Patents Rights and Innovation by Small and Large Firms[1]

Alberto Galasso
University of Toronto and NBER

Mark Schankerman
London School of Economics and CEPR

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Abstract

This paper studies the causal impact of patents on subsequent innovation by the patent holder. The analysis is based on court invalidation of patents by the U.S. Court of Appeals for the Federal Circuit, and exploits the random allocation of judges to control for the endogeneity of the judicial decision. Patent invalidation leads to a 50 percent decrease in patenting by the patent holder, on average, but the impact depends critically on characteristics of the patentee and the competitive environment. The effect is entirely driven by small innovative firms in technology fields where they face many large incumbents. Invalidation of patents held by large firms does not change the intensity of their innovation but shifts the technological direction of their subsequent patenting.

Keywords: patents, innovation, courts.

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

1 Introduction

Innovation is central to economic growth. Modern macroeconomic models of growth emphasise the key role of innovation and the knowledge spillovers it generates (Aghion and Howitt, 1992; Acemoglu and Akcigit, 2012). At the same time, there is a large body of microeconomic evidence documenting knowledge spillovers and 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 an effective policy tool, and how their impact might vary across heterogeneous firms in different competitive environments.

In this paper we investigate how patent rights affect the rate, and direction, of innovation activity by different types of patent owners across a range of technology fields. In particular, we study the impact of judicial invalidation of existing patents on the subsequent innovation activity of the patent owner. Our analysis shows that patent rights are an important stimulus for innovation, but their impact differs sharply for small and large firms and depends on the nature of competition in the technology markets.

The overall impact of patents on innovation depends on two questions: how they affect the innovation incentives for the patent holder and how they affect follow-on innovation by other firms. Patents enhance the ability of firms to capture rents from their innovations but with a static efficiency cost from higher prices. This trade-off is well-known in the innovation literature, beginning with Arrow (1962). More complex trade-offs arise in dynamic settings where innovation is cumulative and patent rights on upstream technologies may affect the incentives to invest in downstream (follow-on) innovations, and indeed could block such innovation in the extreme case (Green and Scotchmer, 1995; Bessen and Maskin, 2009). These dangers have been prominently voiced in public debates on patent policy in the United States (Federal Trade Commission, 2011) and recent decisions by the Supreme Court (e.g., Association for Molecular Pathology v. Myriad Genetics, 133 S. Ct. 2107, 2013).

Recent empirical studies have examined how patent rights affect cumulative innovation by enabling the patent holder to block follow-on innovators (e.g. Murray and Stern, 2007; Williams, 2013; Sampat and Williams, 2015; Galasso and Schankerman, 2015). Overall, these studies show that patents have some blocking effect on subsequent innovation by other firms, but only in very particular contexts where bargaining frictions in technology licensing transactions appear to be more severe. Perhaps surprisingly, the empirical literature has largely overlooked the impact of patents on the subsequent innovation by *patent owners.*[1] One notable exception is Budish, Roin and Williams (2015), who exploit variation in effective patent life for pharmaceuticals (due to regulatory testing requirements) to identify the (positive) impact of longer patent duration on innovation, as measured by clinical trials.

Patent rights can affect subsequent innovation by patent owners 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 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 strengthen the ability of small firms to license their innovations to large firms for commercialisation (Gans, Hsu and Stern, 2002). Second, patents facilitate access to debt and venture capital markets for financially-constrained innovators, especially small (and young) firms for whom information asymmetries are severe and patents may be their primary collateralizable asset (Hochberg, Serrano and Ziedonis, 2014). Finally, patents are often used in cross-licensing agreements, and more generally as bargaining chips, to enhance access to patented inputs required for R&D and to resolve patent disputes without extensive litigation (Lanjouw and Schankerman, 2004).

We develop a simple model that shows how the loss of patent rights affects the incentives to innovate. The basic mechanism is as follows: A firm is assumed to build on its patents in subsequent rounds of innovation. When a patent is invalidated, the firm still retains the knowledge embodied in that patent for future use. However, the loss of patent protection opens up the innovation competition to other firms now able to exploit this knowledge without a license. The resulting competition for the second generation patent reduces the incentives and thus the R&D level of the original owner. The model generates two main predictions. First, the loss of a patent on a core technology – which serves as the basis for subsequent innovation – reduces innovation more for small firms than for large firms. This follows from our assumption that the marginal benefit of owning an extra core patent declines as the portfolio size increases.

[1] There are studies that exploit patent renewal data in order to quantify the incremental incentives provided by patent protection (Schankerman and Pakes, 1986; Schankerman, 1998), and other approaches to estimate the so-called 'patent premium' (Arora, Ceccagnoli and Cohen, 2008). But these studies do not provide causal evidence on the link between patent rights and the level of innovation.

Second, for a small firm the impact of losing a core patent will be 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 reason is that, when there are more potential licensees, the firm is more likely to be able to licenses the technology and to extract greater value from the license (through competition among licensees).

The major empirical challenge in studying how the loss of patent rights affects innovation is that the judicial decision to invalidate an existing patent is potentially endogenous. 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 challenge, we extend the identification methodology developed in Galasso and Schankerman (2015), which exploits decisions by the U.S. Court of Appeal for the Federal Circuit to invalidate patents. This court was established in 1982 and has exclusive jurisdiction in appellate cases involving patents. Each case is decided (majority rule) by a panel of three judges who are randomly assigned by a computer algorithm. We exploit this random allocation of judges, together with variation in their propensity to invalidate patents, to construct an instrumental variable for patent invalidation. This allows us to identify the causal effect of losing patent rights on subsequent innovation by the patent owner. It is worth noting that patents litigated in the Federal Circuit are not representative of the overall population of patents. They are typically higher value patents, as they have gone through the costly litigation process up to the appellate level. However, 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.[2]

There are three main empirical findings in the paper. 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 average treatment effect is driven *exclusively by small innovative firms* that lose patents on technologies that are *core*

[2] In addition, our identification strategy only applies to this sub-population since, unfortunately, judge assignment is not always randomised in cases at the lower (federal district) court level.

to their research focus. We find that there is no significant response by small firms to losing a non-core patent. Even more strikingly, the evidence shows that large firms do not reduce their level of innovation when they lose either a core or a non-core patent. Finally, we show that patents rights affect the direction of innovation by large firms, even though there is no significant impact on their level of innovation.[3] The invalidation of a non-core patent induces large firms to increase their patenting in different (though related) technology areas. Losing patent rights over core technologies does not induce any refocusing of innovation for large firms.

As discussed earlier, there are three main ways in which patent rights affect innovation incentives for small firms: 1) by strengthening their position when they face competition from large incumbent firms; 2) by enhancing access to capital markets; and 3) by facilitating in-licensing of patented inputs needed for their R&D activity. The evidence supports only the first hypothesis: we find that the loss of a core patent has a much larger impact on small firm innovation in technology fields where they face many large firms. In contrast, the data do not support the capital markets or licensing channels. We show that the effect of losing a patent is no stronger for patents that have been pledged as loan collateral, which contradicts the capital market hypothesis, and the impact of invalidation is no larger in technology fields where patent ownership is highly fragmented, as would be predicted by the licensing negotiation hypothesis.

Taken together, our empirical findings show that patent rights affect both small and large firms, but in very different ways. Patents are a powerful source of innovation incentives for small innovators, particularly where they compete with large firms. By contrast, patent rights appear to affect large firms primarily by redirecting their innovation, rather than increasing its level. This important distinction between small and large firms is consistent with recent macroeconomic research which shows that R&D subsidies for small innovative firms have more impact than those targeted at large incumbents (Acemoglu et. al., 2013).

