Patent Rights, Innovation and Firm Exit[1]

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Abstract

We study the causal impact of patent invalidation on subsequent innovation and exit by patent holders. The analysis uses patent litigation data from the U.S. Court of Appeals for the Federal Circuit, and exploits random allocation of judges to control for endogeneity of the decision. Invalidation causes patent holders to reduce patenting over a five-year window by 50 percent on average, but the effect is heterogeneous. The impact is large for small and medium-sized firms, particularly in technology fields where they face many large competitors, and for patents central to their technology portfolio. We find no significant effect for large firms. Invalidation also increases permanent exit from patenting by small firms.

Keywords: patents, innovation, small firms, exit, courts

JEL Codes: O31, O32, O34, K41, L24.

1 Introduction

Innovation lies at the heart of high-tech entrepreneurship and economic growth. Modern macroeconomic growth models give a central role to innovation and the competition that generates incentives for it, including the interaction between small entrants and large incumbents in this process (Aghion and Howitt, 1992; Acemoglu, Akcigit, Bloom and Kerr, 2013). At the same time, a large body of microeconomic evidence shows that there is underinvestment in R&D, with social rates of return being more than twice as large as the private rates (Jones and Williams 1998; Bloom, Schankerman and Van Reenen, 2013). This is a primary justification for government support of innovation, and patent rights are one of the key policy instruments for this purpose. It is important to understand whether patents are actually an effective innovation incentive and, importantly, whether they work equally well for small and large firms and in different competitive environments.

A number of economic and legal scholars have raised serious doubts about whether patent rights actually promote innovation, and there is a widespread view that current patent policy, and debates over patent reform, are not based on empirical evidence (Boldrin and Levine, 2013; Burk, 2016). One of the most prominent legal scholars in the area argues that much of the patent policy discussion is 'faith-based', with "participants on both sides of the IP debates increasingly taking out positions that simply do not depend on evidence at all." (Lemley, 2015). In a recent paper, Williams (forthcoming) provides a thoughtful and balanced analysis of the issues and the evidence on how patent rights affect innovation and welfare, and identifying the gaps in our empirical knowledge that need to be filled to reach definitive conclusions. As she puts it, "While patent systems have been quite widely used both historically and internationally, there is nonetheless a tremendous amount of controversy over whether the patent system is – in practice – improving the alignment between private returns and social contributions."

To address this need for more empirical evidence, in this article we analyze how the loss of patent rights affects a firm's level of subsequent innovation, and the likelihood that a firm exits from patenting activity entirely, for small and large firms across a range of technology fields. To do this, we study the impact of judicial invalidation of existing patents on the owner's subsequent patenting activity over a five year window. Our analysis shows that patents have an impact on future patenting for small and medium-sized firms, but we find no evidence of significant impact on large firms. We also show how the effectiveness of patent rights depends on specific features of competition in the technology markets.

From a theoretical perspective, the impact of patent invalidation on future innovation is not obvious. The conventional view is that patents enhance the ability of firms to capture innovation rent, but at the cost of creating a static efficiency loss from higher prices (Arrow, 1962). We show that more complex interactions arise from two sources when innovation is cumulative. The first is complementarity between the current and subsequent generation of innovation: the ability of a firm to innovate in the future and capture the rents from that innovation will depend on the firm's current stock of patents. Second, patent invalidation triggers a potential patent race building on the innovation by opening up the technology to potential competitors. The model developed in this article highlights the trade-offs involved and shows that the qualitative effect of patent rights on future patenting is ambiguous, as it depends on features of the firm and the technological competition they face. Thus empirical analysis is essential to inform patent policy.

Despite its central importance, there are relatively few studies with causal evidence on whether patent rights are an effective incentive for innovation, and the existing studies do not speak with one voice.[1] For example, Budish, Roin and Williams (2015) show that there is more innovation, as measured by clinical trials, on late-stage cancer drugs that have longer effective patent lives (due to shorter regulatory screening times). Similarly, Farre-Mensa, Hegde and Ljungqvist (2015) use the quasi-random assignment of patent examiners to study the impact of patent rights on new start-up firms. They find that a patent grant strongly increases subsequent patent applications and growth, and also raises the probability of an IPO. On the other hand, Sampat and Williams (2015) use quasi-random assignment of patent examiners to study whether human gene patents affect subsequent innovation by the patentee (and others) and find no significant effect. Even more surprising, Baten, Bianchi and Moser (2015) show that the imposition of compulsory licensing on chemical patents by German firms after WWI increased subsequent patenting by the (large) chemical firms that owned them. Our article develops a model which reconciles these apparently contradictory findings in the literature.

Patent rights can affect innovation, especially for small firms, through several channels. First, patents shape the nature of competition in product and technology markets, especially in settings where small firms interact with large incumbents (Spulber, 2013; Aghion, Howitt

[1] In a related strand of the literature, there are studies that use patent renewal data and other approaches to measure the incremental incentives provided by patent rights (Schankerman and Pakes, 1986; Schankerman, 1998; Arora, Ceccagnoli and Cohen, 2008). They show that patents are associated with greater private value derived from inventions. However, these studies do not provide causal evidence on the link between patent rights and the level of innovation.

and Prantl, 2015). While the relationship between patent rights, competition and innovation is theoretically ambiguous, recent research suggests that patents are particularly effective in providing incentives when competition is intense (Aghion et. al., 2005). Moreover, patents are often the key assets that enable small firms to license their innovations to large firms for commercialisation (Gans, Hsu and Stern, 2002). In this way, patents underpin the mark for innovation which in turn facilitates efficient vertical specialization in innovation, commercialization and enforcement of knowledge assets (Galasso, Schankeman and Serrano, 2013).

Second, patents facilitate access to debt and venture capital markets for financially constrained innovators. This is especially relevant to small (and young) firms for whom information asymmetry is severe and patents may be their primary collateralizable asset (Hochberg, Serrano and Ziedonis, 2014). Finally, patents are often used to secure cross-licensing agreements and as bargaining chips to resolve disputes and gain access to patented inputs needed to conduct research (Lanjouw and Schankerman, 2004).

We develop a model that shows how the loss of patent rights affects incentives to innovate. The basic mechanism is as follows: We assume that a firm builds on its stock of existing patents in subsequent rounds of innovation, and that there are diminishing returns in this process. When a patent is invalidated, the firm retains the knowledge embodied in the patent, but the loss of patent protection allows other firms now to exploit this knowledge without a license. The resulting innovation race has an ambiguous effect on the patentee's incentives. The payoff to future R&D investment declines because the competitive rents are dissipated by the patent race. At the same time, the patent race intensifies incentives because of strategic complementarity in R&D – i.e., the firm needs to raise its effort to win the race to commercialize the technology.

The model generates two main predictions. First, the loss of a patent on a core technology – which serves as the basis for subsequent innovation – affects innovation more for small firms than for large firms. This follows from our assumption of diminishing returns to patent portfolio size as an input to cumulative innovation by the firm. Second, for a small firm the impact of losing a core patent will depend on the number of potential licensees for the technology (in the empirical work, we associate this with the number of large firms in the related technology area). The reason is that the patentee is more likely to be able to license the technology and extract greater value when there are more potential licensees.

The main empirical challenge is the potential endogeneity of court decisions to invalidate an existing patent. This can arise in a variety of way, but of particular concern in our setting is that firms which aggressively patent, filing numerous patent applications some of which are of dubious validity, are more likely to experience invalidation by the courts. To address this concern, we adopt (and extend) the identification strategy in Galasso and Schankerman (2015). We study decisions by the U.S. Court of Appeals for the Federal Circuit, which has exclusive jurisdiction in appellate cases involving patents. Each decision is by majority rule of three-judge panels, which are randomly assigned by a computer algorithm. We exploit this random allocation of judges, together with variation in their propensity to invalidate, to construct an instrumental variable for patent invalidation.

It should be noted that patents litigated in the Federal Circuit are typically high value patents, as they have gone through the costly litigation process up to the appellate level. For purposes of studying how patents affect innovation incentives, it is reasonable to start by analyzing Federal Circuit patents because the distribution of patent values is highly skewed (Schankerman and Pakes, 1986) and the incentives generated by these patents are likely to be more important for welfare.

The main findings in the article are as follows. First, the loss of patent rights due to Federal Circuit invalidation causes, on average, a 50 percent decrease in future patenting (in a five-year window) by the focal patentee. This result is robust to a wide variety of specifications and controls. Second, the impact of patent rights depends critically on the size of the firm, the competitive environment and the nature of the technology. The effect is driven by small innovative firms and by firms losing patents on technologies that are core to their research focus. Third, we find that the loss of a patent has a much larger impact on small firm innovation in technology fields where they face many large firms. This is consistent with the idea that patents are especially important in shaping the competition in product and technology markets, and facilitating the licensing of innovations by small firms to larger incumbents for commercialisation, as discussed above. Finally, we show that losing a patent right sharply increases the probability that a small firm exits the market (as indicated by a complete cessation of patenting). This confirms that patent rights affect not only the level of innovation by ongoing firms, but also the extensive margin of firm survival and thus can be critical for high-tech entrepreneurship.

The magnitude and the heterogeneity in the effect of patent rights we find are not obvious *a priori*. Even in a sample like ours, where patents are valuable as revealed by the substantial litigation cost, we show that only a subset of invalidation cases have any significant impact on future patenting. The findings are consistent with the idea that patents are especially important in shaping the competition in product and technology markets, and facilitating the licensing of innovations by small firms to larger incumbents for commercialization. We think that documenting such heterogeneity is important, and highlights the need of additional research to inform policy makers.

Finally, we combine the estimated effect of patent rights on the *patent holder* from this paper, together with the impact on innovation by *other firms* from Galasso and Schankerman (2015), to perform illustrative computations assessing the overall impact of patent invalidation for the patents in our sample. We conclude that the combined effect of patent rights litigated at the Federal Circuit was to block subsequent innovation by a modest amount, i.e. if all these patents were invalidated, follow-on innovation would have been somewhat higher. From a more law and economics perspective, we also analyze what the overall effect of having the Federal Circuit Court was, relative to not having any appellate court. We conclude that the impact of its decisions to reverse the lower courts (both invalidity and validity rulings) was to stimulate subsequent patenting marginally (by less than two percent).

From a broader innovation perspective, this article shows that the loss of patent rights (on core technologies) sharply reduces innovation, and increases the likelihood of exit, by small firms, but not for large firms. This sharp difference between small and large firms is consistent with recent macroeconomic research showing that R&D subsidies are more effective when targeted at small innovative firms rather than large incumbents (Acemoglu et. al., 2013). Taken together with our earlier study on cumulative innovation (Galasso and Schankerman, 2015), this article documents that patent rights have heterogeneous effects on innovation by both the patentee and other competing firms. This research raises serious questions about whether a 'one size fits all' patent system is desirable. While the practical challenges of designing a more nuanced patent system should not be underestimated, more research on these issues seems warranted.

The article is organized as follows. Section 2 develops a model showing how loss of a patent right can affect innovation incentives for subsequent innovation. Section 3 describes the data set. Section 4 discusses the econometric specification and identification strategy. In Section 5 we present the baseline estimates of the effect of patent invalidation on innovation. In Section 6 we show that the impact of patent rights is heterogeneous, differing sharply for small and large firms, and core and peripheral patents. Section 7 tests several different mechanisms that might explain the impact on small firms. Section 8 shows that the loss of patent rights powerfully affects the exit probability for small firms. Section 9 provides a preliminary assessment of the net effect of patent rights and the impact of the Federal Circuit Court. We conclude with a brief summary of findings and their policy implications.

