Patents Rights, Innovation and Firm Exit [1]

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Abstract

This paper studies the causal impact of patents on subsequent innovation and exit 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 effect is entirely driven by small innovative firms in technology fields where they face many large incumbents and where their patent has been pledged as collateral. In addition, the loss of patent rights significantly increases the likelihood of exit for small firms.

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

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

1 Introduction

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

In this paper we investigate how patent rights affect the level of innovation, and the probability of exit, for small and large firms across a range of technology fields. To do this, we study the impact of judicial invalidation of existing patents on the owner's subsequent patenting activity. Our analysis shows that patents are an important stimulus for innovation for small firms, but we find no evidence of significant impact on large firms. We also demonstrate that the effectiveness of patent rights depends on the nature of competition in the technology markets.

The conventional view is that patents enhance the ability of firms to capture innovation rent, but also create a static efficiency loss from higher prices (Arrow, 1962). In addition to the trade-off between innovation incentives and static efficiency cost, more complex trade-offs arise in settings where innovation is cumulative and patent rights on upstream technologies may impede follow-on innovation by other, competing firms. Recent studies have shown that patents have some blocking effect, but it is localized, found primarily in environments where bargaining frictions are likely to be severe and, especially, when large patentees interact with small downstream innovators (Murray and Stern, 2007; Williams, 2013; Galasso and Schankerman, 2015). In this context too, the distinction between small and large firms appears to be important.

Surprisingly, there has been relatively little empirical research on the effectiveness of patent rights as an incentive to patent owners, and the existing studies do not speak with one voice.[1] For example, Budish, Roin and Williams (2015) show that there is more innovation, as

[1] There have been studies that use patent renewal data and other approaches to measure the incremental

measured by clinical trials, on late-stage cancer drugs that have longer effective patent lives (due to shorter regulatory screening times). Similarly, Farre-Mensa, Hegde and Ljungqvist (2015) use the quasi-random assignment of patent examiners to study the impact of patent rights on new start-up firms. They find that a patent grant strongly increases subsequent patent applications and growth, and also raises the probability of an IPO. On the other hand, Sampat and Williams (2015) use quasi-random assignment of patent examiners to study whether human gene patents affect subsequent innovation by the patentee (and others) and find no significant effect. Even more surprising, Baten, Bianchi and Moser (2015) show that the imposition of compulsory licensing on chemical patents by German firms after WWI *increased* patenting by (large) chemical firms.

Patent rights can affect innovation, especially for small firms, through several channels. First, patents shape the nature of competition in product and technology markets, especially in settings where small firms interact with large incumbents (Spulber, 2013; Aghion, Howitt and Prantl, 2015). While the relationship between patent rights, competition and innovation is theoretically ambiguous, recent research suggests that patents are particularly effective in providing incentives when competition is intense (Aghion et. al., 2005). Moreover, patents are critical assets that enable 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. This is especially relevant to small (and young) firms for whom information asymmetry is severe and patents may be their primary collateralizable asset (Hochberg, Serrano and Ziedonis, 2014). Finally, patents are used in cross-licensing agreements, and as bargaining chips to resolve disputes and gain access to patented inputs needed to conduct research (Lanjouw and Schankerman, 2004).

We develop a simple model that shows how the *loss of patent rights* affects incentives to innovate. The basic mechanism is as follows: We assumed that firm builds on its stock of existing patents in subsequent rounds of innovation, and that there are dimishing returns in this process. When a patent is invalidated, the firm retains the knowledge embodied in the patent, but the loss of patent protection allows other firms now to exploit this knowledge without a license. The resulting innovation race has an ambiguous effect on the patentee's incentives. The payoff to her future R&D investment declines because the competitive rents are dissipated

incentives provided by patent rights (Schankerman and Pakes, 1986; Schankerman, 1998; Arora, Ceccagnoli and Cohen, 2008). But these studies do not provide causal evidence on the link between patent rights and the level of innovation.

by innovation race. At the same time, her incentives to invest go up because the firm needs to win the race to commercialize the technology. In this way, the model helps to rationalise what would appear to be contradictory findings of earlier studies, as discussed above.