The paper is organized as follows. Section 2 develops a model showing how loss of a patent right can reduce innovation incentives for subsequent innovation. Section 3 describes the data set. Section 4 discusses the econometric specification and identification strategy and Section 5 presents the baseline estimates of the average treatment effect of patent rights on the level of 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

[3] Some recent research has emphasised the role of incentives in affecting the direction of innovation, as much as its level (e.g., Acemoglu, 2002; Aghion et al., 2015; Hanlon, 2015).

several different mechanisms that might explain the impact on small firms. Section 8 examines how patent invalidation affects the direction of innovation. In concluding remarks we summarise the main findings and discuss 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 chooses a commercialization strategy for the innovation. We begin by assuming that the firm is endowed with c patents on 'core' technologies and p on 'peripheral' ones, and $n = p + c$ denotes the total number of patents held by the firm. 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.[4] The probability of developing a new innovation is given by $rF(c)$ where r is R&D investment and $F(c)$ is an increasing, concave function with $\lim_{c\to\infty} F_c = 0$. This formulation embodies complementarity between the existing stock of core technologies and current research investment, and diminishing returns of core knowledge on the marginal product of R&D, which is a property of most standard production functions. 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 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, invalidation 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 is thus $rF(c-1)+r\chi(M)(1-F(c-1))$ where M is the number of competing firms in the patent race. The term $rF(c-1)$ indicates the likelihood the focal firm develops a follow-on technology which builds on one of the $c-1$ valid core patents,

[4] 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).

and $\chi(M)$, with $\chi' < 0$ and $\lim_{M\to\infty}\chi(M) = 0$, captures the probability it wins the patent race for the follow-on technology which builds on the invalidated patent. We assume

$$F(c) - F(c-1) \geq \chi(0) \tag{1}$$

which implies that, for a given level of R&D, the likelihood that the focal firm builds on the (invalidated) patent is at least as large with full ownership as in the patent race.[5]

If the firm successfully innovates, it chooses between commercializing the new technology internally or licensing it to another firm for development. If the firm commercializes the technology itself, it obtains revenue given by the increasing and concave function $\Theta(n)$. This means 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 the associated patent right more effectively (Lanjouw and Schankerman, 2004).[6]

Alternatively, the firm can negotiate a licensing deal with one of N symmetric firms, each of whom needs the technology with probability α. 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 $L(N, \overline{\Theta})$ denote the expected payoff of the innovator from this licensing subgame. We assume that $\Theta(1) < L(N, \overline{\Theta})$.

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 'large' firms ($n \geq \kappa$) develop it internally. A firm that retains the litigated patent sets its R&D investment to maximize

$$\Lambda F(c) r - \frac{r^2}{2}$$

[5] It is easy to show that our results extend to the case where the probability of winning the patent race also depends on c, i.e. $\chi(M, c)$, if the equivalent of condition (1) holds.

[6] We also note that our set-up can be easily generalized along two dimensions. First, the functional form generates a simple cut-off rule for the investment strategy but assumes symmetric marginal effect of core and peripheral patents. Our results are robust to using more general functions $\Theta(c, p)$ provided that $\Theta_c(c, p) \geq \Theta_p(c, p)$. Second, one can generalize the framework to allow the patentee to license to more than one party.

where $\Lambda = \{L(N, \overline{\Theta}) \text{ if } n < \kappa, \Theta(n) \text{ if } n \geq \kappa\}$ is the value of commercialising the new technology. If the patent is invalidated, the firm sets R&D to maximise

$$\Lambda \left[F(c-1) + \chi(M)(1 - F(c-1)\right] r - \frac{r^2}{2}.$$

For a small firm ($n < \kappa$), the optimal level of R&D with c valid patents is

$$r_S^*(c) = L(N, \overline{\Theta})F(c)$$

and the optimal level in the case of invalidation is

$$r_S^*(c-1) = L(N, \overline{\Theta}) \left[F(c-1) + \chi(M)(1 - F(c-1))\right].$$

Defining $\Delta r_S = r_S^*(c) - r_S^*(c-1)$, we obtain the impact of patent invalidation on R&D by the small firm:

$$\Delta r_S = L(N, \overline{\Theta}) \left[F(c) - F(c-1) - \chi(M)(1 - F(c-1))\right].$$

This is positive – i.e., losing a core patent reduces R&D – because condition (1) holds. An analogous expression holds for Δr_L (see the Appendix for details).

In the Appendix we show that this model generates two main predictions about how patent invalidation affects innovation by the patent owner. First, the loss of a core patent reduces innovation more for small firms (i.e. those with $n < \kappa$) than for large firms – and the impact goes to zero as firm size increases. This follows from our assumptions that $F(c)$ and $\Theta(n)$ are concave functions, i.e., the marginal benefit of owning an extra patent declines as the portfolio size increases. The loss of a peripheral patent has no effect on later innovation (this follows from our assumption that peripheral patents do not enhance the probability of successful follow-on innovation).

Second, for a small firm the impact of losing a core patent on innovation 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).

In the Appendix 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. We also show that, when competition in the patent race is intense (i.e. M is very large), the comparative statics are robust to a more general specification of the innovation production process, $F(c, r)$ and $C(r)$, under some mild conditions on their curvature.[7]

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 Court of Appeal for the Federal Circuit 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. Since its inception, judges have been 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 reached by the court, and the 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 1469 patent invalidity decisions. Information about each patent in the sample is obtained from the USPTO patent database.

In this paper we focus on how patent invalidation affects innovation at the *firm* level. To do this, for each owner of the patents litigated at the Federal Circuit, we use a number of data sources to construct the patent portfolio at the year of the Federal Circuit decision and her subsequent patenting activity. The USPTO data provide an assignee identification numbers, our main tool to track patenting activity, only for patents granted after 1976. For patents granted before 1976, we retrieve data on the owner's patenting activity 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,

[7] The general specification developed in Appendix A.3 includes a simple recombinant innovation process in the spirit of Weitzman (1998).

exploiting the data described in Li et al (2014). We then track patenting activity over time 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 retrieved the identity of the patentee from the text of the Federal court decision.[8]

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 317 patents in their portfolio and that apply for 200 patents in the five years after the decision, but the portfolio distribution is highly skewed (the median of 11 patents, and 24 percent of the decisions involve firms with only one patent).

We also emphasize that 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 – the number of claims, citations per claim, and measures of patent generality and originality – are all higher for litigated patents than other patents, and even higher for those appealed to the Federal Circuit. However, for the purpose of studying whether patent rights provide

[8] We use the following procedure. First, for each unassigned patent we identified the names of the parties involved in the suit. If one of the litigants is also one of the inventors of the patent, we re-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. Once the re-assignment is identified, we use the USPTO assignee data to retrieve an assignee number of the acquiring firm.

important innovation incentives, and for whom, 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 paper is conducted at the *firm-case level* because we are interested in uncovering the impact of invalidation on the innovation by the firm that loses its patent rights. This requires collapsing the dataset from patent-level observations to firm-level units of analysis. For about 83 percent of the cases in our sample, firms litigate only one patent, but the remaining cases involve decisions related to multiple patents owned by the same firm. We treat the cases involving multiple patents as follows. First, we re-define the invalidity dummy as equal to one if at least one patent is invalidated. Second, we allow multiple age and technology class dummies to be equal to one for a single firm-case. Specifically, the age effects control for all the ages of the patents in the case and the technology effects control for all the fields of the patents in the case.[9]

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.[10] Our main empirical specification is

$$log(PostPatents_i) = \beta \ Invalidity_i + \lambda' X_i + \varepsilon_i \tag{2}$$

where X denotes control variables. The coefficient β captures the effect of invalidation on subsequent patenting by the firm: for example, $\beta < 0$ 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 report heteroskedasticity-robust standard errors. Because some firms litigate their patents more than once, we also confirm significance using standard errors clustered at the firm level.

