Australian Academy of Accounting and Finance Review (AAAFR)

ISSN (Online) 2205-6688

ISSN (Print) 2205-6742

Patent Issuances and Stock Volatility

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Abstract

How do patents affect firm risk? In recent years, the US patent system has experienced a large expansion, granting more patents than ever before. Exploiting the heterogeneity of this expansion between patent classes, this paper asks how the patent system is changing individual firm's stock volatility. Introducing a novel shift-share instrument based on patent applications across industry sectors, I document how patent issuances were volatility increasing before 2000 but volatility reducing since then. This stock volatility reduction effect is concentrated among firms in highly competitive sectors, giving evidence that patents have been used more defensively against competition since 2000 rather than as growth options.

Keywords: Patenting; Firm risk; Real options; Shift-share instrument.

1. Introduction

Do patents increase or decrease risk for corporations? The answer to this question is not straightforward as patent rights can be viewed from two risk-related perspectives. On the one hand, patents are frequently referred to as real options on the underlying net present value (NPV) project (see, e.g., Pakes 1986). If the patented technology becomes successful, patents increase the upside by allowing for a temporary monopoly on commercialization.

In this sense, risky projects will benefit a firm owning patents since the value of the options increases with the volatility of the underlying. On the other hand, patents are temporary monopolies, reducing the risk of competition for firms. For example, the emergence of large portfolios and the notion of patent thickets in software-related fields has sparked much debate about whether patented monopolies might stretch too far and stifle new technologies before they can emerge. In this case, patents reduce the willingness of firms to invest in new projects that might infringe on other patents and existing projects are less likely to face competition.

The question thus arises of how patent systems are shaping financial risk. Patents can incentivize firms to take more risk by following projects that would in the absence of patents not be taken. On the other hand, the temporary monopoly of patents might decrease the willingness to take risks. Put in different words, patents can be used for offensive growth projects or defensively against competitors. Either understanding of patents has important implications for economic growth, financial decisions, and competition. This study aims to improve our understanding of the relationship between risk and patents and what economic consequences this has.

This study is particularly relevant in the face of recent shifts in the patenting system in the US. Since the mid-1990s, some patent classes have virtually vanished, while others have massively expanded, such as software-related patents (see, e.g., Webb et al. 2018). Overall, the number of patent applications has exploded and the growth in patenting has exceeded underlying economic growth.

This stands in sharp contrast to the findings of Bloom et al. (2020) that innovation has become harder to achieve over time. Bloom et al. (2020) mention where this contrast can come from: “Starting in the 1980s, patent grants by the USPTO began growing much faster than before, leading patents per capita and patents per researcher to stabilize and even increase. The patent literature is very rich and has interpreted this fact in different ways. It could suggest, for example, that ideas are no longer getting harder to find. Alternatively, a patent from 50 years ago and a patent today may mean different things because of changes in what can be patented (algorithms, software) and changes in the legal setting [...]. In other words, the relationship between patents and “ideas” may itself not be stable over time [...].”. Indeed, the expansion of the patent system in recent years has been heterogeneous. The overall image points towards a drifting apart of industries: while service sectors experienced a strong increase in patenting, sectors like manufacturing remained rather stable or even decreased in the relative number of patents received. Overall, there is convincing evidence that the patent system has led to the expansion of patenting in some sectors while making patents more difficult to obtain in others, which raises the question of how much patents are reflecting ’offensive’ technology changes versus ’defensive’ protection due to changes in what is patent eligible.

If patents are linked to taking on risky growth projects, stock volatility can increase as a consequence of receiving patents since equity is itself a call option on the underlying assets. On the other hand, Boldrin and Levine (2013) argue that patents are used by more mature firms for purely defensive reasons to stifle new entrants and competition. Patents then would decrease stock risk since they limit the risk of disruption by competitors and make underlying cash flows more stable. The direction of the relation between stock risk and patents is thus ambiguous.

To answer how patents affect stock risk, I exploit the heterogeneous development of patent assignments across industries to estimate the causal impact of receiving patent grants on stock volatility. The identification strategy uses a shift-share instrument for this. Leveraging data from Kogan et al. (2017), the ’share’ component links patent classes to industries by counting the patent classes in which firms file over the sample period. The ’shift’ uses annual application data per patent class, proxying for changes in patent issuances in the following year. For every firm that files at least once a patent in the sample this allows to fit values of patents received per year that are exogenous to the individual firm and allow for causal interpretation.

I find that the relationship between stock volatility and patent assignments has changed significantly after 2000. In prior years, patent assignments led to an increase in stock volatility while assignments after 2000 had the opposite effect. This means patents appear to be more linked to risky growth projects prior to 2000 while serving anti-competitive defensive purposes since then. I also find that the risk reduction effect comes almost exclusively from firms in highly competitive sectors and that for the same firm, technologically more valuable innovations mitigate the risk reduction. These results confirm that around 2000 listed firms shifted toward more defensive usage of patents while the incentive remains to escape competition by realizing promising projects even at the expense of higher volatility.

This study contributes in three main aspects to the existing literature. First, I document how the usage of patents has changed since 2000 toward more defensive risk reduction. This is consistent with recent literature, e.g., Gutiérrez and Philippon (2019) and Gutiérrez and Philippon (2017) showing how competition has declined and how regulatory changes might contribute to this. Similarly, Lee et al. (2021) and Kahle and Stulz (2020) find that the listed firms that the academic literature used to describe as growth firms (i.e., firms with high Tobin’s Q) now rather reflect rent-generating, high-margin firms. This paper thus adds to the literature by providing insight into how patents have contributed to the rapid change toward less competitive listed firms since 2000.