2 Analytical framework

We model the innovation process in two stages. In the first stage a firm invests in R&D which generates a new technology stochastically. In the second stage the firm commercializes the innovation. The firm is endowed with c patents on 'core' technologies and p on 'peripheral' ones. We define core technologies as those that facilitate the development of subsequent innovation. By contrast, peripheral technologies increase the innovation rent that the firm can capture from its core technologies, but do not affect the success probability of follow-on innovation.[2] Let $n = p + c$ denote the total number of patents held by the firm. We assume that the number of core patents a firm owns is a fixed proportion of n, i.e. $c = \lambda n$.[3]

The probability of developing a new innovation when the firm owns c valid core patents is given by $rV(c)$ with $V(c) = 1-(1-\alpha)^c$ and $\alpha < 1$. This formulation embodies complementarity between the existing stock of core technologies, c, and current research investment, r, and implies diminishing returns of core knowledge on the marginal product of R&D, which is a property of most standard production functions. $V(c)$ can be interpreted as the likelihood of getting at least one idea, when ideas are independent draws with probability α from each of the (symmetric) core patents. In the case in which multiple ideas originate from the core patents, we assume that the firm is restricted to develop only one.[4] The cost of R&D is $C(r) = r^2/2$.

A patent on a core technology allows the patentee ('focal firm') to block other innovators

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[2]The original distinction between core and peripheral technologies goes back to the sociologist Thompson (1967), who argued that the role of peripheral technologies is to seal-off core technologies from 'environmental influences'. From an economic perspective, this could take the form of diversifying revenue sources that build on core technologies (entering different product market niches using the same core knowledge) to protect the core idea from idiosyncratic demand shocks in different applications. The economics and management literatures emphasise the related concept of core competencies in shaping a firm's strategies and competitiveness. A recent empirical study shows that the distinction between core and peripheral patents is important in explaining knowledge spillovers through job mobility (Song, Almeida and Wu, 2003).

[3]This assumption simplifies the analysis but is not required. Our results are robust to any strictly increasing function $c = \lambda(n)$ with $c \leq n$.

[4]Our results generalize to the case where the expected number of commercialized technologies increases less than linearly in c. This assumption is consistent with the management literature documenting a tendency for large firms to exploit only a limited fraction of the ideas generated by their scientists (Cassiman and Ueda, 2006; Cohen, 2010).

from building on it. If the patent is invalidated, the focal firm still retains the knowledge about the technology which it can use in developing the next innovation. However, the loss of the patent right means that the firm can no longer block other firms from using the knowledge and thus induces a patent race for the follow-on innovation. The focal firm innovates if it successfully builds on the remaining valid patents or it wins the patent race building on the invalidated patent. The probability that the focal firm innovates becomes $rI(c)$ with

$$I(c) = 1 - (1-\alpha)^c - \alpha(1-\alpha)^{c-1}(1-\chi(r))$$

where $\chi(r)$ captures the probability of winning the patent race for the follow-on technology which builds on the invalidated patent. The term $(1-\alpha)^c$ is the probability of not getting an idea from any of the core patents and $\alpha(1-\alpha)^{c-1}(1-\chi(r))$ is the probability of getting an idea only from the invalidated patent and losing the patent race. We assume that $\chi(r) = r\chi$ where the parameter $\chi < 1$ can be interpreted as the level of rivalry in the patent race (Loury, 1979).

Commercialization of the new technology yields a revenue equal to $\overline{\Theta} < 1$. If the firm has $n \geq \kappa$ patents, it can commercialize the technology itself. Firms with $n < \kappa$ commercialise their innovation through licensing. This captures the idea that internal commercialisation is less profitable for small firms. This can arise in at least two ways. First, small firms are less likely to have access to the requisite complementary assets. Second, large patent portfolios increase the value from commercialization by providing a 'buffer' to protect products incorporating the firm's (core) technologies and enhancing the ability of the firm to enforce patent rights more effectively (Lanjouw and Schankerman, 2004).

In the case of external commercialization, the firm can negotiate a licensing deal with one of N symmetric firms, each of whom needs the technology with probability z. The firm bargains with potential licensees sequentially. If a license is struck, the firm earns $\overline{\Theta}$. The timing of the licensing game is as follows. The firm approaches one potential licensee and makes a take-it-or-leave-it offer for an exclusive license. If the licensee accepts, the licensing subgame ends. If the offer is rejected, the patentee moves to the next firm and payoffs are discounted by δ. We let $L(N, \overline{\Theta}) < \overline{\Theta}$ denote the expected payoff of the innovator from this licensing subgame.

A firm that retains the litigated patent sets its R&D investment to maximize $\Lambda V(c)r - r^2/2$ where $\Lambda = \{L(N, \overline{\Theta}) \text{ if } n < \kappa, \overline{\Theta} \text{ if } n \geq \kappa\}$ is the value of commercialising the new technology. If the patent is invalidated, the firm sets R&D to maximise $\Lambda I(c)r - r^2/2$. The optimal level of R&D with c valid patents is $r_V^*(c) = \Lambda V(c)$, and the optimal level in the case of invalidation is

$$r_I^*(c) = \Lambda \frac{1-(1-\alpha)^{c-1}}{1-2\Lambda\chi\alpha\,(1-\alpha)^{c-1}}.$$

Defining $\Delta r = r_V^*(c) - r_I^*(c)$, we obtain the impact of patent invalidation on R&D by the firm:

$$\Delta r = \Lambda\left(1-(1-\alpha)^c - \frac{1-(1-\alpha)^{c-1}}{1-2\Lambda\chi\alpha\,(1-\alpha)^{c-1}}\right).$$

The following proposition summarizes the predictions of the model about how patent invalidation affects innovation by the patent owner.

Proposition 1 *There exists: (i) an* $\chi^* > 0$ *such that, for* $\chi < \chi^*$, $\Delta r = r^V - r^I > 0$ *and* $\frac{d\Delta r}{dN} > 0$*; (ii) an* $\bar{n} > \kappa$ *such that* $|\Delta r|$ *is larger for firms with* $n < \kappa$ *than for firms with* $n > \bar{n}$.

Proof. See Appendix A.1. ■

The main result of the model is that invalidation has an ambiguous effect on innovation incentives. Loss of a core patent has two countervailing effects (there is no effect for peripheral patents, by assumption). The number of ideas which the firm can develop in the absence of external competitive pressure declines when it loses a patent, and this reduces incentives. However, invalidation opens up the technology field and induces a patent race. Because the probability of winning the race increases with the R&D investment, invalidation also has a positive effect on innovation incentives. Which effect dominates depends on the intensity of the competition in the patent race, reflected in the parameter χ.

Part (i) of the Proposition says that when the firm faces intense competition in the patent race (low χ), the first effect dominates, so invalidation reduces follow-on innovation by the patent holder. When R&D investment by the patent holder substantially affects the likelihood of winning the patent race (low competition, high χ), invalidation increases follow-on innovation. This highlights that the impact of patent rights depends on the characteristics of the competitive environment. In addition, for a small firm facing an intense patent race, the impact of losing a core patent is larger when there are more potential licensees for the technology (in the empirical work, we associate this with the number of large firms in the related technology area). The intuition is that more potential licensees make it more likely that the technology will be licensed (in addition, competition among licensees raises the rent the innovator can extract, though this element is not in the formal model).[5]

[5] While our model takes χ as exogenous, one may expect $\chi'(N) < 0$ because large firms with a diversified research portfolio are best positioned to exploit opportunities and flexibility to shift the focus of their research. This would reinforce our result that the impact of patent invalidation is larger when there are more potential licensees for the technology.

Part (ii) says that there is a size threshold, $\bar{n} > \kappa$ such that the loss of a core patent has a greater impact on small firms ($n < \kappa$) than on large firms ($n > \bar{n}$) – and the impact goes to zero as firm size increases. Because internal commercialization allows large firms to extract greater profits from their patents, the effect of invalidation is stronger for large firms than small firms. However, the concavity of $V(c)$ and $I(c)$ means that the marginal benefit of owning an extra patent declines as the portfolio size increases. For n large enough, the second effect dominates and the loss of a core patent affects innovation by small firms more than large firms.

In Appendix A.2 we show that these predictions hold for a large class of bargaining games, and in particular do not depend on the take-it-or-leave feature of the licensing negotiation. In Appendix A.3 we also show that, when competition in the patent race is intense ($\chi(r)$ is very small), the comparative statics of the model are robust to a more general specification of the innovation production process $V(c, r)$, $I(c, r)$, $\overline{\Theta}(n)$ and $C(r)$, under some mild conditions on their curvature.

3 Data

The empirical work is based on an extended version of the data used in Galasso and Schankerman (2015), which combines the decisions by the Federal Circuit Court with the U.S. Patent and Trademark Office (USPTO) patent dataset.

The Federal Circuit, established by the U.S. Congress in 1982, has exclusive jurisdiction over appeals in cases involving patents (and claims against the federal government in various subject matter) and consists of twelve judges appointed by the President. Judges are assigned to patent cases through a computer program that randomly generates three-judge panels, subject to their availability and the requirement that each judge deals with a representative cross section of the fields of law within the jurisdiction of the court (Fed. Cir. R. 47.2). Decisions are taken by majority rule.

We obtain the full text of patent decisions by the Federal Circuit from the LexisNexis QuickLaw portal. This contains a detailed description of the litigated dispute, the final decision and jurisprudence used to reach the decision. Using keyword searches, we identify each case involving issues of patent validity from the establishment of the court in 1982 until December 2010. For each case we record the following information: docket number, date of the decision, patent identification number, identities of the three judges involved, the plaintiff and the defendant. The final sample covers 1379 patent invalidity decisions. Information about each patent in the sample is obtained from the USPTO patent database.

In this article we focus on how patent invalidation affects innovation at the *firm* level. To do this, for each owner of patents litigated at the Federal Circuit, we use a number of data sources to construct the patent portfolio in the year of the Federal Circuit decision and subsequent patenting activity. The USPTO data provide an assignee identification number, our main tool to track patenting activity, only for patents granted after 1976. For patents granted earlier, we retrieve data through manual searches on 'Google Patents'. Assignee numbers are not provided for patents owned by individual inventors. For each of these patents, we identify the disambiguated name of the first inventor, exploiting the data described in Li et. al. (2014). We then track patenting activity over time by identifying patents with inventors having the same name, city, country and zip-code of the first inventor of the litigated patent. Finally, assignee identification numbers are not available for patents classified as 'unassigned' by the USPTO. For these patents, we identity the patentee from the text of the Federal court decision.[6]

The main variables used in the empirical analysis are described below.

PostPatents: number of patent applications by the patent owner (assignee) in a five year window after the Federal Circuit decision. This is our primary measure of innovation. Because of granting delays, we date the patents using the year in which they were applied for.

Invalidity: a dummy variable equal to one if the Federal Circuit invalidates at least one claim of the litigated patent. This is the main explanatory variable of interest, and represents the removal of patent rights.

PrePatents: number of patents applied for by the patent owner in the ten years preceding the Federal Circuit decision.

Technology field: dummy variables for the six technology classes in Hall, Jaffe and Tratjenberg (2001) – chemicals, computers and communications, pharma, electrical and electronics, mechanicals, and others. We also employ a narrower definition based on the 36 two-digit subcategories.

Table 1 provides summary statistics. The Federal Circuit invalidates in 40 percent of cases. On average the cases involve firms with 336 patents in their portfolio and that apply for

[6] For each unassigned patent, we identify the names of the parties involved in the suit. If one of the litigants is also an inventor listed on the patent, we classify the patent as assigned to that individual. If litigants are firms, we exploit the USPTO re-assignment data to confirm that the patent was assigned to one of the firms and use the USPTO assignee data to retrieve an assignee number of the acquiring firm. We dropped patents where we were unable to match the patent to an entity with confidence.

214 patents in the five years after the decision, but the portfolio distribution is highly skewed (median is 14, and 21 percent of the firms have only one patent).