[9] Our data contain 140 cases involving 2 patents of the same firm and 39 cases involving 3 patents. There are 13 cases with 4 patents and 7 cases with more than 5 patents. Results are robust to redefining age of the litigated patents as the rounded average age of the patents in the case and the technology field as the modal technology field of the patents in the case.

[10] 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.

The main empirical challenge is the potential endogeneity of the Federal Circuit decision to invalidate a patent. Of particular concern is that firms which experience invalidation may be those that follow aggressive patenting strategies, filing numerous patent applications some of which are of dubious validity. This would generate positive correlation between ε_i and $Invalidity_i$ in equation (2) and thus an upward bias in the OLS estimate of β. There could also be measurement error in our measure of invalidation (though we show robustness to alternative definitions below), creating attenuation bias toward zero.

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.[11] This ensures that judges with high propensity to invalidate are not assigned to cases because 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.[12] 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

[11] Our identification strategy is similar to Kling (2006), who uses random assignment of judges to estimate the effects of incarceration on employment and earnings of individuals, and Doyle (2007) who uses randomized assignment of child protection investigators to identify the effects of foster care on long term outcomes. The main difference is that our instrument explicitly recognizes that decisions are made by three-judge panels.

[12] 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 threshold of reasonable doubt differs across judges.

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.[13]

Our estimation approach instruments the invalidated 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

$$Invalidity_i = \alpha \widehat{P}_i + \theta' X_i + u_i \quad (3)$$

$$log(PostPatents_i) = \beta \ \widehat{Invalidity}_i + \lambda' X_i + \varepsilon_i \quad (4)$$

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

In the Appendix (Table A.1) we summarize the relationship between patent invalidation and the composition of judge panels, which is studied more in detail in Galasso and Schankerman (2015). Probit models confirm a strong positive relationship 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.

5 Empirical results

Baseline model

Table 2 examines how Federal Circuit invalidation affects the number of subsequent patent applications by the focal firm. Column 1 presents OLS estimates of the baseline specification relating patenting 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

[13] 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.

factors to affect both the invalidity decision of the Federal Circuit 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. The IV estimate of β 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. This shows that, at least on average, patent rights are an effective incentive for innovation.[15] However, we later show that this average effect hides important heterogeneity, with the impact of patent rights strongly depending on the characteristics of the patentee and the competitive landscape. Before doing that, we perform a variety of tests to confirm the robustness of our main finding.

Robustness tests

We perform a variety of robustness tests 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. There is a concern that, 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 42 to 39 percent.[16] There is essentially no difference in the estimated invalidation effect using this alternative measure. As an additional test, in column 4 we drop the cases involving multiple patents from the sample. Also in this case, the coefficient is very similar to the one in the baseline specification, confirming that our finding is not sensitive to the treatment of cases involving multiple patents.

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[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 Invalidaty, $\widehat{v}$ 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 their past royalty payments if a patent is invalidated (Geffner v. Linear Rotary Bearings, Inc., 124 F.3d 229, Fed. Cir. 1997). This means that our estimate of the incentive effect of patent rights is not confounded by additional financial obligations associated with invalidation.

[16] About 50 percent of cases involving multiple patents result in no patents being invalidated, and about 30 percent result in the invalidation of all the patents in the case. This implies that only for a small sample of cases (34 cases) there is a difference between the two invalidation measures.

Second, the instrument we use is the predicted probability of invalidation which is constructed from a probit regression at the case-firm level (i.e., we aggregate information on all the patents in a given case). As an alternative, we exploit all the information available in our data by running a probit regression that predicts invalidation at the *patent level*. We then use these estimates to construct the probability of observing that at least one patent in a case is invalidated, as well as the probability of observing invalidation of all the patents in a case. We conduct these computations on the assumption that Federal Circuit invalidation decisions on the constituent patents in multi-patent cases are independent draws. The estimated β using these predicted probabilities as instruments are given in Table A2. The point estimates are robust, but they are less precise than those in our baseline model.[17]

Finally, our sample contains 343 cases involving repeat litigants. Specifically, 70 patentees litigate twice, 19 litigate 3 times and 8 patentees litigated more than 3 times. In roughly 70 percent of the cases involving repeat litigants, 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 Table A2 we present the estimates of a regression in which 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. As additional test, we also drop repeat litigants altogether. In this regression, presented in Table A2, the coefficient is very similar to the one in the baseline specification, confirming that our findings are not sensitive to the treatment of cases involving repeat litigants.

6 Unbundling the effect of patent rights

To this point we have assumed that the impact of patent invalidation on future patenting is the same across firms. However, the model developed in Section 2 predicts that the impact of patent rights should depend the characteristics of the patentee (small vs large) and technology (core vs peripheral patent). In this section we unbundle the average treatment effect of patents and explore these dimensions of heterogeneity.

[17] We also use these patent level probabilities to compute the expected number of invalidated patents in each case. When we use this construct as an IV, the estimates confirm a negative impact of invalidation on patenting which is increasing in the number of invalidated patents. But also in this case, the coefficient is estimated less precisely due to the small number of cases involving multiple invalidations ($\hat{\beta} = -0.362$, standard error = 0.209).

6.1 Small vs large firms

The model in Section 2 predicts that the loss of patent rights should reduce innovation incentives more for small patentees. To test this hypothesis, we define a firm as large if the *total* number of its patent applications in the *ten years* prior to the Federal Circuit decision is in the top quartile of our sample (this threshold for large firms corresponds to 75 patents).[18] Simple mean comparison tests indicate a differential impact: in the small firm sample, the mean of *logPostPatents* is 0.55 for firms which do not experience patent invalidation and 0.40 for firms with invalidated patents. We strongly reject equality of these means (p-value=0.03). In contrast, for the large firm sample, the mean of *logPostPatents* is 4.36 for firms experiencing invalidation and 4.39 for firms with no invalidation, and the difference is not statistically significant (p-value=0.93). These comparisons suggests that the loss of patent rights reduces innovation (as measured by patenting) for small firms but has no effect for large firms.

In Table 3 we confirm this finding using *IV* regression models. Columns 1 and 2 present split sample regressions which replicate our baseline model for small and large firms. We find a strong negative effect of invalidation on subsequent patenting of small firms, but no significant effect in the large firm sample. In column 3 we present a full sample regression that allows the invalidity effect to differ for small and large firms. Again we find no statistically significant effect for large patentees, whereas invalidation of a patent owned by small firms causes a statistically significant reduction of 56 percent in future patenting.[19]

We did a series of additional (unreported) regressions that vary the threshold portfolio size to define small firms. The key result in Table 3 is robust to these alternative thresholds: the invalidation coefficient for small firms remains large and highly significant, but there is no significant effect for large firms. In particular, the sharp difference between the impact for small and large firms holds even if we set the portfolio threshold for small firms as low as 30 patents – the point estimate/standard error are -0.652 (0.306). But interestingly, even if the threshold for small is raised to 130 patents (80th percentile of the distribution), the estimated

[18] For the decade 1991-2001, in the USPTO data only 0.05 percent of firms are large according to this definition. If we drop invididuals and unassigned patents, the fraction is 1.5 percent. However, large firms account for about 60 percent of patenting activity in that period.