Second, this study extends the knowledge of how risky underlying assets and patents affect asset prices. There are several studies such as Alfaro et al. (2018) and Barrero et al. (2017) that investigate how different risk measures influence real economic outcomes, however, only Czarnitzki and Toole (2011) have actively tried to measure how patents mitigate the impact of uncertainty on R&D investments. Studies such as Gu (2016) have focused on how asset prices are linked to R&D intensity in competitive markets, ignoring patent rights. The current study, thus, fills an important gap in the literature on how patents influence stock volatility.

Finally, I show how patent systems are shaping economic outcomes. Besides economic history-related works such as in Moser (2011) focused on whether patent systems exist or not, little attention has been given to how changes in policies have shifted what is patent eligible and what types of patents are issued. Forman and Goldfarb (2020) recently documented an increase in the concentration of patents while studies such as Choi and Gerlach (2015) work with the assumption that not all patents are equally strong. Software patents are a good example that shows how patent strength can vary over time: from being non-existent before 1980, via several extensions of patent eligibility over the 1990s, they experienced a quick weakening in the early 2010s due to several Supreme Court decisions. Thus, this study helps to understand better what effects the changes in patent policies and the expansion of the patent system in recent years have on the economy.

2. Institutional background

This section reviews the institutional background and the evolution of the patent system over recent decades.

The patenting system has experienced several changes between the late 1990s and the early 2010s, leading overall to an increased incentive to file patent applications on incremental innovations. The most important legislative changes are the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) in 1995, the American Inventors Protection Act (AIPA) in 1999, and the Leahy–Smith America Invents Act (AIA) in 2011. Several important court decisions also shaped patenting, with some of the most relevant being the *State Street Bank v. Signature Financial Group* decision[1] (*State Street*) in 1998, *In re Bilski*[2] in 2008, and *Alice Corp. v. CLS Bank International*[3] (*Alice*) in 2014. The TRIPS agreement led in the US to a change in the duration of patents from 17 years starting at the grant date to 20 years starting at the application date. Abrams (2009) shows that this increased patent counts and patent citation-weighted patent counts. The AIPA implemented the disclosure of patent applications after 18 months in most cases, which reduced duplication (Lück et al. 2020) and increased early licensing (Hegde and Luo 2018). Kim and Valentine (2021) also show that firms that benefit from rivals' disclosure increased patenting following the AIPA. At around the same time as these laws came into effect, the *State Street* decision affirmed the eligibility of software and business method patents, which was an important expansion of what innovations can be protected by patents (Hall 2003, Lerner et al. 2021). There has been concern about the quality of patents filed after *State Street* (Raskind 1999). A sequence of court decisions between 2008 and 2014, starting with *In re Bilski* and ending with *Alice*, limited the patentability of certain software and medical diagnostics innovations (Ouellette 2015, Eisenberg 2015, Stroud and Kim 2017). Despite this, software-related patents remain an important and rapidly increasing field for patent applications (Webb et al. 2018).

Taken together, the patent reforms and *State Street* in the late 1990s increased the incentive to file patent applications that are more incremental and benefit from knowledge spillovers. In more recent years, this was enforced with the AIA in 2011. The AIA had a substantial effect on the patent system, leading to a shift from "first-to-invent" to a "first-inventor-to-file" system, i.e., patents are awarded to the first inventor to file for an application. This incentivizes earlier application filings and some scholars argue this leads to a 'race to the patent office' and more filings of incremental patents by incumbent firms (and in turn reduces the incentive for small firms to innovate; see, e.g., Case 2013, Braun 2012).

Thus, starting around the late 1990s, the patenting system has contributed to a preference for incremental innovation due to longer patent duration, information spillovers, broader patent eligibility of software and business methods, and the switch to a first-to-file system. It is worth mentioning that innovation and patenting are not the same and many other factors affect innovation, e.g., Oshima and Toma (2023) explore how innovation is accelerated through mediators rather than patents, and Purbasari et al. (2023) show how collaboration across firms affects digital innovation.

1 149 F.3d 1368 (Fed. Cir. 1998).
2 545 F.3d 943 (Fed. Cir. 2008).
3 573 U.S. 208 (2014).

3. Model

This section develops a short model based on Berk, Green, and Naik (1999) and Bloom and Van Reenen (2002) that guides how to interpret the empirical results that follow.

Consider a two-period model. The firm consists of projects in place and growth options. The projects in place follow the cash flow process:

$$C_j = I_j \exp\left[\bar{C} - \frac{1}{2}\sigma_j^2 + \sigma_j \epsilon_j\right]$$

where ϵ_j is the random error term for the cash flow from the project. ϵ_j is serially independent standard normal distributed. The sunk-cost investments I are included for scaling.

With a constant discount rate r, the risk-neutral value of the existing assets in place can be written as the sum over all existing projects K:

$$V_E = \exp[-r]\mathbb{E}\left[\sum_{k=1}^{K} C_k\right] = b\exp[-r+\bar{C}] \quad \text{where} \quad b = \sum_{k=1}^{K} I_k$$

where b can be interpreted as the book value of existing assets.

The firm also has growth options for projects in the future. Their present value is equal to the maximum of the net present value of the underlying asset on the date of maturity and zero, discounted to the present period. Since discounting is independent of the value of the call option on the new project, we can write the value of the growth options as follows:

$$V_G = \exp[-r]\mathbb{E}\left[\sum_{m=1}^{M}\left[\max\{V_m - I_m, 0\}\right]\right]$$

The current value of the firm is $V = V_E + V_G$. In this simplified model with a constant discount rate, the present value of the assets in place and the growth options do not change over time (expanding this simple version by considering a perpetuity instead of single period cash flows and depreciation of assets in place does not change this substantially).

The decision of which projects to invest in will generate risky cash flows in the next period. Assume there are two types of projects: radical or incremental. Incremental projects have low investment costs I_l, with low risk $\sigma_l < \sigma_E$, where σ_E is the average volatility of the assets in place. The idea here is that these innovations are improving existing technologies by reducing their riskiness. Radical innovations, on the other hand, require a higher investment I_h, and are more risky, $\sigma_h > \sigma_E$. This would correspond to innovations with high upside potential, but also high uncertainty.