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

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

It should be noted that patents litigated in the Federal Circuit are typically high value patents, as they have gone through the costly litigation process up to the appellate level. For purposes of studying how patents affect innovation incentives, it is reasonable to start by analyzing Federal Circuit patents because the distribution of patent values is highly skewed (Schankerman and Pakes, 1986) and the incentives generated by these patents are likely to be more important for welfare.[2]

The main findings in the paper are as follows. *First*, the loss of patent rights due to Federal Circuit invalidation causes, on average, a 50 percent decrease in future patenting (in a five-year window) by the focal patentee. This result is robust to a wide variety of specifications

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

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* to their research focus. We do not find any significant response by small firms to losing a non-core patent, or by large firms when they lose either a core or a non-core patent – though the estimates are imprecise and thus the interpretation less clear-cut. *Third*, 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. This is consistent with the idea that patents are especially important in shaping the competition in product and technology markets, and facilitating the licensing of innovations by small firms to larger incumbents for commercialisation, as discussed above.

Fourth, the loss of a patent right reduces innovation by small firms more sharply when the patent had been pledged as collateral in capital markets. This is consistent with the recent empirical literature that emphasises the role of patents in facilitating access to debt and venture capital markets for financially-constrained innovators. We do not find any difference in the impact of invalidation in technology fields where patent ownership is highly fragmented, as would be predicted by the cross-licensing negotiation hypothesis. Finally, we show that losing a patent right sharply increases the probability that a small firm exits the market (as indicated by a complete cessation of patenting). This confirms that patent rights affect not only the level of innovation by ongoing firms, but also the extensive margin of firm survival and thus can be critical for high-tech entrepreneurship.

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

The paper is organized as follows. Section 2 develops a model showing how loss of a patent right can affect innovation incentives for subsequent innovation. Section 3 describes the data set. Section 4 discusses the econometric specification and identification strategy. In Section 5 we present the baseline estimates of the average treatment effect of patent invalidation on innovation. In Section 6 we show that the impact of patent rights is heterogeneous, differing sharply for small and large firms, and core and peripheral patents. Section 7 tests several different mechanisms that might explain the impact on small firms. Section 8 shows that the loss of patent rights powerfully affects the exit probability for small firms. Concluding remarks briefly summarise the findings and policy implications.

2 Analytical framework

We model the innovation process in two stages. In the first stage a firm invests in R&D which generates a new technology stochastically. In the second stage the firm commercializes the innovation. The firm is endowed with c patents on 'core' technologies and p on 'peripheral' ones. We define core technologies as those that facilitate the development of subsequent innovation. By contrast, peripheral technologies increase the innovation rent that the firm can capture from its core technologies, but do not affect the success probability of follow-on innovation.[3] Let $n = p + c$ denote the total number of patents held by the firm. We assume that the number of core patents a firm owns is a fixed proportion of n, i.e. $c = \lambda n$.[4]

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

[3]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).

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

we assume that the firm is restricted to develop only one.[5] 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 becomes $rI(c)$ with

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

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

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

In the case of external commercialization, the firm can negotiate a licensing deal with one of N symmetric firms, each of whom needs the technology with probability z. The firm bargains with potential licensees sequentially. If a license is struck, the firm earns $\overline{\Theta}$. The timing of the licensing game is as follows. The firm approaches one potential licensee and makes a take-it-or-leave-it offer for an exclusive license. If the licensee accepts, the licensing subgame

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

ends. If the offer is rejected, the patentee moves to the next firm and payoffs are discounted by δ. We let $L(N,\overline{\Theta}) < \overline{\Theta}$ denote the expected payoff of the innovator from this licensing subgame.

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

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

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

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

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

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

The proof of Proposition 1 is in Appendix A1. The main result of the model is that the effect of invalidation on innovation incentives is ambiguous. 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). Invalidation of a core patent has two countervailing effects on R&D investments. On one hand, the number of ideas which the firm can develop in the absence of external competitive pressure goes down with invalidation and this reduces innovation incentives. On the other hand, invalidation opens up the technology field inducing a patent race. Because the probability of winning the race increases with the R&D investment, invalidation also has a positive effect on innovation incentives. The first effect dominates, i.e. invalidation reduces follow-on innovation by the patent holder, when the firm faces intense competition in the patent race (χ is low). Conversely, when R&D investments substantially affect the likelihood of winning the patent race (χ is high), innovation incentives increase with patent invalidation. This ambiguous prediction highlights that the impact of patent rights depends on the characteristics of the competitive environment.