[19] At the sample mean of portfolio size for small firms, this effect implies an elasticity of roughly 4. The semi-elasticity for large firms is not statistically significant, indicating that the loss of one patent does not affect their future patenting. It is important to notice that the empirical variation in our data does not allow us to identify a meaningful elasticity for large firms. This is because for many of the large firms in our sample a one percent reduction in portfolio size requires invalidation of a substantial number of patents, whereas in our sample most invalidation decisions involve only one or very few patents.

effect of invalidation for small firms remains significant, though somewhat smaller at -0.750 (0.290), and again it is statistically insignificant for large firms. These results 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. However, the loss of patent rights does not affect the level of subsequent innovation by large firms.

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 technology field.[20] Column 4 presents the parameter estimates using this classification: the results are nearly identical to the coefficients in column 3. This is not surprising given the high rank correlation (0.83) between the absolute and relative measures of firm size in our sample.

As a final robustness check, we exploit USPTO data to examine the difference between small and large firms. Patentees are required to report whether they have 'small entity status' (fewer than 500 employees) when they pay patent renewal fees. These data are available only for patents filed on or after December 12, 1980, which are about 70 percent of our sample. Roughly 30 percent of the matched patentees are classified as small entities and essentially all of the small entities (96.6 percent) have a portfolio with less than 75 patents. The average portfolio size for large entities is 385 patents but there is substantial variation in the distribution, with only 37 percent having more than 75 patents in their portfolio. We ran split sample regressions based on whether patentees had small entity status (not reported for brevity). These show that the invalidation effect is similar for small and large firms, indicating that firms with large employment but small patent portfolio behave similarly to firms that are small on both measures. Patent invalidation has no effect only for firms which are large both in terms of employees and patent portfolios. This is consistent with our model which emphasizes that large firms have commercialization advantages both because they own requisite complementary assets and because large portfolios allow more effective enforcement of patent rights.[21]

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[20] For each litigated patent, we identify all patentees with at least one patent in the same technology class as the litigated patent (36 NBER sub-categories) in the ten years preceding the Federal Circuit decision. For patentees litigating multiple patents, we focus on the modal technology class. We call a firm large if its portfolio in the year of the Federal Circuit decision is in the top 5 percent of the portfolio distribution of patentees that have at least one patent in the same technology class. On this definition, about 24 percent of the firms in our sample are large (parameter estimates are robust to using a 90th percentile threshold).

[21] In an attempt to obtain a finer measure of firms' employment, we tried matching our data with the company level information from Bureau Van Dijk (the Orbis data base). 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

6.2 Core vs peripheral patents

The model developed in Section 2 incorporates a distinction 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). To highlight this distinction, the model assumes that future innovation builds only on core technologies, with the implication that the loss of core patents (not peripheral ones) would reduce incentives for follow-on innovation by the patentee. The more general point is that we expect the loss of patent rights over a core technology would have a larger negative impact on subsequent innovation than the loss of a peripheral patent.

We investigate this hypothesis by constructing two alternative measures of core patents. The first one is based on whether the litigated patent falls in a technology field that represents the main focus of the firm's patenting activity. To do this, 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 60 percent of the patenting of the firm, but there is substantial variation in field shares (with median 0.66 and standard deviation 0.35). For about 32 percent of the litigated patents, all of the firm's portfolio is in the same technology field, but for about 10 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, and is based on the idea that greater self-citation indicates that the focal patent is more central to the research trajectory of the firm. Specifically, 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.[22] On average the patents in our sample receive 11 percent of the maximum possible self-citations, and about 55

period.

[22]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).

percent of the patents receive no self-citations. We set the dummy variable *Core* equal to one if the firm litigates a patent with a fraction of self-cites above the 75th percentile. As before, 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 column 1 we use our first measure of *Core* based on the share of patents in the technology area of the focal patent. The results are striking. 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. We conduct a number of robustness checks to examine sensitivity of the results to this measure of *Core*. 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 48 percent of the firm's patenting on average (with median 0.38 and standard deviation 0.39). As before, we set *Core*=1 if the firm litigates a patent in a field with share above the sample median. We obtain estimates (unreported) which are essentially identical to those in column 1. Second, in Appendix Table A3, 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, indicating that the loss of a core patent is most damaging to innovation when the firm is highly specialized in a technology field (as before, loss of a non-core patent has no significant impact).

In column 2 we exploit the second measure of core patents, based on the degree of self-citation by the focal patentee. Also in this case we find that it is only the loss of core patents that causes a reduction in follow-on innovation. There is no evidence of an effect for the invalidation of peripheral patents. The magnitudes of the coefficients are also in line with those reported in column 1.

We next examine whether small and large firms react differently to the loss of core patents. Large firms are more likely to be diversified across a range of research areas, giving them the potential for reacting both at the intensive margin (within the technology field of the litigated patent) and the extensive margin (shifting focus across technology fields). This flexibility may mitigate the effect of losing a core patent in one technology area. To investigate this idea, we use our earlier definition of a large firm as one with a patent portfolio above 75 (in the ten years before the court decision).[23] Column 3 in Table 4 presents the estimates of

[23]The correlation between *Large* and *Core* is -0.48, indicating that large firms are less likely to litigate core

a full sample regression with four different invalidation effects for the pairwise combinations of firm size and core vs peripheral patents. The *Core* measure used in this regression is based on the share of patenting in the two-digit technology field.

The results show that the negative effect of invalidation on future patenting is concentrated *exclusively* on small firms that litigate core patents. The point estimate implies a large impact: invalidation causes a reduction in the firm's patenting of about 58 percent in the five years following the Federal Circuit decision. The estimated coefficients for the other size-technology pairings are statistically insignificant. For large firms, in particular, the magnitude of the coefficients is much smaller, indicating that firms do not reduce the level of their subsequent innovation when losing either core or peripheral patents. In column 4 we re-estimate the model using the alternative *Core* measure using self-citations. The coefficients are nearly identical to the previous estimates.

The baseline model includes fixed effects for six broad (one-digit) technology fields. The *Core* dummy could be mismeasured if there is unobserved heterogeneity in narrower technology fields. To check robustness, we also estimate specifications which (i) control for the firm's patenting at the more refined two-digit patent classification level (36 technology fields), and (ii) include technology field fixed effects defined at the two-digit level. In both of these (unreported) regressions, we again find that the only statistically significant effect of invalidation is for small firms that litigate core patents, and we cannot reject the null hypothesis that the coefficients are the same as those in column 3.

One final concern is that core patents may be more valuable than peripheral ones, especially for small firms, and that it is losing valuable patents (not core patents) that is important for innovation incentives. To check this, we compare the means for core and peripheral patents of two commonly used indicators of patent value – the number of claims and (non-self) citations received before the Federal Circuit decision. There is no statistically significant difference between these value proxies for core and peripheral patents (at the 10 percent significance level), both for the small firm and large firm sub-samples. We conclude that Core is not simply proxying for the value of the patent in our sample (this perhaps is not surprising given that patents involved in Federal Circuit cases are a selected sample of highly valuable patents).

technologies. About 55 percent of the cases in our sample involve small firms litigating core technologies. Roughly 40 percent of the cases involve peripheral technologies and they are equally split between large and small firms. Only 5 percent of the cases involve large firms' litigation of core technologies.