Federal Circuit cases represent a selected sample of highly valuable patents. For example, in January 2005 the Federal Circuit invalidated the patent for the once-a-week version of Merck's Fosamax, the leading osteoporosis drug in the market at that time. Galasso and Schankerman (2015) show that commonly-used indicators of patent value – e.g., the number of claims and citations per claim – are higher for litigated patents than others, and even higher for those appealed to the Federal Circuit. However, for the purpose of studying whether patent rights provide important innovation incentives, it is reasonable to start with privately valuable patents as they are also likely to be of greatest importance for welfare. In addition, our identification strategy only applies to this sub-population, since unfortunately judges are not always randomized in cases at the lower (district court) level.

Unlike Galasso and Schankerman (2015), this article is conducted at the *firm-case level* because we are interested in identifying the impact of invalidation on innovation by the firm that loses its patent right. This requires collapsing the dataset from patent-level observations to firm-level units of analysis. For about 79 percent of the cases in our sample, firms litigate only one patent, but the remaining cases involve multiple patents owned by the same firm. For multi-patent cases, we define the invalidity dummy as equal to one if at least one patent is invalidated, and allow multiple age and technology field dummies in order to characterize all the patents in the case.[7]

4 Econometric specification and identification strategy

The final dataset is a *cross section* where the unit of observation is a Federal Circuit case involving firm i.[8] Our main empirical specification is

$$log(PostPatents_i + 1) = \beta \ Invalidity_i + \lambda' X_i + \varepsilon_i \tag{1}$$

[7] In the sample, 158 cases involve two patents held by the same firm, 47 have three patents, 14 involve four, and 8 cases have more than five patents. Results are robust to redefining the age of the litigated patents as the average (integer) age, and the technology field as the modal field of the patents in the case.

[8] Even though we have some cases of the same firm more than once, we use the subscript i to denote the case to emphazise that our sample is a cross section.

where X denotes control variables. We include a dummy control variable for observations where the firm has zero patenting in the five-year window after the decision.[9] The coefficient β captures the effect of invalidation on subsequent patenting by the firm: $\beta < 0$ means that firms react to patent invalidation by reducing their subsequent patenting, and thus that patent rights have a positive impact on innovation. To control for firm heterogeneity that may be correlated both with the court decision and later patenting, we include the number of patents received prior to the Federal Circuit decision (*PrePatents*), and a full set of age, decision year and technology field dummies. We also include dummies which capture the most extreme repeat litigants (i.e. firms which appear in 4 or 5 litigation cases in our sample) and an additive dummy for the largest firms in our sample (top 2 percent of portfolio size). Controlling for these outliers is important because the patenting strategies of large firms and repeat litigants may differ substantially from those of other firms in the sample – e.g., the largest firms are likely to invest more in defensive patenting to resolve disputes (Lanjouw and Schankerman, 2004), while the extreme repeat litigants in our sample are likely to have idiosyncratic characteristics.[10] We report robust standard errors clustered at the litigant level.

The main empirical challenge is the potential endogeneity of the Federal Circuit decision to invalidate a patent. The greatest concern in our context is that firms differ in their propensity to patent their innovations. Firms that aggressively patent, filing numerous patent applications some of which are of dubious validity, may be more likely to experience invalidation by the courts. Conversely, firms that are more selective in patenting are more likely to have their patents upheld. This would generate positive correlation between ε_i and $Invalidity_i$ in equation (1) and thus an upward bias in the OLS estimate of β. There could also be measurement error in our measure of invalidation, creating attenuation bias toward zero (though we show robustness to alternative definitions below).

To address endogeneity, we need an instrument that affects the likelihood of patent invalidation but does not belong directly in the patenting equation. We exploit the fact that judges in the Federal Circuit are assigned to patent cases randomly by a computer program. This ensures that judges with high propensity to invalidate are not assigned to cases because

[9] In column 4 of appendix Table A2 we show that the results are robust (and stronger in magnitute) without this dummy.

[10] Controlling for these outliers reduces the residual variance of our dependent variable and helps to sharpen the statistical precision of our estimates. For more details about the repeat litigants and their characteristics see Appendix A4.

of unobservable characteristics that are correlated with firm patenting. Randomization of *judges* is not sufficient to ensure *decisions* are random, however, because information that becomes available to the judges during the litigation process case might be correlated with future patenting of the firm. The instrument we construct below also takes this concern into account.

Our instrumental variable, the Judges Invalidity Propensity (*JIP*) index, is defined for each case involving firm i as

$$JIP_i = f_i^1 f_i^2 f_i^3 + f_i^1 f_i^2 (1 - f_i^3) + f_i^1 (1 - f_i^2) f_i^3 + (1 - f_i^1) f_i^2 f_i^3$$

where f_i^1, f_i^2, f_i^3 are the fractions of votes in favour of invalidity by each of the three judges assigned to the case calculated for all decisions *excluding* the case involving firm i. In other words, the decision for the focal firm does not enter into the computation of the instrument for that decision.[11] This feature ensures that any case-specific information that might be correlated with the decision and future patenting is removed.

Of course, this instrument works only if judges have different propensities to vote for patent invalidity. Galasso and Schankerman (2015) show that the propensity to invalidate patents varies widely among judges over the sample period, ranging from a low of 24.4 percent to a high of 76.2 percent. This is confirmed in the distribution of the *JIP* index across cases, which has a mean of 0.35 but varies from 0.16 to 0.54.[12]

Our estimation procedure instruments the *Invalidity* dummy with the predicted probability of invalidation obtained from the probit model $\widehat{P} = P(JIP, X)$. When the endogenous regressor is a dummy, this estimator is asymptotically efficient in the class of estimators where instruments are a function of *JIP* and other covariates (Wooldridge, 2002). Specifically, we estimate the following two-stage model:

$$Invalidity_i = \alpha \widehat{P}_i + \theta' X_i + u_i \tag{2}$$

$$log(PostPatents_i + 1) = \beta \ \widehat{Invalidity}_i + \lambda' X_i + \varepsilon_i \tag{3}$$

[11] In Galasso and Schankerman (2015) we show that, under plausible assumptions on the dispersion of private information, *JIP* provides a consistent estimate of the probability of invalidation in a strategic voting model where the evidentiary threshold is interpreted differently by different judges.

[12] We use the term 'bias' to refer to this variation in the propensity to invalidate, but it can also reflect differences in their expertise and ability to process information in the different technology fields covered by the patent cases. Part of the variation in *JIP* may reflect year effects because 'biased' judges may be active only for a limited period of time. To address this, we regressed *JIP* against year fixed effects and find that they explain only about 11 percent of the variation.

where the set of controls X is the same in both stages.

In Appendix Table A.1 we summarize the relationship between patent invalidation and judge panels in our data. Probit models confirm a strong positive link between patent invalidation and the *JIP* index, and this is robust to including a set of controls for patent characteristics. Moreover, OLS regressions with *JIP* as dependent variable confirm the randomization of judges to cases. The portfolio size of the patent owner, the age of the patent and its technology class are all unrelated to *JIP*. Only the year effects are significantly correlated with JIP, which arises mechanically because some of the 'biased' judges are active only for a subset of years.[13]

5 Empirical results

Table 2 examines how Federal Circuit invalidation affects subsequent patenting by the focal firm. Column 1 presents OLS estimates of the baseline specification relating the number of patent applications in a five-year window after the court decision to the invalidity dummy and additional controls. There is no statistically significant correlation between patent invalidation and future patents. This result is not causal, however, since we might expect unobservable factors to affect both the invalidity decision and subsequent innovation. This intuition is confirmed by a Rivers-Vuong test that provides strong evidence against the exogeneity of invalidation.[14]

In column 2 we instrument the *Invalidity* dummy with the predicted probability of invalidation obtained from the *firm-level* probit regression from column 2 of Table A1 (we report the first-stage regression for this specification in column 1 of Table A7). The IV estimate of β – which gives the local average treatment effect of invalidation – is highly significant and large. Exponentiation of the coefficient implies that patent invalidation causes a reduction in firm patenting of about 50 percent in the five years following the Federal Circuit decision.[15] Interestingly, the size of this effect is very similar to the finding in in Farre-Mensa, Hegde and Ljungqvist (2015), who study the impact of patent grant on a sample of start-up firms,

[13] A battery of additional tests confirming the exogeneity of the instrument is presented in Galasso and Schankerman (2015).

[14] Following Rivers and Vuong (1998), we regress *Invalidity* on *JIP* and the other controls in a linear probability model. We construct the residuals ($\widehat{v}$) for this model and then regress subsequent patenting on Invalidity, $\widehat{v}$ and other controls. The coefficient on $\widehat{v}$ is positive and statistically significant.

[15] Under U.S. law, the patentee does not generally owe damages or attorney fees to the patent challenger, and licensees do not recover past royalties if a patent is invalidated (Geffner v. Linear Rotary Bearings, Inc., 124 F.3d 229, Fed. Cir. 1997). Thus, our estimate of the incentive effect is not confounded by additional financial obligations associated with invalidation.

exploiting the quasi-random assignment of examiners at the USPTO. We show later that this local average treatment effect hides important heterogeneity, with the impact of patent rights strongly depending on characteristics of the patentee and competitive landscape. Before doing that, we perform a variety of tests to confirm the robustness of our main finding.

First, in the baseline specification the *Invalidity* dummy is defined as one if *any* of the patents litigated in the case is invalidated. In multi-patent cases, this classification may generate measurement error. We conduct two tests to check whether our estimates are sensitive to the treatment of invalidity decisions involving multiple patents. In column 3 of Table 2 we adopt a more restrictive definition of invalidation, where the dummy is one only if *all* the patents in a case are invalidated. With this more stringent definition, the fraction of cases in which invalidation takes place drops from 40 to 36 percent.[16] There is essentially no change in the estimated effect of invalidation. Additionally, in column 4 we drop the cases involving multiple patents from the sample. Again the coefficient is very similar to the baseline estimate, confirming that our finding is not sensitive to the treatment of multi-patent cases.

Second our sample contains 240 cases involving repeat litigants. In about 75 percent of these cases, the spell between the two Federal Circuit decisions is less than 5 years. This is a concern since the impact of the decision of the court is potentially contaminated by another decision taking place in the same time frame. To address this concern, in Appendix Table A2 we present the estimates when we drop cases for which the five year window after the decisions overlaps with another case for the same patentee. The estimated effect of invalidation is stronger (though not statistically different) from the one in our baseline. We also re-estimated dropping all cases with repeat litigants and again the coefficient is very similar to the baseline estimate.[17]

There is also a concern that some Federal Circuit decisions may involve rulings that limit the scope of patentable subject matter rather than simply assessing the validity of the focal patent. To address this, we identified the most important Federal Circuit decisions that relate

[16] About 50 percent of cases involving multiple patents result in no patents being invalidated, and 32 percent result in the invalidation of all patents in the case. Thus the two invalidation measures differ in only about 40 cases.

[17] We also re-estimated a specification of the baseline model that adds an interaction effect between the invalidity dummy and a dummy for extreme repeat litigants. The point estimate of the invalidity effect is -0.529 (standard error of 0.29), which is similar to and not statistically different from the baseline estimate given in column 2 of Table 2. The estimated coefficient on the interaction variable is very small and statistically insignificant, -0.053 (standard error 0.71). In short, we find no evidence that the patent invalidation effect is different for these extreme repeat litigants.

to patentable subject matter during our sample period. Dropping those decisions (only 3 in our sample) and re-estimating the model we obtain coefficients that are nearly identical to the baseline estimates.

Finally, there are 237 cases where we cannot directly retrieve an assignee number from the USPTO data based on the patents litigated in the case. As described in Section 3, for these observations we identify the patentee from the disambiguated name of the inventor and by manual searches on Google patents. In Appendix Table A2 we confirm that our baseline results are robust to dropping these manually-cleaned observations from the sample.

