGrant</i>	0.354	0.980
<i>ΔLnPatentGrant</i>	-9.543***	0.000
<i>LnPatentApp</i>	0.368	0.980
<i>ΔLnPatentApp</i>	-5.854***	0.000
<i>LnPatentGrant (Utility)</i>	0.248	0.975
<i>ΔLnPatentGrant (Utility)</i>	-9.254***	0.000
<i>LnPatentApp (Utility)</i>	0.309	0.978
<i>ΔLnPatentApp (Utility)</i>	-5.876***	0.000
<i>LnPatentUncertain</i>	-1.608	0.480
<i>ΔLnPatentUncertain</i>	-6.709***	0.000
<i>LnPatentUncertain (Utility)</i>	-1.563	0.502
<i>ΔLnPatentUncertain (Utility)</i>	-6.223***	0.000
<i>LnGDP</i>	-1.636	0.464
<i>ΔLnGDP</i>	-4.854***	0.000
<i>LnGovtSize</i>	-1.007	0.751
<i>ΔLnGovtSize</i>	-2.939**	0.041
<i>LnR&D</i>	-0.063	0.953
<i>ΔLnR&D</i>	-2.897**	0.046
<i>Inflation</i>	-1.952	0.308
<i>ΔInflation</i>	-6.696***	0.000
<i>LnEducation</i>	-3.178	0.021
<i>ΔLnEducation</i>	-4.326***	0.000

Notes: The null hypothesis of each test is that the variable is a random walk.

Three Newey-West lags are included in each test.

Asterisks denote the following significance levels: *** $p < 0.01$ and ** $p < 0.05$.

Table 3: Cointegration test using Pesaran et al. (2001) bounds testing procedure

Test statistics	10% critical values		5% critical values		1% critical values		p-value	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
Model 1 (<i>LnPatentGrant</i>)								
F = 4.053*	2.539	3.665	2.973	4.232	3.986	5.548	0.009	0.062
t = -4.540*	-3.046	-4.316	-3.398	-4.739	-4.114	-5.591	0.004	0.070
Model 2 (<i>LnPatentApp</i>)								
F = 8.922***	2.499	3.707	2.937	4.297	3.970	5.676	0.000	0.000
t = -3.881	-2.991	-4.262	-3.353	-4.698	-4.090	-5.580	0.016	0.171
Model 3 (<i>LnPatentGrant</i> (<i>Utility</i>))								
F = 3.698	-3.046	-4.316	-3.398	-4.739	-4.114	-5.591	0.010	0.137
t = -4.102**	2.438	3.770	2.884	4.394	3.946	5.867	0.005	0.048
Model 4 (<i>LnPatentApp</i> (<i>Utility</i>))								
F = 4.431**	2.438	3.770	2.884	4.394	3.946	5.867	0.005	0.048
t = -4.146	-2.909	-4.180	-3.286	-4.637	-4.054	-5.564	0.008	0.105

Notes: Critical values are from Kripfganz and Schneider (2020) for unrestricted constant and restricted time trend.

Statistical significance is determined by the probability values in the last two columns, where the asterisks denote the following significance levels: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 4: Long-run coefficients of patenting uncertainty

Model:	(4.1)	(4.2)	(4.3)	(4.4)
Dependent variable:	<i>LnPatentGrant</i>	<i>LnPatentApp</i>	<i>LnPatentGrant</i> (<i>Utility</i>)	<i>LnPatentApp</i> (<i>Utility</i>)
<i>LnPatentUncertain</i>	-0.134*** (0.0472)	0.0411 (0.0393)		
<i>LnPatentUncertain (Utility)</i>			-0.143*** (0.0516)	0.0342 (0.0391)
<i>LnGDP</i>	0.322 (1.005)	2.403** (1.013)	0.402 (1.178)	3.043*** (1.042)
<i>LnR&D</i>	0.944* (0.499)	0.446 (0.391)	1.262** (0.595)	0.530 (0.357)
<i>LnGovtSize</i>	-1.006** (0.403)	-0.120 (0.250)	-1.000** (0.474)	0.0608 (0.351)
<i>Inflation</i>	0.0127 (0.0134)	0.0361* (0.0198)	0.0165 (0.0158)	0.0445*** (0.0156)
<i>LnEducation</i>	-2.248*** (0.668)	-1.744*** (0.562)	-2.361*** (0.779)	-2.284*** (0.554)
Time Trend	0.0729*** (0.0105)	0.0328** (0.0145)	0.0724*** (0.0126)	0.0340*** (0.0116)
Observations	50	50	50	50
R-Squared	0.616	0.704	0.630	0.761

Notes: Standard errors are in parentheses.