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

Finally, for a small firm facing an intense patent race (small χ) the impact of losing a core patent is larger when there are more potential licensees for the technology (in the empirical work, we associate this with the number of large firms in the related technology area). The intuition is that more potential licensees make it more likely that the technology will be licensed (in addition, competition among licensees raises the rent the innovator can extract, though this element is not in the formal model).[6]

In the Appendix A2 we show that these predictions hold for a large class of bargaining games, and in particular do not depend on the take-it-or-leave feature of the licensing negotiation. In Appendix A3 we also show that, when competition in the patent race is intense (i.e. $\chi(r)$ is very small), the comparative statics of the model are robust to a more general specification of the innovation production process $V(c,r), I(c,r)$, $\overline{\Theta}(n)$ and $C(r)$, under some mild conditions on their curvature.

3 Data

The empirical work is based on an extended version of the data used in Galasso and Schankerman (2015), which combines the decisions by the Court of Appeals 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. Judges are assigned to patent cases through a computer program that randomly generates three-judge panels, subject to their availability and the requirement that each judge deals with a representative cross section of the fields of law within the jurisdiction of the court (Fed. Cir. R. 47.2). Decisions are taken

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

by majority rule. We obtain the full text of patent decisions by the Federal Circuit from the LexisNexis QuickLaw portal. This contains a detailed description of the litigated dispute, the final decision and 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 1379 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 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 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 earlier, we retrieve data through manual searches on 'Google Patents'. Assignee numbers are not provided for patents owned by individual inventors. For each of these patents, we identify the disambiguated name of the first inventor, exploiting the data described in Li et al (2014). We then track patenting activity over time by identifying patents with inventors having the same name, city, country and zip-code of the first inventor of the litigated patent. Finally, assignee identification numbers are not available for patents classified as 'unassigned' by the USPTO. For these patents, we identity the patentee from the text of the Federal court decision.[7]

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 pre-

[7]For each unassigned patent, we identify the names of the parties involved in the suit. If one of the litigants is also an inventor listed on the patent, we 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. We dropped patents where we were unable to match the patent to an entity with confidence.

ceding the Federal Circuit decision.

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

Table 1 provides summary statistics. The Federal Circuit invalidates in 40 percent of cases. On average the cases involve firms with 336 patents in their portfolio and that apply for 214 patents in the five years after the decision, but the portfolio distribution is highly skewed (median is 14, and 21 percent of the firms have only one patent).

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

Unlike Galasso and Schankerman (2015), this paper is conducted at the *firm-case level* because we are interested in identifying the impact of invalidation on innovation by the firm that loses its patent right. This requires collapsing the dataset from patent-level observations to firm-level units of analysis. For about 79 percent of the cases in our sample, firms litigate only one patent, but the remaining cases involve multiple patents owned by the same firm. For multi-patent cases, we define the invalidity dummy as equal to one if at least one patent is invalidated, and allow multiple age and technology field dummies in order to to characterize all the patents in the case.[8]

[8] In the sample, 158 cases involve 2 patents held by the same firm, 47 have 3 patents, 14 cases involve 4, and 8 have more than 5 patents. Results are robust to redefining age of the litigated patents as the average (integer) age, and the technology field as the modal technology field, of the patents in the case.

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.[9] Our main empirical specification is

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

where X denotes control variables. For observations where the firm has zero patenting in the five year window after the decision, we add one to $PostPatents$. The results are robust when we include a dummy control variable for such observations (Appendix Table A2). 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.

The main empirical challenge is the potential endogeneity of the Federal Circuit decision to invalidate a patent. The greatest concern in our context is that firms differ in their propensity to patent their innovations. Firms that agressively patent, filing numerous patent applications some of which are of dubious validity, may be more likely to experience invalidation by the courts. Conversely, firms that are more selective in patenting are more likely to have their patents upheld. This would generate positive correlation between ε_i and $Invalidity_i$ in equation (1) and thus an upward bias in the OLS estimate of β. There could also be measurement error in our measure of invalidation (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.[10]

[9] 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.

[10] For related identification, see Kling (2006) who uses random assignment of judges to study the effects of incarceration on employment and earnings, and Doyle (2007) who uses randomized assignment of child protection investigators to study 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.

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.[11] This feature ensures that any case-specific information that might be correlated with the decision and future patenting is removed.

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

Our estimation 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

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

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

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

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

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

In Appendix Table A.1 we summarize the relationship between patent invalidation and judge panels in our updated data (for more detail, see Galasso and Schankerman, 2015). Probit models confirm a strong positive link between patent invalidation and the JIP index, and this is robust to including a set of controls for patent characteristics. Moreover, OLS regressions with JIP as dependent variable confirm the randomization of judges to cases. The portfolio size of the patent owner, the age of the patent and its technology class are all unrelated to JIP. Only the year effects are significantly correlated with JIP, which arises mechanically because some of the 'biased' judges are active only for a subset of years.