6 Unbundling the effect of patent rights

The preceding analysis shows that patent rights are an important innovation incentive, on average. However, the model developed in Section 2 predicts that the impact of patent rights should depend on characteristics of the patentee (small vs large) and technology (core vs peripheral patent). In this section we unbundle the average effect of patents and explore these, and other, dimensions of heterogeneity.

Small vs large firms

We first test the hypothesis that innovation incentives from patent rights are more important for small patentees than large ones. To do so, we define a 'large firm' dummy variable equal to one for firms in the top quartile of our sample in terms of patent applications in the ten years prior to the Federal Circuit decision (this threshold corresponds to 108 patents).[18] Thus, in the analysis that follows it is best to think of our 'small firm' sub-sample as representing both small and medium-sized firms.

Table 3 present IV regressions that allow for differential impacts of patent rights for small and large firms. In columns 1 and 2, split sample regressions of the baseline model reveal a strong negative effect of invalidation on small firms, but no significant effect for large firms. Column 3 presents a full sample regression that allows the invalidity effect to differ for small and large firms.[19] Again we find no evidence of any effect for large firms – the point estimates

[18] Over the decade 1991-2001, in the aggregte USPTO data only 0.05 percent of firms are large according to this definition. If we drop invididuals and unassigned patents, the fraction is about one percent. However, large firms account for about 50 percent of patenting activity in that period.

[19] To estimate the regression in column 3, we follow Wooldrige (2000) and exploit a two-stage procedure. In the first stage Invalidity×Small is regressed on instruments $\widehat{P}\times$Small and $\widehat{P}\times$Large and other controls. Similarly, Invalidity×Large is regressed on instruments $\widehat{P}\times$Small and $\widehat{P}\times$Large and other controls. In the second stage,

are small, though with large standard errors. By contrast, loss of a patent causes a large and statistically significant reduction of 48 percent in future patenting by small firms, and the two coefficients are statistically different from each other at the 0.05 level.

We did additional regressions that vary the threshold portfolio size to define large firms, which we report in columns 1 and 2 of Appendix Table A3. The results in Table A3 are robust to these alternative thresholds: the invalidation coefficient for small firms remains large and highly significant, but there is no evidence of any effect for large firms. In particular, the difference between the impact for small and large firms holds even if we set the portfolio threshold for large firms as low as 30 patents. But interestingly, when we raise the threshold to 150 patents, the coefficient of invalidation for small firms remains significant, though somewhat smaller, and again it is statistically insignificant for large firms. For both thresholds we reject the hypothesis that the coefficients for small and large firms are the same (p-values=0.03 and 0.01, respectively). These experiments indicate that the importance of patent rights for follow-on innovation is not limited to very small firms, but also extends over the middle range of firm sizes.

To this point we define firms size based on the number of patents in its portfolio. We also checked whether this finding holds if we define firm size in relative, rather than absolute, terms. To do this, we reclassify firms as small or large on the basis on their patent portfolio size relative to other patentees in the same (two-digit) technology field. Column 4 in Table 3 presents the parameter estimates using this classification: the results are nearly identical to the coefficients in column 3.

We also examine a more traditional measure of firm size, the number of employees. To do this, we use USPTO data which requires firms to report their 'small entity status' (less than 500 employees) when they pay patent renewal fees.[20] These data are available only for patents filed on or after December 12, 1980, which are about 70 percent of our sample. Roughly 35 percent of the matched patentees are classified as small entities and nearly all of them (97 percent) have a portfolio smaller than 108 patents. However, only 36 percent of large entities have more than 108 patents in their portfolio. Column 3 in Table A3 reports a regression based on the small

the predicted values from these regressions are used to replace the two endogenous variables. Our specifications include the direct effect of the large dummy along with the interactions with the invalidity dummy.

[20] In an attempt to obtain a finer measure of firms' employment, we matched our data with Bureau Van Dijk (ORBIS) data. Unfortunately, matching was successful only for a very small fraction of our sample because the ORBIS data are very sparse for the early part of our sample period.

entity status which shows that the invalidation effect does not vary with employment size, as measured here, but its dependence on the size of the firm's patent portfolio remains robust.

Core vs peripheral patents

The model in Section 2 distinguishes between core and peripheral technologies, building on ideas in the sociology and management literatures. Core technologies, and the associated patents and business models, create the sustainable competitive advantage for the firm, with peripheral technologies/patents typically building on the core to extract greater value and provide a protective buffer (Thompson, 1967). Our model assumes that future innovation builds *only* on core technologies, which implies that only the loss of a core patent would affect incentives for follow-on innovation by the patentee. The more general point is that we expect patent rights over a core technology to be more important for subsequent innovation than peripheral patents.

We investigate this hypothesis by constructing two measures of core patents. The first is based on whether the litigated patent falls in a technology field that represents the main focus of the firm's patenting activity. We identify the (two-digit) technology field of each patent in our sample and compute the share of the patentee's portfolio belonging to the 'focal' field where the litigated patent is assigned. On average, the litigated patents in our sample belong to technology fields which account for roughly 61 percent of the patenting of the firm, but there is substantial variation in field shares (standard deviation = 0.36). For about 37 percent of litigated patents, all of the firm's portfolio is in the same technology field, but for about 12 percent the share is below 10 percent. We define a dummy variable, $Core$=1 if the firm litigates a patent that belongs to a technology field accounting for at least 66 percent of the firm's patenting (i.e. share above the median). For multi-patent cases, we set $Core$=1 if the case involves at least one core patent.

The second measure exploits the pattern of self-citations made by the patentee. We construct the ratio between the self-citations received by the focal patent before the Federal Circuit decision and the maximum number of self-citations that the focal patent could have received before the decision.[21] On average, patents in our sample receive 8 percent of the maximum possible self-citations and about 60 percent of the patents receive no self-citations. The dummy variable $Core$ is set equal to 1 if the firm litigates a patent with a fraction of

[21] This is equivalent to the degree centrality of the patent in the network generated by the patents applied for by the patentee between the grant of the focal patent and the Federal Circuit decision (Jackson, 2008).

self-cites above the 75th percentile. Also for this measure, in multi-patent cases we set *Core*=1 if the case involves at least one core patent.

Table 4 presents estimates of the invalidation effect for core and peripheral patents. In columns 1 and 2 we present the estimates based on these two alternative measures of *Core.* The results are striking. In both cases it is only the loss of core patents that causes a reduction in follow-on innovation. There is no statistically significant effect for the invalidation of peripheral patents, and we reject the hypothesis that the coefficients are the same for small and large firms (p-values= 0.03 and 0.07, respectively).

We conduct several robustness checks. First, we construct the share of patents in the focal field exploiting a finer classification, the three-digit USPTO classes. Litigated patents belong to (three digits) technology fields that account for about 54 percent of the firm's patenting on average (standard deviation = 0.41). As before, we set *Core*=1 if the firm litigates a patent in a field with share above the sample median. The estimated coefficients (unreported) are nearly identical to those in column 1. Second, in Appendix Table A5, we vary the cut-off share used to classify a patent as core using the two-digit technology classification. As we increase the threshold from 0.25 to 0.75 the estimated effects increase monotonically. This indicates that the loss of a core patent is most damaging to innovation when the firm is highly specialized in the technology field (as before, losing a non-core patent has no significant impact).

Low vs high value patents

We also examine whether invalidation of more valuable patents has a stronger impact on subsequent patenting. Follow-on innovation incentives may be affected not only by invalidation of patents on core technologies that future innovation builds on, but also by the loss of revenue, especially for small, cash-constrained firms that finance innovation with internal funds. To consider this, we examine whether invalidation of more valuable patents has a stronger impact on subsequent patenting. We construct a measure of patent importance exploiting the number of citations received by the patent from other firms (non-self cites) before the Federal Circuit decision. To take into account that the citation profile of patents varies across technology areas and depends on the age of the patent (Mehta et al, 2010), we filter the citations with age dummies and 32 technology subcategory effects.

In column 3 of Table 4 we define a patent as *High Value* if it has (filtered) citations above the 75th percentile in our sample. In column 4 we use the 90th percentile as the threshold. These regressions show that invalidation of more valuable patents has a stronger negative impact on future patenting. Invalidation of low-value patents does not have a statistically significant effect, but the estimates has a large standard error; we can reject that the equality of the impact for the low and high value patents only at the 10 percent level.

Of course, there is the concern that the *High Value* dummy may simply capture core patents. This is not supported by the correlation between *Core* and *High Value,* which is only -0.01; the fraction of core patents is essentially the same within the sets of high and low value patents. To confirm this, we run an IV regression with separate interactions between invalidity and the high value dummy, and invalidity and the core patent dummy. The (unreported) coefficients on both interaction terms are negative and statistically significant. This reinforces the idea that the two variables capture conceptually distinct characteristics of the patent, and that *Core* is not simply a proxy for *High Value*.

7 Explaining the impact for small firms

The empirical results show that patent rights are critically important for innovation by small firms. In this Section we investigate three potential explanations for this finding. First, patents can soften the impact of product market rivalry with large firms and improve the ability of small firms to license their innovation to large firms for commercialisation (Gans, Hsu and Stern, 2002; Gans and Stern, 2003). Second, patents may enhance the ability of small firms to access debt and venture capital finance (Conti, Thursby and Thursby, 2013; Hochberg, Serrano and Zeidonis, 2014). Finally, patents serve as valuable bargaining chips to get access to patented inputs needed for research and help resolve disputes through cross-licensing and other arrangements (Lanjouw and Schankerman, 2004; Galasso, 2012). We want to identify which of these channels are important, not least because they have different policy implications.

Competition with large firms

Patent rights can be crucial for small innovators when they face competition from larger, established firms in technology (and product) markets. There are three reasons for this. First, product market rivalry is likely to be more intense when there are many large firms active in the field. While the relationship between patent rights, competition and innovation is theoretically ambiguous, recent research indicates that patents are particularly important when competition is intense (Spulber, 2013; Aghion, Howitt and Prantl, 2015). Second, the presence of multiple large firms increases the bargaining power of small innovators, and thus the licensing rent they can extract from a patented innovation. Third, large firms are likely to be well-positioned to compete in developing and commercializing innovation that builds on an invalidated patent (thus undermining the original patent owner in the follow-on patent race). This is so because large firms have the requisite complementary assets and greater flexibility in directing their research efforts (Gans and Stern, 2003).

For these reasons, we expect patent invalidation would be more damaging to innovation incentives for small, high-tech firms that operate in fields with many established large firms. To test this hypothesis, we need a measure of the potential competitors among large firms in the technology field of the litigated patent ('focal field'). We identify all firms that have a portfolio of at least 75 patents, in the ten-year window preceding the Federal Circuit decision, and at least 50 percent of their portfolio in the two-digit technology area of the litigated patent. On this measure, the mean number of large firms active in the focal technology field is 38 (median = 13). We then define a dummy variable *Few Large Firms=1* if the number of large patentees in the focal field is in the first quartile of the sample (corresponds to 5 large firms).

Column 1 in Table 5 presents the IV estimates of the invalidation effect for small firms operating in a focal technology field with few versus many large patentees. The results show that patent invalidation reduces innovation only when small firms are in technology fields where large firms are more active. The impact is large: invalidation for these small firms reduces their future patenting by about 67 percent. But invalidation has no statistically significant effect on innovation for small firms in fields where few large firms are present. In Appendix Table A6 we present additional regressions that vary the thresholds for the number of large firms, their share of patenting in the focal field, and the fraction of patenting used to classify a large firm as active in the field. The results in column 1 of Table 5 remain robust.[22]

We next examine whether the effect of patent invalidation for small firms is concentrated in a few specific technology fields, or is more pervasive. To do this, we begin by extending our baseline model (which used a dichotomous breakdown into small and large firms) with a more flexible specification that allows the impact of invalidation to vary continuously with the logarithm of the number of large firms in the field (again defined as those with at least 75

[22] We also examine whether this finding simply reflects instances where there are fewer firms *in total* – less competition overall – rather than being something specific about the interaction between small and large firms. To do this, we construct a measure of the 'equivalent number of firms' in a field, defined as the reciprocal of the Herfindahl concentration index, and include this control variable in the *IV* regressions reported above. These regressions confirm that the impact of invalidation for small firms is larger when small firms face *larger firms* in the focal technology field, controlling for our measure of overall competition in that field.

patents and 50 percent in the focal, two-digit technology field). The *IV* estimates confirm that the negative impact of invalidation is larger (in absolute value) for small firms when they face a greater number of large firms in the technology field. Using these estimates, we compute the implied impact of patent invalidation on small firm innovation for each of the *two-digit* technology fields (36 in total), based on the sample mean number of large firms in each field.