7 Explaining the impact for small firms

The loss of patent rights causes a substantial decline in subsequent innovation by the focal firm, and this is driven exclusively by small firms suffering invalidation of a core patent. In short, patent rights are crucial as innovation incentives for small firms. There are three main mechanisms which can explain our findings. First, patents may allow small firms to soften the impact of product market rivalry with large firms, and to interact more effectively in licensing their innovations to large firms for development and commercialisation (Gans, Hsu and Stern, 2002; Gans and Stern, 2003). Second, patents may be important for follow-on innovation because they enable small firms to access debt and venture capital finance (Conti, Thursby and Thursby, 2013; Hochberg, Serrano and Zeidonis, 2014). Finally, patents may be valuable bargaining chips to get access to patented inputs for conducting innovation and resolving disputes through cross-licensing and other arrangements (Lanjouw and Schankerman, 2004; Galasso, 2012). It is important to distinguish between these explanations because they are likely to have different welfare and policy implications. In this section we provide evidence to test these competing explanations.

7.1 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. This effect works through three main channels. 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 incentives is theoretically ambiguous, recent empirical research indicates that patents are particularly important for innovation incentives when competition is intense (Spulber, 2013; Aghion, Howitt and Prantl, 2015). Second, the presence of multiple large firms increases the bargaining power of start-up innovators, and thus the rent they extract when they license their patents. Third, large firms may be especially well positioned to develop and commercialize follow-on innovation on the basis of an invalidated patent (thus undermining the original patent owner's ability to do so), both 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 that losing patent rights would undermine innovation incentives more 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 39 (median is 12). 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 firms).

Column 1 of Table 5 presents the estimates for small firms operating in focal technology fields with few versus many large patentees. The results are striking: patent invalidation reduces innovation only for small firms in fields where large firms are more active. The impact is large: invalidation for these small firms reduces their future patenting by about 56 percent. But invalidation has no statistically significant effect on innovation for small firms in fields with few large firms present. In Appendix Table A4 we present a series of additional regressions that vary the thresholds for the number of large firms and their share of patenting in the focal field. The results in column 3 of Table 5 remain robust. In a series of unreported regressions we find that the critical threshold for large firms in the field is about 10. Beyond that value we cannot reject the hypothesis that the invalidation effects in fields with many vs few large firms are the same. Second, the results are robust to changing the fraction of patenting used to classify a large firm as active in the field.[24]

We also examine whether this finding might simply reflect instances where there are few firms *in total* (both small and large) – 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 (unreported) 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 the total number of firms in that field. Moreover, we do not find any differential effect of invalidation of small firm patents in fields where the total number of firms is low compared to fields where the total number of firms is high.

[24] As one further check, we examine whether the presence of many large firms has a *differential impact* depending on whether the small firm litigates a core or peripheral patent. This is quite demanding for our data, since the small firm sample is not large and we need to include four instrumented interactions. The only statistically significant effect relates to the invalidation of core patents litigated in fields where many large firms are active (point estimate =-0.700, p-value = 0.01). This provides additional support for our earlier finding that patent rights are particularly important to protect core technologies of small firms.

These tests confirm that patent rights are more important for follow-on innovation for small firms when they face larger competitors, and this is not simply a proxy for more competitive fields. Patent rights appear to have an important role in shaping the competitive interaction between small and large firms.

Heterogeneity across technology fields

We examine whether the effect of patent invalidation on innovation by 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 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.[25] Using these parameter 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 implied impact of patent invalidation varies somewhat across broad one–digit technology fields: the largest effect is in Pharmaceuticals, where the estimate (standard error) is -1.606 (0.440), as compared to a low of -0.566 (0.224) in Electronics.[26] 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 -0.686 in Genetics and Biotechnology to -2.314 in Drugs. In a number of subfields within Chemicals, invalidation has no statistically significant effect (e.g. Agriculture, Food and Textiles) whereas in others it is as large as -1.197 (Resins). This diversity characterizes all of the 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 (the latter account for only about 30 percent of the total variance). In short, while there are technology sectors in which the number of large firms is limited and invalidation has only a modest effect on small firms patenting, these areas are not concentrated in few broad

[25] The estimated coefficient on the direct effect of invalidation is statistically insignificant, 0.311 (0.419) whereas the interaction term is negative and significant, -0.482 (0.185). The regression also includes an additive effect for the log of the number of large firms.

[26] The other estimates are Computers -1.028 (.273), Chemicals -1.014 (.270) and Mechanical -0.691 (.225).

technology fields.

Mahalanobis measure of potential competitors

Thus far we identify large potential competitors for small firms as those large firms (more than 75 patents) with a threshold (50 percent) for specialization in the two-digit technology field of the litigated patent. One limitation of this approach is that it does not recognize that large firms in different*, but technologically related*, fields may also be positioned to exploit the removal of the focal patent by building on it once it is in the public domain. This may introduce systematic measurement error in this critical variable. To address this concern, we build on Bloom, Schankerman and Van Reenen (2013) who propose a 'Mahalanobis' index that measures the technological proximity between different patent classes based on the frequency with which firms tend to patents in specific fields ('co-location of patents'). We compute the number of large firms in each two-digit technology area and then weight them by the Mahalanobis index of proximity between each of those fields and the focal field of the litigated patent (details are provided in the Appendix). This Mahalanobis index is a more refined measure of the number of large potential competitors (the mean and standard deviation of this measure are 80 and 55, respectively).

We re-define the dummy *Few Large Firms=1* if the Mahalanobis index of large patentees is in the bottom decile of the distribution (corresponding to 23 large firms). The *IV* estimates using this measure, presented in Table A4, confirm our earlier results: the coefficient on Invalidity for small firms facing few large firms (where *Few Large Firms=1)* is again statistically insignificant, but invalidation has a strong and significant effect for small firms facing such potential competition. The point estimate is -0.771 (0.212) which is quite similar to the baseline result of -0.837 (0.243).[27] Interestingly, the Mahalanobis adjustment suggests that the bias from measurement error is not a problem in this context. However, this approach to characterizing potential competition might prove more consequential in other contexts, such as empirical models of entry.

7.2 Access to finance

Small firms may face difficulty in financing their innovation activity due to informational asymmetries in the capital markets (Hall and Lerner, 2010). Recent empirical studies show these

[27] If we define *Few Large Firms=1* based on the first quartile of the distribution (corresponding to the equivalent of 38 large firms) rather than the bottom decile, we again find that the coefficient is nearly identical at -0.771 (0.206).

frictions can be mitigated through debt and venture capital secured by patents (e.g., Conti, Thursby and Thursby, 2013; Hochberg, Serrano and Ziedonis, 2014). 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 the approach of 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 third parties which are 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 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 dummies. 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, in column 2 of Table 5, show that there is no statistically significant difference in the effect of invalidation between patents pledged as collateral and those not pledged.[28] This evidence suggests that access to finance is not the main channel through which patent invalidation affects innovation incentives of the small high-technology companies *in our sample* (of course, the relatively small number of patents pledged as collateral may make it hard to detect the effect here). However, this finding does not mean that patents are unimportant for small firms in securing financing more generally since, as we pointed out in Section 3, the patents litigated in the Federal Circuit are more valuable than garden variety patents, and

[28] We also tested wheher the negative 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 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.

their owners may be less constrained in the capital markets. [29]

7.3 Access to external inputs

Another potential explanation for why patent invalidation affects subsequent innovation by small (but not large) firms is that patents can reduce transaction costs of obtaining external inputs protected by patent rights. The patents owned by an innovator can affect her ability to negotiate access to external patent rights in several ways. First, 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). Second, innovators can "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, especially for small firms, to access external patent rights. If this channel plays an important role, we would expect patent invalidation to have a more negative effect on innovation by small firms when they operate in technology fields where the ownership of patent rights is more fragmented, 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 and standard deviation of *Conc4* are 0.08 and 0.06, respectively). In column 3 of Table 5 we contrast the *IV* estimates of patent invalidation for small firms operating in fragmented fields (*Conc4* below the sample median) and concentrated fields (*Conc4* above the sample median). The point estimates are very similar, and not statistically different from each other. We conclude that the negative effect of invalidation on innovation incentives for the small firms in our sample is not driven by access to external (patented) inputs.