Asterisks denote the following significance levels: *** p<0.01, ** p<0.05, and * p<0.1.

Table 5: Error correction model and short-run dynamics of the impact of patenting uncertainty

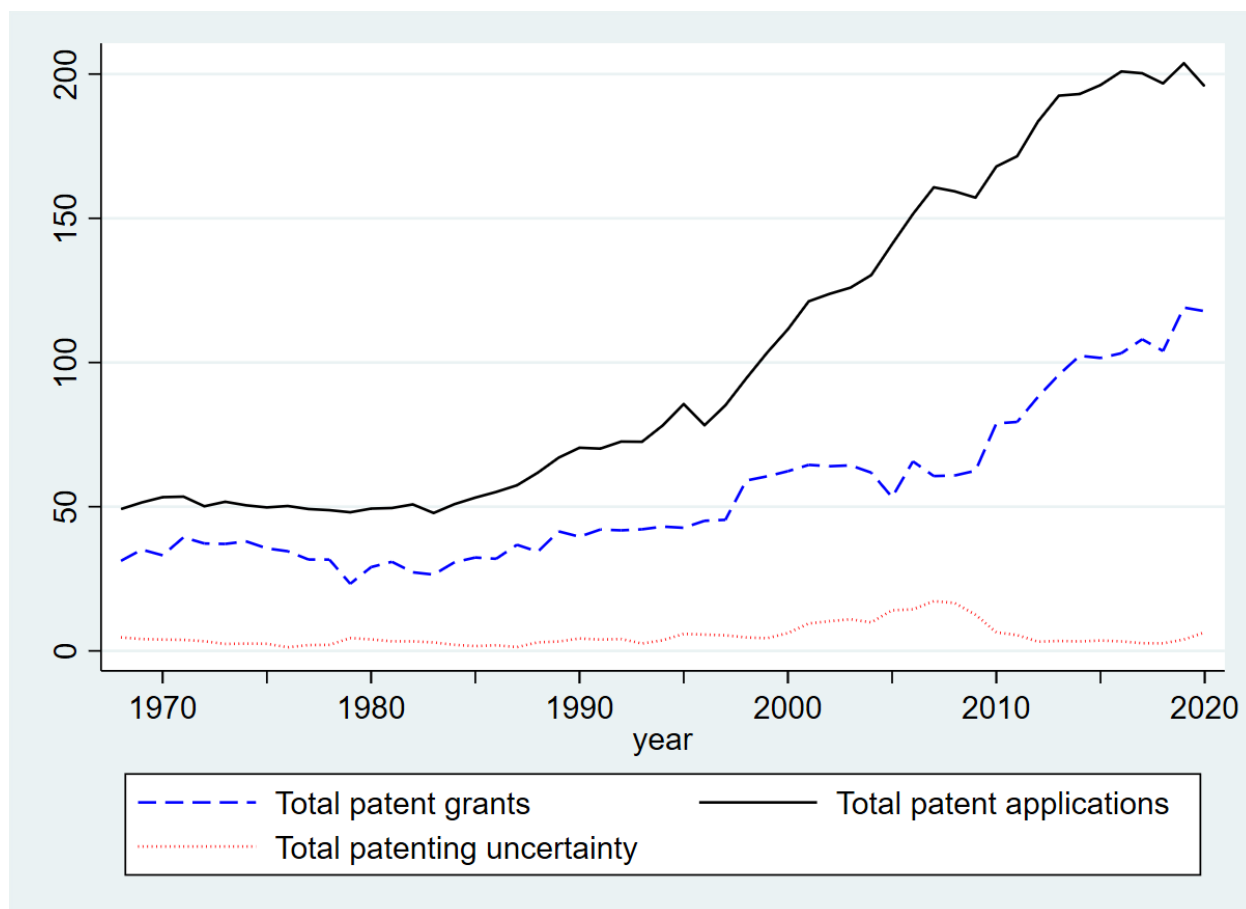
Model:	(5.1)	(5.2)	(5.3)	(5.4)
Dependent variable:	$\Delta \text{LnPatentGrant}_t$	$\Delta \text{LnPatentApp}_t$	$\Delta \text{LnPatentGrant (Utility)}_t$	$\Delta \text{LnPatentApp (Utility)}_t$
$\Delta \text{LnPatentUncertain}_t$	-0.165*** (0.0468)	0.00401 (0.0183)		
$\Delta \text{LnPatentUncertain}_{t-1}$	0.0575 (0.0422)	-0.0387** (0.0169)		
$\Delta \text{LnPatentUncertain}_{t-2}$		-0.0487*** (0.0163)		
$\Delta \text{LnPatentUncertain (Utility)}_t$			-0.195*** (0.0500)	0.0108 (0.0244)
$\Delta \text{LnPatentUncertain (Utility)}_{t-1}$			0.0756 (0.0471)	-0.0464* (0.0226)
$\Delta \text{LnPatentUncertain (Utility)}_{t-2}$				-0.0647*** (0.0215)
ΔLnGDP_t	0.205 (0.634)	0.844*** (0.305)	0.224 (0.647)	0.578 (0.437)
$\Delta \text{LnR\&D}_t$	-0.204 (0.544)	0.100 (0.214)	-0.194 (0.559)	0.177 (0.267)
$\Delta \text{LnR\&D}_{t-1}$		-0.469* (0.242)		-0.790*** (0.278)
$\Delta \text{LnR\&D}_{t-2}$				0.303 (0.288)
$\Delta \text{LnGovtSize}_t$	-0.0386 (0.256)	-0.0421 (0.0891)	-0.0589 (0.260)	-0.179 (0.126)
$\Delta \text{LnGovtSize}_{t-1}$				0.195 (0.167)
$\Delta \text{LnGovtSize}_{t-2}$				-0.213 (0.154)
$\Delta \text{Inflation}_t$	0.00809 (0.00842)	0.00459 (0.00418)	0.00917 (0.00867)	0.00319 (0.00550)
$\Delta \text{Inflation}_{t-1}$		-0.00553 (0.00504)		-0.00981 (0.00664)
$\Delta \text{Inflation}_{t-2}$		0.00666 (0.00446)		
$\Delta \text{LnEducation}_t$	-1.431*** (0.484)	-0.613** (0.283)	-1.312** (0.487)	-0.790 (0.509)
$\Delta \text{LnEducation}_{t-1}$				1.203** (0.564)