The number of available growth options depends on the patents granted to the firm. A more lenient patent system might grant more incremental patents while a more strict patent system might allow only a few but technologically relevant (thus radical) patents. Assuming that there are K existing projects and M new projects, next period cash flows can be written as:

$$C = \sum_{k=1}^{K} C_k + \sum_{m=1}^{M} C_m = \sum_{k=1}^{K} I_k \exp\left[\bar{C} - \frac{1}{2}\sigma_k^2 + \sigma_k\epsilon_k\right] + \sum_{m=1}^{M} I_m \exp\left[\bar{C} - \frac{1}{2}\sigma_m^2 + \sigma_m\epsilon_m\right]$$

With total investment, i.e., book asset + new investments, being $\hat{I}$, the total volatility of the firm,, $\bar{\sigma}^2$ can be approximated as the weighted average of the volatilities of the individual projects (see, e.g., Lo 2013):

$$
\begin{aligned}
\bar{\sigma}^2 \quad &= \sum_{k=1}^{K}\left(\frac{I_k}{\hat{I}}\right)^2 \sigma_k^2 + \sum_{m=1}^{M}\left(\frac{I_m}{\hat{I}}\right)^2 \sigma_m^2 \\
&+2 * \sum_{k=1}^{K}\sum_{m=1}^{M}\frac{I_k I_m}{\hat{I}^2}\sigma_k\sigma_m \operatorname{cov}\left(\varepsilon_k,\varepsilon_m\right) \\
&+2 * \sum_{i=1}^{K}\sum_{j=1}^{k-1}\frac{I_i I_j}{\hat{I}^2}\sigma_i\sigma_j \operatorname{cov}\left(\varepsilon_i,\varepsilon_j\right) \\
&+2 * \sum_{i=1}^{M}\sum_{j=1}^{m-1}\frac{I_i I_j}{\hat{I}^2}\sigma_i\sigma_j \operatorname{cov}\left(\varepsilon_i,\varepsilon_j\right)
\end{aligned}
$$

Note that the risk of the incremental projects is smaller than that of the assets in place since the investments are improving the technologies already in place. We can also observe a decrease in risk due to the diversification effect of investing in several incremental projects. For radical innovations, the risk is higher, increasing $\bar{\sigma}^2$, and with fewer but larger projects also the diversification effect is smaller.

Note also that the expected value of the cash flow next period is $\bar{\mu} = \hat{I}\, exp(\bar{C})$. The average cash flow per investment, $exp(\bar{C})$, can be used to measure competition: if competitors are quick to imitate innovations, the expected cash flow from projects has a high risk of falling to zero, thus leading to an overall smaller $\bar{C}$. Another way of thinking about this could be the risk of creative destruction incorporated into the expected return of a project. Taken together, the firm value for the next period is equal to the log-normal cash flow from all projects and realized growth options.

To calculate the value of growth options, assume the investment cost of the project is paid at the time of the realization of the cash flows. The cost can be thought of as debt funding for the growth plan. A simple functional form would be $D_i = C(I_i) = I_i + c/2\,(I_i)^2$, with $D = \sum_{m=1}^{M} D_m$. A financially constrained firm would face higher marginal funding costs, i.e., higher c. Thus, the risk-neutral firm owner will make a decision based on the expected residual value of the cash flows after paying off the funding expenses. We can use the truncated mean of a log-normal distribution (which is a standard result, see Ingersoll 1987) to define the objective function of the firm owner:

$$
\mathbb{E}[V-D \mid V>D] = \exp\left[\bar{\mu}+\frac{\bar{\sigma}^2}{2}\right]\Phi\left(\frac{\bar{\mu}-\ln D}{\bar{\sigma}}+\bar{\sigma}\right) - D\Phi\left(\frac{\bar{\mu}-\ln D}{\bar{\sigma}}\right)
$$

where Φ is the CDF of the standard normal distribution. For simplicity, ignore the CDF terms; the expressions are very similar for both terms and approach one for firms without much initial debt. We can ask how the marginal investment project would change the expected firm value and what would be the optimal investment decision. For this, we can take the total derivative with respect to $\bar{\mu}$, $\bar{\sigma}$, and I and set the expressions to zero. Broadly speaking, this equates the marginal benefits in terms of gained expected return and volatility with the marginal cost of the project.

$$
\begin{aligned}
\frac{\partial \mathbb{E}[V-D \mid V>D]}{\partial \bar{\mu}}\Delta\mu + \frac{\partial \mathbb{E}[V-D \mid V>D]}{\partial \bar{\sigma}}\Delta\sigma \quad &= \frac{\partial \mathbb{E}[V-D \mid V>D]}{\partial D}(1+c)I \\
(\Delta\mu + \bar{\sigma}\Delta\sigma)\exp\left[\bar{\mu}+\frac{\bar{\sigma}^2}{2}\right] \quad &= (1+c)I \\
\Delta\mu + \bar{\sigma}\Delta\sigma \quad &= \frac{(1+c)I}{V}
\end{aligned}
$$

I replace the expression of the expectation of the log-normal cash flow, $exp\left[\bar{\mu}+\frac{\bar{\sigma}^2}{2}\right]$, with V. Assume for simplicity now that the firm can only choose between two types of projects, H and L, with $\Delta\sigma_H > \Delta\mu_H > \Delta\mu_L > 0 > \Delta\sigma_L$ and $I_H \geq I_L$. This compares a high-risk, high-cost exploration project and a low-risk, low-cost defensive project. We can further ask in which cases the overall value of the low-risk project is higher than the high-risk project:

$$\left(\Delta\mu_L - \bar{\sigma}\Delta\sigma_L\right)\exp\left(\bar{\mu}+\frac{\bar{\sigma}^2}{2}\right)-(1+c)I_L > \left(\Delta\mu_H + \bar{\sigma}\ \Delta\sigma_H\right)\exp\left(\bar{\mu}+\frac{\bar{\sigma}^2}{2}\right)-(1+c)\ I_H > 0$$

where I immediately take the risk-reducing effect of defensive projects into account by using the absolute value of $|\Delta\sigma_L|$ with a negative sign.