[29] Our empirical test shows that invalidation does not have a stronger effect for patentees who had pledged their patents as collateral prior to the time of litigation. However, it is possible that the loss of licensing income (current and prospective) associated with patent invalidation could reduce later innovation for firms that would be liquidity-constrained even if the patent were not used as collateral before the litigation. With the current data, we cannot rule out this channel.

8 Patents and the direction of innovation

We showed that losing a patent in a core technology area causes a large reduction in the *level* of innovation by small firms, but no significant effect for large firms. However, patent rights can also affect the *direction* of innovation. This is particularly so for firms that have the opportunities and flexibility to shift the focus of their research, and we would expect that large firms with a diversified research portfolio are best positioned to respond in this way. There is a growing literature on how economic factors such as input prices and market size affect the direction of technical change (Acemoglu, 2002) but very little on the role of patent rights (the exception is Moser, 2005). In this section we provide evidence on how patent invalidation affects the direction of innovation of small and large firms.

We do this with a series of *patent-level* regressions. First, we use self-citations to the litigated patent as a measure of the propensity of a firm to conduct follow-on research. The distribution of self-citations in our sample is highly skewed (only 15 percent of patents receive any self-citations in the five year window after the Federal Circuit decision, and the mean and standard deviation are 0.81 and 4.83). In an *IV* regression on the pooled data, invalidation has no statistically significant effect on self-cites – the point estimate is -0.091 (0.101). But this conceals surprising heterogeneity, as shown in Table 6 where we allow for the effect of invalidation on self-citations to differ for small versus large firms, and core versus peripheral patents. Column 1 in the table reveals that self-citations drop substantially (about 40 percent) for *large firms* when a *non-core* patent is invalidated, but there is no effect for a core patent. Invalidation has no effect on self-citations for small firms, either for core or peripheral patents.[30]

Our finding that large firms do not react when they lose a core patent is consistent with the idea in our model that there is complementarity between core patents and future innovation. This feature makes it costly for large firms to redirect their research toward different technology fields, as they can no longer (or less effectively) exploit their existing knowledge base. Moreover, if as we assume there is only weak complementarity between current and future innovation for peripheral technologies, there should be less 'inertia' about shifting focus when large firms lose non-core patents. In addition, increased competitive pressure associated with invalidation of a

[30] Because of the extreme skewness in self-cites, we cannot include in this specification a dummy capturing patents which receive zero cites. Results are robust to estimating a linear model in which the dependent variable is a dummy equal to one when the patent receives at least one self-cite.

peripheral patent would reduce the incentive to innovate in that field and induce redirection of innovation effort toward alternative areas.

Second, we examine in more detail where innovation is redirected when the firm loses a patent. To do this, we distinguish between three different levels of redirection: the effect of invalidation on the focal firm's patenting within the same three-digit technology field (column 2 in the table), in different three-digit fields within the same broad two-digit class (column 3), and shifts of its patenting to different two-digit fields (column 4).[31] The parameter estimates highlight two main findings. First, invalidation of a core patent causes a decline in patenting by small firms of roughly the same magnitude across all three levels of technology field aggregations (compare columns 2-4). Put another way, the loss of a patent leads small firms to reduce innovation across the board, rather than to redirect it. This confirms our earlier conclusion (Tables 3 and 4) that patent rights are important for the level of innovation by small firms. The second finding is that large firms react to invalidation of a non-core patent by increasing their patenting in related fields (different three-digit within the same two-digit class), but not in the focal field or unrelated (different two-digit) fields. While there may be some measurement error in the classification of patents at the three-digit level, this redirection of patenting is consistent with the decline in self-citation to the focal patent shown in column 1.

In short, the evidence in this section suggests that patent rights also affect large firms, but in a very different way from small firms.

9 Conclusion and policy implications

This paper estimates the causal effect of patent rights on innovation incentives, using patent invalidation decisions of the U.S. Federal Circuit Court of Appeals. Identification exploits the randomised assignment of judges panels hearing each case. There are three key empirical findings. First, invalidation causes the patent owner to reduce subsequent patenting by about 50 percent on average. Second, the impact of patent invalidation is driven entirely by small firms that lose patent rights on technologies that are core to their innovation activity. The

[31] To clarify the point, consider a hypothetical example of a firm litigating a patent in the three-digit class 704 "Data processing: speech signal processing, linguistics, language translation, and audio compression/decompression." This class belongs to the two-digit subcategory 22 "Communications". The regression in column 2 focuses on the impact of invalidation on patenting of the firm in class 704. Column 3 examines the effect of invalidation on patents belonging to subcategory 22 but not to class 704. Finally, column 4 explores the impact of invalidation to patenting of the firm outsides the "Communications" field, e.g. patents in chemicals, medical devices, etc.

effect is particularly strong for small firms operating in technology fields where large firms are particularly active. Finally, patent invalidation has no effect on the level of patenting by large firms, but it does appear to change the direction of subsequent innovation.

These findings complement the results in Galasso and Schankerman (2015), who study how patent rights affect follow-on innovation by firms other than the patentee. They show that patent invalidation causes an increase in citations to the focal patent by external firms, on average, but the impact is heterogeneous. It depends critically on characteristics of the bargaining environment – the strongest effect is in fields where bargaining failure in licensing is more likely. Moreover, the effect is entirely 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. If we interpret judicial invalidation of a patent as a proxy for a marginal reduction in the strength of patent rights for firms, our findings imply that reducing the strength/scope of large firms' patent rights is likely to encourage follow-on research by small firms and unlikely to reduce innovation incentives for the large firms. In contrast, weakening patent rights held by small firms diminishes their innovation incentives without spurring additional patenting by large firms. This interpretation is consistent with the recent work by Acemoglu et. al (2013), who show that fiscal stimulus policies for R&D by large incumbents is less effective than support targeted at small innovative firms. While the law and economics literature has discussed ways to differentiate patent rights across innovators – including the use of patent application and renewal fees by patent offices, and injunctive relief and the presumption of validity by courts – there are serious practical challenges in implementing such policies effectively. Our results suggest that more research on these approaches is warranted.

However, there are important caveats to bear in mind. The empirical analysis focuses on judicial invalidation of specific patents, not a reduction in the strength of overall patent rights for firms. Our conclusions may also hold for policies that have more pervasive impacts on patent rights, but this remains to be shown. Moreover, our findings certainly do not imply that complete removal of patent rights of large firms would be improve innovation incentives or welfare. In the presence of patent rights, research is conducted under the expectation of rents from the product market and licensing to follow-on innovators. These rents would be expected to (largely) disappear in a regime without patents and this would reduce, perhaps sharply, incentives to conduct such R&D. In addition, the direction of technical change is likely to be different in a regime without patents, as firms would have greater incentives to invest in research that can be more easily protected through trade secrets and where reverse engineering is more difficult (Moser, 2005). All these issues would need to be part of a broader welfare assessment of patent rights, but this is beyond the scope of the paper.