5 Empirical results

Table 2 examines how Federal Circuit invalidation affects subsequent patenting by the focal firm. Column 1 presents OLS estimates of the baseline specification relating the number of patent applications in a five year window after the court decision to the invalidity dummy and additional controls. There is no statistically significant correlation between patent invalidation and future patents. This result is not causal, however, since we might expect unobservable factors to affect both the invalidity decision 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.[13]

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.[14] Interestingly, the magnitude of our results is very close to the one in Farre-Mensa, Hegde and Ljungqvist (2015) who study the impact of patent grant on a sample of start-up firms exploiting quasi-random assignment of examiners at the USPTO.

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

[14] 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.

We show later that this average effect hides important heterogeneity, with the impact of patent rights strongly depending on 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.

First, in the baseline specification the *Invalidity* dummy is defined as one if *any* of the patents litigated in the case is invalidated. In multi-patent cases, this classification may generate measurement error. We conduct two tests to check whether our estimates are sensitive to the treatment of invalidity decisions involving multiple patents. In column 3 of Table 2 we adopt a more restrictive definition of invalidation, where the dummy is one only if *all* the patents in a case are invalidated. With this more stringent definition, the fraction of cases in which invalidation takes place drops from 40 to 36 percent.[15] 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. Again the coefficient is very similar to the baseline specification, confirming that our finding is not sensitive to the treatment of multi-patent cases.

Second our sample contains 240 cases involving repeat litigants. In about 75 percent of these cases the spell between the two Federal Circuit decisions is less than 5 years. This is a concern since the impact of the decision of the court is potentially contaminated by another decision taking place in the same time frame. To address this concern, in 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. We also re-estimated dropping all cases with repeat litigants and again the coefficient is very similar to the baseline specification.

There is also the concern that some Federal Circuit decisions may involve rulings that limit the scope of patentable subject matter rather than simply assessing the validity of the focal patent. To address this, we identified the most important Federal Circuit decisions that relate to patentable subject matter during our sample period. Dropping those decisions and re-estimating the model we obtain coefficients that are nearly identical to the baseline estimates.

Finally, there are 237 cases where we cannot directly retrieve an assignee number from the USPTO data based on the patents litigated in the case. As described in Section 3, for

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

these observations we identify the patentee from the disambiguated name of the inventor and by manual searches on Google patents. In Appendix Table A2 we confirm that our baseline results are robust to dropping these manually cleaned observations from the sample.

6 Unbundling the effect of patent rights

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

6.1 Small vs large firms

We first test the hypothesis that innovation incentives from patent rights are more important for small patentees than large ones. To do so, we define a 'large firm' dummy variable equal to one for firms in the top quartile of our sample in terms of patent applications in the ten years prior to the Federal Circuit decision (this threshold corresponds to 108 patents).[16] Thus, in the analysis that follows it is best to think of our 'small firm' sub-sample as representing both small and medium sized firms.

Simple mean comparison tests indicate a differential impact: in the small firm sub-sample, the mean of *logPostPatents* is 0.55 for firms whose patents are invalidated and 0.77 for firms whose patents are upheld, and the difference is highly significant (p-value=0.01). The corresponding figures for the large firm sample are 4.67 and 4.78, and the difference is not statistically significant (p-value=0.72). This suggests that the loss of patent rights reduces innovation 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 that 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 for the large firm sample. Column 3 presents a full sample regression that allows the invalidity effect to differ for small and large firms. Again we find no evidence of any effect for large firms – the point estimates are small, though with large standard errors. In contrast, the

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

loss of a patent causes a statistically significant reduction of 48 percent in future patenting by small firms.

We did a series of additional (unreported) regressions that vary the threshold portfolio size to define large firms. The results in Table 3 are robust to these alternative thresholds: the invalidation coefficient for small firms remains large and highly significant, but there is no evidence of any effect for large firms. In particular, the difference between the impact for small and large firms holds even if we set the portfolio threshold for large firms as low as 30 patents – the point estimate/standard error are -0.734 (0.311). But interestingly, when we raise the threshold to 150 patents, the coefficient of invalidation for small firms remains significant, though somewhat smaller at -0.640 (0.295), and again it is statistically insignificant for large firms. These experiments indicate that the importance of patent rights for follow-on innovation is not limited to very small firms, but also extends over the middle range of firm sizes.