ECT_{t-1}	-0.637*** (0.140)	-0.351*** (0.0905)	-0.556*** (0.135)	-0.454*** (0.110)
Constant	-85.88*** (22.32)	-28.09* (14.48)	-73.96*** (21.98)	-39.50** (15.55)
Observations	50	50	50	50
Adj. R-squared	0.616	0.704	0.630	0.761
Diagnostic Tests				
ARCH LM test	1.01 [0.315]	0.204 [0.651]	0.239 [0.625]	0.046 [0.830]
Breusch-Pagan test	0.01 [0.912]	0.94 [0.332]	0.45 [0.503]	0.02 [0.884]
RESET test	0.08 [0.970]	0.79 [0.511]	0.90 [0.450]	1.88 [0.160]
Breusch-Godfrey LM test				
1 lag	0.078 [0.781]	1.608 [0.214]	0.531 [0.471]	2.028 [0.166]
3 lags	1.624 [0.202]	1.375 [0.269]	1.507 [0.230]	3.175** [0.042]
Cameron & Trivedi IM-test	68.56 [0.265]	72.76 [0.265]	61.89 [0.480]	73.17 [0.439]
CUSUM Recursive Residuals	0.3918	0.5224	0.4300	0.4346
CUSUM OLS Residuals	0.3539	0.3694	0.3601	0.3283

Notes: The lag lengths are determined by the Akaike Information Criterion (AIC) for a maximum of 3 lags. ECT is the error correction term. Standard errors are in parentheses and probability values are in brackets. The 10% critical value for the CUSUM Recursive Residual (OLS Residuals) is 0.8499 (1.2238)