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Appendix

A1. Analysis of the model

In the text we derived the following expression for the change in R&D due to patent invalidation for a small firm:

$$\Delta r_S = L(N, \overline{\Theta}) \left[F(c) - F(c-1) - \chi(M)(1 - F(c-1))\right]$$

where $L(N, \overline{\Theta})$ is the value of licensing the invention and $\chi(M)$ is the expected gain for the focal firm from the patent race in the case of patent invalidation. 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 $L(1, \overline{\Theta}) = \overline{\Theta}\alpha$. With two firms the payoff is $L(2, \overline{\Theta}) = \overline{\Theta}\alpha(1+\delta(1-\alpha))$. By induction, we obtain

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

Note that $L_N > 0$ and $L_{\overline{\Theta}} > 0$. Using this result, we get the following comparative statics:

$$\begin{aligned}
\frac{d\Delta r_S}{dN} &= L_N \left[F(c) - F(c-1) - \chi(M)(1 - F(c-1))\right] > 0 \\
\frac{d\Delta r_S}{d\overline{\Theta}} &= L_{\overline{\Theta}} \left[F(c) - F(c-1) - \chi(M)(1 - F(c-1))\right] > 0 \\
\frac{d\Delta r_S}{dM} &= L \left[-\chi'(M)(1 - F(c-1))\right] > 0.
\end{aligned}$$

For large firms the profits with and without invalidation are equal to

$$\begin{aligned}
&\Theta(n)F(c)r - \frac{r^2}{2} \\
&\Theta(n-1)\left[F(c) - F(c-1) - \chi(M)(1 - F(c-1))\right] - \frac{r^2}{2}.
\end{aligned}$$

The corresponding optimal R&D investments are:

$$\begin{aligned}
r_L^*(c) &= \Theta(n)F(c) \\
r_L^*(c-1) &= \Theta(n-1)\left[F(c) - F(c-1) - \chi(M)(1 - F(c-1))\right]
\end{aligned}$$

which imply

$$\Delta r_L = \Theta(n)(F(c) - \frac{\Theta(n-1)}{\Theta(n)} F(c-1) - \frac{\Theta(n-1)}{\Theta(n)} \chi(M)(1 - F(c-1))$$

Note that $\Delta r_L > 0$ because $F(c) - \frac{\Theta(n-1)}{\Theta(n)} F(c-1) - \frac{\Theta(n-1)}{\Theta(n)} \chi > F(c) - F(c-1) - \chi > 0$. Assume that a proportion λ of the n patents are core. Then we can write

$$\begin{aligned} \Delta r_L &= \Theta(n)F(\lambda n) - \Theta(n-1)F(\lambda n - 1) - \Theta(n-1)\chi(M)(1 - F(c-1)) \\ &\leq \Theta(n)F(\lambda n) - \Theta(n-1)F(\lambda n - 1) \end{aligned}$$

which tends to zero as n gets larger because both $\Theta(n) - \Theta(n-1)$ and $F(c) - F(c-1)$ tend to zero.

A2. 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 $L(1, \overline{\Theta}) = \alpha\overline{\Theta}(1 - \beta)$. 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 $\Delta = (1 - \alpha) + \beta\alpha$. Solving the problem recursively we obtain

$$L(N, \overline{\Theta}) = \overline{\Theta}\alpha(1 - \beta)\frac{1 - \delta^N \Delta^N}{(1 - \delta\Delta)}. \tag{5}$$

Equation (5) 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 $L_N > 0$ and $L_{\overline{\Theta}} > 0$ 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.[32]

[32] 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.

A3. Generalized functional form

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 $F(c,r)$ is a continuous function satisfying $F_c > 0$, $F_r > 0$, $F_{rr} < 0$, $F_{rc} > 0$ and $\lim_{c\to\infty} F_{rc} = 0$. 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 $C_{rr} > 0$. [33]

As in the baseline model, we assume that after a core patent is invalidated the probability that the patentee develops a follow-on innovation becomes $F(c-1,r) + \chi(M)(1 - F(c-1,r))$ where $\chi(M)$ summarises the patent race building on the invalidated patent.[34] Unlike in the baseline model in the text, we now assume that M is large enough that $\chi(M) \simeq 0$, which implies that competition in the patent race fully dissipates the value of the (now publicly available) knowledge.

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

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

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 $L(N,\overline{\Theta})F_r = C_r$ which implies

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

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

$$\begin{aligned} \frac{d^2r}{dcdN} &= \frac{L_N F_{rc} C_{rr}}{(C_{rr} - LF_{rr})^2} \geq 0 \\ \frac{d^2r}{dcd\overline{\Theta}} &= \frac{L_{\overline{\Theta}} F_{rc} C_{rr}}{(C_{rr} - LF_{rr})^2} \geq 0 \end{aligned}$$

[33] This generalised specification is consistent with a simple recombinant innovation process in the spirit of Weitzman (1988). Suppose a firm employs r scientists to conduct research. Each scientist independently invents by experimenting with pairs of core patents, each of which generates a new idea with probability w. In a firm with c core patents, the probability that a scientist develops an idea is $F(c) = 1-(1-w)^{\frac{c(c-1)}{2}}$ and the probability that the firm innovates is $rF(c)$.This innovation function satisfies the properties in the text.

[34] To illustrate, consider there case where (i) the patentee wins the race with probability ρ (ii) the M competing innovators win with probability $\lambda\rho$ where $\lambda \leq 1$ captures the comparative advantage of the owner in building on the invalidated patent and (iii) the patent is randomly allocated among multiple winners. This setup implies $\chi(M) = \sum_{i=0}^{M} \rho(1-\lambda\rho)^{M-i}\frac{(\lambda\rho)^i}{(1+i)}$.

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 large firms, optimal R&D satisfies $\Theta(n)F_r = C_r$ and thus

$$\begin{aligned} \frac{dr}{dp} &= \frac{\Theta_n F_r}{C_{rr} - \Theta F_{rr}} \geq 0 \\ \frac{dr}{dc} &= \frac{\Theta_n F_r + \Theta F_{cr}}{C_{rr} - \Theta F_{rr}} \geq 0 \end{aligned}$$

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

A3. 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

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

Table 1: Summary Statistics

	Mean	Std. Dev.	Min	Max
Invalidity	0.40	0.49	0	1
PostPatents	200.25	933.40	0	12988
PrePatents	317.89	1118.20	1	14208
PreCites	25.09	54.99	0	893
PreSelfCites	2.40	6.42	0	114
Patent Age	9.94	5.12	1	30

NOTES: Sample of 1469 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 Subsequent Innovation

	(1)	(2)	(3)	(4)
Estimation Method	OLS	IV	IV	IV
Dep Variable	log(PostPat)	log(PostPat)	log(PostPat)	log(PostPat)
Invalidity	-0.060	-0.694**		-0.666**
	(0.077)	(0.313)		(0.312)
All invalidated			-0.613**	
			(0.298)	
log(PrePatents)	0.655***	0.660***	0.659***	0.637***
	(0.024)	(0.024)	(0.023)	(0.027)
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		70.12	80.29	71.36
Sample	full	full	full	drop multi-patent cases
Fed. Circuit Cases	1181	1181	1181	982

NOTES: *significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors 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 Stock and Yogo (2005) weak ID test. We replace PostPatent=1 when PostPatent=0 to include firms with no patenting. Regressions include a dummy which equals one when this correction takes place.

