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ABSTRACT

We study the blocking effect of patents on follow-on innovation by others. We posit that follow-on innovation requires freedom to operate (FTO), which firms typically obtain through a license from the patentee holding the original innovation. Where licensing fails, follow-on innovation is blocked unless firms gain FTO through patent invalidation. Using large-scale data from post-grant oppositions at the European Patent Office, we find that patent invalidation increases follow-on innovation, measured in citations, by 16% on average. This effect exhibits a U-shape in the value of the original innovation. For patents on low-value original innovations, invalidation predominantly increases low-value follow-on innovation outside the patentee's product market. Here, transaction costs likely exceed the joint surplus of licensing, causing licensing failure. In contrast, for patents on high-value original innovations, invalidation mainly increases high-value follow-on innovation in the patentee's product market. We attribute this latter result to rent dissipation, which renders patentees unwilling to license out valuable technologies to (potential) competitors.

Keywords: follow-on innovation, freedom to operate, licensing, patents, opposition.

JEL Classification: O31, O32, O33, O34

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1 Introduction

Modern innovation is to a great extent *cumulative* (Scotchmer, 1991): firms develop new products and processes building on prior ("original") innovations. Such follow-on innovation efforts require firms to have *freedom to operate (FTO)*; the commercialization of their new products or processes is not curtailed by patents on the original innovation. Firms typically obtain FTO for follow-on innovation through licensing.[1] If licensing fails, a firm's follow-on innovation can become the target of litigation and injunctions by the patentee. The prospect of not obtaining a license and the resulting threat of an injunction reduce incentives to invest in follow-on innovation. Consequently, patents on original innovations may *block* follow-on innovation.

Several studies have explored whether a blocking effect on follow-on innovation exists by exploiting the grant or invalidation of individual patents as variation in patent protection (e.g., Murray and Stern, 2007; Galasso and Schankerman, 2015; Sampat and Williams, 2019). In these studies, a negative effect of patent protection on follow-on innovation is interpreted as evidence for bargaining breakdown, implying that the patentee was *unable to license out* because transaction costs eroded the joint surplus of licensing (Green and Scotchmer, 1995). However, this interpretation does not account for the possibility that the patentee might have been *unwilling to license out* due to rent dissipation. That is, the revenues from licensing might not fully compensate for the loss in profits arising from increased product market competition (Arora and Fosfuri, 2003).

In this study, we provide new insights into the relationship between patents and follow-on innovation. We draw predictions regarding the effect of patent invalidation on follow-on innovation from a theoretical model of non-exclusive licensing and validity challenges. Based on a large sample of patents subject to a validity challenge, we find an overall positive effect of patent invalidation on follow-on innovation by other firms. Through heterogeneity analyses, we provide evidence that the invalidation effect on follow-on innovation likely stems from licensing failure due to both transaction costs and rent dissipation, but their relative importance varies substantially with innovation value and product market competition.

Our institutional setting for observing patent validity challenges is post-grant opposition at the European Patent Office (EPO). Opposition is a frequent event as it is comparatively inexpensive and the final opportunity for third parties to challenge a European patent before it splits up into

[1]Examples illustrate the salience of FTO through licensing for firms: In 1999, Novartis Seeds agreed to a royalty-bearing license related to herbicide resistance with Monsanto. According to the CEO of Novartis Seeds at that time, "[t]his agreement ensures freedom to operate and allows us to bring new, improved corn hybrids to farmers in the future." In 2003, Cambridge Antibody Technology entered a licensing agreement with Micromet AG and Enzon Pharmaceuticals, which gave "substantial freedom to conduct research". And in 2015, SAP announced a broad cross-licensing agreement with Google that should "increase freedom to operate and prevent distractions from unnecessary patent litigation."

a bundle of national patents. We compile a sample of more than 38,000 patents opposed between 1993 and 2013, which vary substantially in value. To address the endogeneity of patent invalidation, we exploit plausibly random variation in the participation of the patent's granting examiner in the opposition division (cf. Nagler and Sorg, 2020). Specifically, when the granting examiner is part of the division, the likelihood of the patent being invalidated decreases.

We derive predictions on the effect of patent invalidation on follow-innovation from a model of non-exclusive licensing post-validity challenge. In this model, invalidation provides otherwise unlicensed firms with FTO. The invalidation effect thus increases with licensing failure between the patentee and potential follow-on innovators, caused by either excessive transaction costs or rent dissipation. The effect takes a U-shaped form in relation to the value of the original innovation: it is pronounced for patents on low-value original innovations due to transaction costs, and for patents on high-value original innovations due to rent dissipation. Both the prospect of a valuable follow-on innovation and product market competition reduce the impact of transaction costs while amplifying rent dissipation. This strengthens the invalidation effect for patents on high-value innovations and weakens it for patents on low-value innovations.

As a first step, we successfully replicate the average positive invalidation effect on follow-on innovation found in the prior literature (Galasso and Schankerman, 2015, hereafter GS2015). Specifically, we observe that patent invalidation increases follow-on innovation by 16% on average, as evidenced by patent citations from other parties. This increase can be attributed to a growth in the number of unique follow-on innovators and emerges approximately three years after invalidation. The effect becomes more pronounced when taking into account so-called patent thickets—overlapping patent rights (Shapiro, 2001)—which can curtail the degree to which invalidation creates FTO. Several robustness checks reinforce the notion that the observed invalidation effect does not simply reflect changes in citation behavior.

In line with our theoretical predictions, we find that the effect of patent invalidation on follow-on innovation exhibits a U-shape in the value of the original innovation. To proxy innovation value, we employ several patent value indicators that predict selection into expensive patent litigation. The invalidation effect on citations is most pronounced for patents in both the top and bottom value quartiles of our sample. Conversely, the effect is near zero and insignificant for patents in the medium value range. These findings align with our prediction that patent invalidation increases follow-on innovation in contexts where potential follow-on innovators likely fail to gain FTO through licensing: either when transaction costs exceed the surplus of licensing (for patents in the bottom value quartile) or when rent dissipation deters licensing (for patents in the top value quartile).

We further find that patent invalidation triggers different kinds of follow-on innovation depending on the value of the original innovation. Invalidation leads to a more pronounced increase in high-value citations (i.e., citations from high-value patents) for patents in the top value quartile compared to those in the bottom value quartile. This finding is in line with our prediction that the invalidation effect is stronger when both the original and follow-on innovations hold high value. Similarly, invalidation increases citations from the same technology class, industry, and country substantially more for patents in the top value quartile than for those in the bottom value quartile. This pattern aligns with our prediction that product market competition between the patentee and potential follow-on innovators makes licensing failure due to rent dissipation more likely, resulting in a stronger invalidation effect. Conversely, for patents in the bottom value quartile, invalidation increases primarily low-value citations and those from outside of the patentee's product market. This underscores the relevance of licensing failure due to transaction costs as the leading cause behind the invalidation effect for this group of patents.

In summary, these findings strongly suggest that, at least within our sample of challenged patents, two distinct reasons for licensing failure—excessive transaction costs and competitive rent dissipation—cause the blocking effect on follow-on innovation.

Our study contributes to the literature in three ways. First, we present new evidence on the blocking effect of patents on follow-on innovation and provide a comprehensive theoretical framework for interpretation. Focusing on patents subject to post-grant validity challenges in Europe, we corroborate the positive invalidation effect found by GS2015 for patents challenged within US high-profile litigation disputes. We advance their work by shedding light on the selection of patents into validity challenges and by illustrating how this selection shapes the observed invalidation effect. Additionally, we account for the fact that, irrespective of transaction costs, patentees may simply not license out because the potential licensing income would not make up for lost profits in the product market. This insight is well established in the market for technology literature (e.g., Arora and Fosfuri, 2003; Arora and Ceccagnoli, 2006; Gambardella et al., 2007), but largely absent in the debate on patents and cumulative innovation (see Furman et al. (2017) and Bryan and Williams (2021) for overviews). Indeed, our findings suggest that even in a world of frictionless bargaining, a blocking effect may still arise simply because patentees seek to sustain their competitive advantage.

Second, we add empirical and theoretical insights to the market for technology literature. For one, we illustrate how licensing activities, and the reasons for licensing failure, relate to the value of the underlying technology. This extends the prior literature, which has primarily focused on firm characteristics, IP protection, and technological generality as licensing determinants (Gans et al., 2008; Arora and Gambardella, 2010; Gambardella and Giarratana, 2013). We also expand the patentee's licensing consideration by introducing a dynamic perspective: the prospect of a valuable follow-on innovation can sway activities in the market for technology in different ways. On the one hand, it can help overcome excessive transaction costs linked to licensing an otherwise marginal original innovation. On the other hand, it might make the patentee even more reluctant to license out, as each license can imply more competition for follow-on innovation. These insights enrich recent contributions that examined the role of static competition in licensing decisions (de Bettignies et al., 2022; Moreira et al., 2020).

Finally, we establish freedom-to-operate (FTO) as a key consideration in a firm's decision to innovate. Although the literature on innovation and IP strategy sporadically refers to FTO (e.g., Guellec et al., 2012; Chung et al., 2019; Cappelli et al., 2023), our study is the first to conceptualize its importance for follow-on innovation.

2 Theoretical Framework

This section sets out predictions for the effect of patent invalidation on follow-on innovation. We derive these predictions from a theoretical model presented in Appendix A. In the following, we define the invalidation effect, describe the model, and summarize the predictions and implications for the empirical analysis.

2.1 The invalidation effect

The invalidation of a patent on an original innovation can increase follow-on innovation by others. The extent of this increase depends on the number of otherwise unlicensed firms that gain freedom to operate (FTO) and successfully build on the innovation. We call this the *invalidation effect* on follow-on innovation.

If a patent protects the original innovation, only firms that obtain a license from the patentee have FTO, i.e., "the ability to proceed with the research, development and/or commercial production of a new product or process with a minimal risk of infringing the unlicensed intellectual property rights [...] of third parties" (WIPO, 2005).[2] Firms without FTO are discouraged from pursuing follow-on innovation due to the risk of patent infringement, costly litigation, and damage payments.[3]

[2]To establish their FTO status, firms analyze existing patents on technologies relevant to their R&D activities to ensure they will not infringe upon any third-party rights. When conducting this so-called FTO analysis, firms scrutinize existing patents by their territorial boundaries, (expected) expiry, the claimed scope of protection, and legal validity (WIPO, 2005).

[3]Note that firms do not gain FTO simply by obtaining a patent on their follow-on innovation. A patent provides the owner with the *right to exclude* others but not the *right to use*. Hence, even a patented follow-on innovation can infringe patents on the original innovation.

In contrast, if the patent on the original innovation is invalidated through a validity challenge, all firms gain FTO. Firms can challenge a patent's validity directly after grant at the patent office (Graham and Harhoff, 2014) or later in a court of law (Cremers et al., 2016). The likelihood that a challenged patent is invalidated depends on its validity (i.e., legal quality), which varies across granted patents (Lemley and Shapiro, 2005).

Formally, we quantify the invalidation effect I as the difference in follow-on innovation between two cases: i) the patent is invalidated, and all $(N-1)$ other firms in the market have FTO; ii) the patent continues to protect the original innovation, and only n licensees have FTO. That is,

$$I(n) \equiv \rho \cdot (N-1) - \rho \cdot n\,, \tag{1}$$

where ρ is the probability that a given firm with FTO succeeds in follow-on innovation.[4]

Equation 1 shows that the strength of the invalidation effect depends on the number of firms that fail to obtain a license from the patentee $(N-1-n)$. Such licensing failure arises for two main reasons: rent dissipation and transaction costs. Rent dissipation renders licensing unprofitable for the patentee if the earnings from licensing fees cannot fully offset the lost revenue due to increased product market competition (Arora and Fosfuri, 2003; Fosfuri, 2006). Transaction costs erode an otherwise positive joint surplus from a licensing agreement (Green and Scotchmer, 1995).[5]

In the following, we examine how the number of licenses selected by the patentee, n, and hence the invalidation effect, I, vary with the value of the original innovation, v^o, and the value of the follow-on innovation, v^f. We derive predictions for I that are testable without data on the number of licensing contracts (n). Additionally, we discuss incentives to challenge the patent on the original innovation. This discussion also motivates the methods we employ in the empirical analysis.

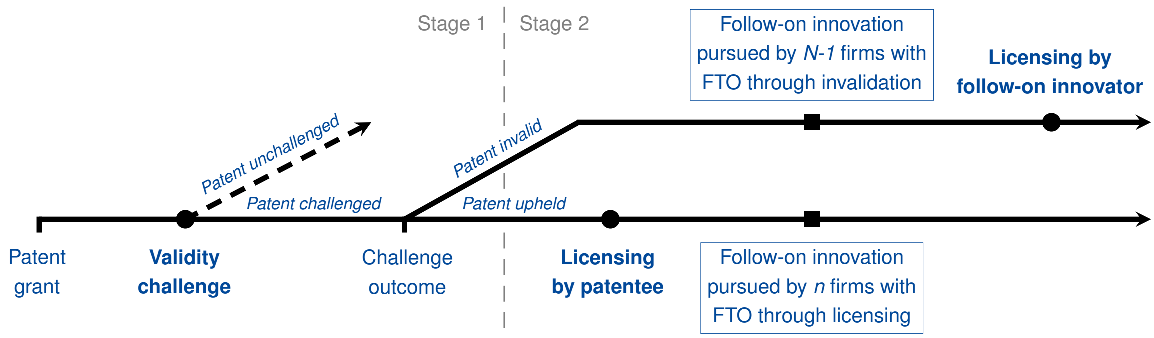
2.2 Model

Building on Arora and Fosfuri (2003), we model technology and product market competition in an oligopoly with a patentee and $N-1$ other firms. The patentee holds a patent on the original innovation. This innovation, with value v^o, increases product market revenues of the patentee and all licensees. The patentee and all licensees have FTO to compete for one single follow-on innovation, with value v^f, to further increase revenues. Patent invalidation provides all firms with the original innovation and FTO to compete for the follow-on innovation.

[4]For simplicity, we assume that ρ is exogenous here. This excludes potential externalities that might arise from firms' decisions to pursue follow-on innovation, as suggested by "prospect theory" (cf. Kitch, 1977; Merges and Nelson, 1994). In the Appendix, we allow that ρ depends on n and show that I declines in n for a wide range of innovation models.

[5]In particular, uncertainty and information asymmetries between the patentee and potential licensees make it costly to reach an agreement (Teece, 1986; Zeckhauser, 1996). Agrawal et al. (2015) find that failure in licensing negotiation is positively associated with due diligence costs, the inability to agree on a license fee, and the number of involved parties.

Figure 1: Structure of the licensing model with validity challenge



Notes: This figure illustrates the structure of a model of non-exclusive licensing with follow-on innovation after a validity challenge. Round nodes represent firm decisions: Validity challenge (Stage 1) and Licensing (Stage 2). Ticks represent exogenous events: Patent grant, Challenge outcome. Rectangular nods represent firm activities depending on firm decisions and exogenous events. The probability that follow-on innovation occurs depends on the endogenous number of firms with FTO: n. Note that the patentee has FTO in either scenario. We focus on the change in FTO as a result of invalidation.

Figure 1 illustrates the sequence of events and firms' actions in the model.[6] Firms interact in two stages. At Stage 1, the patent on the original innovation is challenged by another firm.[7] The validity challenge can result in two outcomes: the patent is either upheld or invalidated. If the patent on the original innovation is upheld, the patentee decides on the number of licenses, thereby providing n firms with FTO. If the patent is invalidated, all $N-1$ firms gain FTO. In this case, the firm that innovates chooses how many licenses to offer.

For simplicity, we assume that the patentee offers licensing contracts with a grant-back clause, ensuring the patentee's right to use the follow-on innovation if a licensee innovates (Ambashi et al., 2019; Leone and Reichstein, 2012). For the same reason, we assume that other licensees also obtain the right to use the follow-on innovation in exchange for additional licensing fees.[8] If the patent is invalidated, the patentee may fail to obtain a license for the follow-on innovation.

Stage 2: Licensing and follow-on innovation

In her licensing decision, the patentee considers her expected profits from three mutually exclusive outcomes: i) with probability ρ, the patentee innovates and obtains π_p, ii) with probability $n \cdot \rho$, one of n licensees innovates and the patentee obtains π_l, or iii) with probability $1-[n+1] \cdot \rho$, there is no follow-on innovation and the patentee obtains π_s. In each outcome, profits are a function of the number of licenses n. Depending on the specific outcome, profits are also functions of the value of the original innovation, v^o, the value of the follow-on innovation, v^f, or both.

[6]More detail on the sequence of moves in the model is provided in Section A.2.1 of the Appendix.

[7]With the validity challenge preceding the licensing decision, our model more closely resembles preemptive post-grant validity challenges rather than validity challenges arising from infringement allegations.

[8]Contracts with exclusive grant-back clauses, which give the patentee the right to license the follow-on innovation to third parties, are common (Murray, 2012). We discuss alternative contracts in Section A.2.1 of the Appendix.

The patentee selects the number of licenses, n, that maximize her expected value of licensing, V:

$$\max_n V = \underbrace{\rho \cdot \pi_p(n, v^f)}_{\text{patentee innovates}} + \underbrace{\rho \cdot n \cdot \pi_l(n, v^o, v^f)}_{\text{a licensee innovates}} + \underbrace{\left[1 - \rho \cdot [n+1]\right] \cdot \pi_s(n, v^o)}_{\text{no follow-on innovation}} - nT - H\ , \qquad (2)$$

which is the sum of the expected profits from the three outcomes minus the transaction costs for each license, T, and the fixed cost of follow-on innovation, H. Given that licensing increases the number of firms with FTO for follow-on innovation, the relative probabilities of the three outcomes also change with n.[9]

Our main interest lies in the relationship between innovation value and the invalidation effect. To see how variation in the value of the original innovation v^o and the value of the follow-on innovation v^f affects the selected number of licenses n and thus the invalidation effect I, we rearrange Equation 2. This reveals that the patentee obtains a static and a dynamic return from licensing:

$$V = \underbrace{\pi_s(n, v^o) - n\ T}_{\text{static return}} + \underbrace{\rho \cdot \left(\left[\pi_p(n, v^f) - \pi_s(n, v^o)\right] + n\ \left[\pi_l(n, v^o, v^f) - \pi_s(n, v^o)\right]\right)}_{\text{dynamic return}} - H\ .$$

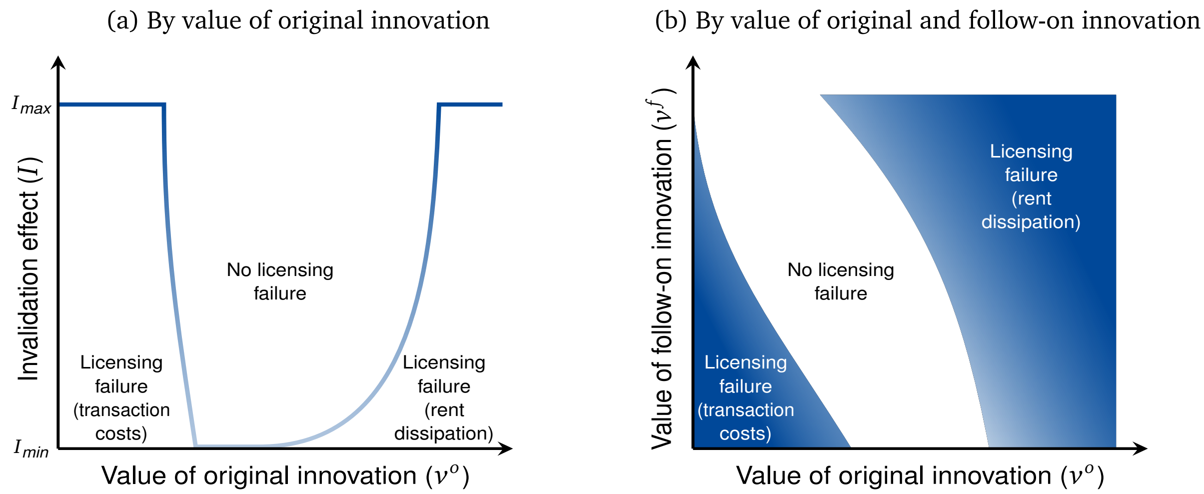
In the outcome with no follow-on innovation, the patentee gains only the static return, which depends on v^o. When v^o is low and transaction costs (T) are high, the static return may turn negative. This leads to complete licensing failure: the patentee does not license out at all ($n = 0$). In the two outcomes with follow-on innovation, the patentee gains the static return and an additional, positive dynamic return. The size of the dynamic return depends on the difference between v^f and v^o. A sufficiently high dynamic return can offset a negative static return, reducing the extent of licensing failure due to transaction costs for low v^o. For high v^o, rent dissipation reduces profits in all outcomes, increasing the extent of licensing failure ($n \to 0$). A high v^f intensifies rent dissipation.

Figure 2 illustrates how the strength of the invalidation effect I varies with the value of the original innovation v^o and the value of the follow-on innovation v^f. Specifically, Figure 2a shows that I has a U-shape in v^o, holding v^f constant. I is strong where transaction costs lead to licensing failure, which is likelier at low v^o. I is also strong where rent dissipation causes licensing failure, which is likelier at high v^o. Conversely, I is the weakest where neither transaction costs nor rent dissipation cause licensing failure; this is most likely at intermediate values of v^o.

Figure 2b illustrates how the strength of the invalidation effect I varies with v^o and v^f in combination. It shows that a higher v^f makes licensing failure due to transaction costs less likely, as the dynamic return compensates for a negative static return. This weakens I at low v^o. Conversely, a higher v^f intensifies rent dissipation making licensing failure of that kind more likely. This strength-

[9] That is, licensing changes the overall probability ($\rho \cdot [n+1]$) that a follow-on innovation arises. Strictly speaking, the probability that any given firm innovates (ρ) has to decrease in n, as discussed in Appendix A. This implies that n also decreases the probability that the patentee innovates. Our results encompass this dependency.

Figure 2: Licensing failure and invalidation effect



Notes: These two figures illustrate the relationship between the invalidation effect (I) and the value of the original innovation (v^o) (Figure 2a), as well as between I, v^o and the value of the follow-on innovation (v^f) (Figure 2b). I increases with the number of unlicensed firms that would obtain FTO only through patent invalidation (cf. Equation A.1). At I_{max}, the extent of licensing failure results in $n = 0$ firms with FTO through licensing. At I_{min}, there is no licensing failure, and $n = N - 1$ firms have FTO through licensing. Darker shades of blue indicate a stronger invalidation effect.

ens I at high v^o. To summarize, relative to a low-value follow-on innovation, a high-value follow-on innovation can either strengthen the invalidation effect (for high-value original innovations) or weaken it (for low-value original innovations).

Extensions We briefly summarize two extensions of the outlined model—patent thickets and (no) product market competition—and their implications for the invalidation effect.[10]

Patent thickets: The original innovation is not necessarily protected by only one single patent. Particularly in complex technology fields, multiple patents may protect different aspects of the original innovation, creating a patent thicket (Cohen et al., 2000; Shapiro, 2001). Here, the invalidation of one patent does not remove the necessity to license the other patents for FTO. While the existence of multiple patents (or rather: patentees) may also affect the extent of licensing failure itself, we expect that patent thickets weaken the invalidation effect I due to a limited increase in FTO.[11]

(No) product market competition: Patentees may not always compete in the product market of their (potential) licensees; they may be active in a different industry or lack vertical integration (Arora and Fosfuri, 2003; Arora and Ceccagnoli, 2006). In this case, rent dissipation does not reduce

[10]We do not extend our model to account for firm heterogeneity due to the variety of potential impact channels. For instance, firm size may impact transaction costs, static and dynamic revenues, and the probability of innovation. This makes the overall effect on follow-on innovation difficult to predict.

[11]The need to obtain licenses from multiple patentees may increase transaction costs (Ziedonis, 2004), strengthening the invalidation effect in complex technology fields. In discrete technology fields, patentees compete with each other for licensees, which lowers rent dissipation—a result previously shown by Arora and Fosfuri (2003). Here, the effect of multiple patentees on the invalidation effect largely depends on the switching costs between the discrete technologies.

the patentee's product market revenues. However, it still influences the patentee's expected value of licensing as every additional license reduces each licensee's profits and thereby lowers the amount the patentee can extract as a licensing fee. Thus, without product market competition, licensing failure due to rent dissipation is less likely, weakening the invalidation effect I at high v^o. At the same time, coordination across product markets is typically considered to be more costly, increasing T.[12] Hence, licensing failure due to transaction costs is more likely absent product market competition, strengthening I at low v^o.

Stage 1: Validity challenge

After analyzing the licensing decision in Stage 2, we shift our focus to Stage 1: the decisions leading to a patent being selected for a validity challenge. These decisions reflect two trade-offs. First, the challenging firm's expected value of pursuing the validity challenge must outweigh its costs. This depends on i) the patent's (latent) validity, ii) the net gain from invalidation, which increases with the extent of licensing failure and, in the case of licensing, the due fees, and iii) the costs of challenging the patent. Second, the patentee's expected value of having the patent's validity affirmed must exceed the value of settling the validity challenge (if that option is available).[13]

These two trade-offs determine the characteristics of patents selected into a validity challenge. In particular, patent validity and innovation value determine whether a patent is challenged and whether the parties fail to settle. Patents are less likely to be challenged if they have a particularly low or high validity. Furthermore, they are less likely to be challenged if v^o and v^f are low. These selection effects intensify with the costs of the validity challenge, meaning that higher costs correspond to a higher minimum v^o (and v^f) for challenged patents.

Our model reveals that patents of high validity are more likely to be challenged if they protect high-value innovations. This selection either generates a positive correlation between patent validity and innovation value—or reinforces a (presumably) already existing correlation within the patent population.[14] This implies that, conditional on a validity challenge, patents on high-value innovations are less likely to be invalidated.[15]

[12] Industry outsiders often lack the bargaining chips needed for more implicit—and therefore less costly—licensing agreements (Lanjouw and Schankerman, 2004; Ziedonis, 2004). Additionally, they face higher information asymmetry concerning industry-specific parameters, such as demand, resulting in higher verification costs.

[13] Settlement may not always be a viable option for the patentee due to the short time frame for negotiations and institutional reasons. That said, winning the validity challenge may offer additional advantages for the patentee, such as bolstering a reputation of toughness or signaling patent validity to others. Somaya (2003) provides empirical evidence for the importance of such asymmetric stakes in patent disputes.

[14] Firms are likely to invest substantially in drafting patent applications for valuable innovations. The aim is to secure their grant and safeguard them against future validity challenges. This may well result in a positive correlation between innovation value and validity in the patent population.

[15] This correlation might be further strengthened by the patentee's incentive to invest more in defending patents of higher value—a relevant point in high-profile, resource-intensive legal disputes over infringement (GS2015).

2.3 Predictions and implications for empirical analysis

The model outlined above provides three testable predictions concerning the effect of patent invalidation on follow-on innovation. In addition, the model has implications for the empirical analysis, which we outline here.

Predictions

We derive three predictions regarding the effect of invalidation on follow-on innovation:

Prediction 1: The invalidation effect follows a U-shape in the value of the original innovation.

Prediction 2: A high follow-on innovation value makes the invalidation effect weaker for low-value and stronger for high-value original innovations.

Prediction 3: Product market competition between patentee and potential licensees makes the invalidation effect weaker for low-value and stronger for high-value original innovations.

Prediction 1 follows from Figure 2a, Prediction 2 follows from Figure 2b, and Prediction 3 follows from the extensions discussed above. We test all three predictions in Section 4. The empirical results based on these predictions will allow us to infer the role of transaction costs and rent dissipation in causing licensing failure.

Implications for empirical analysis

Three additional results of our model bear relevance for our empirical analysis. First, the higher the cost of a validity challenge, the less likely it is that patents on low-value innovations will be subjected to such challenges. Second, the invalidation effect is likely to differ if multiple patents protect the original innovation rather than just a single patent. Third, conditional on being challenged, patents on high-value innovations are less likely to be invalidated.

These results guide the following decisions in our empirical analysis. We will choose an empirical setting where the costs of challenging validity are comparatively low to ensure a sample of patents that covers a broad range of innovation values—a prerequisite to testing our predictions. Furthermore, we will control for patent thickets surrounding the challenged patents to account for the likelihood that multiple patents protect the original innovation. Lastly, we will employ an empirical strategy that overcomes the correlation between innovation value and patent invalidation, allowing for a causal interpretation of the estimated invalidation effect.

3 Empirical Strategy, Setting & Data

In the following, we outline the empirical strategy, detail the setting, specify the data sources, and describe the variables.

3.1 Empirical strategy

We aim to estimate the invalidation effect by comparing subsequent follow-on innovation activities between invalidated patents and those upheld in a validity challenge. By examining the estimated magnitude of the invalidation effect between different sets of patents and different types of follow-on innovation, we can test our theoretical predictions.

We focus on an empirical setting where the costs of challenging validity are comparatively low: post-grant opposition at the EPO. This reduces the impact of selection bias, as the low costs of opposition result in a large sample of challenged patents with substantial heterogeneity in innovation value. As selection is reduced but not neutralized, we will remain cautious about generalizing the observed invalidation effects to the patent population.

We use an instrumental variable that affects patent invalidation but not follow-on innovation to address omitted variable bias. This is necessary as innovation value, being partly unobserved, correlates negatively with invalidation (our treatment variable) and positively with follow-on innovation (our outcome variable), resulting in a negative bias of the estimated invalidation effect. As discussed in Section 2, there likely exists a positive correlation between innovation value and latent validity within samples of challenged patents. This implies a negative correlation between innovation value and invalidation. Furthermore, a positive correlation likely exists between innovation value and the general probability of follow-on innovation.[16]

Theoretically, we could address this omitted variable bias by fully accounting for innovation value with patent value determinants. Yet, with observable patent and firm characteristics, we can only imperfectly capture these determinants. Moreover, patent value also hinges on unobserved factors, such as the degree of product differentiation. Consequently, even with these controls, we expect some residual bias. This prompts us to implement an instrumental variable approach.

3.2 Post-grant opposition at the EPO

Our institutional setting to observe patent validity challenges is post-grant opposition at the European Patent Office (EPO). Within the first 9 months after the EPO's decision to grant a patent, third parties can challenge its validity by filing an opposition.

At the EPO, a technically qualified examiner ("the granting examiner") decides whether a given patent application fulfills all patentability requirements and should be granted. The examiner's decision to grant the patent can be opposed by any party except the patentee herself. The opposition

[16]In practice, it is likely that the overall probability of follow-on innovation, ρ, is positively correlated with the value of the original innovation, v^o. For instance, valuable original innovations may provide more technological opportunities for follow-on innovation, or a generally higher R&D intensity in an industry, which leads to high-value original innovations, might also foster follow-on innovation.

may be filed on the grounds that the subject matter is not new or inventive, the invention is not sufficiently disclosed, or the granted patent extends beyond the application's content as filed.

The opposition division, which consists of three technically qualified examiners, hears the case. On average, about three years after the grant, the opposition division rules the opposed patent as either fully valid, valid but in amended form (i.e., with a narrowed scope), or invalid. Appendix F provides further procedural details on examination and opposition.

Oppositions at the EPO represent low-cost validity challenges. With costs ranging from 6,000 EUR to 50,000 EUR, challenging a patent at the EPO is considerably more affordable than through patent litigation in national courts, where expenses can reach into the millions (Mejer and van Pottelsberghe de la Potterie, 2012). These relatively low costs reduce selection effects.[17] Approximately 6% of patents granted by the EPO are opposed, a rate that significantly exceeds litigation rates both in Europe (Cremers et al., 2017) and the US (Lanjouw and Schankerman, 2004; Bessen and Meurer, 2013). Hence, as we will demonstrate later, the average opposed patent tends to have a lower value than those typically involved in litigation.

3.3 Data sources

We identify opposed patents in the EPO PATSTAT Register. For these patents, we obtain documents related to examination and opposition from the online file inspection system provided by EPO. We extract the names of granting examiners and members of the opposition divisions from these documents (see Appendix G for details). The EPO PATSTAT Register provides us with results and dates of opposition outcomes and the identities of opponents.