In either case, the value of the project must be larger than zero. We have thus two inequalities that need to be fulfilled to prefer defensive projects:

$$(\Delta\mu_L - \Delta\mu_H)\ V - \bar{\sigma}\ (\Delta\sigma_H + |\Delta\sigma_L|)\ V + (1+c)\ (I_H - I_L) > 0 \tag{1}$$

$$(\Delta\mu_L - \bar{\sigma}|\Delta\sigma_L|)\ V - (1+c)I_L > 0 \tag{2}$$

With a similar participation condition for the high-risk projects.

Several points can be learned from this:

1. With high competition, firms may prefer defensive growth projects. Take the derivative of the left-hand side of inequality 2 w.r.t. $\bar{\mu}$: $(\Delta\mu L - \bar{\sigma}|\Delta\sigma L|)\ V$. High competition means lower expected cash flows from projects, thus, it may be more beneficial for firms to pursue defensive projects that promise more certain increases in expected returns, particularly if there are spillover effects through, e.g., additional protections of other cash flows through patent portfolio effects, which in turn would show itself in a stronger decrease in expected volatility.
2. Firms in highly competitive industries still invest in breakthrough innovations. As above, if the current value of $\bar{\mu}$ is small due to high competition, a highly risky project that promises larger returns and an escape from competition is worth the increase in volatility.

Overall, returns (cash flows relative to price) become more volatile if the firm has fewer but more radical investment opportunities. If the patent system allows for more incremental innovations, this will have a volatility-decreasing effect since some firms will realize smaller innovation projects improving existing technologies. Firms that face higher levels of competition may realize more incremental defensive projects that reduce firm risk. At the same time, I would expect offensive growth patents with large technology value to increase expected volatility for those firms as they can use innovation to escape from competition, even at the cost of higher risk. Thus, the expansion of the patenting system would have heterogeneous effects on firms in highly competitive industries depending on the innovation quality.

4. Methodology

For the empirical analysis, I start my investigations with a simple linear regression of the following form:

$$\sigma_{i,t+1} = \beta_i * \log patent_{i,t} + \delta_i * \mathbf{X}_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,t} \tag{3}$$

Where $\sigma_{i,t+1}$ is the volatility of the stock returns, in this case the annual volatility for daily stock returns in the following calendar year (vola), log $patent_{i,t}$ is the log count of patents issued to the firm in the respective year, $\mathbf{X}_{i,t}$ is an additional vector of controls as in Barrero et al. (2017), γ_i and λ_t are firm and time fixed effects, and the error terms $\epsilon_{i,t}$ are clustered on firm level.

Concerning the use of asset volatilities, Schwert (1989) defines $\sigma_{equity} = V/S * \sigma_{asset}$, where V is the market value of the firms and S is the stock value. Thus, we can recover the asset volatility by multiplying the equity volatility with (1 - market leverage) as in, e.g., Lotfaliei 2021). This is similar to the naïve approach in Choi and Richardson (2016) who use a weighted average of stock return and risk-free return (and weights from book value of debt + market value equity) to calculate asset returns. Bharath and Shumway (2008) use a similar approach to define asset volatility as weighted average of stock volatility and debt volatility (which is itself in their naïve approach a liner function of σ_{equity}). Doshi et al. (2019) illustrate the relation between unlevering beta and returns (importantly showing how ideally we would use excess returns). There are also more iterative methods to estimate asset volatility such as in Choi and Richardson (2016) and Levine and Wu (2021), using KMV methods to estimate underlying asset volatility from observable equity and bond data. Eventually, though, the basic observations are in any case stock volatility and equity value. The results remain unchanged if I use asset volatility instead of equity volatility for the following analysis.

4.1. Data

The main data sources are Compustat and CRSP for firm and stock data. In Compustat, industries starting with SIC codes 6, 49, and 9 are excluded, observations are based on calendar years to be more consistent with the stock data. The patent data are sourced from Kogan et al. (2017) and their recent update up to the year 2019. The initial sample starts in 1985, allowing for some years to pass following important changes in the patent system such as the *Diamond v. Diehr* decision in 1981 establishing software patent eligibility, and the Bayh–Dole Act of 1980 enabling universities, nonprofit research institutions, and small businesses to patent and commercialize inventions developed under federally funded research programs.

4.2. Instrumental approach

Patents are in large parts of the innovation literature outcome variables, thus endogenous. To alleviate the endogeneity problem, I propose a novel shift-share instrument that ought to capture the assignment of patents to firms exploiting industry and patent system-wide variation:

$$\widetilde{patents}_{i,t} = \sum_{k=1}^{K} \frac{ind.uspc_{i,k}}{ind_i} * application_{k,t-3} \tag{4}$$

where $\widetilde{patents}_{i,t}$ is the instrument for the count of patent assignments to firms in sector i, $ind.uspc_{i,k}$ is the total number of patents filed by firms in sector i in three-digit USPC class k over the sample period and ind_i is the total number of patents filed by firms in industry i. This 'share' captures which USPC classes the industry files in. The 'shift' is $application_{k,t-3}$, capturing the number of applications filed in USPC class k three years prior. This both accounts for the lag of around three years between filing and patent issue and alleviates concerns of endogeneity since the application number does not directly correspond to the patents issued (many applications are abandoned before issue). Application data are based on Public PAIR data from Graham et al. (2015) and thus are from a separate data source not limited to listed firms. The variation of this instrument comes from the overall economy-wide changes in application filings across all patent classes, making it unlikely that patent issuances to a single firm are influencing this variation alone.