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.[17] 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 (0.75) between the absolute and relative measures of firm size in our sample.

To this point we have used a definition of firm size based on the patent portfolio. However, we also examine a more traditional measure of firm size, the number of employees. To do this, we use USPTO data which requires firms to report their 'small entity status' (less than 500 employees) when they pay patent renewal fees.[18] These data are available only for patents filed on or after December 12, 1980, which are about 70 percent of our sample. Roughly 35 percent of the matched patentees are classified as small entities and nearly all of them (97 percent) have a portfolio smaller than 108 patents. However, only 36 percent of large entities have more than 108 patents in their portfolio. Split sample regressions based on the small entity status

[17]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 27 percent of the firms in our sample are large (parameter estimates are robust to using a 90th percentile threshold).

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

(not reported) show that the invalidation effect does not change with these crude categories of employment size, but depends only on the size of the patent portfolio. This is consistent with our model, where we emphasize the commercialization advantages of large firms due both to their complementary assets and large portfolios that facilitate enforcement of their patent rights.

6.2 Core vs peripheral patents

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

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

The second measure exploits the pattern of self-citations made by the patentee. 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.[19] On average the patents in our sample receive 8 percent of the maximum possible self-citations and about 60 percent of the patents receive no self-citations. The dummy variable *Core* is set equal to 1 if the firm litigates a patent with a fraction of self-cites above the 75th percentile. Also for this measure, in multi-patent cases we set *Core*=1 if the case involves at least one core patent.

Table 4 presents estimates of the invalidation effect for core and peripheral patents. In 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 several robustness checks. First, we construct the share of patents in the focal field exploiting a finer classification, the three-digit USPTO classes. Litigated patents belong to (three digits) technology fields that account for about 54 percent of the firm's patenting on average (standard deviation = 0.41). As before, we set *Core*=1 if the firm litigates a patent in a field with share above the sample median. The estimated coefficients (unreported) are nearly identical to those in column 1. Second, in Appendix Table 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. This indicates that the loss of a core patent is most damaging to innovation when the firm is highly specialized in the technology field (as before, losing a non-core patent has no significant impact). In column 2 we exploit the second measure of core patents, based on the pattern of self-citations by the focal patentee. Again we find that the loss of core patents causes a reduction in follow-on innovation, but no response to the invalidation of peripheral patents. The coefficient is somewhat larger than (but not statistically different from) the estimate 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 focal patent) and the extensive margin (shifting focus across fields). This flexibility might mitigate the effect of losing a core patent in one area. To investigate this idea, we use our

[19] 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).

earlier definition of a large firm (patent portfolio above 108).[20] Column 3 in Table 4 presents the estimates of 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 evidence shows that invalidation reduces future patenting *only* when small firms litigate core patents. The estimated coefficient implies a large impact: invalidation lowers the firm's patenting by about 53 percent in the five years following the court decision. The coefficients for the other size-technology pairings are not statistically significant, but the large standard errors make it hard to say the effects are zero with confidence. In column 4 we re-estimate the model using the *Core* measure based on self-citations. The pattern of coefficients is fairly similar to the previous ones.

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. We conclude that *Core* is not simply a proxy for patent value.

7 Explaining the impact for small firms

The empirical results show that patent rights are a crucial innovation incentive for small firms. In this Section we investigate three potential explanations for this finding. First, patents

[20] In our sample about 45 percent of the cases involve small firms litigating core patents, 50 percent involve peripheral patents and they are equally split between large and small firms and the remainder involve are core patents litigated by large firms.

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

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

Therefore, we expect that patent invalidation would be more damaging to 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 38 (median = 13). We then define a dummy variable *Few Large Firms=1* if the number of large patentees in the focal field is in the first quartile of the sample (corresponds to 5 firms).

Column 1 of Table 5 presents the invalidation impact for small firms operating in focal technology fields with few versus many large patentees. We find that patent invalidation reduces innovation only when small firms are in technology fields where large firms are more active. The impact is large: invalidation for these small firms reduces their future patenting by about 67 percent. But invalidation has no statistically significant effect on innovation for small firms in fields 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, their share of patenting in the focal field, and the fraction of patenting used to classify a large firm as active in the field. The results in column 3 of Table 5 remain robust.[21]

We next examine whether the effect of patent invalidation for small firms is concentrated in a few specific technology fields, or is more pervasive. To do this, we begin by extending our baseline model (which used a dichotomous breakdown into small and large firms) with a more flexible specification that allows the impact of invalidation to vary continuously with the logarithm of the number of large firms in the field (again defined as those with at least 75 patents and 50 percent in the focal two-digit technology field). The IV estimates confirm that the negative impact of invalidation is larger (in absolute value) for small firms when they face a greater number of large firms in the technology field. Using these estimates, we compute the implied impact of patent invalidation on small firm innovation for each of the *two-digit* technology fields (36 in total), based on the sample mean number of large firms in each field.