We further use bibliographic data on opposed patents, patentees, and citations from the EPO Worldwide Patent Statistical Database (2019 Autumn Edition). We obtain information on further aspects of the examination process, such as the assigned technical art unit and the examination location, from the EPO's administrative database EPASYS (April 2015). Finally, we complement the patent data with firm-level microdata (firm size and industry focus) provided by Orbis Intellectual Property (April 2019).

3.4 Dependent variable

Consistent with prior literature (e.g., GS2015, Watzinger et al., 2020), we quantify follow-on innovation by counting the number of citations received by the focal patent from other patents. Our analysis concentrates on EPO citations from the first five years following the opposition outcome,

[17] Institutional factors discourage settlement once the proceeding has started, further reducing selection. The opposed patent may still be invalidated by the opposition division despite the opponent's withdrawal. This makes settlement between the opponent and the patentee at this stage a relatively rare event (∼10%).

using the earliest filing date of the citing patent as an approximation for the actual invention date. Importantly, we focus on citations from patents filed by firms other than the focal patentee.[18]

We test Predictions 2 and 3 by decomposing the overall set of citations into specific citation subsets. To examine how the invalidation effect varies with the value of the follow-on innovation, we distinguish citations by whether the *citing* patent is of above-average value (based on common patent value indicators). To examine how the invalidation effect varies with product market competition between the patentee and the follow-on innovators, we distinguish citations by whether the citing firm is active in the same industry or resides in the same country as the focal patentee.[19] Considering the low granularity and incompleteness of firm-level information, we further distinguish citations by whether the citing patent is in the same IPC4 technology class as the focal patent. While all three binary indicators for product market competition have their shortcomings, they collectively capture key dimensions of competition: industry, geography, and technology.

Citations may capture more than just follow-on innovations that would infringe on the opposed patent, thereby necessitating FTO (Freilich and Shahshahani, 2023). Although EPO citations are known to have high technological relevance (Breschi and Lissoni, 2004), we test the robustness of our main results to subsets of particularly relevant citations (Criscuolo and Verspagen, 2008). Additionally, we count patents with high textual similarity to the focal patent, regardless of whether a citation link between them exists.

In alignment with prior literature, we log-transform the dependent variable to estimate semi-elasticities. This transformation warrants careful consideration if the dependent variable is right-skewed and has a large probability mass at zero (Mullahy and Norton, 2022). Hence, we verify the robustness of our results by using alternative transformations of the dependent variable.

3.5 Independent variables

The independent variable of main interest is invalidation. We complement this with variables capturing characteristics of the patentee, the opponent, the patent, and the technology field.[20]

Invalidation: We create a binary variable ("invalidated") equalling 1 for the opposition outcomes "invalid" and "valid but in amended form", and 0 for "valid", with a mean of 0.71. This operationalization follows GS2015. Our main results are robust to alternative operationalizations.

[18] In robustness tests, we further analyze the effect on follow-on innovation by parties who are not involved in the opposition proceeding. This accounts for the fact that the response to invalidation of firms selecting themselves into validity challenges may differ from the average firm response.

[19] We consider follow-on innovators and patentees to be in the same industry if their NACE codes share the same first 3 digits and relate to manufacturing activities. The NACE codes are a European Industry-standard classification system with a 4-digit hierarchy.

[20] A comprehensive list of the control variables can be found in Appendix Table B-1.

Patentee and opponent characteristics: To account for variation in firms' profits flowing from vertical integration, complementary assets, and competitiveness of product markets, we include variables capturing the sector (corporate entity or not), country of residence (EU, UK, US, JP, RoW), and firm size (small, medium, large).[21]

Patent variables: We draw on several established patent value indicators to capture innovation value. Specifically, we consider patent claims, first claim length, family size, IPC classes, applicants, inventors, and backward citations. Furthermore, we include self and other citations within the first three years after patent filing as additional proxies for patent value. Capturing a patent's underlying innovation value with bibliographic indicators is notoriously difficult (Higham et al., 2021). Although the above patent value indicators are recognized correlates of value, they remain imperfect and can be noisy. To refine our measurement of innovation value *within* our sample of opposed patents, we will investigate which of the above variables best predicts selection into expensive litigation and choose these as our preferred measures to represent innovation value.

Patent thicket density: To account for multiple patents protecting the original innovation, we control for the time-variant density of patent thickets in the focal patent's technology field. We measure patent thicket density by counting citation constellations in which three patentees can mutually block each other (Von Graevenitz et al., 2011). The patent thicket density is higher in complex technology fields and in recent years (see Appendix Figure B-1).

3.6 Instrumental variable

To address omitted variable bias in estimating the invalidation effect, we use an instrumental variable approach. In particular, we leverage random variation in the participation of the patent's granting examiner in the opposition division, which decides on invalidation (see also Nagler and Sorg, 2020, for details).

Granting examiners are suitable and legitimate[22] candidates for the opposition division. In our data, they participate in more than 50% of all opposition proceedings. As one of the three division members, the granting examiner has an equal vote on the opposition outcome.[23]

[21] The size categories are drawn from firm-level data in ORBIS IP. They follow the division of the European Commission, which considers the number of employees, annual turnover, and total assets.

[22] Article 19(2) of the European Patent Convention states the following: "An Opposition Division shall consist of three technically qualified examiners, at least two of whom shall not have taken part in the proceedings for grant of the patent to which the opposition relates."

[23] As voting follows a simple majority, the participation of the granting examiner is most decisive where the other two members of the opposition division disagree on the patent's validity. While we do not find that complier patents (i.e., patents where the instrument affects the treatment status) differ in observable characteristics from the other opposed patents (see Appendix D), it is conceivable that these patents are more contentious. Given that uncertain patent protection complicates licensing agreements (Arora and Ceccagnoli, 2006; Gans et al., 2008), the invalidation effect—if caused by licensing failure due to transaction costs—may be larger among the complier patents in our sample.

We argue and show empirically that the opposed patent is more likely to be upheld if the granting examiner participates. Explanations for this pattern include behavioral biases, career concerns, and knowledge redundancy.

First, the granting examiner may be more likely to reaffirm the patent's validity because she suffers from *confirmation bias*, which makes it more difficult for the opponent to convince her that the initial decision on the patent's validity was incorrect. Indeed, scholars have argued that decisions on patentability may be prone to confirmation bias (Allison and Tiller, 2003; Doyle, 2016). Moreover, the granting examiner may show a preference for *decision consistency*, which makes her stick to the initial grant decision (Falk and Zimmermann, 2018).

Second, the granting examiner's decision-making may be affected by career concerns (Langinier and Marcoul, 2020). Promotions at the EPO are based on a bi-annual performance evaluation, which includes quality of examination (Friebel et al., 2006). Depending on how the granting examiner perceives the EPO's evaluation criteria (e.g., appraisal by peers vs. number of correct granting decisions), it is possible that she seeks an affirmative opposition outcome.

Third, invalidation may become less likely due to the "redundant" knowledge that comes with the granting examiner. Each examiner draws on a unique stock of accumulated prior art knowledge to decide on patentability (Cotropia and Schwartz, 2020). In cases where the granting examiner participates, only two instead of three examiners with new prior art knowledge scrutinize the patent.

Qualitative and quantitative evidence suggests that variation in examiner participation is due to the temporary unavailability of other eligible examiners and is unrelated to characteristics of the opposed patent and beyond the influence of the patentee or the opponent. Interviews with EPO officials revealed that the participation of the granting examiner is due to capacity constraints in the technical art unit at the moment when the opposition division is appointed. These capacity constraints are a function of the art unit's recent recruitment efforts and the examiners' relative workloads, but also depend on mundane events at the examiner level, such as retirement, maternity leave, sick leave, and vacation. We provide evidence on the relationship between examiner participation and temporary capacity constraints in Appendix D.[24]

To minimize the influence of patenting activities in the opposed patent's technology field (which may correlate with follow-on innovation) on examiner participation, we include year fixed effects and fine-grained (>500) technology class fixed effects in our baseline specifications. We also demon-

[24]Even with exogenous examiner participation, the exclusion restriction might be violated. If the patentee or opponent anticipated examiner participation before the outcome, they might alter their behavior. Yet, the opposition division's composition is disclosed late in the process, and, based on our data, an examiner's identity does not consistently predict their participation, as few always or never join opposition proceedings.

strate the robustness of our main results to the inclusion of technology class-year, examiner, and examiner-year fixed effects.

3.7 Sample

We observe around 54,000 patents opposed between 1993 and 2012.[25] We narrow this sample to oppositions with information on the granting examiner and the members of the opposition division,[26] and exclude patents with an opposition outcome after 2013 to mitigate truncation effects. The main sample of analysis consists of 38,271 opposed patents.[27]

Opposed patents are, on average, significantly more valuable than a random set of comparable patents. In Figure 3a, we plot the mean differences of several value indicators between opposed and control patents from the same patent office, filing year, and technology class. More specifically, we compare the patents' 1st claim length (reversed), number of claims, family size, number of inventors, number of IPC classes, and abnormal returns at the time of grant (Lerner, 1994; Novelli, 2015; Kogan et al., 2017; Kuhn and Thompson, 2019). Most of these indicators suggest that opposed patents are significantly more valuable. This finding aligns with the argued selection into validity challenges.[28] That said, there still is substantial variation in patent value within our sample, which we leverage in the empirical analysis.[29]

Opposed patents are, on average, less valuable than *litigation* patents, whose validity has been challenged in high-stakes infringement disputes. In Figure 3a, we further plot the mean differences in the same value indicators, comparing approximately 1,200 litigation patents with their respective control patents.[30] Consistent with being selected into more costly validity challenges, we observe that the standardized mean differences are significantly larger for litigation patents than for opposed patents across three value indicators: number of claims, family size, and the number of IPC classes.[31] As these three indicators seemingly capture a relevant value dimension of patents *conditional* on

[25] Information on the members of the opposition division is unavailable before 1993.

[26] This reduces our sample by about 17% per year (see Appendix Table G-1 for a detailed breakdown). We assume that this selection has little relevance to our subsequent analysis. The fact that the excluded patents are equally distributed over time supports this view (see Appendix Figure B-2).

[27] The control variables in our main specification perfectly predict patent invalidation for about 130 opposed patents. We exclude these patents from our sample.

[28] It also reconfirms findings in prior work on opposition (e.g., Harhoff and Reitzig, 2004)

[29] For instance, patent family size has a sample mean of 10.7 with a standard deviation of 10.9, and the number of claims has a sample mean of 13.6 with a standard deviation of 10.1 (see Appendix Table B-2).

[30] This sample approximates the one used by GS2015. It is based on patent litigation cases at the US Court of Appeals for the Federal Circuit (CAFC) with a decision between 1983 to 2008 as reported in the legal database Darts-IP.

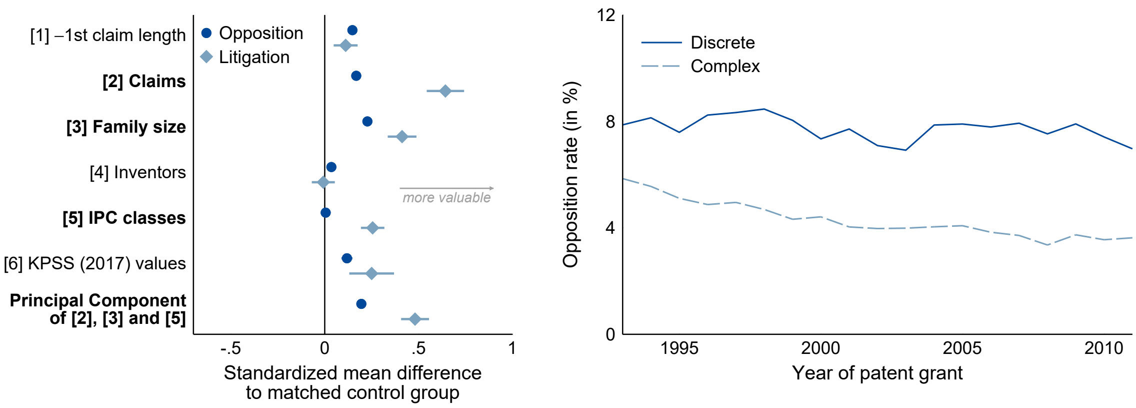
[31] More specifically, we use the EP family size, which corresponds to the number of European countries for which the opposed patent has been validated relative to the total number of eligible European countries at the time. We favor this narrow definition of family size because the DOCDB family can include national patents filed directly in European countries. Since the legal status of these patents is not affected by the opposition outcome, a patent's family size would have an inverse correlation with treatment intensity.

having their validity challenged, we draw on these variables to proxy innovation value. Specifically, we will use the first principal component derived from these three variables to test our predictions about the invalidation effect related to the value of the original innovation.

Figure 3: Patents selected into opposition

(a) Patent value

(b) Opposition rates over time



Notes: The left-hand figure shows the standardized mean differences between EPO opposition (and US litigation) patents and their matched control patents. Every opposition/litigation patent is matched to five randomly drawn granted patents based on jurisdiction, year of (priority) filing, and IPC4 technology class. We standardize the mean differences to facilitate a direct comparison. The corresponding statistics are reported in Appendix Table E-3. 95% confidence intervals are shown. KPSS (2017) values are based on abnormal stock market returns of the patentee at the time of grant (Kogan et al., 2017). This variable is missing for a significant share of our sample. The right-hand figure shows the opposition rate (in %) for all patents granted by the EPO in discrete and complex technology fields over time. The classification of technologies into discrete and complex fields follows Von Graevenitz et al. (2013).

Opposition rates differ noticeably between discrete and complex technologies (Figure 3b). In discrete technology fields, the opposition rate is around 8%. In complex technology fields, the opposition rate is around 6% in the early 1990s, declining further to 4% with time. The difference in opposition rates has been attributed to the large number of overlapping patent rights in complex technology fields, which reduces the incentives to challenge validity (Harhoff et al., 2016). As outlined in Section 2, such patents thickets also matter for the effect of invalidation on follow-on innovation. We will account for time-variant differences in the number of overlapping patent rights between technology fields with the patent thicket density measure.

Opposition involves mostly corporate entities with about 94% of patentees and 97% of opponents as firms. This supports our choice to concentrate on firm licensing decisions in our theoretical framework. The distribution of the patentees' countries of residence mirrors that in the population of granted patents. As patents granted by the EPO primarily impact the activities of firms in Europe, the share of domestic opponents is elevated (58% vs. 83%). The size distributions of patentees and opponents are similar to the population, with 50% classified as large firms.

4 Empirical Analysis

4.1 Econometric model and identification strategy

Our data on oppositions is a cross-section where the unit of observation is the unique patent p. Our basic empirical specification is:

$$\begin{aligned}\log(Citations_p) = \beta_0 \; + \beta_1 \; Invalidated_p \; + \beta_2 \; Patent\ thicket\ density_p \; + \; \beta_3 \; Patent_p \\ + \; \beta_4 \; Patentee_p + \; \beta_5 \; Opponent_p \; + \; \beta_6 \; Age_p \; + \; \beta_7 \; Year_p \; + \; \beta_8 \; Tech_p \; + \; \epsilon_p \,.\end{aligned} \tag{4.1}$$

The dependent variable captures the number of citations within the first five years after the opposition outcome. The coefficient β_1 provides the effect of patent invalidation on the number of citations; this is the effect of primary interest for our analysis. The model also includes the patent thicket density measure and characteristics of the patent, the patentee, and the opponent. Patent age, grant year, decision year, and technology field enter the model as fixed effects.

We estimate a two-stage least squares (2SLS) model in which invalidation is instrumented with the predicted probability of invalidation. The prediction includes the "Examiner participation" dummy and all other covariates $\boldsymbol{x}$:

$$\begin{aligned}Invalidated_p = \alpha_1 \; Predicted\ probability_p + \boldsymbol{\alpha x}_p \; + u_p \\ \log(Citations_p) = \beta_1 \; \widehat{Invalidated}_p \; + \boldsymbol{\beta x}_p \; + \; \epsilon_p \,.\end{aligned} \tag{4}$$

We expand this baseline model to account for variation in the invalidation effect with patent thicket density. To do this, we interact the endogenous "Invalidated" variable with the "Patent thicket density" covariate. This interaction must be treated as a separate endogenous variable that requires its own instrumental variable (Wooldridge, 2010). To this end, we use the interaction of the predicted probability of invalidation with the "Patent thicket density" covariate.

The examiner's participation in the opposition division is a highly significant negative predictor of invalidation (see Table 1). Examiner participation lowers the probability of invalidation by about 7.2 percentage points (pp) in the univariate model (column 1) and by about 4.8 pp in the model with the full set of covariates (column 2). This result is robust to the inclusion of large sets of additional fixed effects (columns 3 and 4).

While we can empirically show the instrument's relevance, its exogeneity cannot be verified. Nonetheless, the results of several empirical analyses are consistent with the argued randomness of examiner participation conditional on technology class and year effects. Importantly, we do not find any (non-)linear relationships between examiner participation and patent value indicators. Likewise, we do not find differences in citation trends between patents with and without examiner participation within the ten years before the decision outcome. Appendix D provides further details.

Table 1: Examiner participation and patent invalidation

	(1)	(2)	(3)	(4)
Estimation method	Probit	Probit	Probit	Probit
Dep var		Invalidated (d)		
Exam. participation (d)	−0.073***	−0.046***	−0.047***	−0.061***
	(0.005)	(0.005)	(0.006)	(0.012)
Covariates	None	Full	Full	Full
Additional fixed effects	–	–	IPC4×yr	Exam.×yr
Dep var mean	0.71	0.71	0.70	0.61
Model degrees of freedom	1	588	3,458	4,998
χ^2-statistic	239.6	2,686.6	5,094.9	3,968.7
Pseudo-R^2	0.005	0.072	0.127	0.146
Observations	38,271	38,271	32,742	20,397

Notes: The probit regressions in columns (1) to (4) show the relevance of the "Examiner participation" dummy for the opposition outcome. The invalidation predictions of the probit regression in column (2)—or equivalent predictions—are used as the instrument in the 2SLS instrumental variables regressions throughout the study. The samples in columns (3) and (4) are reduced due to a large set of fixed effects that perfectly predict patent invalidation. One is added to all citation variables before taking the logarithm to include patents without citations. A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

4.2 Average invalidation effect

We start our analysis by examining the average effect of patent invalidation on follow-on innovation, both to validate our research design and to replicate the positive invalidation effect observed in the prior literature. In Table 2, columns (1) and (3) show OLS regressions of the log-transformed number of citations within five years after the opposition outcome on the invalidation dummy, both with control variables and without them. The estimated effect of patent invalidation on citations is statistically insignificant and close to zero.

Turning to the respective 2SLS instrumental variables (IV) regressions in columns (2) and (4), we find significant positive invalidation effects. The estimated coefficient in column (4), our main specification, implies that patent invalidation increases citations in the five years following the opposition outcome by 0.15 ($p < 0.03$), corresponding to an increase of about 16%. The instrument explains a sizable part of the variation in patent invalidation, underlined by the first stage F-statistic of almost 500—exceeding the Stock and Yogo (2005) critical values for weak identification tests. Additionally, the null hypothesis of exogeneity can be rejected ($p < 0.02$).

The positive difference between the OLS and the IV estimates aligns with the presumed endogeneity of invalidation. As discussed in Section 3.1, the OLS estimates are likely downward biased because invalidation is negatively correlated with unobserved dimensions of patent value, which in turn are positively correlated with the general probability of follow-on innovation.

Taking into account the existence of other patents also protecting the original innovation, we recover substantially larger invalidation effects. In columns (5) and (6), we add an (instrumented)

Table 2: Effect of patent invalidation on follow-on innovation

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(Citations)			
Invalidated (d)	−0.001	0.067***	−0.007	0.148**	0.066***	0.580***
	(0.006)	(0.021)	(0.006)	(0.065)	(0.018)	(0.088)
× Patent thicket density					−0.014***	−0.098***
					(0.003)	(0.013)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.41	0.41	0.41	0.41	0.41	0.41
Underidentification test		2,845.0		253.8		252.1
Weak identification test		3,774.5		482.6		236.1
Endogeneity test		11.4		5.6		49.1
p-value		0.001		0.018		0.000
Observations	38,271	38,271	38,271	38,271	38,271	38,271

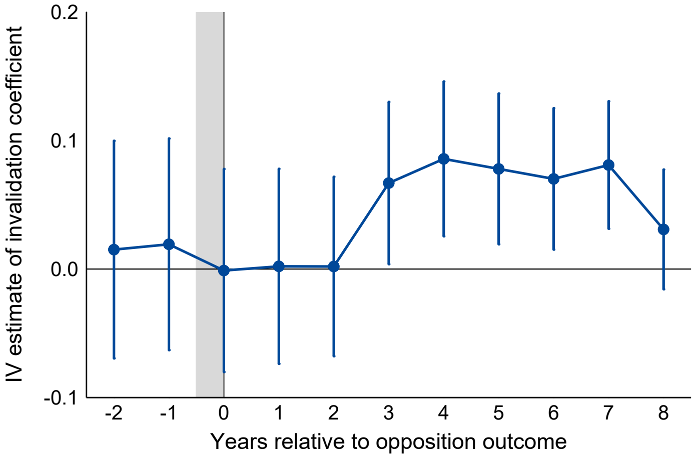
Notes: Columns (1) to (6) compare the OLS and the 2SLS regressions for the effect of invalidation on citations by others in a 5-year window following the opposition outcome. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

interaction term of the invalidation dummy with the patent thicket density. The corresponding interaction effect is negative for both OLS and 2SLS regressions and sizeable. For the 2SLS regression, an increase of one standard deviation in the patent thicket density lowers the invalidation effect on citations by about 0.16. The negative coefficient of the thickets interaction is in line with our reasoning that, in the case of overlapping patent rights, firms do not necessarily obtain FTO for follow-on innovation from the invalidation of a single patent. Hence, the estimated baseline effect of invalidation (with no thicket surrounding the invalidated patent) is large in magnitude (0.58).[32]

The positive effect of invalidation obtained from 2SLS regressions is robust to a large set of alternative variable operationalizations and model specifications (see Appendix C.1). First, the effect of invalidation is highly similar when taking into account appeals to the opposition outcome or when defining patent invalidation by the share of invalidated claims. Second, the effect of invalidation remains positive and significant when limiting the dependent variable to citations with a higher standard of relevance, when counting citations generated by the USPTO (instead of the EPO), and when counting the number of subsequently filed patents with a high text similarity to the opposed patent. Likewise, the effect of invalidation is robust to different transformations of the citation count (binary and hyperbolic sine) and using the non-transformed citation count. Third, the effect of

[32]The observed heterogeneity in the invalidation effect by patent thicket density is also found when splitting the sample into patents surrounded by a patent thicket density above or below the average. Likewise, we find consistent results when using a binary operationalization of patent thicket density as the moderator variable.

Figure 4: Effect of patent invalidation on follow-on innovation – timing



Notes: The figure presents the point estimates and 90% confidence intervals for the instrumented invalidation coefficient on citations estimated for each year after the opposition outcome individually. We account for overdispersion in the dependent variable by replacing the number of citations with a binary variable indicating whether the patent has been cited in the respective year. Otherwise, the model specification is equivalent to that in Table 2, column (4).

invalidation remains practically unchanged when clustering standard errors at the technology field level or when adding further fixed effects (e.g., examiner×year fixed effects) as control variables.[33] Notably, the positive effect of invalidation on citation is driven by an increase in the *number of firms* citing the focal patent. We find highly similar coefficients when limiting the count of citations to one for each citing firm. This increase at the extensive margin suggests that more firms conduct follow-on innovation after patent invalidation.

Examining the timing of the invalidation effect, we find that citations start increasing only from the third year after the opposition outcome (Figure 4). This time lag supports the interpretation that the invalidation effect materializes only after additional R&D has been undertaken. It also renders changes in citation behavior an unlikely explanation for the effect, as one would expect to see them setting in immediately after invalidation.[34]

In summary, these results suggest that patent invalidation led to an overall increase in follow-on innovation activities by other firms—which replicates the positive (albeit considerably larger) invalidation effect found in the prior literature (GS2015). According to our theoretical framework, this pattern indicates that some firms only have FTO for follow-on innovation due to invalidation—they failed to obtain a license from the patentee.

To determine the reasons for this licensing failure, we will now test our predictions concerning the strength of the invalidation effect by original innovation value, follow-on innovation value, and product market competition as set out in Section 2.3.

[33] Our main results also hold when using a Generalized Method of Moments estimator of Poisson regression.

[34] Moreover, the minimal and statistically insignificant estimates of invalidation on citations in the years *prior* to the opposition outcome is consistent with the argued exogeneity of the instrumented opposition outcome.

4.3 Effect heterogeneity by original innovation value

In our theoretical framework, we predict that the invalidation effect follows a U-shape in the value of the original innovation (Prediction 1). This pattern arises from the two reasons why firms may fail to gain FTO through licensing, with the likelihood of each reason largely hinging on the value of the original innovation. The first reason pertains to transaction costs, which can inhibit the licensing of low-value original innovations. The second reason concerns rent dissipation, which discourages patentees from licensing out their more valuable original innovations.

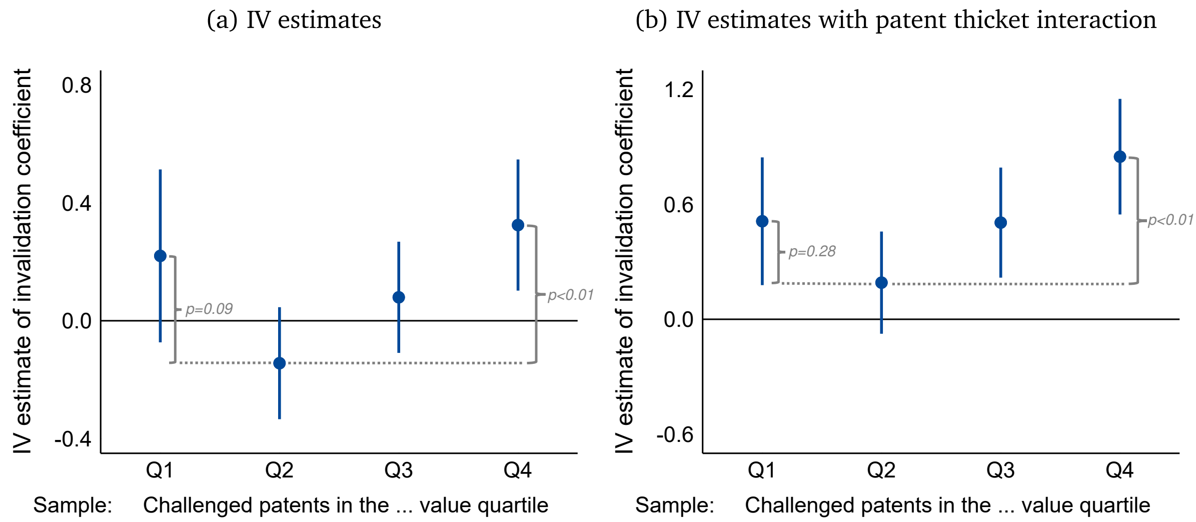
To discern whether the invalidation effect in our sample can be explained by licensing failure due to transaction costs or rent dissipation, we probe the relationship between the invalidation effect and the value of the original innovation. For this purpose, we leverage our sample's substantial heterogeneity in patent value and create four subsamples of roughly equal size divided at the first, second, and third quartiles of the patent value distribution. To measure patent value, we use the first principal component based on the number of claims, the number of IPC classes, and the patent family size. The patent value distribution is then stratified by year and technology field to account for time- and technology-specific variation of patent indicators (Harhoff, 2016; Higham et al., 2021).

We find that the invalidation effect on citations exhibits a U-shape along the patent value distribution. In Figure 5a, we present the invalidation effects obtained from separate instrumental variables regressions on the different subsamples by patent value. The effect is particularly large for patents in *both* tails of the value distribution, although statistically significant only in the top quartile. The coefficient of the invalidation effect in the top value quartile stands at 0.33, approximating 80% of the effect magnitude found for high-value litigation patents in the prior literature (GS2015). In contrast, the invalidation effect is much smaller and statistically indistinguishable from zero in the medium range of the value distribution. This U-shape becomes even more salient when controlling for the moderating effect of the patent thicket density surrounding the opposed patents (Figure 5b). In fact, the baseline invalidation effect in the top value quartile is more than four times as large as in the second value quartile (0.849 vs. 0.191, $p < 0.01$).[35]

The observed U-shape of the invalidation effect is robust to various changes in the regression specification (see also Appendix C.2). First, we find a similar albeit less marked pattern when measuring patent value through other (non-composite) patent indicators (number of claims, patent family size, and number of IPC classes). Moreover, the pattern is robust to sample splits based on different thresholds within the value distribution. Second, we can rule out that the pattern is

[35]Focusing on a subsample of challenged patents with a low patent thicket density, we find the same pattern and coefficients that approximate the baseline effects in Figure 5b.

Figure 5: Effect of patent invalidation on follow-on innovation – original innovation value



Notes: The figure provides the point estimates and 90% confidence intervals for the instrumented invalidation coefficient on citations by others. The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. The statistical significance of coefficient differences is determined by bootstrapping (results in Table C-8). The corresponding regression results are in Appendix Table C-7.

driven by subsample-specific variation in the distribution of the dependent variable. Taking either the inverse hyperbolic sine or a binary variable indicating a positive citation count as the dependent variable leads to the same pattern. Likewise, the U-shape is robust to removing citations by the opponent and focusing exclusively on citations by third parties. Third, we can confirm this pattern when controlling for patentee size. Patent value and firm size are not independent of each other (Arora et al., 2023). To avoid any correlation between firm size and patent value driving our results, we add a second (instrumented) interaction of invalidation with a dummy variable indicating large patentees. The estimated baseline coefficients show a similar U-shape to the one presented here.

In summary, these results suggest that the invalidation effect is the strongest for patents at either end of the value distribution in our sample. The found U-shape of the invalidation effect aligns with Prediction 1 derived from our theoretical framework, in which the extent of licensing failure depends on the value of the original innovation. The invalidation effect for patents on low-value original innovations is best explained by licensing failure due to transaction costs, whereas the invalidation effect for patents on high-value original innovations is best explained by licensing failure due to rent dissipation. At the same time, the invalidation effect is substantially smaller for patents of medium value. Here, the challenged patents appear to cover original innovations that are valuable enough to ensure a joint surplus that exceeds the transaction costs of licensing but not so valuable that rent dissipation makes the patentee systematically unwilling to license out.

4.4 Effect heterogeneity by follow-on innovation value

In our theoretical framework, we posit that not only the value of the original innovation but also the prospect of a valuable follow-on innovation influences the extent of licensing failure and, consequently, the invalidation effect. Specifically, we predict that for high-value follow-on innovations, the invalidation effect becomes weaker for low-value and stronger for high-value original innovations (Prediction 2). This is because high-value follow-on innovation exacerbates rent dissipation, making licensing failure due to rent dissipation even more likely for high-value original innovations. At the same time, such follow-on innovation can raise the surplus of licensing for low-value original innovations, reducing the extent of licensing failure due to transaction costs.