The first stage follows the method used in Bloom et al. (2013) where the log of issued patents is regressed on the instrument in a regression including time and firm fixed effects. Bloom et al. (2013) use this method to predict R&D expenses with their tax credit instrument. For firms to be included in the prediction sample, they only need to have received a patent at least once at any point between 1980 and 2019. Since firm fixed effects are included, there must be at least one non-zero observation to be fitted for the instrument to work. This is the broadest possible definition of sample firms that can be used since firms that never file patents are different from those that do. The inclusion of time and firm fixed effects also alleviates problems of 1) economy-wide time trends of patenting, and 2) some firms persistently filing more patents than others.

Table 1 shows the first stage results for the shift-share instrument as described above in Model 1. I also include several alternative specifications. Model 2 uses for the 'share' part the rolling average of patents filed in the previous five years by firms in the same industry, excluding the focal firm. The idea here is that the filing behavior of industries changes over time and that the firm should be excluded from the instrument as much as possible. Furthermore, Models 3 and 4 provide alternatives for the 'shift' as the average share of applications filed in the respective year and USPC class that receives a final rejection. The idea here is that applications with final rejections are less likely to become patents eventually and the time-varying strictness of the patent office allows for exogenous identification of the number of patents eventually granted. Overall, considering the very high F-statistics, all instruments work quite well (it should be mentioned, though, that Model 4 using both the alternative shift and share has a counterintuitive positive sign, indicating more eventual issuances following a higher fraction of firms with final rejections. One reason might be that the number of applications and the share of final rejections are correlated). Note that ideally for the 'share' linking patent classes and industries, I would use patent applications of firms rather than the eventually granted patents as in Kogan et al. (2017). With most patents being granted, though, the error is limited and the value of using an independent data source for the 'share' part would be reduced.

Finally, the question arises if it is really necessary to use instrumented patent issues for the analysis. To verify this, Table 2 shows regression results of the OLS regression specifications in Tables 3, 4, and 5 and their respective subsamples which include besides the endogenous log patent count also the residual of the fitted patent count values from the first stage (Models 1 and 2 are across the entire sample, Models 3 and 4 are for the subsample from 1985 to 1999, and Models 5 and 6 for the subsample 2000 to 2019). This regression specification can be viewed as a robust alternative to the Hausman

Table 1: First stage results

Dep. Variable	Model 1	Model 2	Model 3	Model 4
	log patent count	log patent count	log patent count	log patent count
lag 3 app. filings - sample avg.	0.0001***			
	[9.8796]			
lag 3 app. filings - firm excl.		0.0001***		
		[7.7455]		
lag 3 final reject. - sample avg.			-0.1222 **	
			[-2.2342]	
lag 3 final reject. - firm excl				0.1755***
				[4.0967]
N	39,315	40,088	39,315	40,088
R-squared	0.8033	0.8018	0.8013	0.8008
R-squared (Overall)	0.7726	0.7714	0.7703	0.7703
F-statistic	26.15	26.40	25.82	26.23
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000
Effects	Firm+Year	Firm+Year	Firm+Year	Firm+Year
Controls	Y	Y	Y	Y

First-stage regression of patent issuances on applications instrument. Observations are on the firm-year level for the year of patent issuance. Dependent variables are in log terms and include '+1'. Models 1 and 3 use for the instrument the industry averages of USPC patent classes relative to all patent filings over the entire sample, models 2 and 4 exclude the respective firm when calculating the industry patent class shares. Models 1 and 2 use as the instrument the log of the numbers of patent applications filed in the USPC class in t-3, models 3 and 4 use the share of applications filed in the USPC class in t-3 that received a final rejection. Standard errors are clustered at the firm level, control variables are defined as in Table 2. Robust t-statistics are reported in brackets, $*p < 0.1$,$**p < 0.05$,$***p < 0.01$.

Table 2: Hausman test regressions with residuals and endogenous variables

Dep. Variable	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)
	1985-2019	1985-2019	1985-1999	1985-1999	2000-2019	2000-2019
	lead vola	lead vola	lead vola	lead vola	lead vola	lead vola
log patent count	-0.0002	0.0000	0.0000	0.0001	-0.0003	-0.0001
	[-1.2353]	[0.2243]	[-0.1170]	[0.1610]	[-1.4589]	[-0.2713]
residual log patent count	-0.0130***	-0.0176***	0.0232***	0.0296***	-0.0172***	-0.0192***
	[-5.6896]	[-6.7520]	[3.5042]	[3.9340]	[-6.4977]	[-6.6343]
leverage		0.0166***		0.0191***		0.0124***
		[11.5936]		[7.0835]		[7.4089]
stock return		-0.0020***		-0.0023***		-0.0015***
		[-9.5309]		[-5.8094]		[-6.0911]
log sale		-0.0013***		-0.0059***		0.0002
		[-3.0942]		[-6.5597]		[0.4198]
roa		-0.0095***		-0.0028		-0.0112***
		[-7.2526]		[-1.1388]		[-6.2335]
fixed assets		0.0001***		0.0000		0.0001***
		[4.9042]		[0.7226]		[4.5507]
tobinsq		-0.0011***		-0.0014***		-0.0008***
		[-8.1804]		[-5.7124]		[-5.0120]
N	36,944	26,886	14,724	11,227	22,220	15,659
R-squared	0.6104	0.6507	0.6920	0.7387	0.6189	0.6626
R-squared (Overall)	0.5499	0.5758	0.6065	0.6403	0.5502	0.5774
F-statistic	10.09	8.69	8.10	7.51	9.00	7.78
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Effects	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year

Hausman test for volatility regressions on patenting. Observations are on the firm-year level. Dependent variables are the stock volatility of daily returns for the firm in the following year. Log patent counts include '+1'. All models include residuals for the first stage regression using as a shift-share instrument the average industry shares of patent filings in USPC classes and the lag number of applications filed in the classes. Models 1 and 2 refer to the entire sample period from 1985 to 2019, models 3 and 4 refer to the period of 1985 to 1999, and models 5 and 6 to the period 2000 to 2019. Standard errors are clustered at the firm level. Robust t-statistics are reported in brackets, $*p < 0.1$,$**p < 0.05$,$***p < 0.01$.