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

One limitation of our approach is that it does not recognize that large firms in different,

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

but technologically related, fields may also be effective potential competitors. This may introduce 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 patent in specific subset of fields (patent co-location). We compute the number of large firms in *each* two-digit technology field and then weight them by the Mahalanobis index of proximity between each field and that 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.

We re-define the dummy *Few Large Firms=1* if the Mahalanobis index of large patentees is in the bottom decile of the distribution. The *IV* estimates using this measure, presented in Table A4, confirm our earlier results: invalidation has a strong and significant effect for small firms facing potential competition from many large firms. 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 face difficulty in financing their innovation due to information asymmetries in capital markets (Hall and Lerner, 2010). Recent empirical studies show these frictions can be mitigated through debt and venture capital secured by patents (e.g., Conti, Thursby and Thursby, 2013; Hochberg, Serrano and Ziedonis, 2014; Farre-Mensa, Hegde and Ljungqvist, 2015). If our finding that patent invalidation causes a decline in innovation by small firms is driven by this channel, we would expect to observe a larger reduction for small firms that rely on the (subsequently invalidated) patent to obtain finance.

To test this, we collect information on whether patents in our sample are used to secure loans. Following 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 banks or other financial institutions A complete description of the nature of the transactions is not provided in the assignment data, but often these assignments are flagged as "security interest" or "collateral assignment," confirming the financial nature of the transactions. About 15.5 percent of the patents in our sample are pledged as collateral at least once during their life, but only 6.5

percent of the patents (96 patents) are pledged as collateral before the Federal Circuit decision. We generate a dummy variable *Collateral=1* if the patent is used as collateral before the Federal Circuit decision, and re-estimate the baseline model that includes an interaction between the invalidation and collateral 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 (column 2, Table 5) show that the impact of patent invalidation is about twice as large for patents pledged as collateral than for patents not pledged.[22] This evidence indicates that patent rights are important for small, high-technology companies to gain access to finance. While our evidence relates to collateral for bank loans, patent rights are likely to play a similar role for venture capital financing. Moreover, even when the patent is not used as collateral before the litigation, it is possible that the loss of licensing income (current and prospective) associated with patent invalidation could reduce later innovation for firms that would be liquidity-constrained. With the current data, we cannot rule out this channel.

7.3 Access to patented inputs

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

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

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

8 Firm exit

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

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

Table 6 presents linear probability estimates of exit using our IV strategy, including controls for technology field, pre-decision patent portfolio size, and firm age dummies for intervals 0-5, 6-10 and greater than 10 years (age is measured as date of the court decision minus date of the firm's first patent application). The results are presented using various (pre-decision) patent portfolio thresholds for defining 'small firms' in order to identify whether the impact of patent invalidation on exit varies with firm size.[23]

The result in column 1 indicates that the loss of patent rights has no effect on exit, when we pool small and large firms. However, this average treatment effect hides an important difference between small and large firms. The results in the other columns show that the loss of a patent sharply increases the exit probability for small firms, and the effect is statistically significant. Not surprisingly, we see no evidence that invalidation increases exit by large firms. Interestingly, the estimated impact of invalidation on exit for small firms monotonically increases as we tighten the definition of small firms (moving from columns 2 to 6). For firms with a patent portfolio less than 30, invalidation raises the exit probability by 0.327, which is about a 53 percent increase relative to the sample mean for this size category.[24] For very small firms, with portfolio of three patents or less, the coefficient corresponds to a 63 percent increase in the sample mean exit rate for that category. In addition, the (unreported) coefficients on the log of *PrePatents* are negative and highly significant indicating that the likelihood of exit declines substantially as firms get larger.

In short, we find that the loss of patent rights has a powerful effect on the exit of small innovating firms, as well as on the intensity of innovation for the continuing firms.