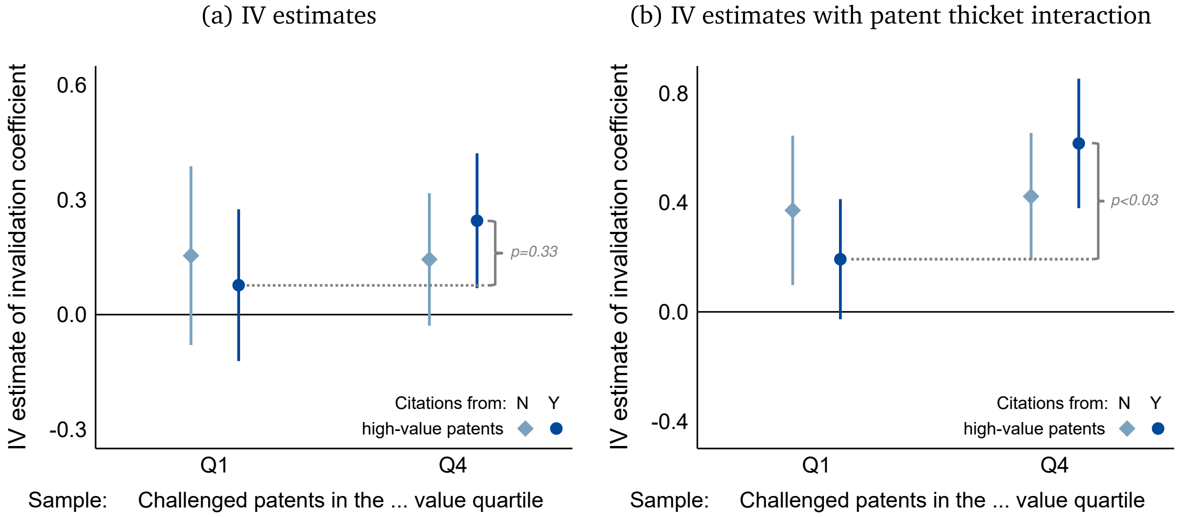
To examine whether the invalidation effect is influenced by the value of the follow-on innovation, we distinguish between citations from low- and high-value *citing* patents (hereafter simply referred to as low- and high-value citations). Based on our theoretical underpinnings, we expect high-value citations to increase predominantly with the invalidation of high-value patents. We split the overall citation count into two subsets, distinguishing whether the citing patent is of above-average value. Our analysis focuses on challenged patents in the bottom and top value quartiles to provide the strongest contrast in effects. Estimates for all four quartiles are presented in Appendix C.3.

We find that the invalidation effect on high-value citations is more pronounced in the top value quartile than in the bottom value quartile, even though the difference is not statistically significant (Figure 6a). When controlling for patent thickets surrounding the challenged patents, we find a substantially larger difference in effect sizes (Figure 6b). In the top value quartile, the invalidation effect on high-value citations is more than three times as large as in the bottom value quartile (0.62 vs. 0.19, $p < 0.03$). In contrast to that, the corresponding effect on low-value citations is roughly equal between patents in the top and in the bottom value quartile (0.42 vs. 0.37).

While the differences in coefficients are not consistently statistically significant, the pattern of results is instructive and aligns with Prediction 2.[36] Confidence in these results is further underscored by the results of several robustness tests (see also Appendix C.3). Employing different patent value indicators (patent family size, patent claims, IPC classes) to measure the value of follow-on innovation, we find a consistent pattern of differences. Moreover, the observed effect differences persist when using either the inverse hyperbolic sine of the citation count or a binary variable indicating a positive citation count as the dependent variable. The same holds true when estimating the invalidation effects in subsamples more extreme than the bottom and top value quartiles.

[36] The reason why the differences are not more distinct may be due to the inherent uncertainty surrounding the potential for follow-on innovation. From an ex-ante perspective, both the patentee and the potential follow-on innovator might be uncertain whether a highly valuable follow-on innovation will materialize.

Figure 6: Effect of patent invalidation on follow-on innovation – original and follow-on innovation value



Notes: The figure provides the point estimates and 90% confidence intervals for the invalidation coefficient on citations by others, respectively. The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year. Citations from high-value patents are those where the citing patent has an above-average patent value (based on the principal component of claims, IPC classes, and family size). The statistical significance of coefficient differences is determined by bootstrapping (results in Table C-16). The corresponding regression results are in Appendix Table C-15.

In summary, the observed heterogeneity in results based on the value of follow-on innovation strengthens the argument that the invalidation effect is caused by licensing failure of different kinds. Licensing failure due to rent dissipation is most relevant for the invalidation effect if the value of both the original and the follow-on innovation is high. Conversely, licensing failure due to transaction costs seems to be most relevant if neither the original innovation nor the follow-on innovation generates a sufficiently large joint surplus of licensing.

4.5 Effect heterogeneity by product market competition

Lastly, our theoretical framework suggests that the relevance of licensing failure due to transaction costs and rent dissipation varies with product market competition between the patentee and the (potential) licensees. More specifically, we predict that product market competition weakens the invalidation effect for low-value and strengthens it for high-value original innovations (Prediction 3). This follows from the theoretical result that rent dissipation is larger when the follow-on innovator competes with the patentee in the same product market. Additionally, when the patentee and the follow-on innovator operate in the same product market, transaction costs should be less pertinent as licensing agreements likely require less coordination.

To test this prediction, we distinguish citations by whether the citing patentee likely competes with the focal patentee in the product market. To this end, we split citations based on whether i) the citing patent belongs to the same technology class as the opposed patent, ii) the citing patentee is active in the same industry as the opposed patentee, and iii) the citing patentee resides in the same country as the opposed patentee. Each of these citation subsets contains roughly the same number of citations.[37] We then examine the effect of invalidation on the citation subsets defined by these three criteria separately.

We find that the invalidation effect on citations, in the presence of product market competition between the patentee and follow-on innovators, is distinctly stronger for patents in the top value quartile than those in the bottom value quartile. Citations from the same technology class exhibit a noticeably larger invalidation effect (0.28 vs. -0.1, $p = 0.03$). However, for citations based on the other two indicators of product market competition, the effect differences are smaller and remain inconclusive due to the estimates' limited precision (Figure 7a). That said, the differences become substantially larger across all three indicators when controlling for patent thicket density (Figure 7b). For citations belonging to the same technology class, the invalidation effect is large for patents in the top value quartile and practically zero for patents in the bottom value quartile (0.56 vs. 0.02, $p = 0.02$). Notably, if we turn our attention to citation subsets wherein the patentee presumably does not compete with the follow-on innovators in the product market, the invalidation effects are comparable, if not larger, for patents in the bottom value quartile.

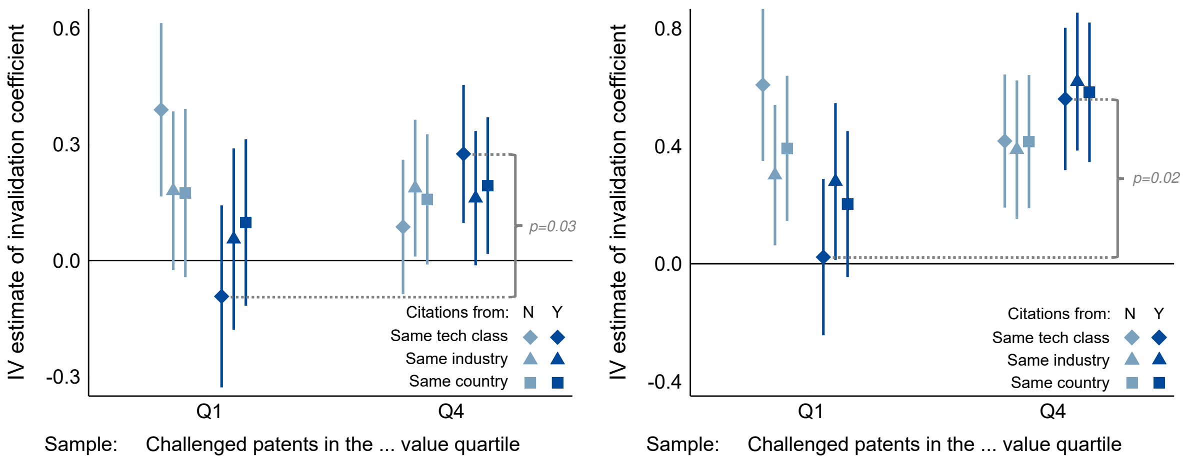
Once again, these patterns are robust to using the inverse hyperbolic sine of the citation count or a binary variable indicating a positive citation count as the dependent variable. Likewise, focusing on citations that are from the same product market according to all three indicators provides similar results. Finally, the observed differences become even more pronounced when estimating the invalidation effects in more extreme subsamples than the bottom and top value quartiles of challenged patents. These robustness results are presented in Appendix C.4.

The observed heterogeneity in the invalidation effects by product market competition is consistent with Prediction 3. It also underpins the interpretation of our earlier results that the invalidation effect is driven by licensing failure due to transaction costs for the low-value patents and by licensing failure due to rent dissipation for the high-value patents in our sample. According to our theoretical framework, the patentee refrains from licensing out where rent dissipation looms large; that is, where innovation value is high *and* licensing would likely cannibalize the patentee's profits in the product market. Consequently, the number of firms that gain FTO only through invalidation should be larger in the patentee's own product market. At the same time, the patentee does not license out

[37]Summary statistics of the citation subsets for each value quartile can be found in Appendix Table B-6.

Figure 7: Effect of patent invalidation on follow-on innovation – original innovation value and product market competition

(a) IV estimates (b) IV estimates with patent thicket interaction



Notes: The figure provides the point estimates and 90% confidence intervals for the instrumented invalidation coefficient on citations by others. The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year. Citations from the same tech class are defined as those where challenged and citing patent share the same primary IPC4 technology code. Citations from the same industry are defined as those where both patentees share the same 3-digit primary NACE Rev. 2 industry code. Citations from the same country are defined as those where both patentees share the same country of residence (EU, UK, US, JP, RoW). The statistical significance of coefficient differences is determined by bootstrapping (results in Table C-20). The corresponding regression results are in Appendix Tables C-18 and C-19.

if transaction costs erode the surplus of licensing; that is, where innovation value is low compared to the costs of reaching a licensing agreement—a condition more likely where the patentee and follow-on innovators need to coordinate across product markets.

In sum, the above heterogeneity results are in line with our predictions concerning the invalidation effect, demonstrating a consistent pattern where both transaction costs and rent dissipation lead to licensing failure under specific conditions. Nonetheless, these empirical results need to be put into perspective. Strictly speaking, uncovering heterogeneity in the causal effects of patent invalidation does not in itself allow a causal interpretation. That is, our estimations do not identify how the invalidation effect would change if, for instance, the value of the original innovation was exogenously altered or potential licensees were randomly removed from the patentee's product market. Moreover, although the observed heterogeneity pattern is consistent with our theoretical predictions concerning the causes and extent of licensing failure, this does not rule out alternative explanations. Future contributions that can illuminate the assumed mechanisms causing the invalidation effect with licensing data would be valuable.

5 Discussion and Concluding Thoughts

In this study, we find a positive invalidation effect across a large sample of patents subject to a post-grant validity challenge. This replicates the invalidation effect in the seminal study of GS2015, who analyze about 1,300 patents whose validity was challenged during high-profile litigation disputes.[38] We expand on their work, both theoretically and empirically, showing that the invalidation effect and the reasons behind it vary with patent value. Indeed, our findings introduce a more nuanced perspective concerning the reasons for licensing failure compared to GS2015. While they attribute the invalidation effect in their sample of high-value patents primarily to transaction costs, our findings suggest this reason is more prevalent among low-value patents. In contrast, we argue that rent dissipation is likely the driving force behind the invalidation effect for high-value patents. The reasons for these different conclusions are intriguing and warrant further investigation.

From a policy perspective, the results of our study suggest that an increase in follow-on innovation after patent invalidation cannot be automatically ascribed to frictions in the market for technology. Among high-value patents, rent dissipation seems to be the more reasonable explanation. This result makes the observed blocking of follow-on innovation much less problematic from a welfare perspective: the patentee's decision to not license out can go hand in hand with productive coordination and align with the patent system's aim to stimulate ex-ante investment incentives.

However, our results do not imply that transaction costs have no role in blocking follow-on innovation. On the contrary, the strong invalidation effect among low-value patents in our sample suggests that transaction costs frequently erode the surplus of licensing, causing bargaining breakdown. Apart from that, there are good reasons to believe that transaction costs create considerable licensing frictions for patented technologies *outside* of our sample. For instance, transaction costs can be substantial if licensing requires the transfer of complementary tacit knowledge (Arora, 1995). Such cases are unlikely to be selected into our sample: potential follow-on innovators have little incentive to challenge patents on technologies where additional know-how from the patentee is necessary. Either way, agreements on technology transfer would be even harder to reach without patent protection, possibly reversing the relationship between patent protection and follow-on innovation in these cases.[39]

From a practical perspective, our research suggests that firms pursuing FTO for follow-on innovation have to be aware that intensified product market competition and the patentee's own innovation

[38]In fact, GS2015 and our study share several findings: the overall positive effect of invalidation on citations, the timing of the effect, and the direction of the endogeneity bias. We present several replication results in Appendix E.

[39]This could explain the null effect of patent grant on follow-on innovation found by Sampat and Williams (2019)—a sample surely more representative of the patent population than patents subject to a validity challenge.

plans can hinder licensing agreements, regardless of their efforts. One strategic implication is that firms need to scan the evolving technology landscape effectively for patents conflicting not only with their current product market activities but also with future R&D projects. Developing the necessary capabilities demands close collaboration of R&D and legal functions. Once developed, firms may also be able to identify conflicting patents more promptly. This opens up low-cost options to seek patent invalidation, allowing firms—in case of a successful validity challenge—to safeguard returns to their R&D investments early on.

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Content of Online Appendix

A Theory

This Appendix underpins Section 2 of the paper. In Section A.1, we expand on the presentation of the invalidation effect in the paper. In Section A.2, we set out a model of non-exclusive licensing and validity challenges. This model generates the three predictions presented in the paper. The model shows how original and follow-on innovation value (v^o, v^f), product market competition, and complexity of technology jointly determine the strength of the invalidation effect.

A.1 The invalidation effect

This section shows that the invalidation effect decreases in the number of licenses provided by the patentee. This is the foundation for the analysis of the number of licenses offered by the patentee in the following section.

The invalidation effect is the difference in follow-on innovation between two cases: i) the patent is invalidated, and all firms (N-1) have FTO; ii) the patent protects the original innovation, and only n licensees have FTO. This is,

$$I(n) \equiv \rho(N-1)\cdot[N-1] - \rho(n)\cdot n \tag{A.1}$$

where $\rho(\tilde{n})$ is the probability that a firm with FTO succeeds in follow-on innovation. In the paper, we assume ρ is exogenous and identical for all firms. This simplifying assumption is adopted for expository purposes. In case at most one firm can obtain the follow-on innovation, ρ will depend on the number of firms with FTO $\tilde{n}$, where $\tilde{n} \in \{(N-1), n\}$. Here we show the invalidation effect is reduced if the patentee provides more licenses, even when ρ depends on $\tilde{n}$.

To begin with, we assume follow-on innovation has one of three outcomes: i) the patentee innovates, ii) a licensee innovates, iii) no firm innovates. The literature on innovation and imperfectly discriminating contests (Loury, 1979; Blavatskyy, 2010) models the probability of successful innovation[40] ρ as a function of three variables: an exogenous likelihood of winning, w, an exogenous likelihood of a draw, d, and the number of firms in the contest, n:

$$\rho(n,w) = \frac{w}{w\cdot[n+1]+d}\ . \tag{A.2}$$

In our context, the number of firms in the contest is the number of firms with FTO, and a draw arises when there is no follow-on innovation. Blavatskyy (2010) provides an axiomatization for imperfectly discriminating contests in which there can be a draw. Note that $\rho(n,w)$ has two relevant characteristics—an increase in the number of firms with FTO: i) reduces the individual probability

[40]Nti (1997) notes that this form of the probability of success is isomorphic to those adopted by Loury (1979) and himself.

of success, but also ii) reduces the likelihood of a draw.

Now consider the effect of providing more licenses on the invalidation effect. The probabilities that a firm with FTO obtains a follow-on innovation or that there is a draw sum to one:

$$1 = \rho \cdot [n+1] + \frac{d}{w \cdot [n+1] + d} \, . \tag{A.3}$$

We can show that:

$$\frac{\partial \rho}{\partial n} = -\rho^2. \tag{A.4}$$

This implies that:

$$\frac{\partial I}{\partial n} = -\rho \, [1 - \rho \cdot n] < 0 \, . \tag{A.5}$$

By Equation A.3, the term in square brackets is positive. The derivation demonstrates that although the probability of success, ρ, declines in the number of licenses offered by the patentee, the overall effect of the marginal license is to reduce the invalidation effect.

The success function we have adopted has one limitation: it does not capture settings in which different follow-on innovations arise simultaneously.[41] We briefly discuss how the invalidation effect behaves in this case.

Assume again that there is a fixed probability of success ρ' along each of at least N parallel research trajectories and that each firm with FTO chooses a separate trajectory. Then the invalidation effect, defined as the probability that there is at least one follow-on innovation, is:

$$I' = \left[1 - \left[1 - \rho'\right]^N\right] - \left[1 - \left[1 - \rho'\right]^n\right] \tag{A.6}$$

It follows that:

$$\frac{\partial I'}{\partial n} = (1 - \rho)^n \ln(1 - \rho) < 0 \, . \tag{A.7}$$

This shows that the invalidation effect decreases in the number of licenses the patentee offers for a wide range of modeling approaches. The question we turn to next is which factors determine how many licenses the patentee will offer, as this determines the strength of the invalidation effect.

A.2 A model of licensing and validity challenges

In this section, we set out a model of the patentee's licensing decisions in the context of validity challenges and competition for a follow-on innovation. The model provides the analytical foundation for the predictions in the paper. It also underpins the empirical strategy we discuss in Section 3.1. In the following, we briefly outline the predictions and link these to our analytical results below.

[41] The success function we adopted above could be extended to such cases by drawing on Blavatskyy (2010), but this is beyond this paper.

We set out three predictions in Section 2.3 of the paper:

Prediction 1: The invalidation effect follows a U-shape in the value of the original innovation.

Prediction 2: A high follow-on innovation value makes the invalidation effect weaker for low-value and stronger for high-value original innovations.

Prediction 3: Product market competition between patentee and potential licensees makes the invalidation effect weaker for low-value and stronger for high-value original innovations.

We provide the results underpinning Predictions 1 and 2 in Section A.3, those underpinning Prediction 3 in Section A.4, and further results extending Predictions 1 and 2 in Section A.5. We further present results illuminating the selection of patents into validity challenges.

The core result we test in our empirical analysis is given in Prediction 1. To derive this first prediction, we incorporate the effects of follow-on innovation into a model of licensing for the original innovation. This involves solving a cubic function to derive the optimal level of licensing.[42] By solving the cubic function, we can also characterize the effect of variation in the value of the follow-on innovation. This underpins the derivation of Prediction 2. The derivation of Prediction 3 is an extension of the analytical results underpinning Prediction 1. We adjust the model such that the patentee does not compete with the licensees in the product market. We show that rent dissipation is reduced in this case.

Firm profits

Our model draws on Arora and Fosfuri (2003), who show that it can be profitable for oligopolistic firms to license out technologies. Their work highlights the effect of rent dissipation in limiting how extensively a technology is licensed. While Arora and Fosfuri (2003) focus on licensing to market entrants, we analyze licensing to incumbents. In this setting, firms' product market profits are those of Cournot oligopolists with positive marginal costs.[43]

There are N firms, each producing one product. Let the inverse demand of firm k be:

$$p_k = \alpha - q_k - \theta \sum_{j \neq k} q_k \,, \tag{A.8}$$

where α measures vertical product quality and $\theta \in \{0, 1\}$ measures the substitutability of products.

[42] In addition to analytical results, we provide further results with the aid of simulations.

[43] Sutton (1998) characterizes this setting as an endogenous sunk cost industry. The number of firms active in such an industry is determined by the level of initial R&D investment required to offer products that are technologically competitive. We assume that firms that do not participate in the initial R&D investment phase lack absorptive capacity and cannot enter the industry (Cohen and Levinthal, 1990). Therefore the patentee is limited to the initial set of R&D active firms when licensing.

With $\theta = 0$, each firm is monopolistic, and as $\theta \to 1$ products become perfect substitutes.[44]

In equilibrium, each firm produces quantity $\hat{q}_k$:

$$\hat{q}_k = \frac{1}{2-\theta}\left((\alpha - c_k) - \frac{\theta}{(2+(N-1)\theta)}\sum_{j=1}^{N}(\alpha - c_j)\right). \tag{A.9}$$

Cournot profits with N_0 competing firms are:

$$\pi_k = (p_k - c_k)q_k = \frac{1}{(2-\theta)^2}\left((\alpha - c_k) - \frac{\theta}{(2+(N_0-1)\theta)}\sum_{j=1}^{N_0}(\alpha - c_j)\right)^2 = \frac{1}{(2-\theta)^2}\hat{q}_k^2. \tag{A.10}$$

To simplify, we define two composite parameters, $\Gamma \equiv \frac{1}{(2-\theta)^2}$ and $\Theta \equiv \frac{\theta}{(2+(N_0-1)\theta)}$. Ex-ante all firms have the same marginal costs $\bar{c}$ and profits π_I:

$$\pi_I = \Gamma\Big((\alpha - \bar{c})\left[1 - N_0\Theta\right]\Big)^2. \tag{A.11}$$

We model innovation as a patented cost-reducing technology that lowers marginal costs from $\bar{c}$ to $c' \in \{\underline{c}, \underline{\underline{c}}\}$ for the patentee and all licensees. If there is no follow-on innovation, the marginal costs of the patentee and all licensees are $\underline{c}$. If there is a follow-on innovation, the patentee cross-licenses with the follow-on innovator and then licenses out the improved technology. This allows the patentee(s) and all licensees to produce with marginal costs $\underline{\underline{c}}$, where $\underline{c} > \underline{\underline{c}}$. Define $\overline{\Delta c} \equiv \bar{c} - \underline{c}$, $\underline{\Delta c} \equiv \bar{c} - \underline{\underline{c}}$, $\widetilde{\Delta c} \equiv \underline{c} - \underline{\underline{c}}$. Firms' profits are increasing in a cost reduction. Therefore the value of a technology is increasing in the cost reduction that the patentee/licensee can obtain. We define the values of the original and follow-on innovations as an increasing function of the change in marginal costs; i.e., $v^o = f(\overline{\Delta c})$, where $\partial f / \partial \overline{\Delta c} > 0$ and $v^f = f(\underline{\Delta c})$, where $\partial f / \partial \underline{\Delta c} > 0$.[45] Unlicensed firms produce at high costs $\bar{c}$ unless the patent on the original innovation is invalidated.

Chance determines which firms have information that the patent on the original innovation is invalid. Throughout, we assume that the patentee obtains a share of the rents which the technology provides to each licensee. We assume that the level of the share (ϕ) is exogenous and fixed.[46] This assumption means that the license fee does not affect firms' output decisions in the product market, simplifying the model.

[44] This inverse demand function is derived from the utility function proposed by Singh and Vives (1984) and generalized to N firms (Sutton, 1998): $U = \sum_{k=1}^{N} \alpha q_k - \frac{1}{2}\left(\sum_{k=1}^{N} q_k^2 + 2\theta \sum_{k \neq j}^{N} q_k q_j\right) + I$. Utility is linear in the consumption of other goods (I) and quadratic in the consumption of the goods in the focal product market. Consumers maximize utility subject to the budget constraint $\sum_k p_k q_k + I \leq M$, where M is income. The price of other goods is normalized to 1.

[45] The model as presented captures industries characterized by process innovations. Sutton (1998) shows this type of model is isomorphic to one in which innovation improves product quality.

[46] We hereby assume that the patentee cannot implement a non-linear license fee to replicate the outcome of a product market cartel. In other words, we assume that competition authorities are able to effectively limit the use of anti-competitive licensing contracts.

A.2.1 Structure of the game

We analyze the following three-stage game, our baseline model G.[47] At Stage 1, the challenging firm and the patentee decide whether to settle a dispute over the validity of the original patent. If the parties fail to settle, the original patent is either upheld or invalidated. Stage 2 is reached if the patent is upheld. In this case, the patentee selects how many licenses to provide. Once FTO is determined, either through invalidation of the original patent or through the patentee's licensing decision, all firms with FTO undertake R&D. Stage 3 is reached if there is a follow-on innovation and the original patent is invalidated. In this case, the firm winning the follow-on innovation chooses how many licenses to provide.

Game G is solved by backward induction. The sequence of actions and exogenous events is that:

- *Chance* determines one firm holding the patent on the original innovation—the original patentee—and one firm holding information on the patent's validity—the challenging firm;

1. The challenging firm pursues the validity challenge if the original patentee and the challenging firm cannot settle;

- Outcome of the patent validity challenge;

2. If the patent is upheld, the original patentee decides how many licenses to provide;

- Firms with FTO for follow-on innovation undertake R&D, and *chance* determines whether there is a follow-on innovation and who is the follow-on innovator;

3. If there is a follow-on innovation and the original patent was invalidated, the follow-on innovator decides on how many licenses to provide.

To keep this game as tractable as possible, we assume that the patentee includes a grant-back clause in licensing contracts offered at Stage 2. This implies that any licensee that succeeds in the follow-on innovation must license back this innovation to the patentee. We also assume that the patentee guarantees each licensee that they will also gain a license to the follow-on innovation. By imposing these assumptions, we avoid a further licensing decision subsequent to Stage 2 in case the original patent is upheld.[48]

Firms' profits in the product market depend on all firms' marginal costs. Equation A.10 characterizes profits from product market competition in the general case. We derive specific variants that depend on the outcomes of licensing and innovation below.

[47] Game G is represented in Figure 1 in Section 2.

[48] In our model, the patentee determines the number of licenses at Stage 2, already taking into account rent dissipation in all subsequent outcomes. In a more complex game with an additional licensing decision after Stage 2, rent dissipation would still be a consideration. Moreover, the patentee would have to take into account that she might not receive a license for the follow-on innovation (lack of grant-back clause) and that the follow-on innovator could have different incentives to license the follow-on innovation than the patentee. This would induce the patentee to further restrict licensing. We leave the derivation of this strategic component of the licensing decision to future work.

A.3 Baseline model – Game G

We start by analyzing the baseline model, game G, in detail. After Stage 2 of game G, four outcomes are possible: I) the original patent was invalidated, and no follow-on innovation arises; II) the original patent was upheld, and no follow-on innovation arises; III) the original patent was upheld, and follow-on innovation arises; IV) the original patent was invalidated, and follow-on innovation arises. Note that in the first three outcomes, Stage 3 is not reached. In the following, we first describe firms' profits under each outcome, allowing for licensing and transaction costs.

In each outcome, Λ denotes the surplus generated by licensing, and ϕ $(0 \leq \phi \leq 1)$ is the surplus share the patentee obtains from licensing. Below we derive Λ for each outcome. The level of the surplus share (ϕ) depends partly on firms' bargaining power and partly on industry practice. We assume the share is exogenous.

Licensing comes with transaction costs. We consider fixed (T) transaction costs that arise for each license. Below we assume that the patentee bears these transaction costs, but this is not material to our results. What is material is that transaction costs reduce the surplus that can be obtained from licensing by the patentee—where the value of the innovation is comparatively low, these costs may be so large that licensing is not profitable.

Outcome I The original patent is invalidated, and no follow-on innovation arises.
All firms produce at marginal cost $\underline{c}$. Profits are:

$$\pi_{in} = \Gamma\Big((\alpha - \underline{c})\left[1 - N_o\Theta\right]\Big)^2 . \tag{A.12}$$

Outcome II The original patent is upheld, and no follow-on innovation arises.
Define $\Psi_{un} \equiv \Big((\alpha - \bar{c})(1 - N_0\Theta) - \Theta\overline{\Delta c}(n+1)\Big)$ and $\Lambda_{un} \equiv \Gamma\Big(\Psi_{un} + \overline{\Delta c}\Big)^2 - \Gamma\Psi_{un}^2 = \Gamma\overline{\Delta c}\Big(2\Psi_{un} + \overline{\Delta c}\Big)$.
Profits of the patentee (π_s) are:

$$\pi_s = \Gamma\Big(\Psi_{un} + \overline{\Delta c}\Big)^2 + n\left(\phi\Lambda_{un} - T\right). \tag{A.13}$$

Outcome IIIa The original patent is upheld, and the patentee is the follow-on innovator. The patentee licenses the follow-on patent to the licensees of the original patent. Define $\Psi_{uf} \equiv \Big((\alpha - \bar{c})(1 - N_0\Theta) - \Theta\underline{\Delta c}(n+1)\Big)$ and $\Lambda_{uf} \equiv \Gamma\underline{\Delta c}\Big(2\Psi_{uf} + \underline{\Delta c}\Big)$. The original patentee's profits (π_p) are:

$$\pi_p = \Gamma\Big(\Psi_{uf} + \underline{\Delta c}\Big)^2 + n\left(\phi\Lambda_{uf} - T\right). \tag{A.14}$$

Outcome IIIb The original patent is upheld, but the original patentee is not the follow-on innovator. Thanks to the grant-back clause, the follow-on patent is licensed to the original patentee and her licensees. Both patentees (original and follow-on patentee) set fees corresponding to their respective innovation's profit increment to licensees.

We define the joint surplus $\widetilde{\Lambda}_{uf} \equiv \Gamma\Big(\Psi_{uf} + \underline{\Delta c}\Big)^2 - \Gamma\Big(\Psi_{uf} + \overline{\Delta c}\Big)^2 = \Gamma\widetilde{\Delta c}\Big(2\Psi_{uf} + \overline{\Delta c} + \underline{\Delta c}\Big)$.

The profits of the original patentee (π_l) are:

$$\pi_l = \Gamma\Big(\Psi_{uf} + \underline{\Delta c}\Big)^2 + n\left(\phi\Lambda_{un} - T\right) - \phi\widetilde{\Lambda}_{uf}\,. \tag{A.15}$$

Outcome IV The original patent is invalidated, and the original patentee is not the follow-on innovator.

Define $\Psi_{if} \equiv \Big((\alpha - \underline{c})(1 - N_0\Theta) - \Theta\underline{\Delta c}(n+1)\Big) = \Theta\underline{\Delta c}\Big[g(\underline{c}, \underline{\underline{c}}) - (n+1)\Big]$ and $\Lambda_{if} \equiv \Gamma\underline{\Delta c}\Big(2\Psi_{if} + \underline{\Delta c}\Big)$.

Profits of the follow-on patentee (π_{ifL}), the licensees (π_{ifl}) and the remaining firms (π_{ifr}) are:

$$\pi_{ifL} = \Gamma\Big(\Psi_{if} + \underline{\Delta c}\Big)^2 + n\left(\phi\Lambda_{if} - T\right), \quad \pi_{ifl} = \Gamma\Big(\Psi_{if} + \underline{\Delta c}\Big)^2 - \phi\Lambda_{if}, \quad \pi_{ifr} = \Gamma\Psi_{if}^2\,. \tag{A.16}$$

Stage 3: Licensing of follow-on innovation

Where the original patent is declared invalid, all N_o firms active in the industry have FTO and compete for a follow-on innovation. Should a follow-on innovation arise, the follow-on patentee decides on licensing her innovation. In this case, profits are set out under outcome IV. The follow-on patentee will choose the number of licensees.

The follow-on patentee maximizes profits by setting the number of licenses n:

$$\max_n \pi_f(n) = \Gamma\Big(\Psi_{if}(n) + \underline{\Delta c}\Big)^2 + n\phi\Gamma\underline{\Delta c}\Big(2\Psi_{if}(n) + \underline{\Delta c}\Big) - nT\,. \tag{A.17}$$

The first order condition (FOC) characterizing this decision is:

$$2\Gamma\underline{\Delta c}\Big(\Psi_{if} + \underline{\Delta c}\Big)\Big[\phi - \Theta\Big] - \phi\Gamma\underline{\Delta c}^2 - 2n\Gamma\phi\underline{\Delta c}^2\Theta - T = 0\,. \tag{A.18}$$

The second order condition (SOC) for this extreme point is $-2\Gamma\underline{\Delta c}^2\Theta\,(2\phi - \Theta) < 0$. The FOC identifies a local maximum as long as the follow-on patentee has a sufficiently large surplus share (ϕ). For homogeneous products ($\theta = 1$), the lower bound for the surplus share is $\phi = 1/[2(N_o + 1)]$. As products become more differentiated, the boundary is even lower. In what follows, we assume $\phi > \Theta$, ensuring we analyze only profit-maximizing licensing decisions.