Table 3: Stock volatility to patent issue, 1985-2019

Dep. Variable	OLS (1)	OLS (2)	OLS (3)	IV (1)	IV (2)	IV (3)
	1985-2019	1985-2019	1985-2019	1985-2019	1985-2019	1985-2019
	lead vola	lead vola	lead vola	lead vola	lead vola	lead vola
log patent count	-0.0009***	-0.0006***				
	[-7.1879]	[-4.6478]				
log citation count			0.0000			
			[-0.6769]			
fitted log patent count				-0.0115***	-0.0154***	
				[-5.5982]	[-5.8829]	

(Contd...)

Table 3: ***(Continued)***

Dep. Variable	OLS (1)	OLS (2)	OLS (3)	IV (1)	IV (2)	IV (3)
	1985-2019	1985-2019	1985-2019	1985-2019	1985-2019	1985-2019
	lead vola	lead vola	lead vola	lead vola	lead vola	lead vola
fitted log citation count						-0.0140***
						[-4.1752]
leverage		0.0167***	0.0167***		0.0166***	0.0145***
		[17.4305]	[17.3977]		[10.2639]	[6.9716]
stock return		-0.0030***	-0.0030***		-0.0019***	-0.0022***
		[-18.1901]	[-18.1917]		[-7.8311]	[-6.6847]
log sale		-0.0030***	-0.0031***		-0.0015***	-0.0010
		[-16.1721]	[-16.6073]		[-3.1556]	[-1.4865]
roa		-0.0053***	-0.0052***		-0.0092***	-0.0106***
		[-7.4287]	[-7.3311]		[-6.2767]	[-5.1846]
fixed assets		0.0001***	0.0001***		0.0001***	0.0002***
		[5.3002]	[5.3320]		[4.2000]	[4.0557]
tobinsq		-0.0007***	-0.0007***		-0.0011***	-0.0008***
		[-7.6822]	[-7.5732]		[-7.0344]	[-4.0551]
N	102,825	70,894	70,894	36,944	26,886	26,886
R-squared	0.5855	0.6418	0.6417	0.5524	0.5541	0.1889
R-squared (Overall)	0.5152	0.5612	0.5610	0.4828	0.4586	0.0151
F-statistic	8.32	7.96	7.96	8.78	6.81	3.74
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Effects	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year

Volatility regressions on patenting and forward citations. Observations are on the firm-year level. The sample period is 1985 to 2019. Dependent variables are the stock volatility of daily returns for the firm in the following year. Log patent counts and log patent citation counts include '+1'. In IV models the patent issuances and forward citations are instrumented using a shift-share instrument with the average industry shares of patent filings in USPC classes and the lag number of applications filed in the classes. Standard errors are clustered at the firm level. Robust t-statistics are reported in brackets, $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 4: Stock volatility to patent issue, 1985-1999

Dep. Variable	OLS (1)	OLS (2)	OLS (3)	IV (1)	IV (2)	IV (3)
	1985-1999	1985-1999	1985-1999	1985-1999	1985-1999	1985-1999
	lead vola	lead vola	lead vola	lead vola	lead vola	lead vola
log patent count	0.0002	0.0004				
	[0.9914]	[1.5393]				
log citation count			0.0002 *			
			[1.9106]			
fitted log patent count				0.0205***	0.0279***	
				[3.2323]	[3.4204]	
fitted log citation count						0.0124***
						[3.0102]
leverage		0.0169***	0.0169***		0.0185***	0.0201***
		[10.7203]	[10.7251]		[6.5468]	[6.7235]
stock return		-0.0036***	-0.0036***		-0.0025***	-0.0028***

(Contd...)

Table 4: ***(Continued)***

Dep. Variable	OLS (1)	OLS (2)	OLS (3)	IV (1)	IV (2)	IV (3)
	1985-1999	1985-1999	1985-1999	1985-1999	1985-1999	1985-1999
	lead vola	lead vola	lead vola	lead vola	lead vola	lead vola
		[-11.8291]	[-11.8357]		[-5.1646]	[-4.8596]
log sale		-0.0027***	-0.0027***		-0.0058***	-0.0061***
		[-7.1397]	[-7.1716]		[-5.6968]	[-5.1462]
roa		-0.0024 **	-0.0024 **		-0.0031	-0.0027
		[-2.4787]	[-2.4875]		[-1.2399]	[-0.9588]
fixed assets		0.0001***	0.0001***		0.0000	0.0000
		[3.5720]	[3.5672]		[0.8072]	[0.5263]
tobinsq		-0.0011***	-0.0011***		-0.0014***	-0.0014***
		[-8.0395]	[-8.0369]		[-5.0467]	[-4.4551]
N	50,377	35,391	35,391	14,724	11,227	11,227
R-squared	0.6194	0.6852	0.6852	0.5994	0.5866	0.4370
R-squared (Overall)	0.5173	0.5723	0.5723	0.4883	0.4309	0.2249
F-statistic	6.07	6.07	6.07	6.23	4.75	3.48
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Effects	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year

Volatility regressions on patenting and forward citations. Observations are on the firm-year level. The sample period is 1985 to 1999. Dependent variables are the stock volatility of daily returns for the firm in the following year. Log patent counts and log patent citation counts include ’+1’. In IV models the patent issuances and forward citations are instrumented using a shift-share instrument with the average industry shares of patent filings in USPC classes and the lag number of applications filed in the classes. Standard errors are clustered at the firm level. Robust t-statistics are reported in brackets, *$p < 0.1$,**$p < 0.05$,***$p < 0.01$.

test for endogeneity since the residual from the first stage is a ’control function’ for the potentially endogenous part of the OLS regressor. The coefficients for the residuals are all significant, confirming that the OLS regression is inconsistent compared to the proposed instrumental approach.