The results (not reported) show that the impact varies somewhat across broad one–digit technology fields: the largest effect is in Pharmaceuticals, where the estimate (standard error) is -1.79 (0.74), as compared to a low of -0.34 (0.42) in Electronics. More striking is the large variation across two-digit areas *within* any given one-digit field. For example, within the Pharmaceuticals category, the invalidation effect on small firms varies from -2.98 (1.28) in Drugs to -0.23 (0.37) in Genetics and Biotechnology. Within Electronics the effect varies from -1.71 (0.72) in Semiconductor Devices to -0.24 (0.36) in Nuclear and X-rays. This diversity characterizes all six one-digit technology areas. It reflects the fact that most of the variation in the number of large firms arises *within* the six broad fields (only 30 percent of the total variance is across one-digit fields), and it is not concentrated in few broad technology fields.

The approach above has a limitation: it does not recognize that large firms in different*, but technologically related*, fields may also be effective potential competitors. To address this concern, we build on Bloom, Schankerman and Van Reenen (2013) who develop a 'Mahalanobis' index that measures the technological proximity between different patent classes based on the frequency with which firms tend to patent in specific subset of fields (patent co-location). We compute the number of large firms in *each* two-digit technology field and then weight them by the Mahalanobis index of proximity between that field and the one in which the litigated patent falls (Appendix A.5 for details). This provides a more refined measure of the number of competition from large firms, which may also prove useful in other contexts, such as empirical models of entry.

We re-define the dummy *Few Large Firms=1* if the Mahalanobis index of large patentees is in the bottom decile of the distribution. The *IV* estimates using this measure, reported in Table A6, confirm our earlier results: invalidation has a strong and significant effect for small firms facing potential competition from many large firms.

Access to finance

Small firms face difficulty in financing their innovation due to information asymmetries in capital markets (Hall and Lerner, 2010). Recent empirical studies show these frictions can be mitigated through debt and venture capital secured by patents (Conti, Thursby and Thursby, 2013; Hochberg, Serrano and Ziedonis, 2014; Farre-Mensa, Hegde and Ljungqvist, 2015). If our finding that patent invalidation causes a decline in innovation by small firms is driven by this channel, we would expect to observe a larger reduction for small firms that rely on the (subsequently invalidated) patent to obtain finance.

To test this, we collect information on whether patents in our sample are used to secure loans. Following Hochberg, Serrano and Ziedonis (2014), we manually examine the assignment records for each of the patents in our sample from the USPTO and Google-Patent databases and identify all instances where patents are assigned to banks or other financial institutions A complete description of the nature of the transactions is not provided in the assignment data, but often these assignments are flagged as "security interest" or "collateral assignment," confirming the financial nature of the transactions. About 15.5 percent of the patents in our sample are pledged as collateral at least once during their life, but only 6.5 percent of the patents (96 patents) are pledged as collateral *before* the Federal Circuit decision. We generate a dummy variable *Collateral=1* if the patent is used as collateral before the Federal Circuit decision, and re-estimate the baseline model that includes an interaction between the invalidation and collateral dummy variables. If financial constraints are an important channel through which loss of patent rights affects innovation, the effect of invalidation should be stronger for the patents used as collateral.

The results (column 2, Table 5) show that the impact of patent invalidation is about twice as large for patents pledged as collateral than for patents not pledged.[23] While the difference between the two coefficients is not statistically significant, the coefficients provide some additional evidence that patent rights are important for small, high-tech companies to gain access to finance. While our evidence relates to collateral for bank loans, patent rights are likely to play a similar role for venture capital financing. We also point out that even if the patent is not used as collateral before the litigation, it is possible that the loss of licensing income (current and prospective) associated with patent invalidation could reduce later innovation for firms that are liquidity-constrained. Our earlier results contrasting the effects of invalidation

[23]We also tested wheher the effect of invalidation on innovation is larger for *young* firms, since this is where informational asymmetries are likley to be most severe. We define age of the patent owner as the difference between the year of the Federal Circuit decision and the application year of the oldest patent in the USPTO data for the specific assignee. We redo the *IV* regressions for small firms allowing for an interaction between *Invalidity* and a dummy for small firms, and another interaction with young firms, using two alternative thresholds for young (5 and 9 years). In both cases, there is no statistically significant difference in the effect of invalidation between patents of young and old firms.

of low vs high-value patents is consistent with this interpretation.

Access to patented inputs

The third channel we consider relates to the role of patents as bargaining chips for enforcing rights and reducing the transaction costs of obtaining external, patented inputs. Patent portfolios shape the expectation of repeated interaction between patentees, which allows firms to resolve disputes 'cooperatively' without resorting to the courts (Lanjouw and Schankerman, 2004). Moreover, innovators 'trade' patent rights through cross-licensing agreements to avoid costly litigation and preserve their 'freedom to operate' in innovation (Galasso, 2012). Losing a patent may make it more difficult to access external patent rights, especially for firms with small patents portfolios. If this channel is important, we would expect patent invalidation to have a more negative effect on small innovators when they operate in technology fields with fragmented ownership of patent rights – this is where firms need to engage in multiple licensing negotiations and the risks of hold-up and bargaining failure are more severe (Ziedonis, 2004; Galasso and Schankerman, 2010).

To test this hypothesis, we construct a concentration measure *Conc4*, equal to the patenting share of the four largest assignees in the two-digit technology field of the litigated patent during the five years preceding the Federal Circuit decision (the mean/standard deviation of *Conc4* are 0.08/0.06, respectively). In column 3 we contrast the IV estimates of patent invalidation for small firms operating in fragmented fields (*Conc4* below the median) and concentrated fields (*Conc4* above the median). The point estimates are very similar, and not statistically different from each other. We conclude that the impact of invalidation on innovation by small firms in our sample is not driven by access to external (patented) inputs.

8 Exit from patenting

We have shown that the loss of a patent sharply reduces subsequent innovation by small firms, and that this is due both to reduced access to capital markets and intensified competition by large firms. In this section we investigate whether losing patent rights increases the risk that the firm exits from the technology competition entirely. One of the hallmarks of entrepreneurship is the well-documented fact that small firms have both high rates of entry and exit (e.g., Dunne et al, 1989). In high technology markets where the incentives for innovation are key, it is important to understand the role of patent rights in affecting this process.

In this Section we examine how patent invalidation affects exit. To do this, we define a dummy variable for exit equal to one if the focal firm in the litigation does not apply for *any* patents in the five-year window after the court decision (for such presumptive exiters, we also confirmed that they do not apply for patents in any subsequent part of sample period beyond this window). This measure may overestimate the degree of exit for two reasons. First, the firm may stop patenting but remain in the product market (though for high-technology firms, this seems unlikely). Second, for invalidation decisions late in the sample period, censoring may lead us to ascribe exit when patenting will occur after the end of the sample. One final concern is that small firms are often acquired and thus wrongly appear as not engaging in any further innovation activity. But it is not clear whether patent invalidation makes this more or less likely (the firm would be a less patent-rich target for acquisition, but at the same time less expensive).

Table 6 presents IV estimates of a linear probability model of exit, including controls for technology field, pre-decision patent portfolio size, and firm age dummies for intervals 0-5, 6-10 and greater than 10 years (age is measured as date of the court decision minus date of the firm's first patent application). The results are presented using various (pre-decision) patent portfolio thresholds for defining 'small firms' in order to identify whether the impact of patent invalidation on exit varies with firm size.[24]

Column 1 shows that the loss of patent rights has no effect on exit, when we pool small and large firms. However, this local average treatment effect hides an important difference between small and large firms. The results in the other columns show that the loss of a patent sharply increases the exit probability for small firms, and the effect is statistically significant. Not surprisingly, we see no evidence that invalidation increases exit by large firms. Interestingly, the estimated impact of invalidation on exit for small firms monotonically increases as we tighten the definition of small firms (moving from columns 2 to 6). For firms with a patent portfolio less than 30, invalidation raises the exit probability by 0.347, which is about a 53 percent increase relative to the sample mean for this size category.[25] For very small firms, with portfolio of three patents or less, the coefficient corresponds to a 63 percent increase in the

[24] Given the sample size, we are not able to estimate separate coefficients for multiple size categories at the same time.

[25] For these firms the average exit rate is roughly 62 percent, which is broadly consistent with an *annual* exit probability of about 10 percent in a five year window. While such survival rate is in line with the estimates in the literature, our findings cannot be easily contrasted with other studies because our measure of exit only tracks absence of patenting after the Federal Circuit decision.

sample mean exit rate for that category.

In summary, the evidence shows that losing a patent sharply both reduces the level of innovation for continuing, small firms and raises the probability of exit (from patenting activity).

9 Assessing the impact of patent rights and the Court

In our earlier study, we examined the impact of patent invalidation on *follow-on innovation by other firms*, as measured by citations (Galasso and Schankerman, 2015). The main empirical finding is that invalidation raises subsequent citations by about 50 percent on average, but the impact is localized. It is predominantly driven by the invalidation of patents owned by large firms, which increases later innovation by small firms. There was no significant effect of invalidation for other firm size pairings. By contrast, the current article studies the impact of patent invalidation on *follow-on innovation by the patent owner*, and finds that invalidation reduces subsequent patenting by small firms, but has no significant impact on large firms.

In this section, we combine these findings to assess the overall impact of patent rights on follow-on innovation for the (selected) sample of patents litigated in the Federal Circuit Court, and the impact of the Court itself. We perform several counterfactual exercises which weigh up the negative impact on follow-on innovation from invalidation of small firm patents against the positive effect from invalidation of patents held by large firms (Appendix A6 provides details).

Impact of patent rights in the Federal Circuit sample

In our first counterfactual we estimate what the effect on later innovation would have been if the Federal Circuit had invalidated all the patents litigated during the sample period. This exercise provides a measure of how much the patents rights on those innovations affected follow-on innovation.

We find that invalidating all Federal Circuit patents would have increased follow-on innovation. The positive impact from invalidating all the large firm patents in our sample (small firms are induced to do more patenting) is larger than the negative effect from invalidating all the small firm patents (reduction by the patent owners). The increase in patenting by small firms is 80 percent larger than the decline, leading to a net increase in follow-on innovation of roughly 3,000 patents. To gauge the magnitude, this represents roughly a 30 percent increase in small firms firm patenting relative to what would happen if the Federal Circuit always upheld the lower court decisions. If we adjust for quality (lifetime citations) of the follow-on patents, the effect remains positive but is much smaller - the increase is 20 percent larger than the reduction, implying a net increase of about 16,000 citations, which represents a 8 percent increase over the same benchmark measured in citations.

Impact of the Federal Circuit Court

The second exercise we conduct is to compute the overall effect of Federal Circuit *reversal decisions* on follow-on innovation (i.e., all cases where the appellate court reversed the lower court's ruling, either upholding or invalidating the patent). This calculation gives an estimate of the impact of having the Federal Circuit itself – as compared to leaving all lower court judgements uncontested. We find that, on average, reversal decisions by the Federal Circuit had essentially no effect on subsequent patenting. The positive and negative effects of its reversals of lower court decisions approximately compensate each other and lead to a very small change in the total level of patenting relative to the benchmark above - 0.7 percent decline in patent counts and 2 percent increase in quality-adjusted patenting (citations).