The follow-on patentee provides n^* licenses to maximize her profits:

$$n^* = \frac{1}{\Theta(2\phi - \Theta)}\left(\left(\frac{(\alpha - \underline{c})}{\underline{\Delta c}}(1 - N_0\Theta) + (1 - \Theta)\right)\Big[\phi - \Theta\Big] - \frac{\phi}{2} - \frac{T}{2\Gamma\underline{\Delta c}^2}\right). \tag{A.19}$$

Next, we analyze when the follow-on patentee licenses all firms in the industry. Define:

$$\Omega \equiv \phi\left(1 + 2(N_o - 1)\Theta\right) - 2\left[1 - N_o\Theta\right](\phi - \Theta)\,. \tag{A.20}$$

$\Omega > 0$ as long as $3N_o > (2 - \theta)/\theta$. Where products are highly differentiated $\Omega < 0$.

The follow-on patentee licenses her innovation to all firms in the industry as long as $n^* \geq (N_o - 1)$. However, the follow-on patentee restricts licenses to some firms in the industry if:

$$n^* < N_o \Leftrightarrow \frac{\left[(\alpha - \underline{c})(1 - N_o\Theta)(\phi - \Theta)\right]^2}{\Omega^2} - \frac{T}{\Gamma\Omega} < \left(\underline{\Delta c} - \frac{(\alpha - \underline{c})(1 - N_o\Theta)(\phi - \Theta)}{\Omega}\right)^2 \quad \text{(A.21)}$$

There are two solutions to this inequality:

$$\underline{\Delta c}^u = \frac{(\alpha - \underline{c})(1 - N_o\Theta)(\phi - \Theta)}{\Omega} + \sqrt{\frac{\left[(\alpha - \underline{c})(1 - N_o\Theta)(\phi - \Theta)\right]^2}{\Omega^2} - \frac{T}{\Gamma\Omega}} \quad \text{(A.22)}$$

$$\underline{\Delta c}^l = \frac{(\alpha - \underline{c})(1 - N_o\Theta)(\phi - \Theta)}{\Omega} - \sqrt{\frac{\left[(\alpha - \underline{c})(1 - N_o\Theta)(\phi - \Theta)\right]^2}{\Omega^2} - \frac{T}{\Gamma\Omega}} \quad \text{(A.23)}$$

The follow-on patentee will license all firms in the industry as long as the cost reduction offered by the follow-on innovation lies on the interval $[\underline{\Delta c}^l, \underline{\Delta c}^u]$. Notice that the lower limit of this interval is zero when transaction costs are zero. As transaction costs increase, the lower limit increases and the upper limit decreases.

This analysis provides two insights: i) the follow-on patentee restricts the number of licenses as the value of the follow-on innovation increases—this is due to rent dissipation; ii) the follow-on patentee does not license out low-value follow-on innovations—this is due to transaction costs. Both rent dissipation and transaction costs determine the range of follow-on innovations for which all firms in the industry can obtain a license. A comparable analysis can be applied to the original patentee's decision to license out the original innovation in the next subsection.

Stage 2: Licensing of original innovation

At Stage 2, the original patentee selects how many licenses to provide. As noted above, we simplify the model by assuming that competition for the follow-on innovation is a contest in which, at most, one firm succeeds. The likelihood of winning for each firm in the contest is fixed as w, and the probability of a draw (no follow-on innovation arises) is $d/[(n+1)w+d]$.[49] If there is no follow-on innovation, the firms' profits are as described in Outcome II above.

When the original patent is invalidated, there is no decision at Stage 2. All N_o firms in the industry employ the original innovation and compete for the follow-on innovation. Each firm innovates with probability $w/[N_o w + d]$. When the original patent is upheld, the original patentee must decide how many licenses to provide. This decision has a static and a dynamic aspect. The static trade-off mirrors the trade-off we analyzed at Stage 3 of the game: the original patentee must choose between rent dissipation and licensing income. The dynamic trade-off is between the intensity of R&D competition for the follow-on innovation and any licensing income flowing from that innovation.

[49]Here we draw on Nti (1997) and Blavatskyy (2010). Compare the discussion in Section A.1.

Drawing on the profits set out for Outcomes IIIa and IIIb above, we can express the value of follow-on innovation for the original patentee (V_p^u):

$$V_p^u(\underline{\Delta c}, n) = \frac{1}{(n+1)w+d}\left(w\pi_p + wn\pi_l + d\pi_s\right) - H(w)\,. \tag{A.24}$$

Note that $H(w)$ is the fixed cost of R&D corresponding to the exogenous likelihood of winning the follow-on innovation w. Equation A.24 corresponds to Equation 2 in Section 2. Remember that the value of the original innovation v^o and the follow-on innovation v^f are increasing functions of the respective innovation sizes $\overline{\Delta c}$ and $\underline{\Delta c}$. The expected value of licensing for the patentee[50] (V_p^u) can be decomposed into a static (π_s) and a dynamic return to licensing (π_{dyn}) and the costs of follow-on R&D ($H(w)$):

$$V_p^u \;=\; \pi_s(n, \overline{\Delta c}, T) \;+\; \underbrace{\rho\Big(\big(\pi_p(n, \underline{\Delta c}) - \pi_s(n, \overline{\Delta c})\big) + n\cdot\big(\pi_l(n, \overline{\Delta c}, \underline{\Delta c}) - \pi_s(n, \overline{\Delta c})\big)\Big)}_{\pi_{dyn}} \;-\; H(w) \quad . \tag{A.25}$$

The static return to licensing We first characterize the number of licenses offered by the original patentee for the case that dynamic returns to licensing are negligible ($\hat{n}_s$).

The FOC characterizing static licensing incentives is:

$$2\Gamma\overline{\Delta c}\Big(\Psi_{un} + \overline{\Delta c}\Big)(\phi - \Theta) - \Gamma\phi\overline{\Delta c}^2 - 2\Gamma n\phi\Theta\overline{\Delta c}^2 - T = 0\,. \tag{A.26}$$

This FOC characterizes a local maximum if $-2\Gamma\overline{\Delta c}^2\Theta(2\phi - \Theta) < 0$.[51] The original patentee will select $\hat{n}_s$ licenses:

$$\hat{n}_s = \frac{1}{\Theta\big(2\phi - \Theta\big)}\left(\Big(\frac{(\alpha - \bar{c})}{\overline{\Delta c}}(1 - N_0\Theta) + (1-\Theta)\Big)(\phi - \Theta) - \frac{\phi}{2} - \frac{T}{2\Gamma\overline{\Delta c}^2}\right)\,. \tag{A.27}$$

This condition reveals that the optimal number of licenses $\hat{n}_s$ is decreasing in the size of the original innovation $\overline{\Delta c}$ due to rent dissipation. Note that absent transaction costs, $\hat{n}_s > N-1$ for original innovations of low value (low $\overline{\Delta c}$). Here, the patentee licenses all $(N-1)$ firms. Rent dissipation affects $\hat{n}_s$ when the value of the original innovation is sufficiently large so that $\hat{n}_s \leq N-1$.

Now consider the joint effects of transaction costs and rent dissipation. The optimal number of licensees is determined in the same manner as at Stage 3 (Equation A.19). We can show that the original patentee licenses all firms if the original innovation lies in the interval $[\overline{\Delta c}^l, \overline{\Delta c}^u]$:

$$\overline{\Delta c}^u = \frac{(\alpha - \bar{c})(1 - N_o\Theta)(\phi - \Theta)}{\Omega} + \sqrt{\frac{\big[(\alpha - \bar{c})(1 - N_o\Theta)(\phi - \Theta)\big]^2}{\Omega^2} - \frac{T}{\Gamma\Omega}} \tag{A.28}$$

$$\overline{\Delta c}^l = \frac{(\alpha - \bar{c})(1 - N_o\Theta)(\phi - \Theta)}{\Omega} - \sqrt{\frac{\big[(\alpha - \bar{c})(1 - N_o\Theta)(\phi - \Theta)\big]^2}{\Omega^2} - \frac{T}{\Gamma\Omega}} \tag{A.29}$$

[50] The expected value of licensing for the licensees $V_{s,i}^u$ can be derived in a comparable manner. We suppress the expressions here as they do not contribute to our analysis.

[51] The condition is satisfied under the assumption that $\phi > \Theta$.

We derive two results:

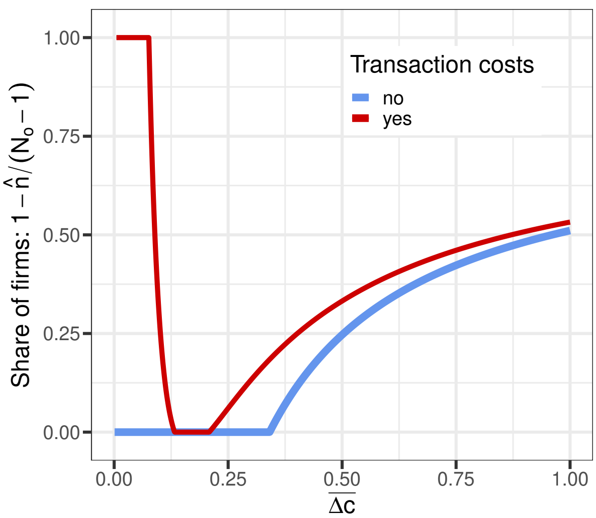
Result 1 The original patentee licenses to all $N-1$ firms if the size of the original innovation $\overline{\Delta c}$ is in the range $(\overline{\Delta c}^l, \overline{\Delta c}^u)$.

Note that $\overline{\Delta c}^l > 0$ if $T > 0$.

Result 2 The range $(\overline{\Delta c}^l, \overline{\Delta c}^u)$ shrinks as transaction costs T increase.

These results generate a U-shaped relationship between the share of firms in the market that do not receive a license from the original patentee and the value of the original innovation. By extension, the invalidation effect is also U-shaped, as all unlicensed firms in the market obtain FTO through invalidation.

Figure A-1: Invalidation effect: Variation in original innovation size



Notes: This figure presents a simulation of the share of firms that obtain FTO through invalidation of the original patent as a function of the size of the original innovation ($\overline{\Delta c}$). The values for transaction costs in the simulation are either $T = 0$ (no transaction costs) or $T = 0.03$ (transaction costs). To simulate the static limit of our model, we minimize the probability of follow-on innovation: follow-on innovation size is 10^{-6} and the relative probability of a draw is 10^5. The simulation is based on the following other set parameters: $N = 11$, $\alpha - \bar{c} = 3$, $\phi = 0.8$, $\theta = 0.7$.

In Figure A-1, we simulate the static case as the limit of the dynamic model in which follow-on innovation is highly unlikely and small in value. Two solutions are presented: i) no transaction costs and ii) transaction costs at a level that induces licensing failure for low-value original innovations. For positive transaction costs, Figure A-1 reveals a U-shape for the share of firms obtaining FTO through patent invalidation.

The dynamic return to licensing We now consider how the dynamic return to licensing alters the U-shaped invalidation effect derived above. Note that the dynamic return is the net change in profits in the two outcomes with follow-on innovation as compared to the outcome with no follow-on innovation:

$$\begin{aligned}\pi_p-\pi_s =&\Gamma\left(\Psi_{uf}^2-\Psi_{un}^2\right)+(1+n\phi)\left(\Lambda_{uf}-\Lambda_{un}\right)\\ =&\left(\underline{\Delta c}-\overline{\Delta c}\right)\Gamma\Big((1-\Theta+n(\phi-\Theta))\left[\Psi_{uf}+\Psi_{un}\right]+(1+n\phi)\left(\underline{\Delta c}+\overline{\Delta c}\right)(1-\Theta(n+1))\Big)\end{aligned}$$

$$\begin{aligned}\pi_l-\pi_s =&\Gamma\left(\Psi_{uf}^2-\Psi_{un}^2\right)+\left(\Lambda_{uf}-\Lambda_{un}\right)(1-\phi)+2\Gamma\phi\overline{\Delta c}\left(\Psi_{uf}-\Psi_{un}\right)\\ =&\left(\underline{\Delta c}-\overline{\Delta c}\right)\Gamma\Big(\left[\Psi_{uf}+\Psi_{un}\right](1-\phi-\Theta(n+1))+\left(\underline{\Delta c}+\overline{\Delta c}\right)(1-\Theta(n+1))(1-\phi)-2\phi\Theta(n+1)\overline{\Delta c}\Big).\end{aligned}$$

We can show the dynamic return to licensing is:

$$\pi_{dyn}=\Gamma\left(\underline{\Delta c}-\overline{\Delta c}\right)(n+1)[1-\Theta(n+1)]\left(\left(\Psi_{uf}+\Psi_{un}\right)+\left(\underline{\Delta c}+\overline{\Delta c}\right)-2\overline{\Delta c}\frac{n\Theta\phi}{1-\Theta(n+1)}\right). \tag{A.30}$$

Recall that $\underline{\Delta c}-\overline{\Delta c}=\underline{c}-\underline{\underline{c}}$ is the follow-on innovation's cost reduction over the cost reduction embodied in the original innovation. Four results follow from Equation A.30:

Result 3 The dynamic return to licensing π_{dyn} is positive.

To see this, note that π_{dyn} is the sum of two positive terms.

Result 4 The dynamic return to licensing π_{dyn} is not a function of transaction costs T.

Result 5 The dynamic return to licensing π_{dyn} increases in the size of the follow-on innovation $\underline{\Delta c}$.

Result 6 The expected dynamic return to licensing $\rho\pi_{dyn}$ is a concave function in n.

To see this latter result, note that the first and second derivatives of $\rho\pi_{dyn}$ with respect to n are:

$$\begin{aligned}\frac{\partial\rho\pi_{dyn}}{\partial n}=&\left(\underline{\Delta c}-\overline{\Delta c}\right)\Gamma\Bigg[\frac{dw}{[(n+1)w+d]^2}\Big(\left[\left(\Psi_{uf}+\Psi_{un}\right)+\left(\underline{\Delta c}+\overline{\Delta c}\right)\right][1-\Theta(n+1)]-2\overline{\Delta c}n\Theta\phi\Big)\\ &-\Theta\left(1-\frac{d}{(n+1)w+d}\right)\Big(\left[\overline{\Delta c}+\underline{\Delta c}\right][1-\Theta(n+1)]+\left[\left(\Psi_{uf}+\Psi_{un}\right)+\left(\underline{\Delta c}+\overline{\Delta c}\right)\right]+2\overline{\Delta c}\phi\Big)\Bigg]\end{aligned} \tag{A.31}$$

$$\begin{aligned}\frac{\partial^2\rho\pi_{dyn}}{\partial n^2}=&-2\Gamma\left(\underline{\Delta c}-\overline{\Delta c}\right)\Bigg[\left(\overline{\Delta c}+\underline{\Delta c}\right)\Big[\frac{d}{(n+1)w+d}\left(\Theta+\frac{w[1-\Theta(n+1)]}{[(n+1)w+d]}\right)^2-\Theta^2\Big]\\ &+\frac{2dw}{(n+1)w+d]^2}\Big(\left[(\alpha-\bar{c})(1-N_0\Theta)\right]\left(\Theta+\frac{w[1-\Theta(n+1)]}{[(n+1)w+d]}\right)+\overline{\Delta c}\phi\Theta\Big[1-\frac{wn}{(n+1)w+d}\Big]\Big)\Bigg]\end{aligned} \tag{A.32}$$

The second derivative is negative, indicating concavity, where products are differentiated and where the industry is well established.[52]

These four results show that the dynamic return to licensing will increase the surplus from licensing for low-value original innovations, which can allow licensing to occur in spite of the effect of transaction costs. At the same time, the dynamic return to licensing is also subject to rent dissipation (Result 6): for high-value original innovations, rent dissipation affects both static and dynamic returns to licensing.

Next, we consider how the dynamic return influences the optimal number of licenses. This requires that we solve a cubic FOC. To simplify the expressions, we define additional composite parameters: $A \equiv \left(1+\Theta\frac{d}{w}\right)$, $B(n) \equiv 1-\Theta(n+1)$, $C \equiv \frac{\overline{\Delta c}}{\left(\underline{\Delta c}+\overline{\Delta c}\right)}$, $E \equiv \frac{\underline{\Delta c}^2}{\overline{\Delta c}^2}-1$ and $F \equiv \frac{[(\alpha-\bar{c})(1-N_0\Theta)]}{\overline{\Delta c}}$. Applying these definitions to the derivative of the static return to licensing with respect to n (Equation A.26) gives:

$$2\Gamma\overline{\Delta c}^2\Big(J+B(2\phi-\Theta)\Big)=0\,,\text{where } J \equiv \Big(F(\phi-\Theta)+\phi\Theta-\frac{T}{2\Gamma\overline{\Delta c}^2}-\phi\frac{3}{2}\Big). \tag{A.33}$$

The expected dynamic return to licensing ($\rho\pi_{dyn}$) can be expressed as:

$$\pi_{dyn}=\Gamma\overline{\Delta c}^2E\frac{1-B}{(A-B)}\Bigg(2C(F+\phi)B+B^2-2C\phi(1-\Theta)\Bigg). \tag{A.34}$$

Allowing for dynamic and static returns, the FOC for the optimal number of licenses $\hat{n}$ is:

$$0=\Bigg[J+B(2\phi-\Theta)\Bigg]+E\Theta\frac{(A-1)}{[A-B]^2}\Bigg(C(F+\phi)B+\frac{1}{2}B^2-C\phi(1-\Theta)\Bigg)-E\Theta\frac{1-B}{A-B}\Bigg(C(F+\phi)+B\Bigg) \tag{A.35}$$

The SOC for $\hat{n}$ is:

$$-\Theta\overbrace{\Big[2\phi-\Theta\frac{\underline{\underline{\Delta c}}^2}{\overline{\Delta c}^2}\Big]}^{\tau}-\frac{\frac{d}{w}E}{\left(\frac{d}{w}+(n+1)\right)^3}\Bigg[A^2+2ACF+2C\phi(A-1)+2C\phi\Theta\Bigg]. \tag{A.36}$$

This condition is negative as long as τ is positive. Where the value of the original innovation is low ($\overline{\Delta c}\rightarrow 0$), the second derivative is positive and the FOC identifies a minimum of the value function V_p^u with respect to n. The locus in the $\overline{\Delta c}-\hat{n}$ space along which the value function's extreme value switches from a local maximum to a local minimum is given by:

$$\tilde{\hat{n}}=\sqrt[3]{-\frac{\frac{d}{w}E}{\Theta\tau}\Bigg[A^2+2ACF+2C\phi(A-1)+2C\phi\Theta\Bigg]}. \tag{A.37}$$

Note that this locus only lies on the real plane where $\tau<0$; i.e., where the follow-on innovation is sufficiently more valuable than the original innovation.

[52] In an established industry, the value of the original- and follow-on innovations will usually be smaller than the sum of all preceding innovations up to that point. This implies that $\Big[(\alpha-\bar{c})(1-N_0\Theta)\Big]>\Big(\overline{\Delta c}+\underline{\Delta c}\Big)$.

Define $Z \equiv (A-B)^{(-1)}$ and $\omega \equiv E\Theta(A-1)\Big(C\phi(A-1+\Theta)+\frac{1}{2}A^2+ACF\Big) \geq 0$. Then the FOC is:

$$Z^3 + Z\omega^{-1}\overbrace{\Big(J + A(2\phi - \Theta - E\Theta) - E\Theta\Big(C(F+\phi) + \frac{1}{2}(A-1)\Big)\Big)}^{\sigma} - \omega^{-1}\tau = 0\,. \tag{A.38}$$

This is a depressed cubic equation in Z (Blinn, 2006). A cubic may have between one and three real solutions. The number of solutions depends on the cubic's polynomial discriminant.

The solution to the cubic function (Equation A.38) draws on the following composite variables: $Q \equiv (1/3)\omega^{-1}\sigma$ and $R \equiv -(1/2)\omega^{-1}\tau$ and the polynomial discriminant $D \equiv Q^3 + R^2 = \big((1/27)\omega^{-3}\sigma^3 + (1/4)\omega^{-2}\tau^2\big)$. The solution of the cubic function is:

$$Z = \sqrt[3]{R+\sqrt{D}} + \sqrt[3]{R-\sqrt{D}}, \text{ which implies that } n = \frac{1}{Z\Theta} - \frac{d}{w} - 1. \tag{A.39}$$

The expression for Z has one unique real root when the polynomial discriminant is positive ($D > 0$) and three real roots when it is negative. In all cases, the solutions for n may lie outside the interval $[0, N-1]$. In such cases, the profit-maximizing solution may be a corner solution.

Due to the possible multiplicity of real solutions for n, we simulate the model (Figure A-2). This reveals the share of firms obtaining FTO by the invalidation of the original patent remains a U-shaped function in the size of the original innovation. These results are captured in Prediction 1.

Next, we derive the results underpinning Prediction 2. Consider the effect of varying the size of the follow-on innovation $\underline{\Delta c}$ for the optimal number of licenses, holding all else constant. To derive the effect, we use the implicit function theorem.

Where the FOC—Equation A.35—is equal to zero, we have a function $L(\hat{n}, \underline{\Delta c}) = 0$, and:

$$\frac{\partial \hat{n}}{\partial \underline{\Delta c}} = -\frac{\partial L}{\partial \underline{\Delta c}} \Big/ \frac{\partial L}{\partial \hat{n}}\,. \tag{A.40}$$

The denominator is negative as long as the SOC is negative, indicating that $\hat{n}$ is a maximum. The numerator's sign depends on the sign of the following derivative:

$$\frac{\partial L}{\partial \underline{\Delta c}} = \left[F + \phi\Theta\frac{\frac{d}{w}+1}{A} + \frac{\underline{\Delta c}}{\overline{\Delta c}}\right]\left(\frac{(A-1)A}{[A-B]^2} - 1\right) + 2\frac{\underline{\Delta c}}{\overline{\Delta c}}\Theta(n+1)\,. \tag{A.41}$$

We can show that the term in round brackets is positive if:

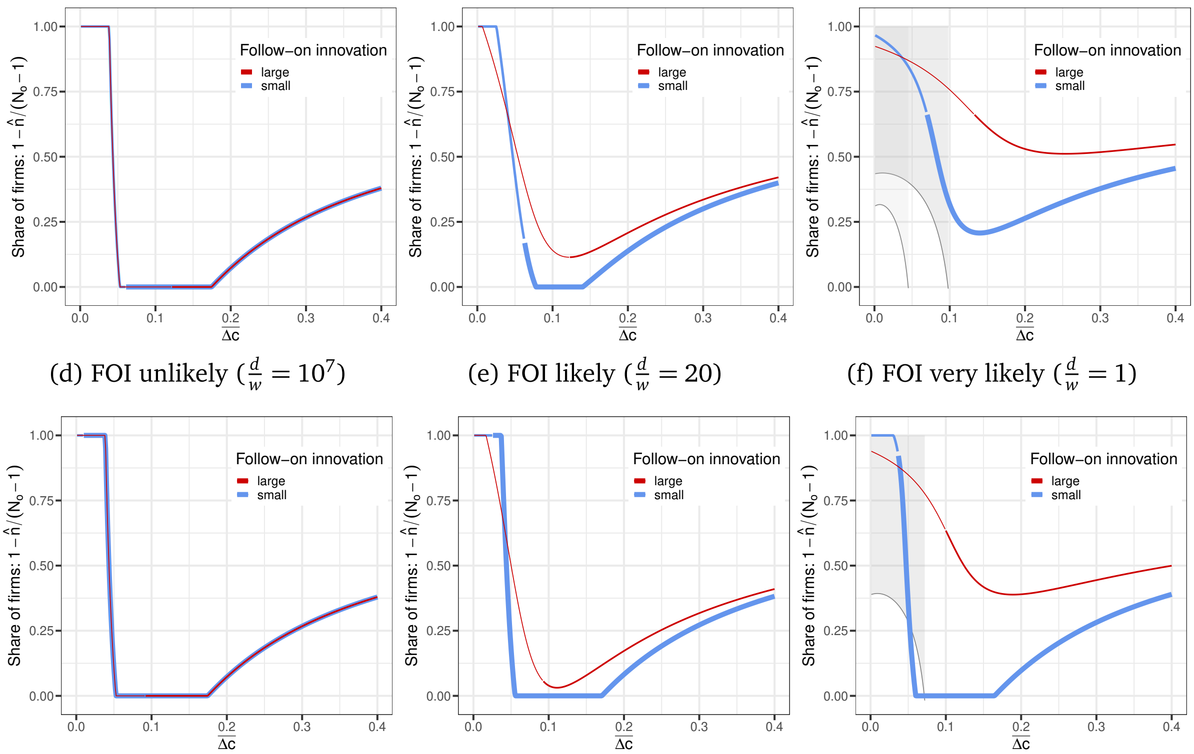
$$\frac{d}{w} > \frac{\Theta(\hat{n}+1)^2}{1-2\Theta(\hat{n}+1)} \text{ where } (1-2\Theta(\hat{n}+1)) > 0\,. \tag{A.42}$$

To interpret this expression, notice that if $\overline{\Delta c} \to 0$, there will be few or no licenses ($\hat{n} = 0$). If there are no licenses and products are perfect substitutes, the derivative is positive as long as $d/w > (N-1)^{(-1)}$. Where products become highly differentiated ($\Theta \to 0$), the derivative is always positive in the limit. The inequality shows that $L(\hat{n}, \underline{\Delta c})$ increases in $\underline{\Delta c}$ if the original innovation is small.

Figure A-2: Invalidation effect: Variation in original and follow-on innovation size

(a) FOI unlikely ($\frac{d}{w} = 10^7$) (b) FOI likely ($\frac{d}{w} = 20$) (c) FOI very likely ($\frac{d}{w} = 1$)

(d) FOI unlikely ($\frac{d}{w} = 10^7$) (e) FOI likely ($\frac{d}{w} = 20$) (f) FOI very likely ($\frac{d}{w} = 1$)



Notes: This figure shows that the U-shape arises across a wide range of parameter constellations. Each graph plots the share of firms receiving FTO only through patent invalidation. We compare this share for two distinct follow-on innovation sizes (red and blue). From left to right, we increase the probability that follow-on innovation arises. Between the top and bottom rows, we vary the levels of follow-on innovation size: small: 0.2 / large: 0.4 (top row) and small: 0.03 / large: 0.3 (bottom row). The SOCs are shown in grey. The simulation is based on the following other set parameters: $N = 11$, $T = 0.01$, $\alpha - \bar{c} = 2$, $\phi = 0.8$, $\theta = 0.7$.

Result 7 For a small original innovation, the optimal number of licenses $\hat{n}$ increases in the size of the follow-on innovation $\underline{\Delta c}$.

Next, consider the case in which the original innovation size is large so that $\hat{n} > 0$. Unless products are highly differentiated, it is likely that $2\Theta(\hat{n}+1) > 1$. In this case, the optimal number of licenses decreases in the size of the follow-on innovation.

Result 8 For a sufficiently large original innovation, the optimal number of licenses $\hat{n}$ decreases in the size of the follow-on innovation $\underline{\Delta c}$ unless products are highly differentiated.

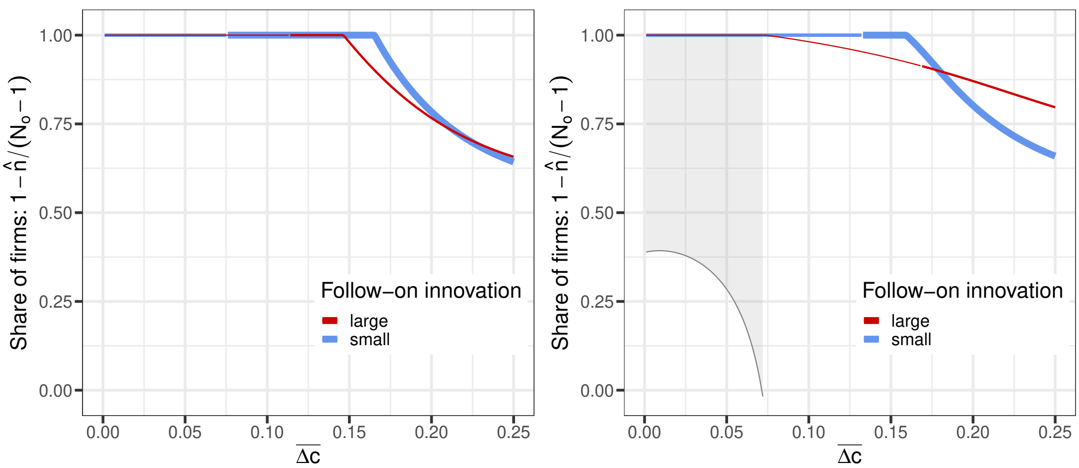
This latter result is due to rent dissipation. That is, for a large original innovation, an increase in the size of the follow-on innovation intensifies rent dissipation, decreasing the optimal number of licenses and thereby strengthening the invalidation effect. This is true unless products are highly differentiated, such that rent dissipation is negligible.

These results underpin Prediction 2. A valuable follow-on innovation weakens the invalidation effect for low-value original innovations, i.e., where few or no licenses are provided. Conversely, a valuable follow-on innovation likely strengthens the invalidation effect for high-value original innovations.

Note that the boundary for what constitutes a "sufficiently large original innovation" depends on the relative likelihood that no follow-on innovation arises, i.e., d/w. The greater this relative likelihood, the greater the range of the original innovation within which the optimal number of licenses is increasing in the size of follow-on innovation. Figure A-3 below illustrates this shift in range in detail: as d/w falls, the range in which an increase in follow-on innovation size increases the number of licenses shrinks.

Figure A-3: Invalidation effect: Detail of crossing functions

(a) Follow-on innovation likely ($\frac{d}{w} = 20$) (b) Follow-on innovation very likely ($\frac{d}{w} = 1$)



Notes: This figure shows that the crossing point, where the number of firms that obtain FTO through invalidation is lower for more valuable follow-on innovation is higher, shifts to lower values of the original innovation as the probability that no follow-on innovation arises becomes comparatively less likely. Each graph plots the share of firms receiving FTO only through patent invalidation. We compare this share for two distinct follow-on innovation sizes (red and blue). The SOCs are shown in grey. In both panels, the follow-on innovation sizes are 0.03 (blue) and 0.3 (red). The simulation is based on the following other set parameters: $N = 11$, $T = 0.05$, $\alpha = 2$, $\phi = 0.8$, $\theta = 0.7$.

Figure A-3 shows that the invalidation effect is weakened as the value of the follow-on innovation increases. This effect arises because the greater value of the follow-on innovation compensates for the transaction costs. As the value of the original innovation increases, the patentee provides so many licenses that rent dissipation overwhelms the effect of transaction costs. Here, an increase in the value of the follow-on innovation reduces the invalidation effect. Overall the loci of solutions to the problem of selecting the optimal size of the invalidation effect vary with the value of the follow-on innovation. We select two of these loci and demonstrate that they cross.

Stage 1: Challenging patent validity

Validity challenges arise where the patent on the original innovation is probabilistic (Lemley and Shapiro, 2005); i.e., there is a possibility that the patent can be invalidated through a validity challenge. There are two kinds of patent validity challenges: i) post-grant opposition, filed shortly after patent grant and typically before licensing, and ii) litigation, which involves infringement allegations and generally follows licensing decisions. We focus on post-grant opposition, which is the kind of validity challenges we observe in our data.

We model validity challenges arising from asymmetric stakes: the joint surplus from settlement is lower than the surplus from taking the validity challenge forward.[53] When the probability of invalidation is sufficiently high, the challenging firm's expected value of gaining FTO may outweigh the costs of a validity challenge. The patentee may benefit from not settling if winning the validity challenge raises her future profits. Winning a validity challenge can make the patentee appear tough or may raise the perceived probability that her patent is valid.[54]

To explain which firm challenges a patent, we assume that there is a probability ζ with which each firm in the market has information that the patent may be invalid. Even if ζ is low, the overall probability of a validity challenge will increase with the number of firms in the market N_o. That is, the overall probability g that the patent is challenged by at least one firm is:

$$g(N_o) = 1 - (1-\zeta)^{(N_o-1)} \,. \tag{A.43}$$

Note that the number of challenging firms per patent is typically very low. Without loss of generality, we assume below that there is just one challenging firm. A firm with information on the patent's invalidity has two options: either to pursue the validity challenge or to accept a settlement proposed by the patentee (if available).