9 Concluding remarks

In this paper we estimate the causal effect of patent rights on innovation using patent invalidation decisions of the U.S. Federal Circuit Court. Identification exploits the randomised assignment of judges panels hearing each case. There are three key empirical findings. First, loss of a patent right causes the owner to reduce subsequent innovation (patent activity) by about 50 percent, on average. Second, this effect is driven entirely by small firms that lose patents on technologies that are core to their innovation focus. The impact is especially strong when small firms operate in technology areas where large firms are particularly active, and

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

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

when their patents have been pledged as collateral. Finally, we find that the loss of patent rights also sharply increases the probability of exit for small (but not large) firms.

These findings complement Galasso and Schankerman (2015), who show that patent invalidation increases innovation by *other firms*, but the effect 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. Our findings suggest that reducing the strength/scope of large firms' patent rights is likely to encourage follow-on research by small firms, and unlikely to reduce significantly innovation incentives for large firms. This conclusion is consistent with recent work by Acemoglu et. al (2013), who show that fiscal stimulus policies for are more effective when targeted at small firms. While the law and economics literature has discussed possible instruments to differentiate patent rights across innovators – e.g., patent filing and renewal fees, the scope for injunctions, and presumption of validity by courts– there are serious practical challenges in implementing such policies. Our results suggest that more research on these issues is warranted.

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

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Appendix

A1. Analysis of the model

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

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

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

$$\Delta r=\Lambda\left(1-(1-\alpha)^{c}-\frac{1-(1-\alpha)^{c-1}}{1-2\Lambda\chi\alpha\left(1-\alpha\right)^{c-1}}\right) \tag{4}$$

which is decreasing in c and n given that $c=\lambda n$. For small firms $|\Delta r|$ is minimized when $c=\lambda\kappa$ with value:

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

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

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

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

Notice now that (4) can be positive or negative. For example, if $\Lambda=1$, $c=2$, $\alpha=0.5$ then $\Delta r=(0.25-0.375\,\chi)\,/(1-0.5\chi)$ which is negative for $\chi>.66$. Moreover (4) decreases in χ with $\Delta r=\Lambda\alpha(1-\alpha)^{c-1}>0$ when $\chi=0$. This implies that for all parameter values there exists an χ' such that $\Delta r>0$ if $\chi<\chi'$. The derivative of (4) respect to N is equal to

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

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

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 $L(1, \overline{\Theta}) = z\overline{\Theta}(1-\beta)$. When two firms remain, the patentee negotiates with the first firm with an outside option of $\delta L(1, \overline{\Theta})$. This gives $L(2, \overline{\Theta}) = L(1, \overline{\Theta})\left[1 + \Delta\delta\right]$ where $\Delta = (1-z) + \beta z$. Solving the problem recursively we obtain

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

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 $L'(N) > 0$ 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.[25]

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 $V(c, r)$ is a continuous function satisfying $V_c > 0$, $V_r > 0$, $V_{rr} < 0$, $V_{rc} > 0$ and $\lim_{c \to \infty} V_{rc} = 0$. These properties are satisfied by most standard production functions with decreasing returns. We also generalize R&D costs to any continuous function, $C(r)$ with $C_r > 0$ and $C_{rr} > 0$.

[25] 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.

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

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

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

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

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

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

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

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

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

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

A4. 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	213.95	961.87	0	12988
PrePatents	335.93	1150.56	1	14208
PreCites	25.62	56.33	0	893
PreSelfCites	2.34	6.58	0	114
Patent Age	9.79	5.04	1	30

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

Table 2: Patent Invalidation and Subsequent Innovation

	(1)	(2)	(3)	(4)
Estimation Method	OLS	IV	IV	IV
Dep Variable	log(PostPat)	log(PostPat)	log(PostPat)	log(PostPat)
Invalidity	-0.070	-0.692**		-0.592*
	(0.083)	(0.346)		(0.365)
All invalidated			-0.631**	
			(0.319)	
log(PrePatents)	0.640***	0.648***	0.647***	0.623***
	(0.028)	(0.028)	(0.028)	(0.032)
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		66.79	80.51	59.59
Sample	full	full	full	drop multi-patent cases
Fed. Circuit Cases	1038	1038	1038	811