These computations are only illustrative, and two important caveats should be kept in mind. First, the invalidation impacts we estimate are local average treatment effects and thus they apply only to the sub-population of Federal Circuit patents that are induced into treatment (invalidation) by the instrument. Second, these computations do not take into account the effects that changes in Federal Circuit decisions may have had on the selection of patents into litigation and appeal. Different behavior by the Federal Circuit, or not having the appellate court at all, would presumably change the settlement and litigation strategies of the parties to the dispute.

Most importantly, these findings do not imply that removal of patent rights would necessarily be beneficial. Invalidation of patents in a regime with patent rights is very different from a regime without patent rights. First, in the presence of patent rights, R&D is conducted under the expectation of obtaining rents in the form of product market monopoly profits and licensing royalties. Without patent protection, firms would use other means of capturing rents (including secrecy) and if these are less remunerative, the level of innovation (and information diffusion) would be reduced. Second, patents play an important signalling role in capital markets, and in particular, enable small firms to attract venture capital investors more effectively. Third, we would expect the direction of technical change to be different in a regime without patents. Innovators will have greater incentives to invest in research that is more easily protected through trade secrets and less susceptible to reverse engineering and copying. These considerations would need to be accounted for in a full assessment of the net benefits of patent rights.

10 Concluding remarks

In this article we estimate the causal effect of patent invalidation on innovation using decisions of the U.S. Federal Circuit Court. Identification exploits the randomised assignment of judges panels hearing each case. There are three key empirical findings. First, loss of a patent right causes the owner to reduce subsequent innovation (patent activity) by about 50 percent, on average. Second, this effect is driven by small firms that lose patents on technologies that are core to their innovation focus. The impact is especially strong when small firms operate in technology areas where large firms are particularly active. Finally, we find that the loss of patent rights also sharply increases the probability of exit from patenting by small (but not large) firms.

These findings complement Galasso and Schankerman (2015), who show that patent invalidation increases innovation by *other firms*, but the effect is localized in particular technology fields and is driven by invalidation of patents owned by large patentees that triggers more follow-on innovation by small firms. Taken together, these two studies show that patent rights affect innovation by small and large firms very differently. This suggests that limited reduction in the strength/scope of large firms' patent rights might be expected to promote follow-on research by small firms, and unlikely to reduce significantly innovation incentives for large firms. This conclusion is consistent with recent work by Acemoglu et al. (2013), who show that fiscal stimulus policies for are more effective when targeted at small firms. While the law and economics literature has discussed possible instruments to differentiate patent rights across innovators – e.g., patent filing and renewal fees, the scope for injunctions, and presumption of validity by courts– there are serious practical challenges in implementing such policies. Our results suggest that more research on these issues is warranted.

Finally, there is one important caveat to bear in mind. We focus on judicial invalidation of specific patents, not a reduction in the strength of overall patent rights. It remains to be shown whether or not our conclusions hold for policies that would affect the strength or scope of patent rights more broadly. It would be wrong to jump to that conclusion on the basis of this analysis.

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Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Max
Invalidity	0.40	0.49	0	1
PostPatents	213.9	961.9	0	12,988
PrePatents	335.9	1150.6	1	14,208
PreCites	25.6	56.3	0	893
PreSelfCites	2.3	6.6	0	114
Patent Age	9.8	5.0	1	30

NOTES: Sample of 1379 patents involved in Federal Circuit invalidity decisions for period 1983-2010. Invalidated=1 if Federal Circuit invalidates at least one claim of focal patent.

Table 2: Patent Invalidation and Innovation

	(1)	(2)	(3)	(4)
Estimation Method	OLS	IV	IV	IV
Dep Variable	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)
Invalidity	-0.057	-0.681**		-0.597*
	(0.082)	(0.344)		(0.367)
All invalidated			-0.669**	
			(0.323)	
log(PrePatents)	0.548***	0.554***	0.553***	0.518***
	(0.029)	(0.030)	(0.029)	(0.033)
Year Effects	YES***	YES**	YES***	YES***
Tech. Effects	YES	YES	YES	YES
Age Effects	YES	YES	YES	YES
Instrument		predicted probability from probit	predicted probability from probit	predicted probability from probit
IV Test		52.31	65.71	46.44
Sample	full	full	full	drop multi-patent cases
Fed. Circuit Cases	1038	1038	1038	811

NOTES: *significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors clustered at the litigant level are reported in parentheses. PostPatents= number of patent applications of assignee in 5 year window after Federal Circuit decision. Invalidity=1 if at least one patent in the case is invalidated. All invalidated=1 if all patents in the case are invalidated. PrePatents = number of patent applications of assignee in 10 year window before Federal Circuit decision. Age = age dummies in years from filing date of patents at Federal Circuit decision. Year= year of Federal Circuit Decision. Technology fields= 6 categories defined in Hall et al (2001). IV test is the F-statistics from the Stock and Yogo (2005) weak ID test. We add 1 to PostPatent to include firms with no patenting. Regressions include a dummy for firms with no patents, a dummy for firms in the top 2 percent of patent portfolio size, and dummies for serial litigants.

Table 3: Impact of Patent Invalidation by Firm Size

	(1)	(2)	(3)	(4)
Estimation Method	IV	IV	IV	IV
Dep Variable	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)
Sample	large	small	full	full
Invalidity	0.369	-0.604***		
	(1.014)	(0.198)		
Invalidity X Small			-0.638***	-0.548**
			(0.244)	(0.267)
Invalidity X Large			0.801	0.128
			(0.748)	(0.417)
Fed Circuit Decisions	261	777	1038	1038
IV test	7.55	55.78	25.56	51.36
Equality test: p-value			0.04	0.03
Cutoff for large firm	>108 patents	>108 patents	>108 patents	>95th percentile in field

NOTES: * significant at 10 percent ** significant at 5 percent and *** significant at 1 percent. Robust standard errors clustered at the litigant level are reported in parentheses. All regressions control for log(PrePatents), a dummy for patentees in the top2 percent of portfolio size, dummies for repeat litigants, age, technology and year effects. In columns 1-3: Large=1 if portfolio in 10 year window >108 patents. In column 4 Large=1 if portfolio is above 95th percentile of assignees with at least one patent in tech field. IV test is the F-statistics from the Stock and Yogo (2005) weak ID test. The p-value of the difference is obtained from testing equality between InvalidityXSmall and InvalidityXLarge. Columns 3 and 4 include direct effect for the dummy Large.

Table 4: Invalidation of Core and High-Value Patents

	(1)	(2)	(3)	(4)
Estimation Method	IV	IV	IV	IV
Dep Variable	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)
Invalidity X Core	-0.977***	-1.019***		
	(0.309)	(0.372)		
Invalidity X NoCore	-0.162	-0.356		
	(0.436)	(0.354)		
Invalidity X High-Value			-1.277**	-1.600**
			(0.595)	(0.764)
Invalidity X Low-Value			-0.226	-0.373
			(0.314)	(0.315)
Fed Circuit Decisions	1038	1038	1038	1038
IV test	30.84	30.63	28.71	32.61
Equality test: p-value	0.03	0.07	0.04	0.08
	Core from share in 2 digit fields	Core from self-citations	High value if cites above 75th percentile	High value if cites above 90th percentile

NOTES: * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent. Robust standard errors are reported in parentheses clustered at the litigant level. All regressions control for log(PrePatents), age, technology, year effects and dummies for largest patentees and repeat litigants. In column 1 Core=1 if share of patents in the focal 2-digit technology class is above the median. In column 2 Core=1 if the ratio between the self-citations received and maximum possible number of self-citations that the focal patent could receive is in top quartile. In column 3 High Value=1 if filtered citations received before the decision is above the 75th percentile. In column 4 High Value=1 if filtered citations received before the decision is above the 90th percentile. Columns 1 and 2 include direct effect for the dummy Core, columns 3 and 4 include direct effect for the dummy High-Value.

Table 5: Testing Alternative Mechanisms

	(1)	(2)	(3)
Estimation Method	IV	IV	IV
Dep Variable	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)
Invalidity X Many Large Firms	-0.939***		
	(0.287)		
Invalidity X Few Large Firms	-0.246		
	(0.224)		
Invalidity X Collateral		-1.175**	
		(0.546)	
Invalidity X NoCollateral		-0.551***	
		(0.198)	
Invalidity X Fragmented Field			-0.649***
			(0.238)
Invalidity X Concentrated Field			-0.593**
			(0.262)
Fed Circuit Decisions	777	777	777
IV test	20.18	35.85	27.99
Equality test: p-value	0.02	0.25	0.84
Sample	Small Firms	Small Firms	Small Firms

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors clustered at the litigant level are reported in parentheses. All regressions control for log(PrePatents), age, technology and year effects. Collateral=1 if patent is transferred to a bank for security interest. Fragmented field= C4 index of patentees below sample median. Many large firms=1 if more than 5 large patentees in the field with at least 50% of portfolio in field. Each regression includes the direct effect for interacted dummies.

Table 6: Invalidation and Exit from Patenting

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation Method	IV	IV	IV	IV	IV	IV
Dep Variable	Exit	Exit	Exit	Exit	Exit	Exit
Invalidity	0.204					
	(0.142)					
Invalidity X Small		0.266**	0.277**	0.347**	0.435***	0.514**
		(0.129)	(0.137)	(0.146)	(0.166)	(0.222)
Invalidity X Large		-0.056	-0.012	-0.033	0.058	0.103
		(0.148)	(0.134)	(0.142)	(0.133)	(0.125)
Fed Circuit Decisions	1038	1038	1038	1038	1038	1038
IV test	53.63	24.99	26.80	26.34	25.04	14.89
Equality test: p-value		0.01	0.02	<0.01	0.01	0.03
Cut-off for large firms		108 pats	50 pats	30 pats	5 pats	3 pats

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors clustered at the litigant level are reported in parentheses. All regressions control for log(PrePatents), age of patent, technology effects, year effects, dummies for largest firms, dummies for repeat litigants, dummies for firms with age 0-5, 6-10 and a dummy for individual inventors. The dependent variable is equal to one if there is no patenting activity by the patentee after the Federal Circuit decision. Columns 2-6 include direct the effect for the dummy Large.

Patent Rights, Innovation and Firm Exit
ONLINE APPENDICES

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A.1. Analysis of the model

First, we need to obtain the expression for $L(N, \overline{\Theta})$. If there is only one large firm, the expected payoff of the small firm in the licensing subgame is $L(1, \overline{\Theta}) = \overline{\Theta} z$. With two firms the payoff is $L(2, \overline{\Theta}) = \overline{\Theta} z(1 + \delta(1 - z))$. By induction, we obtain

$$L(N, \overline{\Theta}) = \overline{\Theta} z \sum_{i=0}^{N-1} \delta^i (1 - z)^i = \overline{\Theta} z \frac{1 - \delta^N (1 - z)^N}{1 - \delta(1 - z)}.$$

Note that $L'(N) > 0$. The impact of invalidation is

$$\Delta r = \Lambda \left(1 - (1 - \alpha)^c - \frac{1 - (1 - \alpha)^{c-1}}{1 - 2\Lambda\chi\alpha\,(1 - \alpha)^{c-1}} \right) \tag{1}$$

which is decreasing in c (and n given our assumption that $c = \lambda n$). Thus for small firms $|\Delta r|$ is minimized when c is set at the upper bound of the size range for small firms, namely $c = \lambda\kappa$. The corresponding value is

$$L(N) \left(1 - (1 - \alpha)^{\lambda\kappa} - \frac{1 - (1 - \alpha)^{\lambda\kappa - 1}}{1 - 2L(N)\chi\alpha\,(1 - \alpha)^{\lambda\kappa - 1}} \right).$$

Consider a large firm with $n_L > \kappa$ patents. The invalidation effect is larger for the small firm if

$$\begin{aligned} & \left| L(N) \left(1 - (1 - \alpha)^{\lambda\kappa} - \frac{1 - (1 - \alpha)^{\lambda\kappa - 1}}{1 - 2L(N)\chi\alpha\,(1 - \alpha)^{\lambda\kappa - 1}} \right) \right| \\ > \; & \left| \overline{\Theta} \left(1 - (1 - \alpha)^{n_L} - \frac{1 - (1 - \alpha)^{\lambda n_L - 1}}{1 - 2\overline{\Theta}\chi\alpha\,(1 - \alpha)^{\lambda n_L - 1}} \right) \right|. \end{aligned}$$

Because $\overline{\Theta} > L(N)$ and the right hand side of the inequality is monotonic in n_L and tends to zero as $n_L \to \infty$, there exists an $\bar{n} > \kappa$ for which the left hand side is equal to the right hand side. This proves the first part of the proposition.