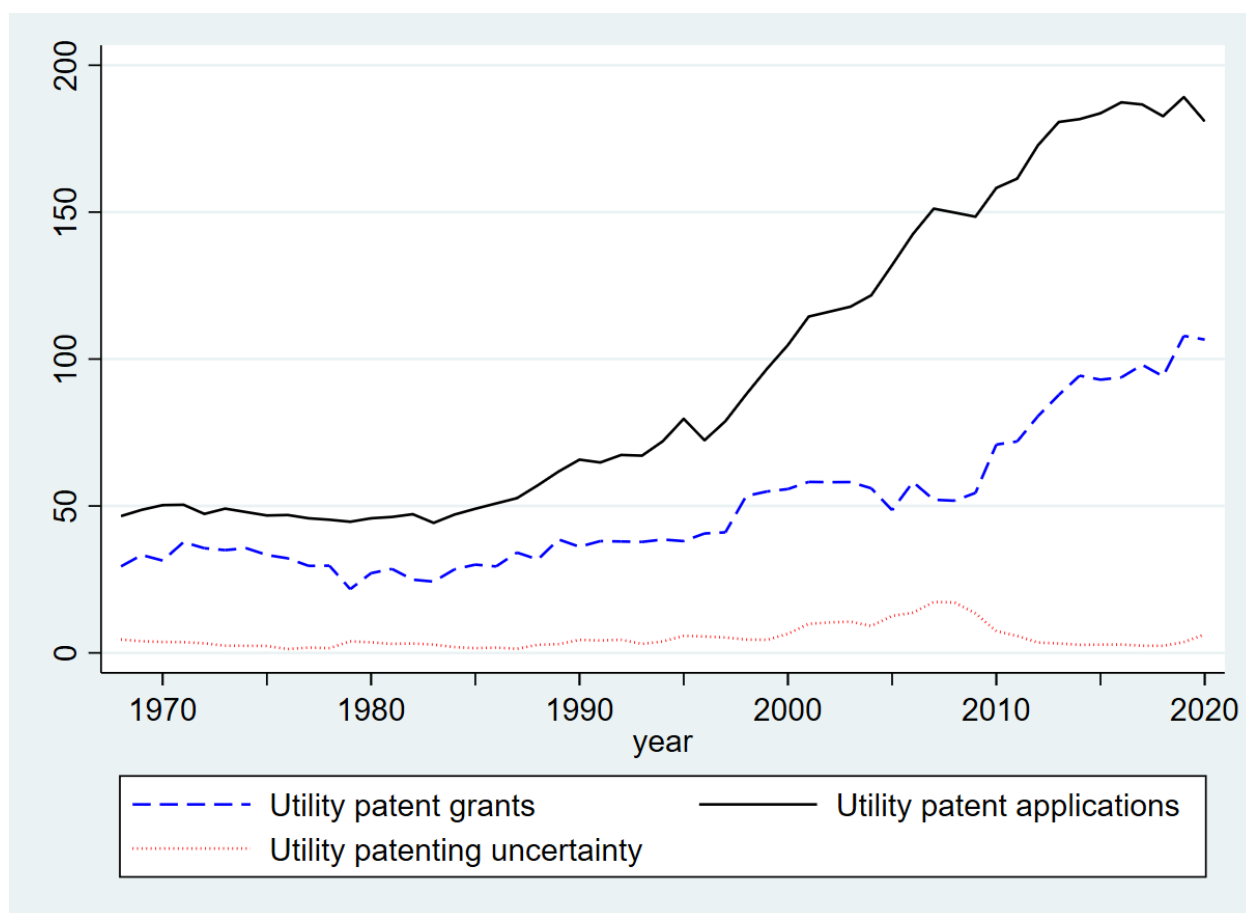
Asterisks denote the following significance levels: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Figure 1: Patent grants and applications, and patenting uncertainty



Notes: Variables are scaled by 100,000 population (also see Table 1a)

Figure 2: Utility patent grants and applications, and utility patenting uncertainty



Notes: Variables are scaled by 100,000 population (also see Table 1a)

Appendix

Table 4A: Long-run coefficients of patenting uncertainty (America Invents Act (AIA))

Model:	(4A.1)	(4A.2)	(4A.3)	(4A.4)
Dependent variable:	<i>LnPatentGrant</i>	<i>LnPatentApp</i>	<i>LnPatentGrant</i> (Utility)	<i>LnPatentApp</i> (Utility)
<i>LnPatentUncertain</i>	-0.245*** (0.0541)	0.0801* (0.0437)		
<i>LnPatentUncertain (Utility)</i>			-0.276*** (0.0694)	0.0850* (0.0454)
<i>LnGDP</i>	-1.314* (0.724)	3.184*** (0.964)	-2.704** (1.231)	3.238*** (1.014)
<i>LnR&D</i>	1.411*** (0.332)	0.201 (0.302)	1.770*** (0.412)	0.304 (0.325)
<i>LnGovtSize</i>	-1.962*** (0.338)	0.0916 (0.302)	-2.281*** (0.466)	0.0529 (0.322)
<i>Inflation</i>	0.0535*** (0.0159)	0.0164 (0.0107)	0.0625*** (0.0189)	0.0207* (0.0113)
<i>LnEducation</i>	-2.056*** (0.466)	-1.821*** (0.532)	-1.950*** (0.553)	-1.966*** (0.546)
<i>AIA</i>	-0.388*** (0.132)	0.203** (0.0899)	-0.583*** (0.198)	0.191* (0.0955)
Time Trend	0.111*** (0.0159)	0.0148 (0.0151)	0.137*** (0.0247)	0.0169 (0.0154)
Observations	50	50	50	50
R-Squared	0.799	0.766	0.802	0.758

Notes: See Table 4. Standard errors are in parentheses.