5. Results

The first question is how the changes in the patent system affected firms in their risk before and after 2000. The proposed regression models are run over the entire sample period and then separately for the period of 1985 to 1999 and 2000 to 2019. In every table, first OLS results with and without controls are presented, then IV results with and without controls (the controls are only shown in tables 3 to 5, other specifications only indicate whether controls are included or not).

Table 3 shows that over the entire sample, receiving patents has a slightly negative effect when only observing the OLS results. If a firm receives one patent (which corresponds to a value of log patent count of 0.6931 since the variable is in log terms plus one to account for the large number of zeros in the sample, and ln(1+1)-ln(1)=0.6931), the total stock volatility of the firm decreases in the following year by around 1% (since the average value of vola is 0.040584, -0.0006*0.6931/0.040584 ≈ -1%). Accounting for the endogeneity of the patent count and using instrumented values, the impact is much stronger with a decrease in volatility of around 20%. Looking now at subperiods in Tables 4 and 5, there is a stark difference: in the period prior to 2000, the impact of patents was positive while after 2000 patents had a strong volatility-reducing effect. In the pre-2000 period, receiving one patent increased the stock volatility by more than 30%, while after 2000, receiving a patent decreased stock volatility by around 27%. These are quite extreme values, and almost certainly due to the simplistic approach used in this empirical setting. Nevertheless, the results are significant and invariant to the inclusion of controls or adjusting for patent quality by weightings with forward citations. Thus, this

Table 5: Stock volatility to patent issue, 2000-2019

Dep. Variable	OLS (1)	OLS (2)	OLS (3)	IV (1)	IV (2)	IV (3)
	2000-2019	2000-2019	2000-2019	2000-2019	2000-2019	2000-2019
	lead vola	lead vola	lead vola	lead vola	lead vola	lead vola
log patent count	-0.0011***	-0.0009***				
	[-6.7400]	[-4.6269]				
log citation count			0.0001			
			[0.9403]			
fitted log patent count				-0.0159***	-0.0183***	
				[-5.6440]	[-5.4378]	
fitted log citation count						-0.0326 **
						[-2.2810]
leverage		0.0120***	0.0120***		0.0128***	0.0152***
		[9.8032]	[9.7902]		[5.9190]	[3.1075]
stock return		-0.0021***	-0.0021***		-0.0014***	-0.0025***
		[-11.5707]	[-11.6778]		[-4.5373]	[-2.9779]
log sale		-0.0019***	-0.0020***		0.0000	0.0008
		[-5.0831]	[-5.3780]		[0.0786]	[0.4732]
roa		-0.0069***	-0.0067***		-0.0105***	-0.0113 **
		[-6.0303]	[-5.9527]		[-4.9720]	[-2.5635]
fixed assets		0.0001***	0.0001***		0.0001***	0.0003 **
		[3.5076]	[3.4662]		[3.6315]	[2.5238]
tobinsq		-0.0004 **	-0.0004 **		-0.0009***	-0.0002
		[-2.5011]	[-2.3769]		[-4.0286]	[-0.5328]
N	52,448	35,503	35,503	22,220	15,659	15,659
R-squared	0.6342	0.6931	0.6929	0.4887	0.5075	-1.4984
R-squared (Overall)	0.5636	0.6137	0.6135	0.3965	0.3831	-2.1290
F-statistic	8.98	8.73	8.72	6.71	5.33	1.05
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0388
Effects	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year

Volatility regressions on patenting and forward citations. Observations are on the firm-year level. The sample period is 2000 to 2019. Dependent variables are the stock volatility of daily returns for the firm in the following year. Log patent counts and log patent citation counts include '+1'. In IV models the patent issuances and forward citations are instrumented using a shift-share instrument with the average industry shares of patent filings in USPC classes and the lag number of applications filed in the classes. Standard errors are clustered at the firm level. Robust t-statistics are reported in brackets, $*p < 0.1$,$**p < 0.05$,$***p < 0.01$.

evidence suggests that patents prior to 2000 served a different purpose for the firms in Compustat/CRSP than after 2000.

Trying to differentiate in which cases patents reduce and increase stock volatility, I include in Tables 6 and 7 an interaction term between the main explanatory variable of patent counts and a dummy for firms that are in the respective year in the bottom tercile of the HHI distribution, calculated on three-digit SIC level. This identifies firms in highly competitive industries. The results show that the observed volatility reduction effect of patent issuances is driven by firms in the most competitive industries, while the risk-increasing effect prior to 2000 is not significantly different for the highly