We assume the validity challenge has two outcomes: the patent is either upheld or invalidated. The expected value of competing for the follow-on innovation after invalidation (V^I) is:

$$V^I = \frac{w}{w(n+1)+d}\pi_{ifL} + \frac{wn}{w(n+1)+d}\left(\frac{n}{N_o-1}\pi_{ifl} + \frac{N_o-n-1}{N_o-1}\pi_{ifr}\right) + \frac{d}{w(n+1)+d}\pi_{in} - H(w) \,.$$

[53] Validity challenges also arise for other reasons such as asymmetric information (Lanjouw and Lerner, 2000). As it is more challenging to explain how asymmetric information persists, we do not pursue this explanation here.

[54] In the cases outlined above, the patentee can expend greater resources to win a challenge than the challenging firm. This imbalance may lead to a positive correlation between the patentee's profits in the product market and the probability of a challenged patent being upheld. This can contribute to a positive correlation between innovation value and patent validity.

Firm incentives to challenge the original patent Assume the patent is found invalid with probability η, then $1-\eta$ is a measure of patent validity. A challenge is filed where:

$$\eta V^I + (1-\eta)\underline{V}^u_{s,i} - C_o > V^u_{s,i}\,, \tag{A.44}$$

where C_o represents the costs of challenging the patent, $\underline{V}^u_{s,i}$ is the challenging firm's expected profit if being excluded from the pool of licensees, and $V^u_{s,i}$ is the challenging firm's expected payoff from not challenging the patent. The boundary on patent validity $(1-\eta)$ below which a validity challenge will be pursued is:

$$1 - \frac{V^u_{s,i} - \underline{V}^u_{s,i}}{V^I - \underline{V}^u_{s,i}} - \frac{C_o}{V^I - \underline{V}^u_{s,i}} \geq (1-\eta)\,. \tag{A.45}$$

Higher costs of challenging decrease the probability of a validity challenge. Notice that as the original innovation size $(\overline{\Delta c})$ increases, the patentee licenses fewer firms. This reduces the cost of being excluded from the pool of licensees: $\lim_{\overline{\Delta c}\to(\alpha-\underline{c})}(V^u_{s,i} - \underline{V}^u_{s,i}) = 0$. Note also that V^I is not a function of $\overline{\Delta c}$ and that $\underline{V}^u_{s,i}$ is decreasing in $\overline{\Delta c}$ since the challenging firm is excluded from the pool of licensees. Overall this implies that as the value of the original innovation increases, patents with higher validity are more likely to be challenged.

Now consider the effect of variation in the size of the follow-on innovation $\underline{\Delta c}$. An increase in $\underline{\Delta c}$ reinforces the rent dissipation effect and reduces the number of licenses offered, reducing $V^u_{s,i} - \underline{V}^u_{s,i}$. V^I increases in $\underline{\Delta c}$. By implication, as the value of the follow-on innovation increases, patents with higher validity are more likely to be challenged.

Result 9 The likelihood of a high-validity patent being challenged increases in the size of the original innovation $\overline{\Delta c}$ and the size of the follow-on innovation $\underline{\Delta c}$.

Patentee incentives to contest the challenge We define $\gamma \geq 1$ as a parameter capturing an increase in the expected value of the patentee's profits after winning a patent validity challenge. As noted above, winning a patent validity challenge reduces the likelihood of future challenges, raising profits. The patentee will prefer to contest the validity challenge where:

$$\eta V^I + (1-\eta)V^u_p\gamma - C_o > V^u_p\,. \tag{A.46}$$

The boundary on validity above which the patentee contests the challenge to a decision is:

$$(1-\eta) > 1 - (\gamma-1)\frac{V^u_p}{\left[V^u_p\gamma - V^I\right]} + \frac{C_o}{\left[V^u_p\gamma - V^I\right]}\,. \tag{A.47}$$

Where the increase in expected value from winning a challenge outweighs the costs of a validity challenge $(V^u_p(\gamma-1) - C_o > 0)$, the patentee will not settle a challenge brought against her patent.

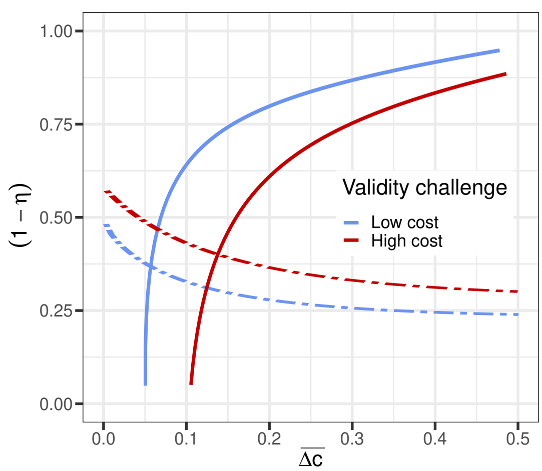
The boundary above which the patentee contests the validity challenge is declining in the size of the original innovation ($\overline{\Delta c}$) as long as $V^I/(V^I - C_o) > \gamma$.

Result 10 The likelihood of a low-validity patent being challenged decreases in the size of the follow-on innovation $\underline{\Delta c}$.

Selection into validity challenges The challenging firm's and the patentee's incentives to pursue the validity challenge have implications for the relationship of patent validity and patent value (capturing both the value of the original and the follow-on innovation) among patents selected into validity challenges. If the patentee does not have the option to settle the validity challenge, then Result 8 by itself leads to a positive correlation between patent validity and patent value. Conversely, if the patentee has the option to settle the validity challenge, then both Result 8 and Result 9 combined lead to the same positive correlation.

Now consider the effect of the cost of a validity challenge. Figure A-4 illustrates which patents, characterized by their validity and innovation size, are selected into a validity challenge: patents that are below the solid (A.45) and above the dashed boundary (A.47). Increasing the cost of a validity challenge shifts both boundaries, resulting in a smaller set of patents selected into a validity challenge. The upper boundary shifts down, while the lower boundary shifts up: the two boundaries for the high-cost setting are contained wholly within those for the low-cost setting.

Figure A-4: Selection into validity challenge by patent validity $(1-\eta)$ and innovation size ($\overline{\Delta c}$)



Result 11 The average original innovation size of patents being challenged increases in the cost of the validity challenge C_o.

A.4 Extension 1: One external patentee – Game G^e

This extension underpins Prediction 3. We set out how the original patentee's licensing incentives change when she does not compete with the licensees in the product market. In other words, the original patentee is external to the licensees' product market. The lack of competition between the patentee and her licensees in the product market removes the direct rent dissipation effect. However, the patentee takes into account that the marginal license still reduces the rents of infra-marginal licensees. By implication, rent dissipation still limits the number of licenses the patentee offers. Note that we assume that there are N_o firms in the licensees' product market as previously.

Again, we compare different outcomes depending on whether follow-on innovation arises and whether the patentee is the follow-on innovator.

Outcome I^e The original patent is invalidated, and no follow-on innovation arises. The patentee makes no profits, and all remaining firms make profits π_{in}, as defined above.

Outcome II^e The original patent is upheld, and no follow-on innovation arises.

Define $\Psi^e_{un} \equiv \left((\alpha-\bar{c})(1-N_0\Theta)-\Theta\overline{\Delta c}n\right)$ and $\Lambda^e_{un} \equiv \Gamma\left(\Psi^e_{un}+\overline{\Delta c}\right)^2-\Gamma(\Psi^e_{un})^2$. Profits are:

$$\pi^e_s = n\left(\phi\Lambda^e_{un}-T\right). \tag{A.48}$$

Outcome IIIa^e The original patent is upheld, and the original patentee is the follow-on innovator. The original patentee licenses the follow-on patent to the n firms that also licensed the original patent. Define $\Psi^e_{uf} \equiv \left((\alpha-\bar{c})(1-N_0\Theta)-\Theta\underline{\Delta c}n\right)$ and $\Lambda^e_{uf} \equiv \Gamma\underline{\Delta c}\left(2\Psi^e_{uf}+\underline{\Delta c}\right)$. Profits are:

$$\pi^e_p = n\left(\phi\Lambda^e_{uf}-T\right). \tag{A.49}$$

Outcome IIIb^e The original patent is upheld, but the patentee is not the follow-on innovator. In this case, the original patentee's profits remain at π^e_s. As a result, the dynamic returns to licensing derive only from the outcome in which the original patentee also secures the follow-on innovation.

Outcome IV^e The original patent is invalidated, and follow-on innovation arises. The patentee makes no profits, and all remaining firms make profits π^e_{ifL}, π^e_{ifl}, π^e_{ifr}, as defined above.

We focus our discussion on the analysis of Stage 2 of the game. This is where differences between the licensing incentives for an internal and an external patentee arise.

The value of follow-on innovation for the patentee ($V^{u,e}_p$) is:

$$V^{u,e}_p = \pi^e_s + \frac{1}{n^e w+d}\underbrace{\left(w\left(\pi^e_p-\pi^e_s\right)\right)}_{\pi^e_{uf}} - H(w)\,. \tag{A.50}$$

Here, π^e_{uf} is the dynamic return of licensing for an external patentee. Substituting out terms in the dynamic return shows the expected dynamic return is the product of a probability that increases in the number of licenses and a difference term only subject to indirect rent dissipation.

$$V_p^{u,e} = \pi_s^e + \frac{n^e w}{n^e w + d}\left(\phi\left(\Lambda_{uf}^e - \Lambda_{un}^e\right)\right) - H(w)\,. \tag{A.51}$$

Note that these terms are also present in the dynamic returns of the internal patentee. However, the internal patentee's dynamic returns also subsume additional terms reflecting direct rent dissipation. This lowers the dynamic returns to licensing relative to the case of the external licensee.

Next, we focus on the static return to licensing and demonstrate that the absence of the direct rent dissipation effect increases the patentee's incentives to license out.

The static optimization problem for the original patentee is:

$$\max_{n_s^e} \pi_s^e(n_s^e) = n_s^e \phi \Gamma \overline{\Delta c}\left(2\Psi_{un}^e + \overline{\Delta c}\right) - n_s^e T\,. \tag{A.52}$$

The original patentee selects $\hat{n}_s^e$ licenses :

$$\hat{n}_s^e = \frac{1}{2\Theta}\left(\frac{(\alpha - \bar{c})}{\overline{\Delta c}}(1 - N_0\Theta) + \frac{1}{2} - \frac{T}{2\phi\Gamma\overline{\Delta c}^2}\right). \tag{A.53}$$

Result 12 If static licensing returns are not negligible, the optimal number of licenses $\hat{n}$ increases with no product market competition between the original patentee and the licensees.

To see this, note that:

$$\hat{n}_s^e - \hat{n}_s = \frac{1}{2(2\phi - \Theta)}\left(\frac{(\alpha - \bar{c})}{\overline{\Delta c}}(1 - N_0\Theta) + \frac{(T)}{\phi\Gamma\overline{\Delta c}^2} + \frac{1}{2}(3 + (\phi - \Theta))\right) > 0\,.$$

A similar result is derived by Arora and Fosfuri (2003).

In sum, if there is no product market competition with the licensees, the patentee has stronger incentives to license out than the patentee in the baseline model due to the lack of a direct rent dissipation effect. However, the patentee and potential licensees may face higher transaction costs T across product markets. These countervailing forces underpin Prediction 3.

A.5 Extension 2: Multiple original patentees – Game G'

This section extends our analysis to settings with multiple original patentees and discusses the implications for the patentee's licensing decision and the invalidation effect. We note the implications of this discussion in Section 2.2.

For simplicity, we limit our case to two original patentees, each holding one of two cost-reducing original innovations (A and B, respectively). We assume that firm A's original patent is challenged; this is without loss of generality.

A.5.1 Substitute technologies

We start with the case where A and B are perfect substitutes: licensees can license either original innovation A or B to the same effect.

The main insight here is that competition in the market for technology, i.e., competition between the two original patentees for licensees, generates higher aggregate levels of licensing than in the baseline case with a single original patentee. The incentive to license to more firms has two reasons: i) each patentee is seeking licensing income but ignores the resulting rent dissipation effect for the other patentee, and ii) each patentee anticipates that a follow-on innovation building on the other patentee's innovation will reduce her licensing income and product market profits (if licensees can switch between technologies). Overall we expect that:

Result 13 In the case of substitute original innovations, the optimal number of licenses of the two original patentees is jointly larger than that of the single original patentee.

The implication is that the invalidation effect is weakened (fewer firms obtain FTO only through invalidation) in this case relative to the baseline case.

A.5.2 Multiple patentees with complement technologies

Now consider the case in which the patentees license out original innovations that are complementary technologies. We assume that each innovation reduces licensees' costs by δ_k where $k \in \{A, B\}$. The combination of both can be super-additive: $\underline{c} = \bar{c} - (\delta_A + \delta_B)^{\xi}$, where $\xi \geq 1$.

Super-additivity has a number of implications: i) a firm with a license of one of the two innovations will benefit more from licensing the other innovation than another firm without a license on the first innovation, ii) the two patentees have very strong incentives to cross-license each other, and (iii) the patentee licensing out innovation B after the patent on A has been invalidated will act as if she is licensing out an innovation of value $\Delta c - \delta_A$.

These considerations suggest that we can expect the original patentees to coordinate their licensing activities; for instance, in the form of a formal or informal patent pool (Lerner and Tirole, 2004). In a patent pool, the patentees cross-license and jointly license out their innovations. With respect to licensing, a pool behaves like a single patentee. The only difference is that each patentee's profit is reduced by a fixed cost to set up the pool. This does not necessarily affect the equilibrium number of licenses offered by the pool ($\hat{n}^P = \hat{n}$) as these costs are independent of the number of licenses the pool issues. Nonetheless, transaction costs may still be larger simply due to the larger number of involved patentees. This would further reduce the optimal number of licenses relative to the baseline model.

Where no pool can be formed, the patentees set license fees independently. The theoretical literature has shown that this lack of coordination leads to royalty stacking (Shapiro, 2001): the fee paid by licensees is much higher and may cause the market for technology to break down. In such a case, there would only be cross-licensing between the two patentees. We focus on the case of the pool to simplify the following analysis.

Result 14 In the case of complementary original innovations, the optimal number of licenses of the two original patentees is weakly smaller than that of the single original patentee.

The most interesting aspect of complements relates to the consequences when the patent of one of the innovations is invalidated. The remaining patentee faces a situation in which her patent is the only patent to be licensed.

When patent A is invalidated, all firms in the market are able to reduce their marginal costs by δ_A. Against this backdrop, the remaining patentee acts as if she was licensing an innovation of value $\Delta c - \delta_A$, leading her to offer more licenses than the pool would have offered for both innovations. This effect is larger the more valuable the original innovation of the invalidated patent relative to the other original innovation, i.e., the larger δ_A relative to δ_B.

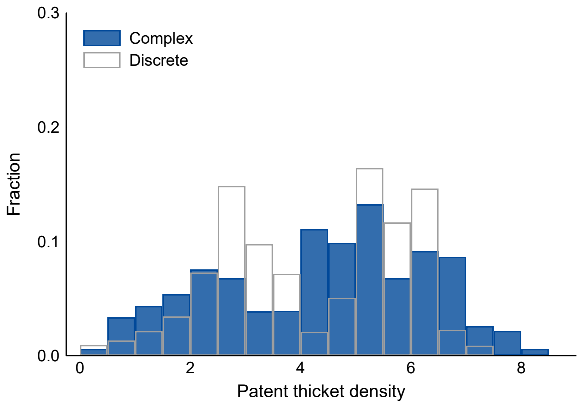
The implication is that patent invalidation typically will not result in every firm in the market obtaining FTO through invalidation. Rather invalidation has a muted effect on FTO as the second patentee will likely restrict licensing:

Result 15 In the case of complementary original innovations of equal size, the number of firms that obtain FTO through invalidation is smaller than that in the case of a single original patentee.

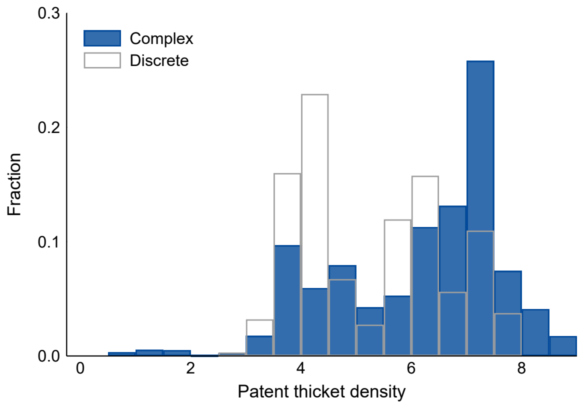
B Additional Descriptives

Figure B-1: Distribution of patent thicket density in discrete and complex technology areas

(a) 1993-2000

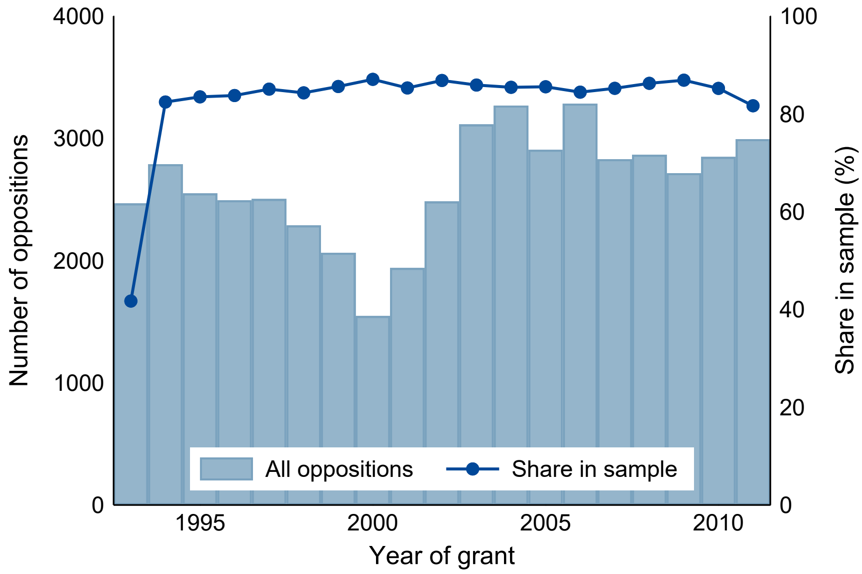


(b) 2001-2013



Notes: This figure shows the distribution of the patent thicket density. Panel (a) shows the distribution of the patent thicket density for patents granted between 1993 and 2000. Panel (b) shows the distribution of triples for patents invalidated granted between 2001 and 2013. The measure of patent thicket density is based on the log-transformed number of citation constellations in which three patentees can mutually block each other (Von Graevenitz et al., 2011). The level of observation is the opposed patent.

Figure B-2: Annual number of opposed patents and sample rate



Notes: This graph includes all opposition proceedings (at the patent level) with a grant date between 1993 and 2011. The low sample rate in the first year is due to the fact that the EPO introduced the grant document type that contains examiner names only in mid-1993. The sample includes oppositions with an outcome after 2013.

Table B-1: Groups of control variables

Group name	**Variables in group**
Year effects	Dummies for grant year Dummies for opposition outcome year
Age effects	Dummies for age in years
Technology effects	Dummies for IPC4 technology class (567) Dummies for technology field (34) [alternatively]
Patent characteristics	log(Number of claims) log(1 + 3 yr self citations) log(1 + 3 yr other citations) log(1 + Patent thicket density) log(1 + Number of patent literature references) Dummy for PCT application Dummy for accelerated examination Dummy for examination in Munich Dummies for publication language Family size Number of IPC classes Number of inventors Principal component (claims, family size, IPC classes) Duration of examination Duration of wait until examination
Patentee characteristics	Number of applicants Dummies for patentee country Dummy for patentee corporation Dummies for patentee size (Orbis): tertiles within technology: small – medium – large
Opponent characteristics	Number of opponents Dummies for opponent country Dummy for opponent corporation Dummies for opponent size (Orbis): tertiles within technology: small – medium – large

Table B-2: Summary statistics of patent and opposition characteristics

	Mean	SD	Min	Max
Patent characteristics				
Self citations (3 yrs after filing)	0.39	0.98	0	19
Other citations (3 yrs after filing)	0.81	1.74	0	82
Other citations (5 yrs after decision)	0.80	1.43	0	32
Age of patent (yr)	8.94	2.56	3	26
DOCDB family size	10.73	10.94	1	269
EP family size	0.38	0.26	0	1
No of applicants	1.07	0.31	1	13
No of inventors	2.64	1.79	1	21
No of claims	13.59	10.09	1	329
No of IPC tech classes	2.64	2.35	1	50
Principal component	-0.00	1.12	-2	16
Patent backward references	4.98	2.94	0	57
PCT application (d)	0.45	0.50	0	1
Year of first filing	1996.37	5.25	1978	2009
Year of grant	2002.13	5.15	1993	2012
Examined in Munich (d)	0.81	0.39	0	1
Duration filing to examination (yrs)	1.77	1.27	0	19
Duration of examination (yrs)	3.99	1.87	0	16
Accelerated examination (d)	0.12	0.32	0	1
Opposition proceeding				
Number of opponents	1.22	0.62	1	18
Examiner participation (d)	0.58	0.49	0	1
Year of first outcome	2005.30	5.27	1994	2013
Outcome: valid (d)	0.29	0.45	0	1
Outcome: invalid (d)	0.71	0.45	0	1
Appeal	0.47	0.50	0	1
Outcome reversed	0.08	0.27	0	1
Observations		38,405		

Notes: This table presents the patent and opposition proceeding characteristics. The level of observation is the opposed patent.

Table B-3: Summary statistics of patentee and opponent characteristics

	Patentees				Opponents			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Sector								
Corporate (d)	0.94	0.24	0	1	0.97	0.17	0	1
Country of residence								
EU (d)	0.58	0.49	0	1	0.83	0.38	0	1
GB (d)	0.04	0.20	0	1	0.04	0.20	0	1
US (d)	0.23	0.42	0	1	0.10	0.30	0	1
JP (d)	0.11	0.32	0	1	0.02	0.14	0	1
RoW (d)	0.03	0.16	0	1	0.01	0.10	0	1
Size								
Small (d)	0.23	0.42	0	1	0.26	0.44	0	1
Medium (d)	0.23	0.42	0	1	0.22	0.42	0	1
Large (d)	0.54	0.50	0	1	0.51	0.50	0	1
Patent portfolio size	670.97	1574.85	0	14007	714.55	1651.78	0	14007
Observations		38,405				38,405		

Notes: This table presents the patentee and opponent characteristics. In the case of multiple patentees or opponents per opposed patent, we give preference according to the ordering of sector, country of residence, and size. Size categories are drawn from firm-level data in ORBIS. Patent portfolio size is the total number of EP patent applications filed during the last five years prior to the opposition decision. The level of observation is the opposed patent.

Table B-4: Summary statistics of citation characteristics

	Citations (other)			
	Mean	SD	Min	Max
Publication authority				
EPO	0.60	0.49	0	1
WIPO	0.40	0.49	0	1
Citation characteristics				
XY citation	0.53	0.50	0	1
Citation lag (yrs)	10.99	2.83	4	26
Same tech class	0.55	0.50	0	1
Same industry	0.52	0.50	0	1
Same country	0.56	0.50	0	1
Family size	6.41	6.18	1	268
No of claims	16.63	14.56	1	500
No of IPC tech classes	1.60	1.56	1	40
Citing patentee				
Corporate (d)	0.94	0.24	0	1
Age (in yrs)	16.60	9.91	-3	38
Country of residence				
EU (d)	0.59	0.49	0	1
GB (d)	0.04	0.19	0	1
US (d)	0.23	0.42	0	1
JP (d)	0.09	0.29	0	1
RoW (d)	0.05	0.22	0	1
Size				
Small (d)	0.26	0.44	0	1
Medium (d)	0.20	0.40	0	1
Large (d)	0.54	0.50	0	1
Patent portfolio size	738.19	1678.52	0	17416
Observations	36,314			

Notes: This table reports the characteristics of the citing EP patents held by entities other than the focal patentee. In case of multiple citing applicants, we give preference according to the ordering of sector, country of residence, and size. Size categories are drawn from firm-level data in ORBIS. Patent portfolio size is the total number of EP patent applications filed during the last five years prior to the opposition decision. The unit of observation is the citation.

Table B-5: Summary statistics of patent value indicators

All patents (N= 38,405)	Mean	SD	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)
(1) –1st claim length	-142.76	92.05	-2746.00	-1.00						
(2) Claims	13.59	10.09	1.00	329.00	-0.002					
(3) Family size	0.38	0.26	0.00	1.00	0.082	0.088				
(4) Inventors	2.64	1.79	1.00	21.00	-0.022	0.121	-0.004			
(5) IPC classes	2.64	2.35	1.00	50.01	0.006	0.076	0.166	0.091		
(6) KPSS (2017) values	24.29	55.65	0.00	966.44	0.029	0.017	0.083	-0.001	0.083	
(7) Princ. comp. of (2), (3) and (6)	-0.00	1.12	-1.89	16.24	0.044	0.516	0.642	0.106	0.737	0.100

Notes: This table reports summary statistics of several value indicators of the opposed patents. Family size is the EP patent family size (i.e., the share of countries in which the respective EP patent has been validated). The unit of observation is the opposed patent.

Table B-6: Summary statistics of citation subset characteristics in the full sample and in patent value quartiles

All patents (N= 38, 405)	Mean	SD	Min	Max	(1)	(2)	(3)	(4)
(1) log(Citations)	0.41	0.55	0	3.50				
(2) - with high value	0.22	0.41	0	2.94	0.788			
(3) - in same industry	0.31	0.49	0	3.37	0.872	0.691		
(4) - in same country	0.22	0.42	0	3.33	0.731	0.567	0.640	
(5) - in same tech class	0.24	0.43	0	3.50	0.759	0.592	0.669	0.568
Patents in value Q1 (N= 9, 859)	Mean	SD	Min	Max	(1)	(2)	(3)	(4)
(1) log(Citations)	0.31	0.48	0	2.71				
(2) - with high value	0.15	0.34	0	2.48	0.737			
(3) - in same industry	0.24	0.43	0	2.71	0.869	0.643		
(4) - in same country	0.16	0.35	0	2.64	0.707	0.489	0.605	
(5) - in same tech class	0.19	0.38	0	2.71	0.770	0.578	0.679	0.558
Patents in value Q2 (N= 9, 514)	Mean	SD	Min	Max	(1)	(2)	(3)	(4)
(1) log(Citations)	0.36	0.51	0	3.50				
(2) - with high value	0.19	0.38	0	2.94	0.766			
(3) - in same industry	0.27	0.46	0	2.89	0.865	0.667		
(4) - in same country	0.20	0.39	0	2.89	0.729	0.557	0.632	
(5) - in same tech class	0.22	0.41	0	3.50	0.776	0.590	0.679	0.586
Patents in value Q3 (N= 9, 678)	Mean	SD	Min	Max	(1)	(2)	(3)	(4)
(1) log(Citations)	0.42	0.54	0	3.22				
(2) - with high value	0.23	0.41	0	2.71	0.780			
(3) - in same industry	0.32	0.49	0	2.94	0.870	0.686		
(4) - in same country	0.23	0.42	0	2.48	0.739	0.562	0.646	
(5) - in same tech class	0.25	0.44	0	3.22	0.755	0.579	0.661	0.570
Patents in value Q4 (N= 9, 354)	Mean	SD	Min	Max	(1)	(2)	(3)	(4)
(1) log(Citations)	0.53	0.62	0	3.37				
(2) - with high value	0.32	0.49	0	2.77	0.824			
(3) - in same industry	0.41	0.56	0	3.37	0.874	0.719		
(4) - in same country	0.28	0.48	0	3.33	0.727	0.599	0.646	
(5) - in same tech class	0.30	0.49	0	3.26	0.734	0.599	0.650	0.546

Notes: This table reports summary statistics of the citation subsets used as dependent variables in the heterogeneity analyses. Citations from high-value patents are those where the citing patent has an above-average patent value (based on the principal component of claims, IPC classes, and family size). Citations from the same tech class are defined as those where challenged and citing patent share the same primary IPC4 technology code. Citations from the same industry are defined as those where both patentees share the same 3-digit primary NACE Rev. 2 industry code. Citations from the same country are defined as those where both patentees share the same country of residence (EU, UK, US, JP, RoW). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. The unit of observation is the opposed patent.