Asterisks denote the following significance levels: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 5A: Error correction model and short-run dynamics of the impact of patenting uncertainty (America Invents Act (AIA))

Model:	(5A.1)	(5A.2)	(5A.3)	(5A.4)
Dependent variable:	$\Delta \text{LnPatentGrant}_t$	$\Delta \text{LnPatentApp}_t$	$\Delta \text{LnPatentGrant (Utility)}_t$	$\Delta \text{LnPatentApp (Utility)}_t$
$\Delta \text{LnPatentGrant}_{t-1}$	0.366** (0.168)			
$\Delta \text{LnPatentGrant (Utility)}_{t-1}$			0.344** (0.164)	
$\Delta \text{LnPatentUncertain}_t$	-0.194*** (0.0497)	0.0226 (0.0206)		
$\Delta \text{LnPatentUncertain}_{t-1}$	0.184*** (0.0606)	-0.0408* (0.0204)		
$\Delta \text{LnPatentUncertain}_{t-2}$		-0.0619*** (0.0176)		
$\Delta \text{LnPatentUncertain (Utility)}_t$			-0.208*** (0.0556)	0.0261 (0.0244)
$\Delta \text{LnPatentUncertain (Utility)}_{t-1}$			0.213*** (0.0679)	-0.0477** (0.0224)
$\Delta \text{LnPatentUncertain (Utility)}_{t-2}$				-0.0705*** (0.0212)
ΔLnGDP_t	-1.605* (0.905)	0.659 (0.404)	-1.411 (1.056)	0.667 (0.434)
$\Delta \text{LnR\&D}_t$	-0.360 (0.655)	0.177 (0.239)	-0.682 (0.640)	0.214 (0.257)
$\Delta \text{LnR\&D}_{t-1}$	-0.858 (0.663)	-0.789*** (0.253)	-0.645 (0.622)	-0.757*** (0.269)
$\Delta \text{LnR\&D}_{t-2}$	-1.601** (0.685)	0.440* (0.241)	-1.883** (0.743)	0.459* (0.258)
$\Delta \text{LnGovtSize}_t$	-0.426 (0.280)	-0.144 (0.118)	-0.278 (0.297)	-0.171 (0.126)
$\Delta \text{LnGovtSize}_{t-1}$	0.609 (0.522)	0.354** (0.143)		0.378** (0.154)
$\Delta \text{Inflation}_t$	0.0301** (0.0111)	-0.00240 (0.00438)	0.0406*** (0.0133)	-0.00129 (0.00481)
$\Delta \text{Inflation}_{t-1}$	-0.0613*** (0.0188)		-0.0660*** (0.0203)	
$\Delta \text{Inflation}_{t-2}$	-0.0268* (0.0149)		-0.0131 (0.0123)	
$\Delta \text{LnEducation}_t$	-3.232** (1.270)	-0.461 (0.426)	-3.675** (1.370)	-0.614 (0.461)
$\Delta \text{LnEducation}_{t-1}$	0.869	0.954*	0.110	1.122**

	(1.000)	(0.508)	(1.246)	(0.544)
$\Delta \ln Education_{t-2}$	1.759		2.114*	
	(1.082)		(1.101)	
ΔAIA_t	-0.0537	0.0941**	-0.102	0.0901*
	(0.119)	(0.0422)	(0.114)	(0.0455)
ΔAIA_{t-1}	0.332***		0.367***	
	(0.107)		(0.116)	
ECT_{t-1}	-1.221***	-0.464***	-1.047***	-0.472***
	(0.227)	(0.0979)	(0.203)	(0.0980)
Constant	-236.6***	-24.62*	-239.8***	-26.99*
	(45.60)	(14.39)	(49.30)	(14.95)
Observations	50	50	50	50
Adj. R-squared	0.799	0.766	0.802	0.758

Notes: See Table 5. The lag lengths are determined by the Akaike Information Criterion (AIC) for a maximum of 3 lags. ECT is the error correction term. Standard errors are in parentheses and probability values are in brackets.

Asterisks denote the following significance levels: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.