Table 3: Impact of Patent Invalidation by Firm Size

	(1)	(2)	(3)	(4)
Estimation Method	IV	IV	IV	IV
Dep Variable	log(PostPat)	log(PostPat)	log(PostPat)	log(PostPat)
Sample	large	small	full	full
Invalidity	-0.355	-0.738***		
	(1.090)	(0.210)		
Invalidity X Small			-0.824***	-0.685**
			(0.286)	(0.287)
Invalidity X Large			0.128	0.071
			(0.809)	(0.712)
Fed Circuit Decisions	296	885	1181	1181
Large Firm	>75 patents	>75 patents	>75 patents	above 95th percentile in field

NOTES: * significant at 10 percent ** significant at 5 percent and *** significant at 1 percent. Robust standard errors are reported in parentheses. All regressions control for log(PrePatents), age, technology and year effects. Small=1-Large. In columns 1-3: Large=1 if portfolio in 10 year window >75 patents. In column 4 Large=1 if patentee portoflios above 95th percentile of assignees with at least one patent in tech field.

Table 4: Invalidation of Core and Peripheral Patents

	(1)	(2)	(3)	(4)
Estimation Method	IV	IV	IV	IV
Dep Variable	log(PostPat)	log(PostPat)	log(PostPat)	log(PostPat)
Invalidity X Core	-0.939***	-0.961***		
	(0.309)	(0.327)		
Invalidity X NoCore	0.008	-0.107		
	(0.516)	(0.431)		
Invalidity X Core X Small			-0.886***	-0.948***
			(0.239)	(0.305)
Invalidity X NoCore X Small			-0.537	-0.468
			(0.452)	(0.374)
Invalidity X Core X Large			-0.454	1.082
			(1.372)	(1.620)
Invalidity X NoCore X Large			0.184	0.415
			(0.884)	(0.851
Fed Circuit Decisions	1181	1181	1181	1181
Core constructed from	share in 2 digit fields	self-citations	share in 2 digit fields	self-citations

NOTES: * significant at 10 percent, ** significant at 5 percent, *** significant at 1 percent. Robust standard errors are reported in parentheses. All regressions control for log(PrePatents), age,technology and year effects. Small=1-Large. Large=1 if portfolio in 10 year window >75 patents. In columns 1 and 3 Core=1 if share of patents in the focal 2-digit technology class is above the median. In columns 2 and 4 Core=1 if the ratio between the self-citations received and maximum possible number of self-citations that the focal patent could recieve is in top quartile.

Table 5: Testing Alternative Mechanisms

	(1)	(2)	(3)
Estimation Method	IV	IV	IV
Dep Variable	log(PostPat)	log(PostPat)	log(PostPat)
Invalidity X Many Large Firms	-0.837***		
	(0.243)		
Invalidity X Few Large Firms	-0.043		
	(0.354)		
Invalidity X Collateral		-0.718**	
		(0.351)	
Invalidity X NoCollateral		-0.708***	
		(0.231)	
Invalidity X Fragmented field			-0.681***
			(0.211)
Invalidity X Concentrated Field			-0.778**
			(0.320)
Fed Circuit Decisions	885	885	885
Sample	Small Firms	Small Firms	Small Firms

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors are reported in parentheses. All regressions control for log(PrePatents), age,technology and year effects. Small=1-Large. Large=1 if portfolio in 10 year window >75 patents. 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.

Table 6: Patent Invalidation and Direction of Innovation

	(1)	(2)	(3)	(4)
Estimation Method	IV	IV	IV	IV
Dep Variable	log(SelfCites)	log(PostPat) in field	log(PostPat) in related fields	log(PostPat) in unrelated fields
Invalidity X Core X Small	-0.016	-0.668***	-0.494**	-0.562***
	(0.117)	(0.217)	(0.214)	(0.217)
Invalidity X NoCore X Small	-0.217	-0.499	0.192	-0.521
	(0.148)	(0.318)	(0.238)	(0.323)
Invalidity X Core X Large	-0.093	-0.275	-0.005	0.366
	(0.324)	(0.636)	(0.649)	(0.522)
Invalidity X NoCore X Large	-0.498***	-0.151	1.208**	0.427
	(0.187)	(0.467)	(0.548)	(0.551)
Fed Circuit Patents	1469	1469	1469	1469

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors are reported in parentheses. All regressions control for log(PrePatents), age,technology and year effects. Small=1-Large. Large=1 if portfolio in 10 year window >75 patents. Core=1 if share of patents in the focal technology 2-digit class is above the median. Dependent Variables: in column 1 is log of SelfCitations received by the patent in the 5 years after invalidation, in column 2 is a patent applications in the 3-digit class, in column 3 is patent applications in other 3-digit classes belonging to the same 2 digit class and in column 4 is the total number of applications outside the 2 digit class.

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)	2.915***	2.264***		
	(0.666)	(0.819)		
log(PrePatents)		0.013	0.001	0.001
		(0.016)	(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	1181	1181	1181	1181

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)	log(PostPat)	log(PostPat)	log(PostPat)
Sample	full	full	no overlapping cases	no repeated litigants
Invalidity	-0.544*		-0.813**	-0.811***
	(0.315)		(0.320)	(0.316)
All Invalidated		-0.567*		
		(0.339)		
Instrument	predicted probability constructed from patent-level probit	predicted probability constructed from patent-level probit	predicted probability from probit	predicted probability from probit
IV Test	68.99	59.78	61.61	59.43
Fed. Circuit Cases	1181	1181	996	948

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors 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 invalidated=1 if all patents in the case are invalidated. IV test is Stock and Yogo (2005) weak ID test. We replace PostPatent=1 when PostPatent=0 to include firms with no patenting. Regressions include a dummy which equals one when this correction takes place. All regressions control for log(PrePatents), technology, age and year effects. Columns 1-2 control for the number of patents in the case

Table A3: Core Technologies - Robustness

	(1)	(2)	(3)	(4)
Estimation Method	IV	IV	IV	IV
Dep Variable	log(PostPat)	log(PostPat)	log(PostPat)	log(PostPat)
Invalidity X Core	-0.703**	-0.808**	-0.939***	-0.953***
	(0.300)	(0.291)	(0.309)	(0.307)
Invalidity X NoCore	-0.157	0.103	0.008	-0.261
	(0.775)	(0.613)	(0.516)	(0.470)
Fed Circuit Decisions	1181	1181	1181	1181
Core share	0.25	0.5	0.66	0.75

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

Table A4: Large Firm Competition in the Technology Field- Robustness

	(1)	(2)	(3)	(4)	(5)
Estimation Method	IV	IV	IV	IV	IV
Dep Variable	log(PostPat)	log(PostPat)	log(PostPat)	log(PostPat)	log(PostPat)
Invalidity X Many Large Firms	-0.826***	-0.784***	-0.946***	-0.726***	-0.771***
	(0.225)	(0.224)	(0.248)	(0.272)	(0.212)
Invalidity X Few Large Firms	-0.149	-0.391	0.069	-0.478*	0.117
	(0.388)	(0.344)	(0.354)	(0.255)	(0.854)
Fed Circuit Decisions	885	885	885	885	885
Sample	small firms	small firms	small firms	small firms	small firms
Many Large Firms Definition	>9 large firms with 50% portfolio in field	>12 large firms with 50% porftolio in field	>12 large firms with 33% portfolio in field	>12 large firms with 66% of portfolio in field	>23 large firms identified with Mahalanobis norm

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors are reported in parentheses. All regressions control for log(PrePatents), age,technology and year effects. Small=1-Large. Large=1 if portfolio in 10 year window >75 patents.