C Additional Results and Robustness Checks

C.1 Average invalidation effect

Table C-1: Effect of patent invalidation on follow-on innovation (additional fixed effects)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			Invalidated (d)			
Invalidated (d)	−0.009	0.187***	−0.008	0.099*	−0.017**	0.165**
	(0.007)	(0.058)	(0.006)	(0.059)	(0.008)	(0.066)
Covariates	Full	Full	Full	Full	Full	Full
Additional fixed effects	IPC4×yr	IPC4×yr	Examiner	Examiner	Exam.×yr	Exam.×yr
Dep var mean	0.41	0.41	0.41	0.41	0.41	0.41
Model degrees of freedom	85	3,459	651	2,627	636	5,447
Underidentification test		374.9		373.6		276.6
Weak identification test		524.3		512.7		276.8
Observations	36,451	32,744	37,548	35,441	30,491	20,285

Notes: The probit regressions in columns (1) and (2) show the relevance of the "Examiner participation" dummy for the opposition outcome. Columns (1) to (6) compare the OLS and the 2SLS regressions for the effect of invalidation on citations by others in a 5-year window following the opposition outcome. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-2: Effect of patent invalidation on follow-on innovation – (other operationalizations of "Invalidated")

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(Citations)			
Invalidated (appeal) (d)	0.011*	0.108***	0.003	0.181***	0.078***	0.573***
	(0.006)	(0.022)	(0.006)	(0.065)	(0.019)	(0.087)
× Patent thicket density					−0.015***	−0.092***
					(0.003)	(0.015)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.41	0.41	0.41	0.41	0.41	0.41
Underidentification test		2,684.1		270.4		263.5
Weak identification test		3,540.7		579.7		275.2
Observations	38,250	38,250	38,250	38,250	38,250	38,250
	(7)	(8)	(9)	(10)	(11)	(12)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(Citations)			
Invalidated (no reversal) (d)	0.014**	0.131***	0.005	0.180***	0.080***	0.580***
	(0.006)	(0.023)	(0.006)	(0.062)	(0.019)	(0.086)
× Patent thicket density					−0.015***	−0.094***
					(0.004)	(0.015)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.41	0.41	0.41	0.41	0.41	0.41
Underidentification test		2,676.0		307.2		298.8
Weak identification test		3,520.1		638.2		300.9
Observations	38,245	38,245	38,245	38,245	38,245	38,245
	(13)	(14)	(15)	(16)	(17)	(18)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(Citations)			
Invalidated claims>p(50) (d)	−0.023***	−0.037*	−0.022***	0.106*	0.054***	0.548***
	(0.006)	(0.020)	(0.006)	(0.062)	(0.017)	(0.091)
× Patent thicket density					−0.015***	−0.092***
					(0.003)	(0.013)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.41	0.41	0.41	0.41	0.41	0.41
Underidentification test		3,144.9		95.9		96.8
Weak identification test		4,288.3		483.0		243.4
Observations	38,226	38,226	38,226	38,226	38,226	38,226
	(19)	(20)	(21)	(22)	(23)	(24)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(Citations)			
Invalidated claims (share)	−0.040***	0.083***	−0.037***	0.173**	0.043**	0.717***
	(0.006)	(0.026)	(0.006)	(0.075)	(0.019)	(0.115)
× Patent thicket density					−0.015***	−0.126***
					(0.003)	(0.017)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.41	0.41	0.41	0.41	0.41	0.41
Underidentification test		1,990.6		118.0		122.7
Weak identification test		2,317.6		242.7		125.8
Observations	38,226	38,226	38,226	38,226	38,226	38,226

Notes: Columns (1) to (6), (7) to (12), (13) to (18), and (19) to (24) correspond to the OLS and 2SLS regression specifications in Table 2, with alternative operationalization of patent invalidation. "Invalidated (appeal)" is based on the latest (i.e., appeal) outcome. "Invalidated (no reversal)" is based on invalidation outcomes irrespective of the first outcome or the appeal outcome. "Invalidated claims>p(50)" splits amendments at the median of the share of lost claims. "Invalidated claims (share)" is a linear variable. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-3: Effect of patent invalidation on follow-on innovation (different citation sets and similar patents)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(Examiner citations)			
Invalidated (d)	−0.002	0.056***	−0.007	0.170***	0.066***	0.602***
	(0.006)	(0.021)	(0.006)	(0.064)	(0.018)	(0.088)
× Patent thicket density					−0.014***	−0.098***
					(0.003)	(0.013)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.41	0.41	0.41	0.41	0.41	0.41
Underidentification test		2,845.0		253.8		252.1
Weak identification test		3,774.5		482.6		236.1
Observations	38,271	38,271	38,271	38,271	38,271	38,271
	(7)	(8)	(9)	(10)	(11)	(12)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(XY-type citations)			
Invalidated (d)	0.014***	0.155***	0.002	0.078	0.064***	0.343***
	(0.005)	(0.016)	(0.005)	(0.050)	(0.014)	(0.067)
× Patent thicket density					−0.012***	−0.060***
					(0.003)	(0.010)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.24	0.24	0.24	0.24	0.24	0.24
Underidentification test		2,844.4		253.1		251.6
Weak identification test		3,772.1		483.1		236.5
Observations	38,271	38,271	38,271	38,271	38,271	38,271
	(13)	(14)	(15)	(16)	(17)	(18)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(USPTO citations)			
Invalidated (d)	0.082***	1.200***	−0.018*	0.062	0.071**	0.732***
	(0.012)	(0.044)	(0.009)	(0.106)	(0.028)	(0.140)
× Patent thicket density					−0.018***	−0.152***
					(0.005)	(0.021)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	1.07	1.07	1.07	1.07	1.07	1.07
Underidentification test		2,857.0		254.7		253.0
Weak identification test		3,790.3		483.0		236.2
Observations	38,271	38,271	38,271	38,271	38,271	38,271
	(19)	(20)	(21)	(22)	(23)	(24)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(Similar patents)			
Invalidated (d)	−0.024***	−0.280***	0.000	0.077**	0.008	0.098*
	(0.005)	(0.017)	(0.004)	(0.039)	(0.013)	(0.057)
× Patent thicket density					−0.002	−0.005
					(0.002)	(0.008)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.12	0.12	0.12	0.12	0.12	0.12
Underidentification test		2,846.3		253.7		252.4
Weak identification test		3,777.7		485.0		237.8
Observations	38,271	38,271	38,271	38,271	38,271	38,271

Notes: Columns (1) to (6), (7) to (12), (13) to (18), and (19) to (24) correspond to the OLS and 2SLS regression specifications in Table 2, with alternative measures of follow-on innovation: citations of higher technical relevance (examiner citations, XY-type citations), citations from a different patent (USPTO citations), and patents with high textual similarity to the respective opposed patent. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table C-4: Effect of patent invalidation on follow-on innovation (alternative operationalization / Poisson regressions)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			asinh(Citations)			
Invalidated (d)	−0.002	0.086***	−0.009	0.193**	0.084***	0.749***
	(0.008)	(0.027)	(0.008)	(0.083)	(0.024)	(0.114)
× Patent thicket density					−0.018***	−0.126***
					(0.004)	(0.017)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.52	0.52	0.52	0.52	0.52	0.52
Underidentification test		2,845.0		253.8		252.1
Weak identification test		3,774.5		482.6		236.1
Observations	38,271	38,271	38,271	38,271	38,271	38,271
	(7)	(8)	(9)	(10)	(11)	(12)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			Citations > 0 (d)			
Invalidated (d)	−0.003	0.015	−0.003	0.128**	0.049***	0.426***
	(0.006)	(0.019)	(0.006)	(0.058)	(0.017)	(0.080)
× Patent thicket density					−0.010***	−0.068***
					(0.003)	(0.012)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.41	0.41	0.41	0.41	0.41	0.41
Underidentification test		2,845.0		253.8		252.1
Weak identification test		3,774.5		482.6		236.1
Observations	38,271	38,271	38,271	38,271	38,271	38,271
	(13)	(14)	(15)	(16)	(17)	(18)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			Citations			
Invalidated (d)	0.008	0.253***	−0.014	0.286	0.185***	1.477***
	(0.016)	(0.056)	(0.016)	(0.188)	(0.046)	(0.242)
× Patent thicket density					−0.039***	−0.271***
					(0.009)	(0.035)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.80	0.80	0.80	0.80	0.80	0.80
Underidentification test		2,845.0		253.8		252.1
Weak identification test		3,774.5		482.6		236.1
Observations	38,271	38,271	38,271	38,271	38,271	38,271
	(19)	(20)	(21)	(22)	(23)	(24)
Estimation method	Poiss	IV Poiss	Poiss	IV Poiss	Poiss	IV Poiss
Dep var			Citations			
Invalidated (d)	0.003	0.253***	−0.023	0.291	0.230***	1.715***
	(0.020)	(0.084)	(0.020)	(0.205)	(0.057)	(0.460)
× Patent thicket density					−0.050***	−0.318***
					(0.011)	(0.070)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.81	0.81	0.81	0.81	0.81	0.81
Observations	36,391	36,391	36,391	36,391	36,391	36,391

Notes: Columns (1) to (6), (7) to (12), (13) to (18), and (19) to (24) correspond to the OLS and 2SLS regression specifications in Table 2, with different operationalizations of the dependent variable (inverse hyperbolic sine transformation, binary transformation, and a simple count). In columns (19) to (24), the IV estimation method is a Generalized Method of Moments estimator of Poisson regression. Note that this latter method necessitates excluding a significant number of observations within small technology fields due to the fixed effects, making it ill-suited for any subsample analyses. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-5: Effect of patent invalidation on follow-on innovation (clustered standard errors)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(Citations)			
Invalidated (d)	−0.001	0.067**	−0.007	0.148**	0.066***	0.580***
	(0.008)	(0.032)	(0.007)	(0.067)	(0.022)	(0.126)
× Patent thicket density					−0.014***	−0.098***
					(0.004)	(0.019)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.41	0.41	0.41	0.41	0.41	0.41
SEs clustered at			IPC4 level			
Underidentification test		118.0		52.0		49.6
Weak identification test		6,229.5		484.8		229.2
Observations	38,271	38,271	38,271	38,271	38,271	38,271
	(7)	(8)	(9)	(10)	(11)	(12)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(Citations)			
Invalidated (d)	−0.001	0.067*	−0.007	0.148***	0.066***	0.580***
	(0.008)	(0.040)	(0.007)	(0.056)	(0.021)	(0.115)
× Patent thicket density					−0.014***	−0.098***
					(0.004)	(0.018)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.41	0.41	0.41	0.41	0.41	0.41
SEs clustered at			TF34 level			
Underidentification test		24.8		19.7		19.2
Weak identification test		3,154.3		323.6		138.9
Observations	38,271	38,271	38,271	38,271	38,271	38,271

Notes: Columns (1) to (6) and (7) to (12) correspond to the OLS and 2SLS regression specifications in Table 2, with standard errors clustered. The top part shows the results with standard errors clustered at IPC4 level (>500 clusters). The lower part shows the results with standard errors clustered at technology field level (34 clusters). One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

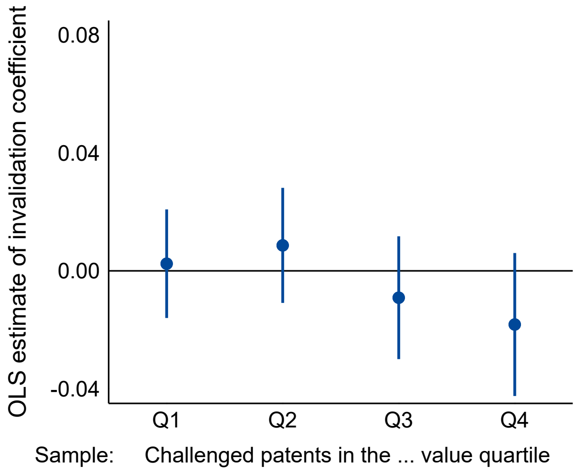
Table C-6: Effect of patent invalidation on unique follow-on innovators (extensive margin)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dep var			log(Citations - extensive margin)			
Invalidated (d)	−0.002	0.050***	−0.006	0.134**	0.059***	0.514***
	(0.006)	(0.019)	(0.006)	(0.059)	(0.017)	(0.081)
× Patent thicket density					−0.013***	−0.086***
					(0.003)	(0.012)
Covariates	None	None	Full	Full	Full	Full
Dep var mean	0.38	0.38	0.38	0.38	0.38	0.38
Underidentification test		2,845.2		253.7		252.0
Weak identification test		3,774.8		482.6		236.2
Observations	38,271	38,271	38,271	38,271	38,271	38,271

Notes: Columns (1) to (6) correspond to the OLS and 2SLS regression specifications in Table 2, with only one (i.e., the earliest) citation per follow-on innovator considered. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

C.2 Effect heterogeneity by original innovation value

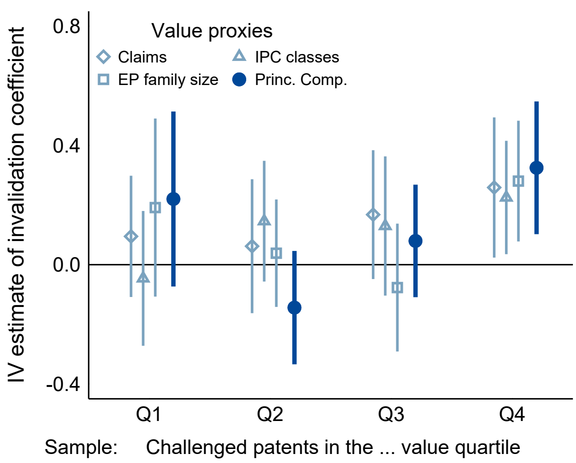
Figure C-1: Effect of patent invalidation on follow-on innovation – original innovation value (OLS estimates)



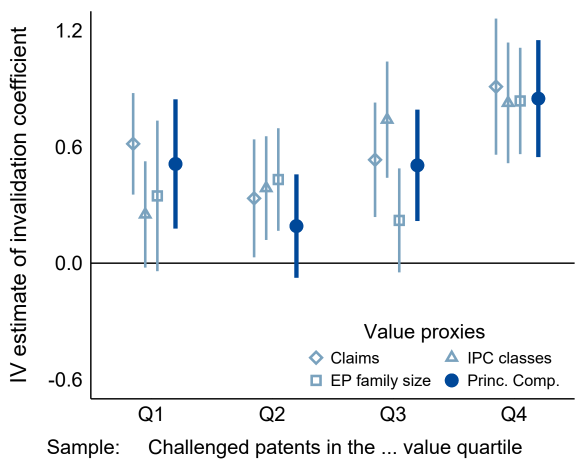
Notes: The figure provides the point estimates and 90% confidence intervals for the instrumented invalidation coefficient on citations by others. The model specifications are equivalent to the one in Table 2, column (3). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. The corresponding regression results can be found in Appendix Table C-7.

Figure C-2: Effect of patent invalidation on follow-on innovation – original innovation value (alternative value proxies)

(a) IV estimates

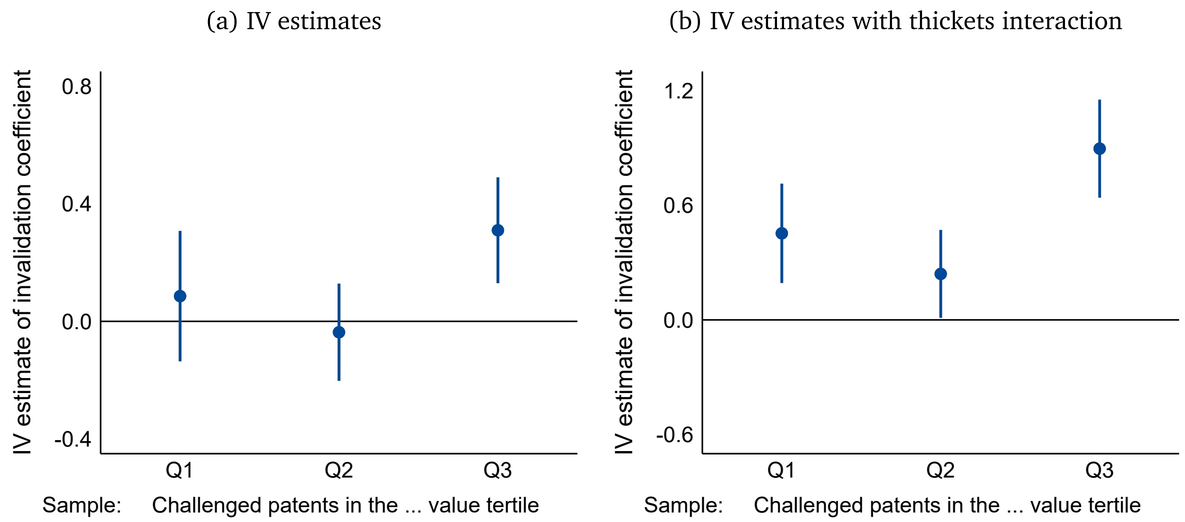


(b) IV estimates with thickets interaction



Notes: The figure provides the point estimates and 90% confidence intervals for the instrumented invalidation coefficient on citations by others. The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with the respective patent value proxy in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation.

Figure C-3: Effect of patent invalidation on follow-on innovation – original innovation value (alternative sample split)

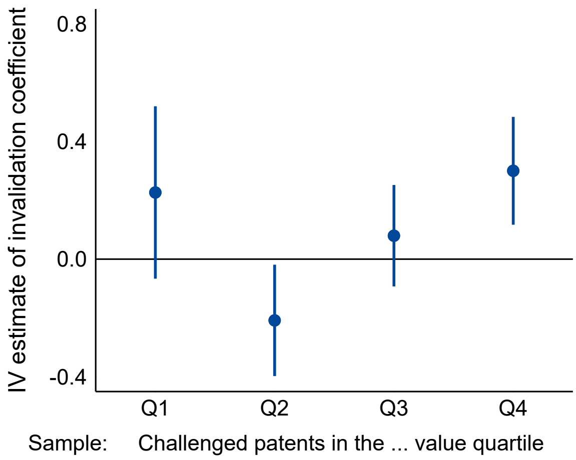


Notes: The figure provides the point estimates and 90% confidence intervals for the instrumented invalidation coefficient on citations by others. The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated tertile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation.

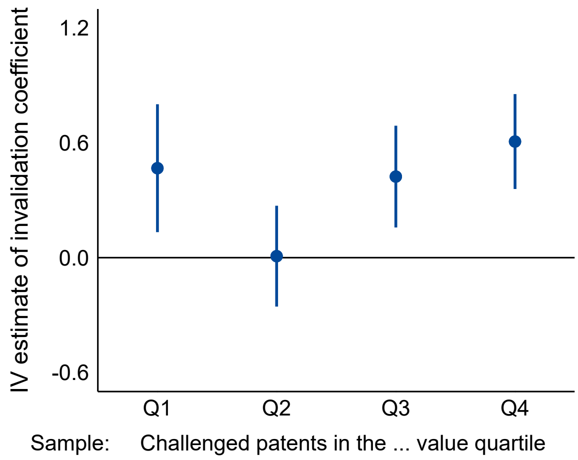
Figure C-4: Effect of patent invalidation on follow-on innovation – original innovation value (alternative transformations of dependent variable)

Binary transformation of citation count

(a) IV estimates

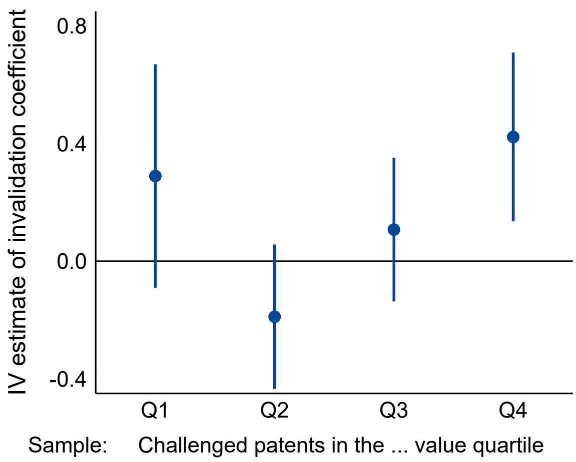


(b) IV estimates with thickets interaction

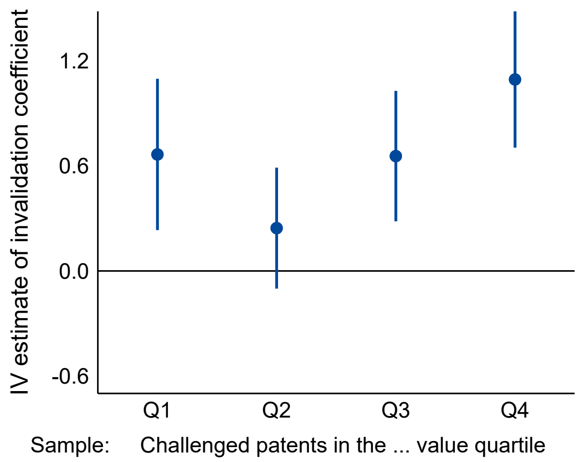


Inverse hyperbolic sine transformation of citation count

(c) IV estimates



(d) IV estimates with thickets interaction



Notes: The figure provides the point estimates and 90% confidence intervals for the instrumented invalidation coefficient on citations by others, with different operationalizations of the dependent variable (binary transformation and inverse hyperbolic sine transformation). The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. The corresponding regression results can be found in Appendix Tables C-11 and C-12.

Table C-7: Effect of patent invalidation on follow-on innovation – original innovation value

	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	OLS	OLS
Dep var	log(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.002	0.009	−0.009	−0.018
	(0.011)	(0.012)	(0.013)	(0.015)
Covariates	Full	Full	Full	Full
Dep var mean	0.31	0.36	0.42	0.53
Adjusted-R^2	0.061	0.061	0.068	0.111
Observations	9,851	9,514	9,678	9,354

	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var	log(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.220	−0.144	0.080	0.325**
	(0.178)	(0.116)	(0.115)	(0.135)
Covariates	Full	Full	Full	Full
Dep var mean	0.31	0.36	0.42	0.53
Underidentification test	39.4	35.2	93.6	102.8
Weak identification test	38.9	121.0	145.7	139.8
Observations	9,816	9,484	9,647	9,324

	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var	log(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.512**	0.191	0.505***	0.849***
	(0.203)	(0.162)	(0.175)	(0.183)
× Patent thicket density	−0.068**	−0.074***	−0.099***	−0.118***
	(0.026)	(0.027)	(0.030)	(0.027)
Covariates	Full	Full	Full	Full
Dep var mean	0.31	0.36	0.42	0.53
Underidentification test	38.3	34.3	92.7	102.4
Weak identification test	18.8	57.4	69.4	69.8
Observations	9,816	9,484	9,647	9,324

Notes: Columns (1) to (4), (5) to (8), and (9) to (12) correspond to the OLS and 2SLS regression specifications in Table 2, columns (3), (4) and (6), respectively. The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-8: Coefficient comparison (Table C-7)

	(1)	(2)	(3)	(4)
Comparison betw/ patents in different value quartiles	Q1 vs. Q2	Q1 vs. Q3	Q4 vs. Q2	Q4 vs. Q3
Δ Invalidated (d)	0.364*	0.141	0.469***	0.245
	(0.217)	(0.194)	(0.175)	(0.199)
Replications	100	100	100	100

	(5)	(6)	(7)	(8)
Comparison betw/ patents in different value quartiles	Q1 vs. Q2	Q1 vs. Q3	Q4 vs. Q2	Q4 vs. Q3
Δ Invalidated (d)	0.321	0.007	0.658***	0.344
	(0.300)	(0.273)	(0.198)	(0.271)
Replications	100	100	100	100

Notes: This table compares the invalidation coefficients from Table C-7, columns (5) to (8) and (9) to (12) through a bootstrap procedure with 100 replications each. Bootstrapped standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-9: Effect of patent invalidation on follow-on innovation – original innovation value (interaction with patentee size included)

	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	OLS	OLS
Dep var	log(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	−0.007	−0.008	0.022	−0.004
	(0.016)	(0.017)	(0.017)	(0.020)
× Large patentee (d)	0.017	0.030	−0.060**	−0.029
	(0.022)	(0.023)	(0.025)	(0.028)
Covariates	Full	Full	Full	Full
Dep var mean	0.31	0.36	0.42	0.53
Adjusted-R^2	0.061	0.061	0.069	0.111
Observations	9,851	9,514	9,678	9,354

	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var	log(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.302*	−0.106	0.132	0.382***
	(0.179)	(0.125)	(0.130)	(0.136)
× Large patentee (d)	−0.211***	−0.071	−0.106	−0.141
	(0.079)	(0.086)	(0.091)	(0.096)
Covariates	Full	Full	Full	Full
Dep var mean	0.31	0.36	0.42	0.53
Underidentification test	38.4	35.3	92.5	100.7
Weak identification test	19.0	60.6	72.8	68.0
Observations	9,816	9,484	9,647	9,324

	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var	log(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.576***	0.207	0.555***	0.879***
	(0.203)	(0.166)	(0.188)	(0.183)
× Patent thicket density	−0.065**	−0.073***	−0.099***	−0.115***
	(0.026)	(0.027)	(0.030)	(0.027)
× Large patentee (d)	−0.200**	−0.044	−0.101	−0.110
	(0.079)	(0.086)	(0.092)	(0.097)
Covariates	Full	Full	Full	Full
Dep var mean	0.31	0.36	0.42	0.53
Underidentification test	37.4	34.5	92.2	100.6
Weak identification test	12.3	38.2	46.5	45.4
Observations	9,816	9,484	9,647	9,324

Notes: Columns (1) to (4), (5) to (8), and (9) to (12) correspond to the OLS and 2SLS regression specifications in Table 2, columns (3), (4) and (6), respectively. The interaction of Invalidation with a dummy indicating a large patentee is additionally included. Patentee size is based on Orbis IP firm-level data. The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-10: Effect of patent invalidation on follow-on innovation – original innovation value (opponent citations excluded)

	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	OLS	OLS
Dep var	log(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.002	0.013	−0.015	−0.022
	(0.011)	(0.011)	(0.012)	(0.014)
Covariates	Full	Full	Full	Full
Dep var mean	0.28	0.32	0.37	0.48
Adjusted-R^2	0.058	0.069	0.066	0.108
Observations	9,851	9,514	9,678	9,354
	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var	log(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.201	−0.165	−0.078	0.155
	(0.165)	(0.104)	(0.109)	(0.125)
Covariates	Full	Full	Full	Full
Dep var mean	0.28	0.32	0.37	0.48
Underidentification test	39.5	34.9	93.4	103.1
Weak identification test	39.0	121.3	145.9	140.7
Observations	9,816	9,484	9,647	9,324
	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var	log(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.503***	0.210	0.238	0.621***
	(0.189)	(0.151)	(0.167)	(0.170)
× Patent thicket density	−0.070***	−0.083***	−0.073***	−0.105***
	(0.025)	(0.026)	(0.028)	(0.026)
Covariates	Full	Full	Full	Full
Dep var mean	0.28	0.32	0.37	0.48
Underidentification test	38.4	34.0	92.6	102.8
Weak identification test	18.9	57.4	69.6	70.2
Observations	9,816	9,484	9,647	9,324

Notes: Columns (1) to (4), (5) to (8), and (9) to (12) correspond to the OLS and 2SLS regression specifications in Table 2, columns (3), (4) and (6), respectively. The citation count excludes citations by the opponent. The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-11: Effect of patent invalidation on follow-on innovation – original innovation value (binary transformation of dependent variable)

	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	OLS	OLS
Dep var	Citations > 0 (d)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.010	0.006	−0.012	−0.008
	(0.011)	(0.011)	(0.012)	(0.012)
Covariates	Full	Full	Full	Full
Dep var mean	0.34	0.39	0.44	0.50
Adjusted-R^2	0.048	0.044	0.050	0.069
Observations	9,851	9,514	9,678	9,354

	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var	Citations > 0 (d)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.227	−0.208*	0.080	0.300***
	(0.178)	(0.115)	(0.105)	(0.111)
Covariates	Full	Full	Full	Full
Dep var mean	0.34	0.39	0.44	0.50
Underidentification test	39.4	35.2	93.6	102.8
Weak identification test	38.9	121.0	145.7	139.8
Observations	9,816	9,484	9,647	9,324

	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var	Citations > 0 (d)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.468**	0.008	0.424***	0.607***
	(0.203)	(0.160)	(0.162)	(0.151)
× Patent thicket density	−0.056**	−0.048*	−0.080***	−0.069***
	(0.026)	(0.027)	(0.027)	(0.022)
Covariates	Full	Full	Full	Full
Dep var mean	0.34	0.39	0.44	0.50
Underidentification test	38.3	34.3	92.7	102.4
Weak identification test	18.8	57.4	69.4	69.8
Observations	9,816	9,484	9,647	9,324

Notes: Columns (1) to (4), (5) to (8), and (9) to (12) correspond to the OLS and 2SLS regression specifications in Table 2, columns (3), (4) and (6), respectively. The citation count is transformed into a binary variable indicating a positive citation count. The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-12: Effect of patent invalidation on follow-on innovation – original innovation value (Inverse hyperbolic sine transformation of dependent variable)

	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	OLS	OLS
Dep var	asinh(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.003	0.011	−0.011	−0.024
	(0.015)	(0.015)	(0.016)	(0.019)
Covariates	Full	Full	Full	Full
Dep var mean	0.40	0.47	0.54	0.69
Adjusted-R^2	0.061	0.061	0.068	0.110
Observations	9,851	9,514	9,678	9,354
	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var	asinh(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.290	−0.189	0.108	0.423**
	(0.231)	(0.149)	(0.149)	(0.175)
Covariates	Full	Full	Full	Full
Dep var mean	0.40	0.47	0.54	0.69
Underidentification test	39.4	35.2	93.6	102.8
Weak identification test	38.9	121.1	145.7	139.8
Observations	9,816	9,484	9,647	9,324
	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var	asinh(Citations)			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.666**	0.245	0.656***	1.094***
	(0.263)	(0.210)	(0.227)	(0.237)
× Patent thicket density	−0.087**	−0.096***	−0.128***	−0.151***
	(0.034)	(0.035)	(0.038)	(0.035)
Covariates	Full	Full	Full	Full
Dep var mean	0.40	0.47	0.54	0.69
Underidentification test	38.3	34.3	92.7	102.4
Weak identification test	18.8	57.4	69.4	69.8
Observations	9,816	9,484	9,647	9,324

Notes: Columns (1) to (4), (5) to (8), and (9) to (12) correspond to the OLS and 2SLS regression specifications in Table 2, columns (3), (4) and (6), respectively. The citation count is transformed into its inverse hyperbolic sine. The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-13: Effect of patent invalidation on follow-on innovation – original innovation value (low thickets density subsample)

	(1)	(2)	(3)	(4)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var		log(Citations)		
Sample: Challenged patents with low thickets density (Q1) and in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.382	−0.231	−0.011	0.358*
	(0.507)	(0.257)	(0.208)	(0.200)
Covariates	Full	Full	Full	Full
Dep var mean	0.33	0.39	0.43	0.57
Underidentification test	4.7	18.8	31.7	33.6
Weak identification test	4.0	18.2	39.0	38.5
Observations	2,445	2,337	2,381	2,296

Notes: Columns (1) to (4), (5) to (8), and (9) to (12) correspond to the OLS and 2SLS regression specifications in Table 2, columns (3), (4) and (6), respectively. The sample is reduced to patents with the bottom quartile of the patent thicket density. The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-14: Effect of patent invalidation on follow-on innovation – original innovation value (binary patent thickets operationalization)

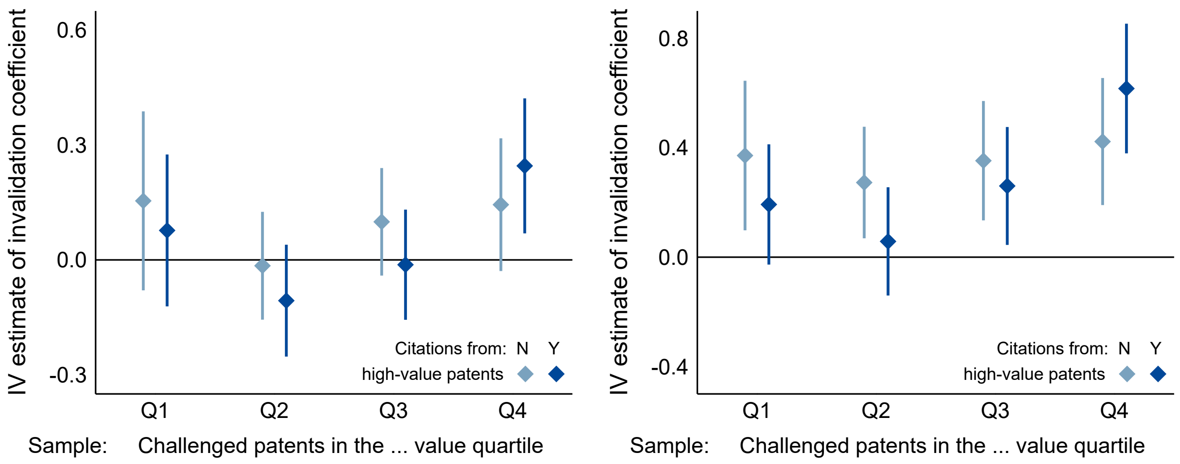
	(1)	(2)	(3)	(4)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var		log(Citations)		
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.260	−0.150	0.118	0.341**
	(0.183)	(0.115)	(0.115)	(0.136)
× Patent thicket density (d)	−0.080**	0.012	−0.089***	−0.042
	(0.031)	(0.032)	(0.032)	(0.035)
Covariates	Full	Full	Full	Full
Dep var mean	0.31	0.36	0.42	0.53
Underidentification test	39.3	35.1	93.7	102.8
Weak identification test	19.4	60.6	72.8	70.0
Observations	9,816	9,484	9,647	9,324

Notes: Columns (1) to (4), (5) to (8), and (9) to (12) correspond to the OLS and 2SLS regression specifications in Table 2, columns (3), (4) and (6), respectively. The continuous patent thicket density variable is transformed into a binary variable indicating an above-average patent thicket density. The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

C.3 Effect heterogeneity by follow-on innovation value

Figure C-5: Effect of patent invalidation on follow-on innovation – original and follow-on innovation value (all value quartiles)

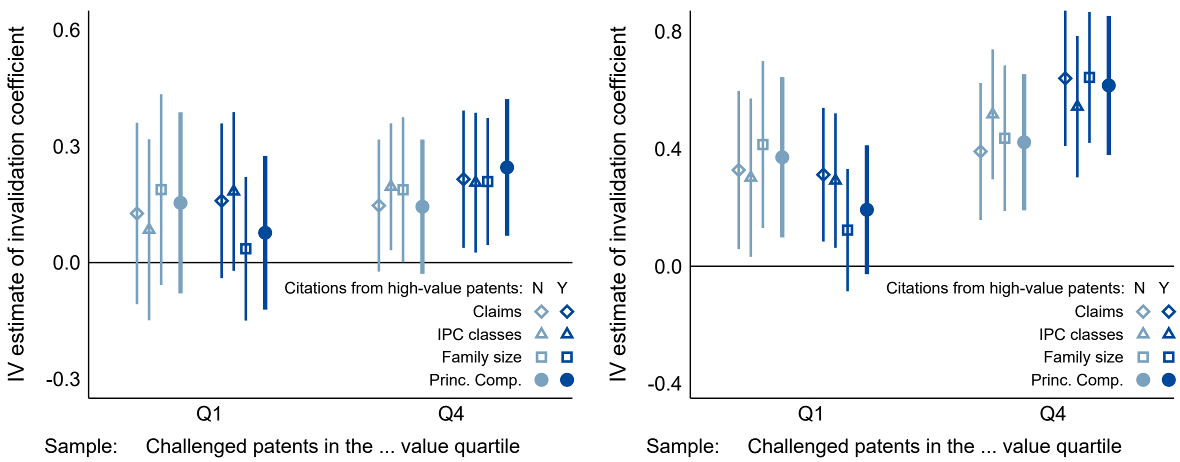
(a) IV estimates (b) IV estimates with patent thicket interaction



Notes: The figure provides the point estimates and 90% confidence intervals for the invalidation coefficient on citations by others, respectively. The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from high-value patents are those where the citing patent has an above-average patent value (based on the principal component of claims, IPC classes, and family size). The corresponding regression results are in Appendix Table C-17.