Table 6: Stock volatility to patent issue - HHI interactions, 1985-1999

Dep. Variable	OLS (1)	OLS (2)	OLS (3)	IV (1)	IV (2)	IV (3)
	1985-1999	1985-1999	1985-1999	1985-1999	1985-1999	1985-1999
	lead vola	lead vola	lead vola	lead vola	lead vola	lead vola
low hhi dummy	0.0004	-0.0018	-0.0019	0.0074	0.0007	0.0033
	[0.5726]	[-0.7323]	[-0.7654]	[1.3825]	[0.1691]	[0.5941]
log patent count	0.0001	0.0002				
	[0.3160]	[0.7223]				
log patent count * low hhi dummy	0.0003	0.0003				
	[1.2350]	[0.7946]				
log citation count			0.0001			
			[0.9409]			
log citation count * low hhi dummy			0.0001			
			[0.7922]			
fitted log patent count				0.0359***	0.0451***	
				[2.5964]	[2.5913]	
fitted log patent count * low hhi dummy				-0.0175	-0.0221	
				[-1.3790]	[-1.3304]	
fitted log citation count						0.0151 **
						[2.4824]
fitted log citation count * low hhi dummy						-0.0041
						[-0.6955]
N	50,377	35,391	35,391	14,724	11,227	11,227
R-squared	0.6194	0.6856	0.6856	0.4722	0.4285	0.3610
R-squared (Overall)	0.5173	0.5727	0.5727	0.3256	0.2125	0.1195
F-statistic	6.07	6.07	6.07	4.72	3.42	3.06
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Effects	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year
Controls	N	Y	Y	N	Y	Y

Volatility regressions on patenting and forward citations, interaction for competitive industries. Observations are on the firm-year level. The sample period is 1985 to 1999. Dependent variables are the stock volatility of daily returns for the firm in the following year. Log patent counts and log patent citation counts include '+1'. In IV models the patent issuances and forward citations are instrumented using a shift-share instrument with the average industry shares of patent filings in USPC classes and the lag number of applications filed in the classes. Patenting variables are interacted with a dummy variable that is one if the respective three-digit SIC industry of the firm is in the bottom tercile for industry concentration measured by the HHI index. Standard errors are clustered at the firm level. Robust t-statistics are reported in brackets, $*p < 0.1$,$**p < 0.05$,$***p < 0.01$.

competitive industries. This confirms the view that patents prior to 2000 are more linked to risky growth projects while after 2000 patents serve mostly defensive, anti-competitive purposes.

We can ask next if firms in competitive industries are more likely to invest in risky growth projects that have more technological value. If some of the additional patents issued after 2000 are breakthrough innovations, and thus receive more forward citations from other patents, firms in competitive industries

Table 7: Stock volatility to patent issue - HHI interactions, 2000-2019

Dep. Variable	OLS (1)	OLS (2)	OLS (3)	IV (1)	IV (2)	IV (3)
	2000-2019	2000-2019	2000-2019	2000-2019	2000-2019	2000-2019
	lead vola	lead vola	lead vola	lead vola	lead vola	lead vola
low hhi dummy	0.0022***	0.0019	0.0019	0.0065***	-0.0027	-0.0049
	[4.7293]	[0.7773]	[0.7905]	[3.3340]	[-0.4706]	[-0.7636]
log patent count	-0.0008***	-0.0008***				
	[-4.1719]	[-4.1230]				
log patent count * low hhi dummy	-0.0008***	0.0000				
	[-3.1314]	[-0.0911]				
log citation count			-0.0001			
			[-0.4889]			
log citation count * low hhi dummy			0.0004 **			
			[2.0082]			
fitted log patent count				-0.0081***	-0.0099***	
				[-2.9212]	[-3.1296]	
fitted log patent count * low hhi dummy				-0.0123***	-0.0153***	
				[-3.5140]	[-2.6668]	
fitted log citation count						-0.0210 **
						[-2.5354]
fitted log citation count * low hhi dummy						0.0102***
						[3.5205]
N	52,447	35,503	35,503	22,220	15,659	15,659
R-squared	0.6344	0.6938	0.6936	0.5043	0.5065	0.0353
R-squared (Overall)	0.5638	0.6145	0.6143	0.4149	0.3815	-0.2090
F-statistic	8.99	8.75	8.74	6.93	5.31	2.72
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Effects	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year	Firm+Year
Controls	N	Y	Y	N	Y	Y

Volatility regressions on patenting and forward citations, interaction for competitive industries. Observations are on the firm-year level. The sample period is 2000 to 2019. Dependent variables are the stock volatility of daily returns for the firm in the following year. Log patent counts and log patent citation counts include '+1'. In IV models the patent issuances and forward citations are instrumented using a shift-share instrument with the average industry shares of patent filings in USPC classes and the lag number of applications filed in the classes. Patenting variables are interacted with a dummy variable that is one if the respective three-digit SIC industry of the firm is in the bottom tercile for industry concentration measured by the HHI index. Standard errors are clustered at the firm level. Robust t-statistics are reported in brackets, $*p < 0.1$,$**p < 0.05$,$***p < 0.01$.

might be more willing to invest in them since the upside of moving out of stiff competition outweighs the risk increase. This view is confirmed in Tables 6 and 7 for the specification with forward citation-weighted patent counts as the main explanatory variable: the coefficient for the interaction term halves the magnitude of the (negative) coefficient for log forward citations in the post-2000 period. Thus the risk reduction effect of quality-weighted patent issues is around 17% smaller for firms in highly competitive industries. This might indicate that firms in highly competitive industries are more willing to take up risky growth projects that are more technologically relevant or that the potential for risk reduction is limited for these projects.

6. Conclusion

Patents are options on future projects. They affect directly how the risk profile of firms changes over time. In this study, I investigate how the expansion of the US patent system in the late 1990s led to more defensive patents being issued which in turn contributed to lower stock volatility after 2000 for patenting firms. In contrast, the more narrow patenting system before 2000 issued patents on more radical innovations and led to increased firm volatility. I show that firms in highly competitive industries benefit from more defensive patent issuances after 2000 lowering the risk of disruption by competitors. At the same time, the same firms have more incentive to invest in promising high-risk growth projects to escape competition. I provide a new perspective on how institutional settings such as the leniency of the patenting system have effects on firms, their investment decisions, and financial outcomes. Future research may ask how different types of patents such as process vs. non-process patents affect the risk of firms, and what patenting policies incentivize growth-increasing innovation and not excessive risk-taking.

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