Notice that (1) can be positive or negative.[1] Moreover (1) decreases in χ and $\Delta r = \Lambda\alpha(1 - \alpha)^{c-1} > 0$ when $\chi = 0$. This implies that, for all parameter values, there exists an χ' such that $\Delta r > 0$ if $\chi < \chi'$. The derivative of (1) respect to N is equal to

[1] For example, if $\Lambda = 1$, $c = 2$ and $\alpha = 0.5$ then $\Delta r = (0.25 - 0.375\,\chi)/(1 - 0.5\chi)$ which is negative for $\chi > .66$.

$$
\begin{aligned}
\frac{d\Delta r}{dN} &= L'(N)\left(1-(1-\alpha)^{c}-\frac{1-(1-\alpha)^{c-1}}{1-2L(N)\chi\alpha\,(1-\alpha)^{c-1}}\right) \\
&\quad -L(N)\frac{2L'(N)\chi\alpha\,(1-\alpha)^{c-1}\left(1-(1-\alpha)^{c-1}\right)}{\left(1-2L(N)\chi\alpha\,(1-\alpha)^{c-1}\right)^{2}}.
\end{aligned}
$$

The first term is positive when $\chi < \chi'$. The second term is negative and goes to zero as $\chi \to 0$. This implies that there is an $\chi^* \leq \chi'$ for which $\frac{d\Delta r}{dN} > 0$ if $\chi < \chi^*$.

A.2. Generalized bargaining framework

Our model assumed take-it-or-leave-it offers for exclusive licensing deals. We now show robustness to more general bargaining models. Consider a setting in which the patentee approaches one of the firms. If the firm needs the technology, there is Nash bargaining between the firm and the licensee with weights β and $1-\beta$, respectively. If the firm does not need the technology, the patentee moves to the next firm and payoffs are discounted by δ. We solve the game by backward induction. When only one large firm is left, the Nash bargaining solution is computed maximizing $\left(\overline{\Theta}-x\right)^{\beta} x^{1-\beta}$ which gives $L(1,\overline{\Theta}) = z\overline{\Theta}(1-\beta)$. When two firms remain, the patentee negotiates with the first firm with an outside option of $\delta L(1,\overline{\Theta})$. This gives $L(2\,,\overline{\Theta}) = L(1,\overline{\Theta})\,[1+\Delta\delta]$ where $\Delta = (1-z)+\beta z$. Solving the problem recursively we obtain

$$
L(N,\overline{\Theta}) = \overline{\Theta}z(1-\beta)\frac{1-\delta^{N}\Delta^{N}}{(1-\delta\Delta)}. \tag{2}
$$

Equation (2) provides a substantial generalization of our baseline game. When $\beta = 0$ the model collapses to our baseline model in which the patentee has full bargaining power. As β increases the patentee has greater negotiating power. When $\beta = 1/2$ the solution is equivalent to the equilibrium payoff of the Rubinstein's alternating offer game with no discounting, as shown in Binmore, Rubinstein and Wolinsky (1986). More importantly, note that $L'(N) > 0$ as long as $\beta < 1$. In other words, our comparative statics hold in more general bargaining environments as long as the bargaining power of the patentee is not zero.[2]

[2] This is consistent with the results in Segal and Whinston (2003) showing that in common agency models the payoff of the principal increases with the number of agents N in a wide class of games. They show robustness of this result to settings in which agent's utility depends on the principal's unobservable contracts with other agents.

A.3. Generalized innovation production

We now generalize the functional form for the probability of successful innovation and show that, under mild conditions, the comparative statics results still hold. We assume that $V(c, r)$ is a continuous function satisfying $V_c > 0$, $V_r > 0$, $V_{rr} < 0$, $V_{rc} > 0$ and $\lim_{c\to\infty} V_{rc} = 0$. These properties are satisfied by most standard production functions with decreasing returns. We also generalize R&D costs to any continuous function, $C(r)$ with $C_r > 0$ and $C_{rr} > 0$.

If the firm commercializes the technology itself, it obtains revenue given by the increasing and concave function $\Theta(n)$.Alternatively, the firm can negotiate a licensing deal with one of N symmetric firms, each of whom needs the technology with probability z. The firm bargains with potential licensees sequentially. If a license is struck, the firm earns $\overline{\Theta}$. We assume that $\Theta(1) < L(N, \overline{\Theta})$ and $L(N, \overline{\Theta}) < \lim_{n\to\infty} \Theta(n)$. Under these assumptions, there is a portfolio threshold size κ – defined by $\Theta(\kappa) = L(N, \overline{\Theta})$ – where firms with $n < \kappa$ ('small firms') choose to commercialise their innovation through licensing and firms with $n \geq \kappa$ develop it internally. Unlike in the baseline model in the text, we now assume that $\chi(r) \simeq 0$, which implies that $I(c, r) = V(c - 1, r)$. That is, competition in the patent race fully dissipates the value of the (now publicly available) knowledge.

Then the firm chooses its $R\&D$ to maximise

$$\begin{aligned} L(N, \overline{\Theta})V(c, r) - C(r) \;\; \text{if } n &< \kappa \\ \Theta(n)V(c, r) - C(r) \;\; \text{if } n &\geq \kappa \end{aligned}$$

where κ is defined as the portfolio threshold for which $\Theta(\kappa) = L(N, \overline{\Theta})$. In this setting the optimal level of R&D investment for a small firm satisfies $L(N, \overline{\Theta})V_r = C_r$ which implies

$$\frac{dr}{dc} = \frac{LV_{rc}}{C_{rr} - LV_{rr}} \geq 0.$$

Thus R&D investment declines when the small firm loses a core patent. Moreover

$$\frac{d^2r}{dcdN} = \frac{L_N V_{rc} C_{rr}}{(C_{rr} - LV_{rr})^2} \geq 0$$

$$\frac{d^2r}{dcd\overline{\Theta}} = \frac{L_{\overline{\Theta}} V_{rc} C_{rr}}{(C_{rr} - LV_{rr})^2} \geq 0$$

which implies that the effect of invalidation is stronger where there are more potential licensees in the technology field and where the value of licensing is larger. By assumption (that only core patents facilitate subsequent innovation), there is no effect from losing a peripheral patent for small firms. For firms with $n \geq \kappa$, optimal R&D satisfies $\Theta(n)V_r = C_r$ and thus

$$\frac{dr}{dp} = \frac{\Theta_n V_r}{C_{rr} - \Theta V_{rr}} \geq 0$$

$$\frac{dr}{dc} = \frac{\Theta_n F_r + \Theta V_{cr}}{C_{rr} - \Theta V_{rr}} \geq 0$$

These derivatives go to zero as $n \to \infty$ and $c \to \infty$ because Θ_n and F_{cr} are decreasing functions.

A.4. Accounting for repeat litigant outliers

We checked the identity of the eight extreme repeat litigants in our sample (those involved in four or five Federal Circuit cases). Two of them are prominent universities, five are large bio-pharmaceutical companies and one is a leading agro-chemical firm. Notably, none of the repeat litigants are patent assertion entities in our sample. Including the two dummy variables for extreme repeat litigants reduces the residual variance of our dependent variable and helps sharpen the statistical precision of our estimates of the effect of invalidation for small and large firms, and the difference between them. This is because, conditional on other observable factors, firms involved in multiple litigations may be firms experiencing unusual growth in patenting, with the largest patenting outliers more likely to be involved in many cases.

The estimated coefficients for these dummies are reported in column 1 of Appendix Table A4. As expected, there is a large and positive effect for four-time litigants but, surprisingly, an insignificant effect for five-time litigants. A closer inspection of the data (and the coefficients on the individual firm dummies for each of the extreme repeat litigants) shows that this counterintuitive, non-monotonic pattern is driven by two of the five-times litigants: Monsanto and the Beecham Group. In column 2 of Table A4, we drop from our sample the cases involving Beecham and Monsanto and find that the repeat litigant dummies display the expected monotonic behavior. Column 3 confirms that this result also holds when we include these observations but add dummies for these two firms.

In short, the anomalies are Monsanto and Beecham. To understand why, we examined the recent history of these companies and found that major restructuring events, which happen to have occurred about the same time as their Federal Circuit cases, largely explains the large drops in patenting for these two outliers, as we now explain.

The Federal Circuit decisions on the five cases involving the Beecham Group all occurred in the period 2002-2006. It turns out that the Beecham Group merged with GlaxoSmithKline in 2000 (Moore et. al., 2000), and patenting after 2000 only captures the innovations of a relatively small spin-out GSK subsidiary operating in England (which alone inherited the Beecham name). As a consequence, none of the post-merger patents in the U.S. by the *original* Beecham Company are captured after 2000 and this accounts for the sharp decline in measured patents for this company and thus the large negative coefficient on the dummy in column 3.

Similarly, the Federal Circuit decision in the cases involving Monsanto all occurred in the period 2001-2007. Monsanto had three main lines of business: chemicals, agriculture, and biotechnology-pharmaceuticals. We discovered from the company history that Monsanto spun off its chemicals business in 1997 and then merged with Pharmacia-Upjohn in 1999, and was renamed Pharmacia Corporation (Deogun et. al., 1999). The agricultural business was spun off and became the Monsanto Ag Company, later renamed just Monsanto, and was limited to specific agro-biotech technologies. Thus, in the post-merger period, after the year 2000, patenting under the name Monsanto only refers to the limited agro-biotech activity of the spin-out. Again, this explains the large negative coefficient on its dummy variable in column 3.

A.5. Mahalanobis measure of potential competition

The measure of potential competition is specific to each litigated patent. Let i denote the technology field of the litigated patent. We identify all the N large firms (with > 75 patents) active in the ten-year window before the Federal Circuit decision and measure their patenting across the 426 USPTO three-digit technology classes. Let s_{kj} denote the share of firm k's patenting that falls in class j. We define the $(N, 426)$ matrix X that contains the normalized patent class shares across firms, and the $(426, 426)$ matrix $W = X'X$. Each element in W, denoted by w_{ij}, is the uncentered correlation coefficient between the different three-digit technology fields. If technology fields i and j coincide frequently within a given firm (i.e., there is a lot of patent co-location), then w_{ij} will be close to one; if they never coincide w_{ij} is zero.

To compute the number of large firms potentially active in the technology field i of the litigated patent, we define weights for each of the N large firms, denoted by θ_k , $k \in (1, N)$:

$$\theta_k = \sum_{i=1}^{426} w_{ij} s_{kj}.$$

The weight for each large firm (potential competitor) depends on its distribution of patents across the three-digit technology fields and on how close those fields are to the techology class of the litigated patent. A firm with all its patents in the same three-digit class of the litigated patent receives a weight of one. Firms with a large amount of patents in classes that tend to overlap frequently with the class of the litigated patent receive a weight close to one, those patenting heavily in more distant classes receive a weight of zero.