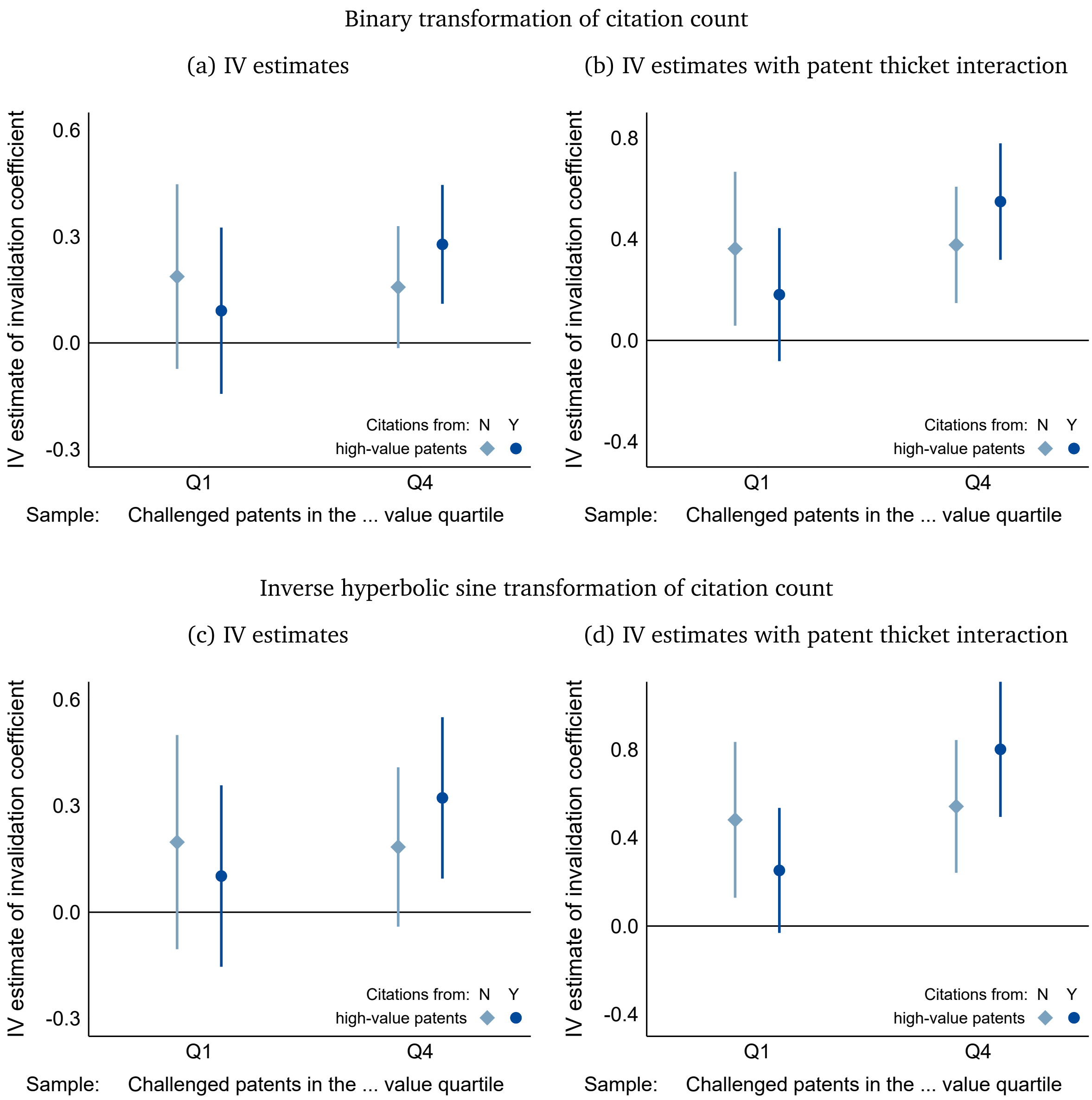
Figure C-6: Effect of patent invalidation on follow-on innovation – original and follow-on innovation value (alternative value proxies)

(a) IV estimates (b) IV estimates with patent thicket interaction



Notes: The figure provides the point estimates and 90% confidence intervals for the invalidation coefficient on citations by others. The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated percentile range. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from high-value patents are those where the citing patent has an above-average patent value (based on the principal component of claims, IPC classes, and family size).

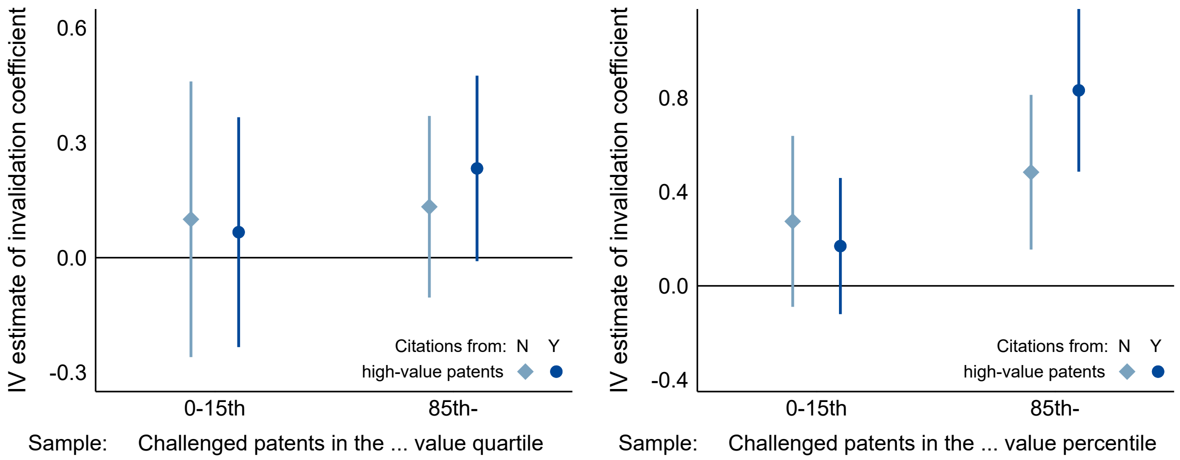
Figure C-7: Effect of patent invalidation on follow-on innovation – original and follow-on innovation value (alternative transformations of the dependent variable)



Notes: The figure provides the point estimates and 90% confidence intervals for the invalidation coefficient on citations by others, with different operationalizations of the dependent variable (binary transformation and inverse hyperbolic sine transformation). The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from high-value patents are those where the citing patent has an above-average patent value (based on the principal component of claims, IPC classes, and family size).

Figure C-8: Effect of patent invalidation on follow-on innovation – original and follow-on innovation value (alternative value thresholds)

(a) IV estimates　　(b) IV estimates with patent thicket interaction



Notes: The figure provides the point estimates and 90% confidence intervals for the invalidation coefficient on citations by others, respectively. The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated percentile range. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from high-value patents are those where the citing patent has an above-average patent value (based on the principal component of claims, IPC classes, and family size).

Table C-15: Effect of patent invalidation on follow-on innovation – original and follow-on innovation value

	(1)	(2)	(3)	(4)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var: log(Citations) from	low-value patents		high-value patents	
Sample: Challenged patents in the ... value quartile	Q1	Q4	Q1	Q4
Invalidated (d)	0.154	0.144	0.077	0.246**
	(0.142)	(0.105)	(0.121)	(0.107)
Covariates	Full	Full	Full	Full
Dep var mean	0.19	0.29	0.15	0.32
Underidentification test	39.6	104.0	39.5	101.9
Weak identification test	39.0	141.1	39.1	139.0
Observations	9,816	9,324	9,816	9,324

	(1)	(2)	(3)	(4)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var: log(Citations) from	low-value patents		high-value patents	
Sample: Challenged patents in the ... value quartile	Q1	Q4	Q1	Q4
Invalidated (d)	0.372**	0.423***	0.193	0.616***
	(0.166)	(0.141)	(0.134)	(0.144)
× Patent thicket density	−0.050**	−0.063***	−0.027	−0.083***
	(0.022)	(0.021)	(0.017)	(0.022)
Covariates	Full	Full	Full	Full
Dep var mean	0.19	0.29	0.15	0.32
Underidentification test	38.5	103.8	38.4	101.5
Weak identification test	18.9	70.5	19.0	69.3
Observations	9,816	9,324	9,816	9,324

Notes: Columns (1) to (8) report the 2SLS regressions for the effect of invalidation on citations by others in a 5-year window following the opposition outcome. The dependent variable concerns citations from patents of either above or below-average patent value (based on the principal component of claims, IPC classes, and family size). The model specifications are equivalent to those in Table 2, columns (4) and (6), respectively. The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-16: Coefficient comparison (Table C-15)

	(1)	(2)
Dep var: log(Citations) from	high-value patents	
	N	Y
Δ Invalidated (d) in Q4 vs. Q1	−0.010	0.169
	(0.185)	(0.175)
Replications	100	100

	(3)	(4)
Dep var: log(Citations) from	high-value patents	
	N	Y
Δ Invalidated (d) in Q4 vs. Q1	0.051	0.424**
	(0.232)	(0.191)
Replications	100	100

Notes: This table compares the invalidation coefficients from Table C-15, columns (1) to (4) and (5) to (8) through a bootstrap procedure with 100 replications each. Bootstrapped standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-17: Effect of patent invalidation on follow-on innovation – original and follow-on innovation value (all value quartiles)

	(1)	(2)	(3)	(4)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from low-value patents			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.154	−0.015	0.099	0.144
	(0.142)	(0.086)	(0.085)	(0.105)
Covariates	Full	Full	Full	Full
Dep var mean	0.19	0.21	0.24	0.29
Underidentification test	39.6	34.8	93.9	104.0
Weak identification test	39.0	121.6	146.0	141.1
Observations	9,816	9,484	9,647	9,324

	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from high-value patents			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.077	−0.106	−0.013	0.246**
	(0.121)	(0.089)	(0.087)	(0.107)
Covariates	Full	Full	Full	Full
Dep var mean	0.15	0.19	0.23	0.32
Underidentification test	39.5	35.3	93.2	101.9
Weak identification test	39.1	121.2	144.6	139.0
Observations	9,816	9,484	9,647	9,324

	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from low-value patents			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.372**	0.273**	0.353***	0.423***
	(0.166)	(0.124)	(0.133)	(0.141)
× Patent thicket density	−0.050**	−0.064***	−0.059**	−0.063***
	(0.022)	(0.021)	(0.023)	(0.021)
Covariates	Full	Full	Full	Full
Dep var mean	0.19	0.21	0.24	0.29
Underidentification test	38.5	33.9	93.2	103.8
Weak identification test	18.9	57.5	69.8	70.5
Observations	9,816	9,484	9,647	9,324

	(13)	(14)	(15)	(16)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from high-value patents			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.193	0.058	0.260**	0.616***
	(0.134)	(0.120)	(0.131)	(0.144)
× Patent thicket density	−0.027	−0.036*	−0.064***	−0.083***
	(0.017)	(0.020)	(0.022)	(0.022)
Covariates	Full	Full	Full	Full
Dep var mean	0.15	0.19	0.23	0.32
Underidentification test	38.4	34.5	92.1	101.5
Weak identification test	19.0	57.6	68.7	69.3
Observations	9,816	9,484	9,647	9,324

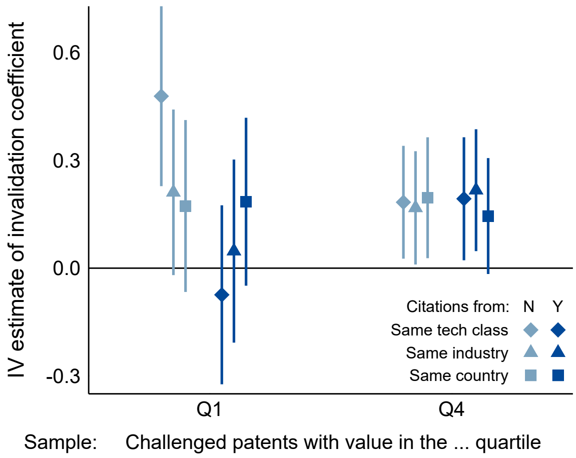
Notes: Columns (1) to (8) report the 2SLS regressions for the effect of invalidation on citations by others in a 5-year window following the opposition outcome. The dependent variable concerns citations from patents of either above or below-average patent value (based on the principal component of claims, IPC classes, and family size). The model specifications are equivalent to those in Table 2, columns (4) and (6), respectively. The four subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

C.4 Effect heterogeneity by product market competition

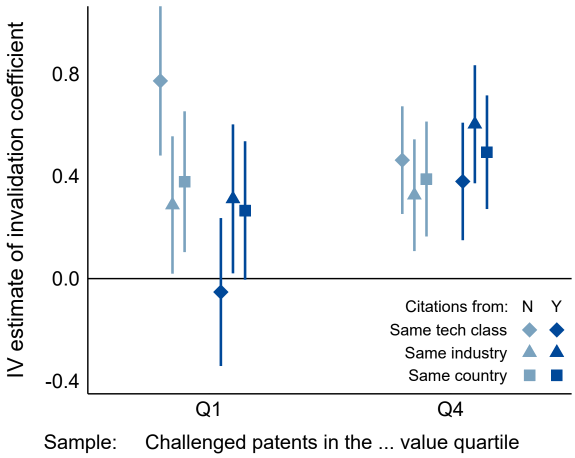
Figure C-9: Effect of patent invalidation on follow-on innovation – original innovation value and product market competition (alternative transformations of the dependent variable)

Binary transformation of citation count

(a) IV estimates

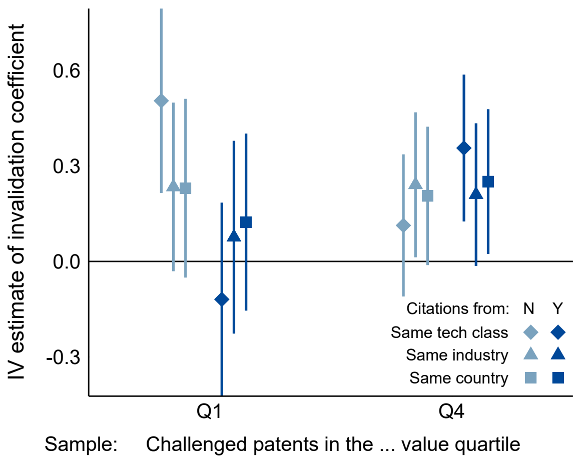


(b) IV estimates with patent thicket interaction

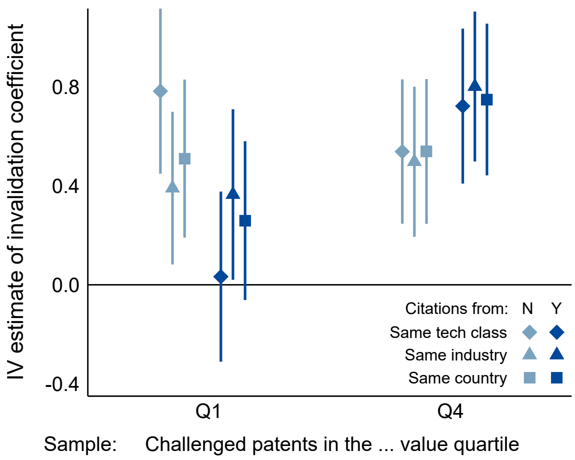


Inverse hyperbolic sine transformation of citation count

(c) IV estimates

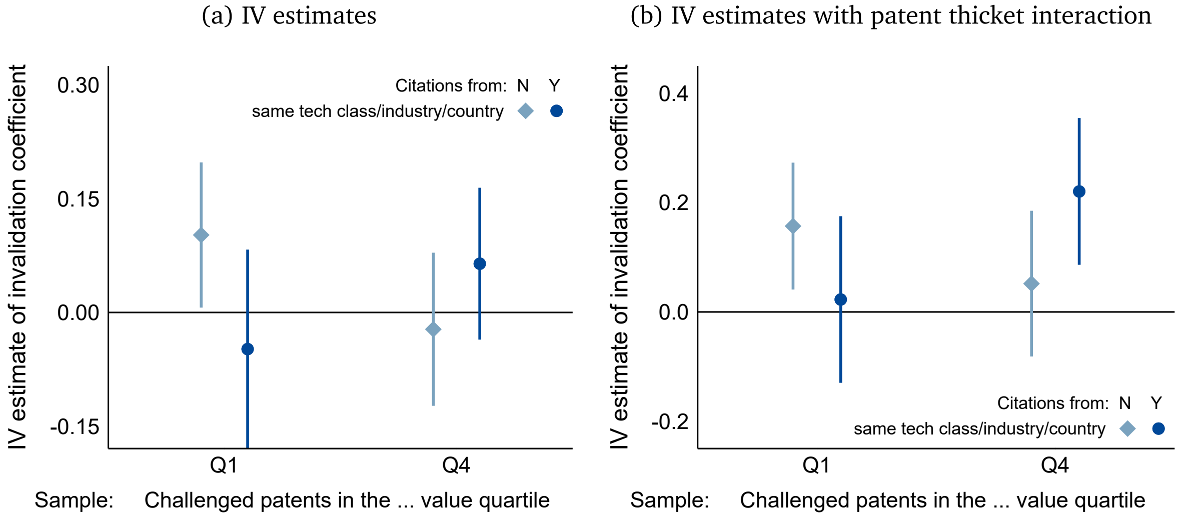


(d) IV estimates with patent thicket interaction



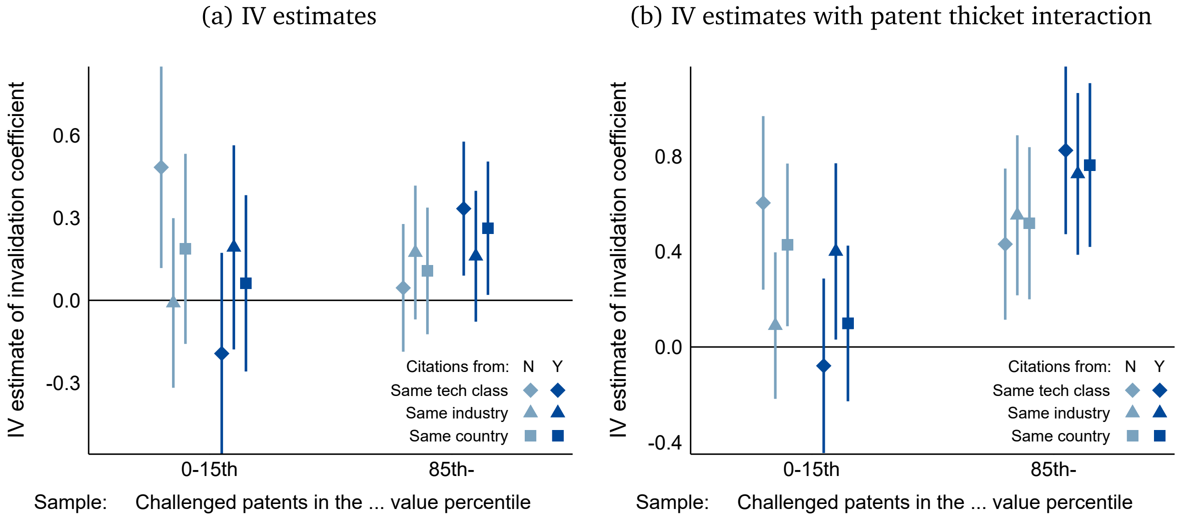
Notes: The figure provides the point estimates and 90% confidence intervals for the invalidation coefficient on citations by others, with different operationalizations of the dependent variable (binary transformation and inverse hyperbolic sine transformation). The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from the same tech class are defined as those where both challenged and citing patent share the same primary IPC4 technology code. Citations from the same industry are defined as those where both patentees share the same 3-digit primary NACE Rev. 2 industry code. Citations from the same country are defined as those where both patentees share the same country of residence (EU, UK, US, JP, RoW).

Figure C-10: Effect of patent invalidation on follow-on innovation – original innovation value and product market competition (all criteria combined)



Notes: The figure provides the point estimates and 90% confidence intervals for the invalidation coefficient on citations by others, with different operationalizations of the dependent variable (binary transformation and inverse hyperbolic sine transformation). The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from the same tech class are defined as those where both challenged and citing patent share the same primary IPC4 technology code. Citations from the same industry are defined as those where both patentees share the same 3-digit primary NACE Rev. 2 industry code. Citations from the same country are defined as those where both patentees share the same country of residence (EU, UK, US, JP, RoW).

Figure C-11: Effect of patent invalidation on follow-on innovation – original innovation value and product market competition (alternative value thresholds)



Notes: The figure provides the point estimates and 90% confidence intervals for the invalidation coefficient on citations by others, with different operationalizations of the dependent variable (binary transformation and inverse hyperbolic sine transformation). The model specifications in panels (a) and (b) are equivalent to those in Table 2, columns (4) and (6), respectively. The interaction effect with patent thicket density is omitted in panel (b). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated percentile range. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from the same tech class are defined as those where both challenged and citing patent share the same primary IPC4 technology code. Citations from the same industry are defined as those where both patentees share the same 3-digit primary NACE Rev. 2 industry code. Citations from the same country are defined as those where both patentees share the same country of residence (EU, UK, US, JP, RoW).

Table C-18: Effect of patent invalidation on follow-on innovation – original innovation value and product market competition

	(1)	(2)	(3)	(4)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var: log(Citations) from	different tech class		same tech class	
Sample: Challenged patents in the ... value quartile	Q1	Q4	Q1	Q4
Invalidated (d)	0.390***	0.087	−0.092	0.276**
	(0.136)	(0.106)	(0.143)	(0.108)
Covariates	Full	Full	Full	Full
Dep var mean	0.15	0.28	0.19	0.30
Underidentification test	40.0	103.3	39.6	102.5
Weak identification test	39.5	140.3	39.1	140.0
Observations	9,816	9,324	9,816	9,324

	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var: log(Citations) from	different industry		same industry	
Sample: Challenged patents in the ... value quartile	Q1	Q4	Q1	Q4
Invalidated (d)	0.180	0.187*	0.055	0.161
	(0.125)	(0.107)	(0.142)	(0.105)
Covariates	Full	Full	Full	Full
Dep var mean	0.14	0.27	0.19	0.31
Underidentification test	39.9	103.0	39.4	103.4
Weak identification test	39.4	140.4	38.9	140.3
Observations	9,816	9,324	9,816	9,324

	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var: log(Citations) from	different country		same country	
Sample: Challenged patents in the ... value quartile	Q1	Q4	Q1	Q4
Invalidated (d)	0.175	0.158	0.098	0.194*
	(0.132)	(0.102)	(0.131)	(0.107)
Covariates	Full	Full	Full	Full
Dep var mean	0.18	0.31	0.16	0.28
Underidentification test	40.6	103.2	39.4	102.5
Weak identification test	40.2	138.9	38.9	139.8
Observations	9,816	9,324	9,816	9,324

Notes: Columns (1) to (12) report the 2SLS regressions for the effect of invalidation on citations by others in a 5-year window following the opposition outcome. The model specifications are equivalent to the one in Table 2, column (4). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from the same tech class are defined as those where both challenged and citing patent share the same primary IPC4 technology code. Citations from the same industry are defined as those where both patentees share the same 3-digit primary NACE Rev. 2 industry code. Citations from the same country are defined as those where both patentees share the same country of residence (EU, UK, US, JP, RoW). One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-19: Effect of patent invalidation on follow-on innovation – original innovation value and product market competition

	(1)	(2)	(3)	(4)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var: log(Citations) from	different tech class		same tech class	
Sample: Challenged patents in the ... value quartile	Q1	Q4	Q1	Q4
Invalidated (d)	0.608***	0.417***	0.023	0.560***
	(0.157)	(0.138)	(0.162)	(0.147)
× Patent thicket density	−0.051**	−0.074***	−0.027	−0.064***
	(0.021)	(0.020)	(0.020)	(0.022)
Covariates	Full	Full	Full	Full
Dep var mean	0.15	0.28	0.19	0.30
Underidentification test	38.9	103.1	38.5	102.2
Weak identification test	19.2	70.1	19.0	69.9
Observations	9,816	9,324	9,816	9,324

	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var: log(Citations) from	different industry		same industry	
Sample: Challenged patents in the ... value quartile	Q1	Q4	Q1	Q4
Invalidated (d)	0.301**	0.388***	0.280*	0.619***
	(0.145)	(0.143)	(0.162)	(0.142)
× Patent thicket density	−0.028	−0.045**	−0.052**	−0.103***
	(0.019)	(0.021)	(0.021)	(0.022)
Covariates	Full	Full	Full	Full
Dep var mean	0.14	0.27	0.19	0.31
Underidentification test	38.9	102.8	38.3	103.0
Weak identification test	19.1	70.1	18.9	70.0
Observations	9,816	9,324	9,816	9,324

	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var: log(Citations) from	different country		same country	
Sample: Challenged patents in the ... value quartile	Q1	Q4	Q1	Q4
Invalidated (d)	0.392***	0.415***	0.203	0.583***
	(0.150)	(0.138)	(0.151)	(0.144)
× Patent thicket density	−0.050***	−0.058***	−0.024	−0.088***
	(0.019)	(0.021)	(0.020)	(0.022)
Covariates	Full	Full	Full	Full
Dep var mean	0.18	0.31	0.16	0.28
Underidentification test	39.5	102.9	38.3	102.2
Weak identification test	19.5	69.2	18.8	69.8
Observations	9,816	9,324	9,816	9,324

Notes: Columns (1) to (12) report the 2SLS regressions for the effect of invalidation on citations by others in a 5-year window following the opposition outcome. The model specifications are equivalent to the one in Table 2, columns (6). The subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from the same tech class are defined as those where both challenged and citing patent share the same primary IPC4 technology code. Citations from the same industry are defined as those where both patentees share the same 3-digit primary NACE Rev. 2 industry code. Citations from the same country are defined as those where both patentees share the same country of residence (EU, UK, US, JP, RoW). One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-20: Coefficient comparison (Tables C-18 and C-19)

Dep var: log(Citations) from	(1)	(2)	(3)	(4)	(5)	(6)
	same tech class		same industry		same country	
	N	Y	N	Y	N	Y
Δ Invalidated (d) in Q4 vs. Q1	−0.302	0.368**	0.007	0.106	−0.016	0.095
	(0.192)	(0.170)	(0.190)	(0.167)	(0.175)	(0.192)
Replications	100	100	100	100	100	100
Dep var: log(Citations) from	(7)	(8)	(9)	(10)	(11)	(12)
	same tech class		same industry		same country	
	N	Y	N	Y	N	Y
Δ Invalidated (d) in Q4 vs. Q1	−0.191	0.538**	0.087	0.339*	0.023	0.380*
	(0.204)	(0.240)	(0.215)	(0.206)	(0.208)	(0.216)
Replications	100	100	100	100	100	100

Notes: This table compares the invalidation coefficients from Tables C-18 and C-19 through a bootstrap procedure with 100 replications each. Bootstrapped standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-21: Effect of patent invalidation on follow-on innovation – original innovation value and product market competition: same technology class (all value quartiles)

	(1)	(2)	(3)	(4)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from different tech class			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.390***	−0.055	0.074	0.087
	(0.136)	(0.084)	(0.081)	(0.106)
Covariates	Full	Full	Full	Full
Dep var mean	0.15	0.17	0.20	0.28
Underidentification test	40.0	35.7	94.7	103.3
Weak identification test	39.5	121.3	145.0	140.3
Observations	9,816	9,484	9,647	9,324
	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from same tech class			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	−0.092	−0.073	0.040	0.276**
	(0.143)	(0.088)	(0.093)	(0.108)
Covariates	Full	Full	Full	Full
Dep var mean	0.19	0.22	0.25	0.30
Underidentification test	39.6	34.9	93.7	102.5
Weak identification test	39.1	121.4	146.7	140.0
Observations	9,816	9,484	9,647	9,324
	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from different tech class			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.608***	0.090	0.293**	0.417***
	(0.157)	(0.118)	(0.125)	(0.138)
× Patent thicket density	−0.051**	−0.032	−0.051**	−0.074***
	(0.021)	(0.020)	(0.022)	(0.020)
Covariates	Full	Full	Full	Full
Dep var mean	0.15	0.17	0.20	0.28
Underidentification test	38.9	34.6	93.9	103.1
Weak identification test	19.2	57.3	69.3	70.1
Observations	9,816	9,484	9,647	9,324
	(13)	(14)	(15)	(16)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from same tech class			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.023	0.182	0.300**	0.560***
	(0.162)	(0.124)	(0.139)	(0.147)
× Patent thicket density	−0.027	−0.057***	−0.061**	−0.064***
	(0.020)	(0.022)	(0.024)	(0.022)
Covariates	Full	Full	Full	Full
Dep var mean	0.19	0.22	0.25	0.30
Underidentification test	38.5	34.0	92.9	102.2
Weak identification test	19.0	57.5	70.0	69.9
Observations	9,816	9,484	9,647	9,324

Notes: Columns (1) to (12) report the 2SLS regressions for the effect of invalidation on citations by others in a 5-year window following the opposition outcome. The model specifications are equivalent to those in Table 2, columns (4) and (6). The four subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from the same tech class are defined as those where both challenged and citing patent share the same primary IPC4 technology code. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-22: Effect of patent invalidation on follow-on innovation – product market competition: same industry – all value quartiles

	(1)	(2)	(3)	(4)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from different industry			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.180	−0.204**	0.057	0.187*
	(0.125)	(0.096)	(0.090)	(0.107)
Covariates	Full	Full	Full	Full
Dep var mean	0.14	0.18	0.21	0.27
Underidentification test	39.9	34.7	94.0	103.0
Weak identification test	39.4	120.6	146.2	140.4
Observations	9,816	9,484	9,647	9,324
	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from same industry			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.055	0.071	0.027	0.161
	(0.142)	(0.087)	(0.088)	(0.105)
Covariates	Full	Full	Full	Full
Dep var mean	0.19	0.21	0.24	0.31
Underidentification test	39.4	35.1	93.4	103.4
Weak identification test	38.9	121.3	145.4	140.3
Observations	9,816	9,484	9,647	9,324
	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from different industry			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.301**	−0.034	0.350***	0.388***
	(0.145)	(0.129)	(0.135)	(0.143)
× Patent thicket density	−0.028	−0.038*	−0.068***	−0.045**
	(0.019)	(0.021)	(0.022)	(0.021)
Covariates	Full	Full	Full	Full
Dep var mean	0.14	0.18	0.21	0.27
Underidentification test	38.9	33.8	93.3	102.8
Weak identification test	19.1	57.1	69.8	70.1
Observations	9,816	9,484	9,647	9,324
	(13)	(14)	(15)	(16)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from same industry			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.280*	0.319**	0.196	0.619***
	(0.162)	(0.125)	(0.133)	(0.142)
× Patent thicket density	−0.052**	−0.055**	−0.039*	−0.103***
	(0.021)	(0.022)	(0.023)	(0.022)
Covariates	Full	Full	Full	Full
Dep var mean	0.19	0.21	0.24	0.31
Underidentification test	38.3	34.1	92.5	103.0
Weak identification test	18.9	57.4	69.2	70.0
Observations	9,816	9,484	9,647	9,324

Notes: Columns (1) to (12) report the 2SLS regressions for the effect of invalidation on citations by others in a 5-year window following the opposition outcome. The model specifications are equivalent to those in Table 2, columns (4) and (6). The four subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from the same industry are defined as those where both patentees share the same 3-digit primary NACE Rev. 2 industry code. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table C-23: Effect of patent invalidation on follow-on innovation – product market competition: same country – all value quartiles

	(1)	(2)	(3)	(4)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from different country			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.175	−0.020	0.080	0.158
	(0.132)	(0.083)	(0.085)	(0.102)
Covariates	Full	Full	Full	Full
Dep var mean	0.18	0.20	0.22	0.31
Underidentification test	40.6	35.6	95.3	103.2
Weak identification test	40.2	121.4	146.1	138.9
Observations	9,816	9,484	9,647	9,324

	(5)	(6)	(7)	(8)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from same country			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.098	−0.098	0.004	0.194*
	(0.131)	(0.087)	(0.087)	(0.107)
Covariates	Full	Full	Full	Full
Dep var mean	0.16	0.20	0.23	0.28
Underidentification test	39.4	35.0	94.0	102.5
Weak identification test	38.9	122.2	146.7	139.8
Observations	9,816	9,484	9,647	9,324

	(9)	(10)	(11)	(12)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from different country			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.392***	0.174	0.359***	0.415***
	(0.150)	(0.117)	(0.131)	(0.138)
× Patent thicket density	−0.050***	−0.043**	−0.065***	−0.058***
	(0.019)	(0.020)	(0.022)	(0.021)
Covariates	Full	Full	Full	Full
Dep var mean	0.18	0.20	0.22	0.31
Underidentification test	39.5	34.6	94.1	102.9
Weak identification test	19.5	57.5	69.5	69.2
Observations	9,816	9,484	9,647	9,324

	(13)	(14)	(15)	(16)
Estimation method	2SLS	2SLS	2SLS	2SLS
Dep var:	log(Citations) from same country			
Sample: Challenged patents in the ... value quartile	Q1	Q2	Q3	Q4
Invalidated (d)	0.203	0.094	0.252*	0.583***
	(0.151)	(0.125)	(0.130)	(0.144)
× Patent thicket density	−0.024	−0.043**	−0.058**	−0.088***
	(0.020)	(0.021)	(0.023)	(0.022)
Covariates	Full	Full	Full	Full
Dep var mean	0.16	0.20	0.23	0.28
Underidentification test	38.3	34.1	93.2	102.2
Weak identification test	18.8	57.9	70.0	69.8
Observations	9,816	9,484	9,647	9,324

Notes: Columns (1) to (12) report the 2SLS regressions for the effect of invalidation on citations by others in a 5-year window following the opposition outcome. The model specifications are equivalent to those in Table 2, columns (4) and (6). The four subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated quartile. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. Citations from the same country are defined as those where both patentees share the same country of residence (EU, UK, US, JP, RoW). One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

D Instrumental Variable

In the following, we provide additional information on our instrumental variable: the granting examiner's participation in the opposition division.