NOTES: *significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors are reported in parentheses. PostPatents= number of patent applications of assignee in 5 year window after Federal Circuit decision. Invalidity=1 if at least one patent in the case is invalidated. All invalidated=1 if all patents in the case are invalidated. PrePatents = number of patent applications of assignee in 10 year window before Federal Circuit decision. Age = age dummies in years from filing date of patents at Federal Circuit decision. Year= year of Federal Circuit Decision. Technology fields= 6 categories defined in Hall et al (2001). IV test is the F-statistics from the Stock and Yogo (2005) weak ID test. We 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	0.158	-0.718***		
	(1.129)	(0.222)		
Invalidity X Small			-0.628**	-0.511*
			(0.294)	(0.294)
Invalidity X Large			-0.043	-0.064
			(0.845)	(0.637)
Fed Circuit Decisions	261	777	1038	1038
Large Firm	>108 patents	>108 patents	>108 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. In columns 1-3: Large=1 if portfolio in 10 year window >108 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	-0.854***	-1.168***		
	(0.326)	(0.415)		
Invalidity X NoCore	-0.148	-0.443		
	(0.464)	(0.391)		
Invalidity X Core X Small			-0.748**	-1.130***
			(0.311)	(0.427)
Invalidity X NoCore X Small			-0.449	-0.341
			(0.358)	(0.308)
Invalidity X Core X Large			-0.671	-0.858
			(0.961)	(0.834)
Invalidity X NoCore X Large			-0.001	0.472
			(0.980)	(1.139)
Fed Circuit Decisions	1038	1038	1038	1038
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. Large=1 if portfolio in 10 year window >108 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	-1.126***		
	(0.330)		
Invalidity X Few Large Firms	-0.272		
	(0.263)		
Invalidity X Collateral		-1.418**	
		(0.637)	
Invalidity X NoCollateral		-0.622***	
		(0.222)	
Invalidity X Fragmented Field			-0.791***
			(0.273)
Invalidity X Concentrated Field			-0.671**
			(0.296)
Fed Circuit Decisions	777	777	777
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. 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 Exit

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation Method	IV	IV	IV	IV	IV	IV
Dep Variable	Exit	Exit	Exit	Exit	Exit	Exit
Invalidity	0.182					
	(0.112)					
Invalidity X Small		0.247**	0.256**	0.327**	0.411***	0.486**
		(0.118)	(0.127)	(0.136)	(0.156)	(0.209)
Invalidity X Large		-0.081	-0.020	-0.038	0.046	0.09
		(0.144)	(0.127)	(0.128)	(0.123)	(0.115)
Fed Circuit Decisions	1038	1038	1038	1038	1038	1038
Cut-off for large firms		108 pats	50 pats	30 pats	5 pats	3 pats

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

Table A1: Composition of Judge Panels and Patent Invalidation

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

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

Table A2: Robustness of Baseline Regressions - IV Estimates

	(1)	(2)	(3)	(4)
Dep Variable	log(PostPat)	log(PostPat)	log(PostPat)	log(PostPat)
Sample	no overlapping cases	no repeat litigants	drop manually matched firms	full
Invalidity	-0.902**	-0.572*	-0.761**	-0.710**
	(0.413)	(0.332)	(0.349)	(0.367)
Dummy for PostPat=0	YES	YES	YES	NO
Instrument	predicted probability from probit	predicted probability from probit	predicted probability from probit	predicted probability from probit
Fed. Circuit Cases	848	798	801	1038

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 regressions control for log(PrePatents), technology, age and year effects.

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	-0.550*	-0.813***	-0.854***	-1.056***
	(0.318)	(0.308)	(0.326)	(0.349)
Invalidity X NoCore	-0.218	0.009	-0.148	-0.262
	(0.715)	(0.549)	(0.464)	(0.443)
Fed Circuit Decisions	1038	1038	1038	1038
Core share	0.25	0.50	0.66	0.75

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors 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)
Estimation Method	IV	IV	IV	IV
Dep Variable	log(PostPat)	log(PostPat)	log(PostPat)	log(PostPat)
Invalidity X Many Large Firms	-0.942***	-0.807***	-0.840***	-0.712***
	(0.288)	(0.249)	(0.260)	(0.210)
Invalidity X Few Large Firms	-0.418	-0.209	-0.274	0.037
	(0.284)	(0.378)	(0.382)	(0.935)
Fed Circuit Decisions	777	777	777	777
Sample	small firms	small firms	small firms	small firms
Many Large Firms if	>8 large firms	>6 large firms	>6 large firms	>23 large firms
Large firm in the field if	50% portfolio in field	40% portfolio in field	33% portfolio in field	identified with Mahalanobis norm

NOTES: * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Robust standard errors are reported in parentheses. All regressions control for log(PrePatents), age,technology and year effects.