Our Mahalanobis measure of potential competition for the litigated patent, N_p^m, is then defined as

$$N_p^m = \sum_{k \in N} \theta_k.$$

A.6. Assessing the impact of patent rights and the Court

Patents owned by large firms (which are upheld) receive on average 4.4 citations by small firms in the five-year window after the Federal Circuit decision. In our earlier study, we found that invalidation increases citations to the focal patent by small firms by 520 percent in the five-year window, but that about 20 percent of this effect comes from the downstream innovators substituting from other patents to the focal (invalidated) patent. That is, 80 percent of the overall citation effect reflects an increase in follow-on innovation (and thus patents) by small firms. Thus, in our sample, invalidation of a large firm patent generates, on average, about 18 new patents by small firms ($4.4 \times 5.2 \times 0.8 = 18.3$). In Section 6, we estimate that invalidation of a small firm patent causes a 47 percent reduction in follow-on patenting by the patentee. In our sample, small firms that do not experience invalidation file 8 patents in the five years after invalidation, on average. This implies that invalidation of a patent owned by a small firms reduces subsequent innovation by the patent holder by roughly 4 patents ($8 \times 0.47 = 3.8$).

Impact of patent rights in the Federal Circuit sample There are 986 small firm patents in our sample and 393 large firm patents. Thus, invalidation of all the Federal Circuit patents would generate 7,074 new patents (393×18) and at the same time prevent 3,944 new patents (986×4). This implies an overall increase in cumulative innovation (3,130), with a positive effect 80 percent larger than the negative effect.

To adjust for patent quality we look at the lifetime citations received: (i) by the patents of small firms that build on Federal Circuit patents of large firms and (ii) by patents of small firms litigating at the Federal Circuit. On average, patents of small firms that are upheld by the Federal Circuit receive 21.2 citations. If we look instead at the citations received by patents of small firms which cite Federal Circuit patents owned by large firms in our sample, we find that they receive 14.4 citations on average. This suggest that, on average, the value of the patent induced by Federal Circuit invalidation is lower than the value of the patent prevented by Federal Circuit invalidation.

Adjusting for patent quality, we still find a positive effect but of smaller magnitude. Invalidation of large firms generates 99,036 citation-weighted patents ($7,074 \times 14$) and prevents 82,824 citation-weighted patents ($3,944 \times 21$). Thus the increase is 19 percent larger than the corresponding decrease and quality adjusted patents go up by 16,212 cites.

The benchmark level of patenting is obtained by looking at the entire set of patents validated and invalidated by district courts, and computing the total amount of follow-on innovation by small firms if decisions were not reversed. This is done assuming that an invalidated patent of a large firm generates 22 follow-on small firms patents, a validated patent of a large firms generates 4 patents, a validated small firm patent generates 8 and a small firm invalidated patent generates 4. Multiplying these number with the number of decisions of each type we find that in the absence of Federal Circuit reversals, we would observe 10,588 follow-on patents and 192,192 follow-on cites.

Notice that the patenting effect (3,130) is 29 percent of the follow-on patents in the absence of Federal Circuit (10,588) and the quality adjusted effect (16,212) is 8.4 percent of the benchmark level of 192,192 cites.

Impact of Federal Circuit court In our sample, the Federal Circuit reversed about 27 percent of the lower court decisions. Reversal is more common for invalidity decisions (about 38 percent) than for validity decisions (about 13 percent). The reversal rate appear similar for large and small firms (about 27 percent).

Our data shows that, compared to district court decisions, Federal Circuit reversals lead to 42 fewer large firm patents invalidated and 171 fewer small firms patent invalidated. Multiplying these figures by the effect of invalidation of small and large firm patents in our sample, we find that Federal Circuit decisions reduced follow-on innovation by 72 patents ($171 \times 4 - 42 \times 18$). Once we adjust for patent quality, the conclusion is slightly different. Federal Circuit reversals increased follow-on innovation by 3,780 citation-weighted patents ($171 \times 4 \times 21 - 42 \times 18 \times 14$).

Compared to the benchmark level, the overall effect of Federal Circuit reversals is quite small: -72 patents is equivalent to a 0.7 percent decline and +3,780 citation-weighted patents is equivalent to a 1.96 percent increase.

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Table A1: Composition of Judge Panels and Patent Invalidation

	1	2	3	4
Estimation Method	Probit	Probit	OLS	OLS
Dependent Variable	Invalidated	Invalidated	JIP	JIP
Judges Invalidity Propensity (JIP)	2.748***	2.207***		
	(0.708)	(0.832)		
log(PrePatents)		0.008	-0.001	-0.001
		(0.017)	(0.001)	(0.001)
Year Effects	NO	YES***	NO	YES***
Age Effects	NO	YES	NO	YES
Tech. Effects	NO	YES	NO	YES
Fed. Circuit Cases	1038	1038	1038	1038

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors are reported in parentheses. Invalidated=1 if at least one patent in the case is invalidated. PrePatents = number of patent applications of assignee in 10 year window before Federal Circuit decision. Age = age dummies in years from filing date of patents at Federal Circuit decision. Year= year of Federal Circuit Decision. Technology fields= 6 categories defined in Hall et al (2001).

Table A2: Robustness of Baseline Regressions - IV Estimates

	(1)	(2)	(3)	(4)
Dep Variable	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)
Sample	no overlapping cases	no repeat litigants	drop manually matched firms	full
Invalidity	-0.672**	-0.629**	-0.645*	-1.895***
	(0.309)	(0.291)	(0.344)	(0.426)
Dummy for PostPat=0	YES	YES	YES	NO
Instrument	predicted probability from probit	predicted probability from probit	predicted probability from probit	predicted probability from probit
IV test	57.05	56.57	57.28	67.43
Fed. Circuit Cases	848	798	801	1038

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors clustered at the litigant level are reported in parentheses. PostPatents= number of patent applications of assignee in 5 year window after Federal Circuit decision. Invalidated=1 if at least one patent in the case is invalidated. All regressions control for log(PrePatents), technology, age, year effects and dummies for largest firms and repeat litigants.

Table A3: Impact of Patent Invalidation by Firm Size- Robustness

	(1)	(2)	(3)
Estimation Method	IV	IV	IV
Dep Variable	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)
Invalidity X Small	-0.664***	-0.848***	-0.816
	(0.252)	(0.273)	(0.535)
Invalidity X Large	1.221	0.164	-0.647*
	(0.808)	(0.519)	(0.349)
Fed Circuit Decisions	1038	1038	768
IV test	24.77	32.93	13.66
Equality test: p-value	0.01	0.03	0.72
Large Firm	>150 patents	>30 patents	not small entitity status at USPTO

NOTES: * significant at 10 percent ** significant at 5 percent and *** significant at 1 percent. Robust standard errors clustered at the litigant level are reported in parentheses. All regressions control for log(PrePatents), a dummy for patentees in the top2 percent of portfolio size, dummies for repeat litigants, age, technology and year effects. IV test is the F-statistics from the Stock and Yogo (2005) weak ID test. The p-value of the difference is obtained from testing equality between InvalidityXSmall and InvalidityXLarge. Regressions include the direct effect for the dummy Large.

Table A4: Impact of Patent Invalidation by Firm Size-Accounting for Repeat Litigant Outliers

	(1)	(2)	(3)
Estimation Method	IV	IV	IV
Dep Variable	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)
Invalidity X Small	-0.638***	-0.498**	-0.517**
	(0.244)	(0.239)	(0.237)
Invalidity X Large	0.801	0.876	0.754
	(0.748)	(0.740)	(0.690)
Repeat litigant (4 cases)	1.044**	0.843**	0.867**
	(0.515)	(0.385)	(0.379)
Repeat litigant (5 cases)	-0.113	1.286***	1.283***
	(0.741)	(0.185)	(0.182)
Monsanto			-2.121***
			(0.159)
Beecham			-1.181***
			(0.223)
IV test	25.56	25.66	30.132
Equality test: p-value	0.04	0.04	0.05
Federal Circuit Decisions	1038	1028	1038
Sample	full	Drop Beecham and Monsanto	full

NOTES: * significant at 10 percent ** significant at 5 percent and *** significant at 1 percent. Robust standard errors clustered at the litigant level are reported in parentheses. All regressions control for log(PrePatents), a dummy for patentees in the top2 percent of portfolio size, age, technology and year effects. IV test is the F-statistics from the Stock and Yogo (2005) weak ID test. The p-value of the difference is obtained from testing equality between InvalidityXSmall and InvalidityXLarge. Regressions include the direct effect for the dummy Large.

Table A5: Core Technologies - Robustness

	(1)	(2)	(3)	(4)
Estimation Method	IV	IV	IV	IV
Dep Variable	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)
Invalidity X Core	-0.631**	-0.918***	-0.977***	-0.978***
	(0.300)	(0.292)	(0.309)	(0.319)
Invalidity X NoCore	-0.321	-0.016	-0.162	-0.156
	(0.721)	(0.515)	(0.436)	(0.404)
Fed Circuit Decisions	1038	1038	1038	1038
IV test	21.08	27.43	30.84	32.07
Equality test: p-value	0.64	0.05	0.03	0.02
Core share	0.25	0.50	0.66	0.75

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors clustered at the litigant level are reported in parentheses. All regressions control for log(PrePatents), age, technology effects, year effects and dummies for largest firms and repeat litigants. Core=1 if share of patents in the focal 2-digit technology class is above the specific cut-off. Regressions include the direct control for the dummy Core.

Table A6: Large Firm Competition in the Technology Field- Robustness

	(1)	(2)	(3)	(4)
Estimation Method	IV	IV	IV	IV
Dep Variable	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)	log(PostPat+1)
Invalidity X Many Large Firms	-0.861***	-0.708***	-0.759***	-0.598***
	(0.264)	(0.211)	(0.219)	(0.177)
Invalidity X Few Large Firms	-0.339	-0.142	-0.154	-0.019
	(0.226)	(0.303)	(0.305)	(0.793)
Fed Circuit Decisions	777	777	777	777
Sample	small firms	small firms	small firms	small firms
IV test	21.94	33.96	30.23	24.55
Many Large Firms if	>8 large firms	>6 large firms	>6 large firms	>23 large firms
Large firm in the field if	50% portfolio in field	40% portfolio in field	33% portfolio in field	identified with Mahalanobis norm

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors clustered at the litigant level are reported in parentheses. All regressions control for log(PrePatents), age, technology effects, year effects and the direct effect of Many Large Firms.

Table A7: First Stage Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Variable	Invalidity	Invalidity X Large	Invalidity X Small	Invalidity X Core	Invalidity X No Core	Invalidity X High Value	Invalidity X Low Value
Baseline Regression							
$\hat{P}$	0.969***						
	(0.122)						
Split Sample							
$\hat{P}$ X Large		0.812***	-0.053				
		(0.138)	(0.089)				
$\hat{P}$ X Small		-0.031	1.062***				
		(0.050)	(0.099)				
$\hat{P}$ X Core				1.063***	-0.025		
				(0.188)	(0.093)		
$\hat{P}$ X No Core				-0.003	0.953***		
				(0.047)	(0.120)		
$\hat{P}$ X High Value						0.826***	-0.007
						(0.125)	(0.089)
$\hat{P}$ X Low Value						-0.013	1.059***
						(0.052)	(0.115)
Exit Regressions							
$\hat{P}$ X Large		0.932***	-0.052				
		(0.110)	(0.048)				
$\hat{P}$ X Small		-0.075	0.900***				
		(0.092)	(0.142)				

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors clustered at the firm level are reported in parentheses. Large if portfolio > 108 patents. Core=1 if share of patents in the focal 2-digit technology class is above the median. High Value=1 if filtered citations received before the decision is above the 75th percentile. Regressions include the direct effects for the interacted dummies along with all the other second-stage controls.