Variation

Interviews with EPO officials revealed that the reasons for the participation of the examiner are found in the temporary non-availability of other eligible examiners with expertise in the particular technology field. Figure D-1 provides evidence for this. The average participation rate is well above 60% before 2003 but then declines to an average rate of about 55% with variation between technology areas. This drop is caused by a sharp increase in the number of examiners eligible to participate in proceedings due to a large-scale training and promotion effort at the EPO.

We provide additional evidence on the correlation between the examiner participation rate and capacity constraints at the technical art unit level in Table D-1. To this end, we measure capacity constraints by the share of patent applications whose search report was not completed before the first publication 18 months after priority filing (see Haeussler et al. (2014) for details). Controlling for a full set of technical art unit and time fixed effects, concurrent capacity constraints are positively associated with the examiner participation rate. Notably, capacity constraints at the technical art unit before (and after) the appointment of the opposition division have a considerably weaker effect on the examiner participation rate, which supports the notion that *temporal* staff shortages drive the decision to appoint the granting examiner to the opposition division (see Figure D-2).

Finally, the distribution of examiner-specific participation rates is not concentrated at zero or at one, which makes it unlikely that the applicant, who knows the granting examiner's identity, can anticipate her participation/absence in the opposition division (see Appendix Figure D-3).

Exogeneity

We present a range of tests that strongly suggest the instrumental variable's randomness conditional on technology class and year fixed effects. First, we test whether particular patentee or opponent characteristics explain the correlation between examiner participation and the opposition outcome (see Table D-2). To this end, we take the specification in column (2) of Table 1 and extend the set of controls to patentee/opponent fixed effects in columns (1) and (2) and patentee/opponent $\times$ year fixed effects in columns (3) and (4). Adding these fixed effects has virtually no effect on the coefficient of "Examiner participation".

Second, we provide a conditional mean comparison of patent characteristics with respect to the opposition outcome and examiner participation (see Tables D-3 and D-4). Patents with and without examiner participation do not differ systematically.

Third, we explore non-linear relationships between patent value indicators and examiner participation. To this end, we run nonparametric regressions with examiner participation as the dependent variable and decile bins of the patent value indicator (see Table D-5). We add controls for the patent's technology field and opposition outcome year. We find no significant correlation between the patent value indicator bins and examiner participation despite a considerable correlation with patent invalidation. We illustrate the lack of any systematic relationship between patent value indicators and examiner participation in binned scatter plots (see Figure D-5). Finally, in Table D-7, we show that patent characteristics of the patentee/opponent do not have any systematic effect on examiner participation in the opposition proceeding.

One legitimate concern is that the duration of examination or opposition may affect the likelihood of examiner participation as well as follow-on citations. In Tables D-8 and D-9, we present the main result based on samples that exclude particular cases related to examination and opposition characteristics. We remove cases with accelerated examination, cases with particularly early/late examinations (relative to filing date), and cases with particularly slow/fast examination. Moreover, we remove patents that were not examined at the headquarter in Munich. Likewise, we exclude different quintiles of the overall sample based on the length of opposition. The estimates are statistically indistinguishable from our main estimate.

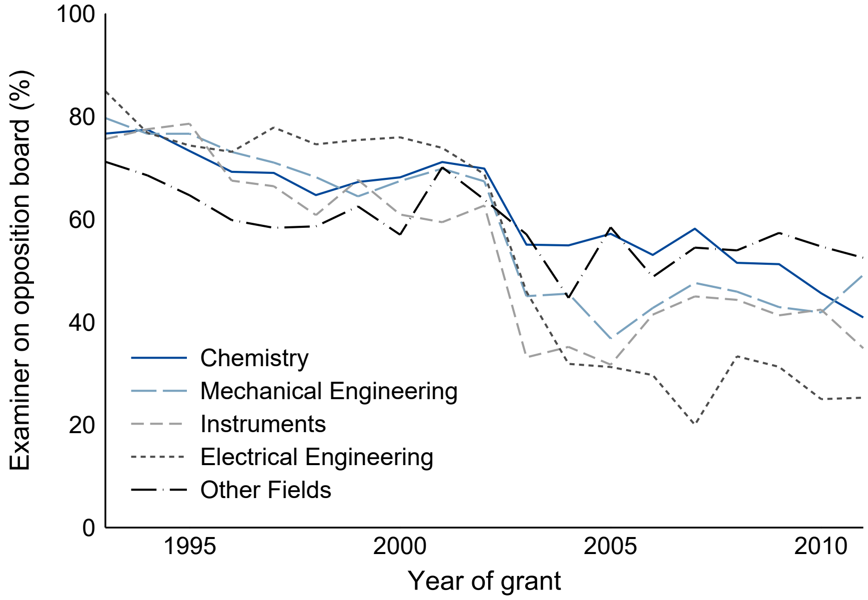
Relevance

In Figure D-6, we plot the Lasso coefficient paths for several independent variables, including "Examiner participation", for the opposition outcome. The figure is based on a penalized regression approach ("Lasso") that selects covariates by shrinking some regression coefficients to zero. The selection of the optimal value of the Lasso regularization parameter is based on the Akaike information criterion. "Examiner participation" enters as the second variable overall, and the coefficient size remains constant over the remaining search grid. This suggests that "Examiner participation" is a highly relevant explanatory variable for the opposition outcome.

Complier analysis

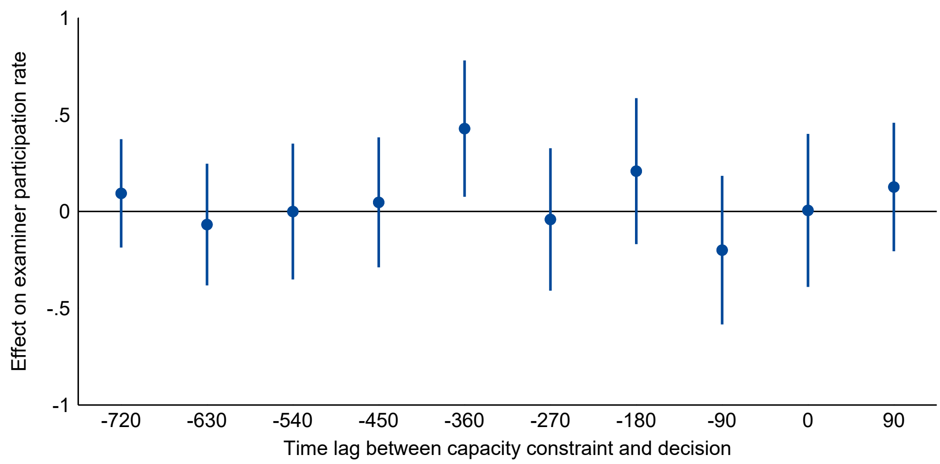
We further examine the characteristics of "complier" observations (Imbens and Angrist, 1994); i.e., patents whose invalidation status can be changed by the instrument. Tables D-10 and D-11 report the size and the characteristics of the complier patent subpopulation. Depending on the (binary) instrument, complier patents are estimated to constitute a share of around 6% to 20% of the patent population. The composition of the complier subpopulation is found to be very similar to the composition of the entire sample with respect to a diverse range of characteristics.

Figure D-1: Annual rate of examiner participation in opposition proceeding



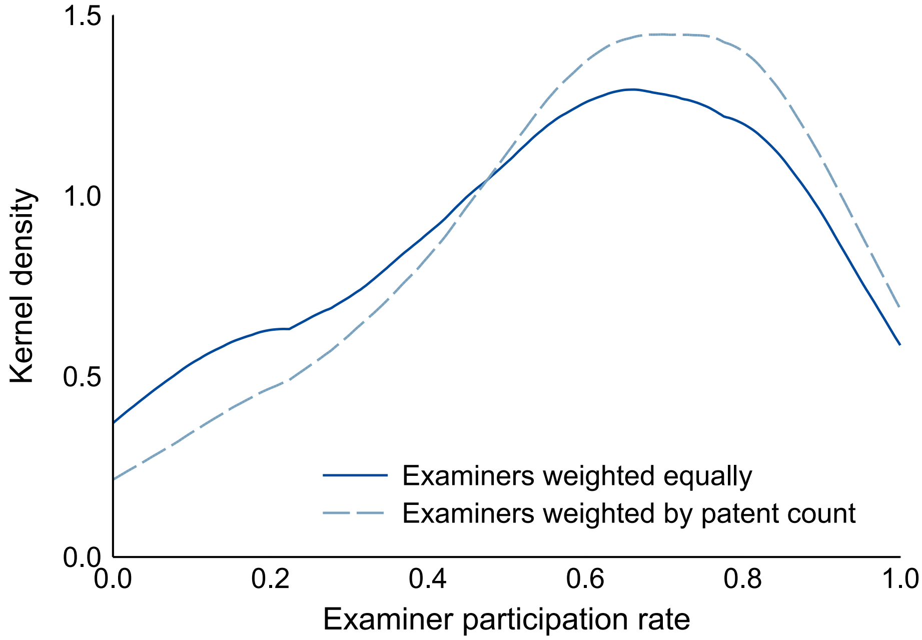
Notes: This graph shows the annual rate of examiner participation in opposition proceedings by technology main area.

Figure D-2: Capacity constraints and examiner participation



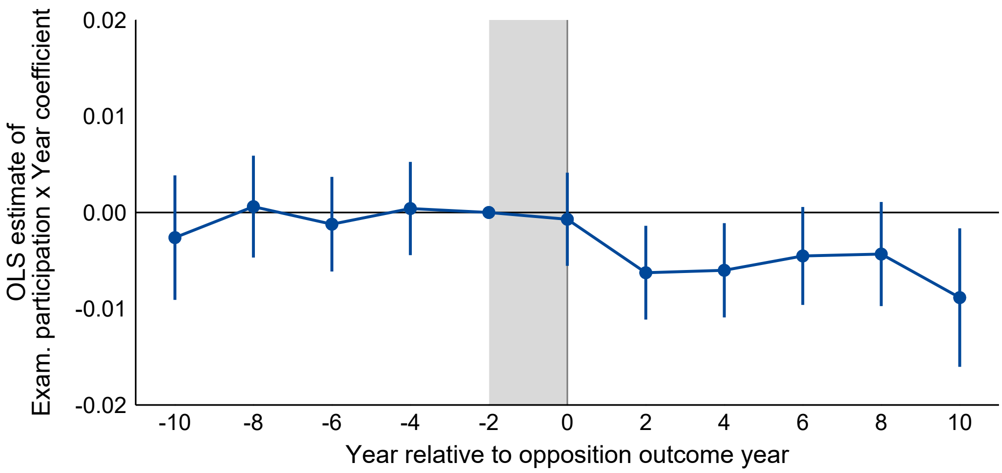
Notes: The graph depicts depicts the effects of quarterly capacity constraints on examiner participation at technical art unit level (see Table D-1, column (3)). Error bars show the corresponding lower and upper 90% confidence limits.

Figure D-3: Examiner-specific participation rates



Notes: The graph shows the densities of participation rates at the examiner level (simple and weighted). Examiners with fewer than 10 observations are excluded.

Figure D-4: Citation trends by examiner participation – event study

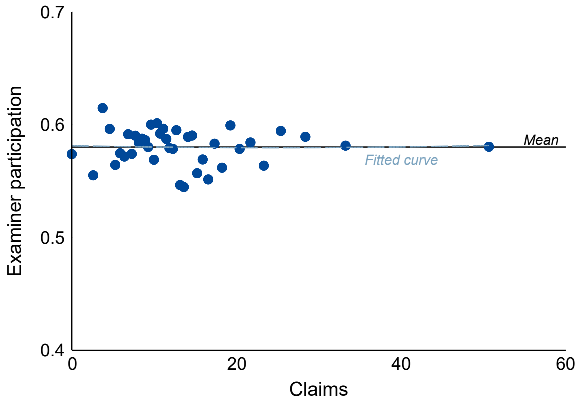


Notes: This figure provides the point estimates of the interaction of examiner participation with binned year dummies from 10 years before to 10 years after the opposition outcome conditional on calendar year, age, and technology class fixed effects. The annual citations of patents with and without examiner participation have a common trend up to the year of opposition outcome. The divergence in annual citations after the opposition outcome is consistent with the relevance of examiner participation on invalidation: examiner participation makes invalidation less likely, leading to relatively fewer citations in the years afterward.

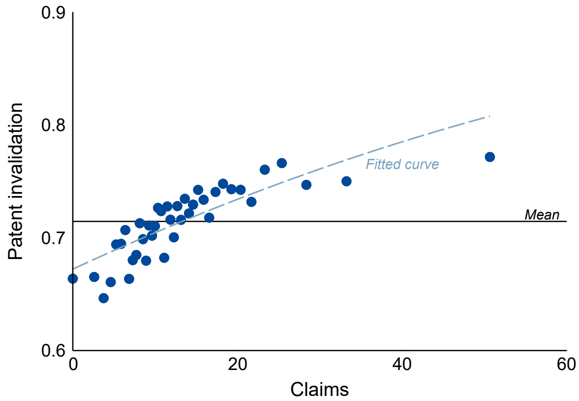
Figure D-5: Patent characteristics by examiner participation and by patent invalidation

Patent claims

(a) Examiner participation

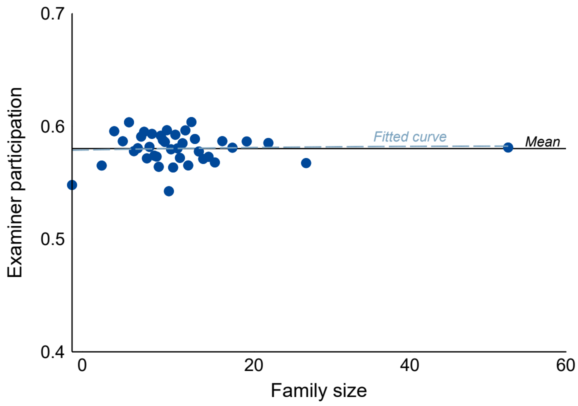


(b) Patent invalidation

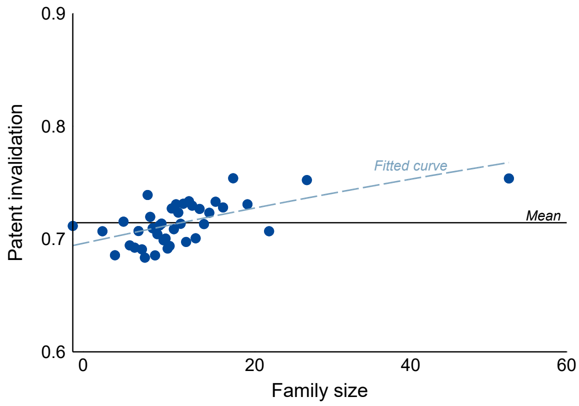


Patent family size

(c) Examiner participation

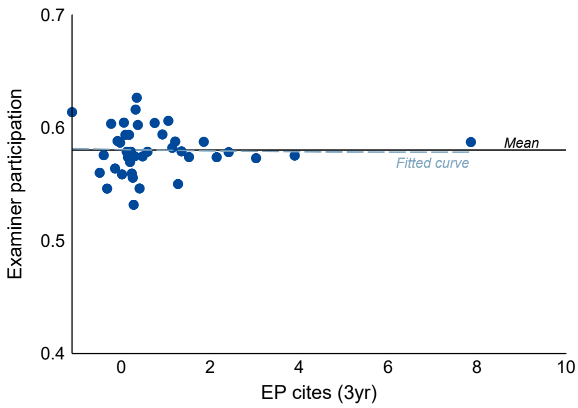


(d) Patent invalidation

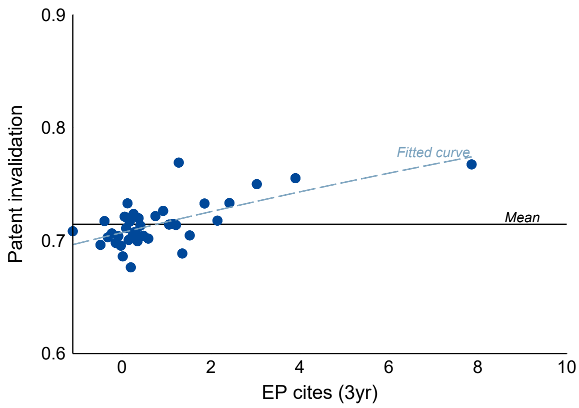


Citations (3yrs)

(e) Examiner participation

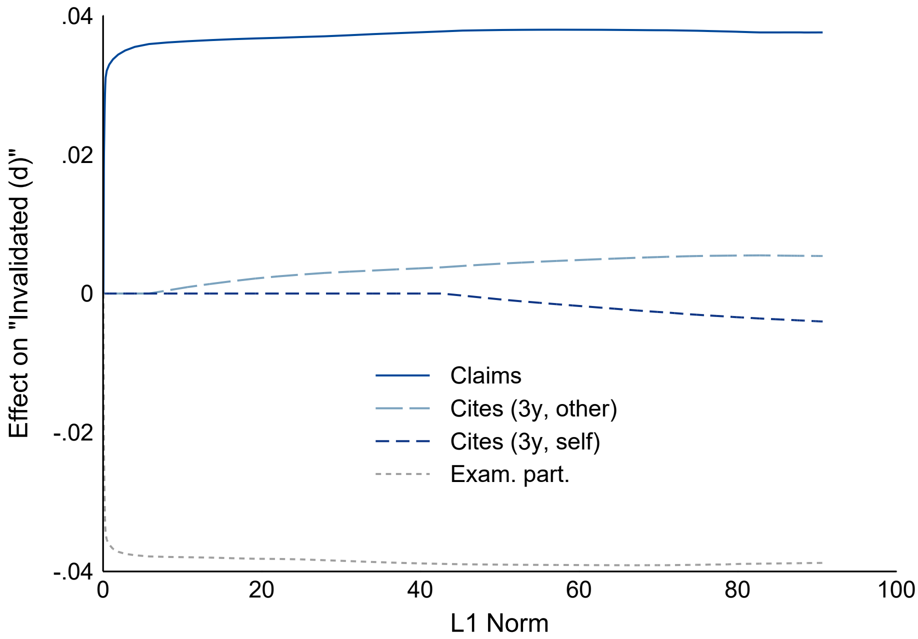


(f) Patent invalidation



Notes: This figure provides the mean of “Examiner participation” (“Patent invalidation”) and the mean of “Patent claims”, “Patent family size”, “Citations (3yrs)”, and “IPC classes” for 40 bins each. The black lines indicate the respective residualized mean of “Examiner participation” (“Patent invalidation”). The dashed lines depict quadratic fitted curves. The disaggregated level of observation is the opposed patent. Controls for technology class and opposition outcome year included.

Figure D-6: Lasso coefficient paths for selected variables on opposition outcome



Notes: This figure depicts the Lasso coefficient paths for several independent variables with the dependent variable "Invalidated". Coefficient path plots show the path of the coefficients over the search grid for the Lasso penalty parameter. "Examiner participation" enters as the second variable overall, and the coefficient size remains constant over the remaining search grid.

Table D-1: Examiner participation rate and technical art unit capacity constraints

	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	OLS	OLS
Dep Var:	Exam. part. rate	Exam. part. rate	Exam. part. rate	Exam. part. rate
Capacity constraint	−0.042	0.585***	0.525***	0.428**
	(0.060)	(0.091)	(0.111)	(0.214)
– 4 quarter lag				0.093
				(0.170)
– 3 quarter lag				−0.068
				(0.191)
– 2 quarter lag				−0.001
				(0.213)
– 1 quarter lag				0.047
				(0.204)
– 1 quarter lead				−0.041
				(0.224)
– 2 quarter lead				0.208
				(0.229)
– 3 quarter lead				−0.200
				(0.233)
– 4 quarter lead				0.005
				(0.240)
– 5 quarter lead				0.126
				(0.202)
Tech unit effects	No	Yes	Yes	Yes
Time effects	No	No	Yes	Yes
Dep Var mean	0.63	0.63	0.63	0.63
Model degrees of freedom	1	32	81	90
Adjusted R^2	-0.000	0.197	0.289	0.287
Observations	1,481	1,481	1,481	1,481

Notes: This table explores the relationship between concurrent capacity constraints and examiner participation at the technical art unit level. The level of observation is the technical art unit (32 in total) over time (calendar year quarters). Capacity constraints are captured by the share of patent applications whose search report was not completed before the first publication 18 months after priority filing (see Haeussler et al. (2014) for details). We link the measure of capacity constraints to the quarter one year prior to the oral proceeding and opposition decision—the time when the technical art unit's director typically allocates the opposition file to the opposition division (see p. 26 of the EPO's Quality Report 2016). Columns (1) to (3) show the effect of the concurrent capacity constraints on the examiner participation rate. Column (4) shows the effect of the capacity constraints variable with a set of lags/leads. Robust standard errors are presented in parentheses. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table D-2: Examiner participation and opposition outcome (additional fixed effects)

	(1)	(2)	(3)	(4)
Estimation method	Probit	Probit	Probit	Probit
Dep var	Invalidated (d)			
Exam. participation (d)	-0.045^{***}	-0.047^{***}	-0.048^{***}	-0.062^{***}
	(0.006)	(0.006)	(0.009)	(0.007)
Covariates	None	Full	Full	Full
Additional fixed effects	Patentee	Opponent	Patentee×yr	Opponent×yr
Dep var mean	0.70	0.70	0.65	0.67
Model degrees of freedom	1,889	2,479	3,093	3,252
χ^2-statistic	.	15,657.0	2,936.9	3,595.6
Pseudo-R^2	0.132	0.126	0.161	0.143
Observations	26,008	28,152	14,082	19,764

Notes: The high-dimensional fixed effects probit regressions in columns (1) to (4) illuminate the relevance of the "Examiner participation" dummy for the outcome of the opposition proceeding. One is added to all citation variables before taking the logarithm to include patents without citations. A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table D-3: Differences between patents by opposition outcome

Dependent variable	β(Invalidated)	Std Err	t	p
Cites (3yrs, other)	0.091^{***}	0.017	5.439	0.000
Cites (3yrs, self)	0.021^{*}	0.011	1.939	0.053
DOCDB family size	0.603^{***}	0.103	5.878	0.000
EP family size	0.004	0.003	1.395	0.163
No of claims	1.190^{***}	0.103	11.544	0.000
No of IPC classes	0.004	0.024	0.163	0.870
Principal component	0.066^{***}	0.011	6.075	0.000
No of applicants	−0.001	0.003	−0.174	0.862
No of inventors	0.085^{***}	0.019	4.434	0.000
No of PL refs	0.165^{***}	0.032	5.211	0.000
PCT application (d)	0.020^{***}	0.005	3.691	0.000

Notes: Results from OLS regressions of different patent characteristics on first opposition outcome and sets of indicator variables for technology class and opposition outcome year. Each row shows the coefficient, the robust standard error, the t-statistic, and the p-value of the indicator for invalidation. The two groups of patents differ significantly, indicating the necessity of the instrumental variable approach. One is added to all citation variables before taking the logarithm to include patents without citations. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table D-4: Differences between patents by examiner participation

Dependent variable	β(Ex. part.)	Std Err	t	p
Cites (3yrs, other)	−0.004	0.019	−0.216	0.829
Cites (3yrs, self)	0.009	0.011	0.817	0.414
DOCDB family size	0.003	0.119	0.023	0.982
EP family size	−0.001	0.002	−0.591	0.554
No of claims	0.019	0.111	0.175	0.861
No of IPC classes	0.000	0.024	0.011	0.991
Principal component	−0.003	0.011	−0.228	0.820
No of applicants	0.002	0.004	0.426	0.670
No of inventors	0.031	0.019	1.638	0.101
No of PL refs	−0.012	0.032	−0.380	0.704
PCT application (d)	0.013**	0.005	2.502	0.012

Notes: Results from OLS regressions of different patent characteristics on the instrumental participation variable and sets of indicator variables for technology class and opposition outcome year. Each row shows the coefficient, the robust standard error, the t-statistic, and the p-value of the "Examiner participation" indicator. Patents with and without the participation of the granting examiner in opposition do not differ significantly. One is added to all citation variables before taking the logarithm to include patents without citations. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table D-5: Patent value indicators and examiner participation (non-parametric relationship) I

	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	OLS	OLS
Dep Var:	Exam. part. (d)	Invalidated (d)	Exam. part. (d)	Invalidated (d)
Indep Var:	Claims	Claims	IPC classes	IPC classes
1.decile	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
2.decile	0.002	0.017	0.014	0.024**
	(0.011)	(0.011)	(0.011)	(0.010)
3.decile	0.006	0.029**	−0.010	0.019*
	(0.013)	(0.013)	(0.011)	(0.010)
4.decile	0.009	0.030***	0.005	0.017*
	(0.010)	(0.010)	(0.011)	(0.010)
5.decile	0.012	0.046***	0.003	0.006
	(0.011)	(0.011)	(0.011)	(0.010)
6.decile	0.012	0.058***	−0.011	0.001
	(0.011)	(0.011)	(0.011)	(0.010)
7.decile	−0.010	0.070***	−0.018	0.016
	(0.011)	(0.011)	(0.011)	(0.010)
8.decile	−0.005	0.076***	−0.010	−0.001
	(0.011)	(0.010)	(0.011)	(0.011)
9.decile	−0.002	0.084***	−0.007	0.005
	(0.011)	(0.011)	(0.011)	(0.011)
10.decile	0.006	0.097***	0.001	0.011
	(0.011)	(0.011)	(0.011)	(0.011)
Dep Var mean	0.58	0.71	0.58	0.71
Model degrees of freedom	563	563	563	563
Adjusted-R^2	0.109	0.036	0.109	0.032
Observations	38,365	38,365	38,365	38,365

Notes: The linear regressions in columns (1) and (3) illuminate the non-linear relationship between patent value indicators and examiner participation in the opposition proceeding. The linear regressions in columns (2) and (4) illuminate the non-linear relationship of patent value indicators on the opposition outcome. Technology class (567) and opposition outcome year fixed effects included. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table D-6: Patent value indicators and examiner participation (non-parametric relationship) II

	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	OLS	OLS
Dep Var:	Exam. part. (d)	Invalidated (d)	Exam. part. (d)	Invalidated (d)
Indep Var:	EP family size	EP family size	Princ. Comp.	Princ. Comp.
1.decile	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
2.decile	−0.002	−0.010	0.005	0.003
	(0.011)	(0.010)	(0.011)	(0.010)
3.decile	0.001	−0.013	−0.003	0.020*
	(0.011)	(0.010)	(0.011)	(0.010)
4.decile	0.012	−0.018*	0.003	0.023**
	(0.011)	(0.010)	(0.011)	(0.010)
5.decile	−0.001	−0.008	−0.004	0.019*
	(0.011)	(0.011)	(0.011)	(0.011)
6.decile	0.006	−0.024**	0.000	0.027**
	(0.010)	(0.010)	(0.011)	(0.011)
7.decile	0.010	−0.002	−0.009	0.026**
	(0.011)	(0.010)	(0.011)	(0.011)
8.decile	0.017	−0.004	0.005	0.035***
	(0.011)	(0.011)	(0.011)	(0.011)
9.decile	0.002	−0.004	0.015	0.035***
	(0.011)	(0.011)	(0.011)	(0.011)
10.decile	−0.009	0.005	−0.015	0.055***
	(0.012)	(0.011)	(0.012)	(0.011)
Dep Var mean	0.58	0.71	0.58	0.71
Model degrees of freedom	563	563	563	563
Adjusted-R^2	0.109	0.032	0.109	0.032
Observations	38,365	38,365	38,365	38,365

Notes: The linear regressions in columns (1) and (3) illuminate the non-linear relationship between patent value indicators and examiner participation in the opposition proceeding. The linear regressions in columns (2) and (4) illuminate the non-linear relationship of patent value indicators on the opposition outcome. Technology class (567) and opposition outcome year fixed effects included. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table D-7: Examiner participation and patent, patentee, and opponent characteristics

	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	OLS	OLS
Dep Var:	Exam. part. (d)	Exam. part. (d)	Exam. part. (d)	Exam. part. (d)
log(No of claims)		−0.007	−0.006	−0.006
		(0.007)	(0.007)	(0.007)
log(CitEPAllPre3Other)		0.001	0.001	0.001
		(0.005)	(0.005)	(0.005)
log(CitEPAllPre3Self)		0.008	0.008	0.009
		(0.006)	(0.006)	(0.006)
DOCDB family size		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
EP family size		−0.006	−0.007	−0.004
		(0.027)	(0.027)	(0.027)
No of inventors		0.002	0.002	0.003*
		(0.001)	(0.001)	(0.001)
No of IPC tech classes		−0.001	−0.001	−0.001
		(0.003)	(0.003)	(0.003)
Principal component		0.007	0.007	0.007
		(0.010)	(0.010)	(0.010)
PCT application (d)		0.007	−0.001	−0.001
		(0.005)	(0.006)	(0.006)
log(Patent backward references)		−0.003	−0.003	−0.003
		(0.005)	(0.005)	(0.005)
Publication language: German (d)		0.007	0.008	0.007
		(0.010)	(0.010)	(0.010)
Publication language: English (d)		0.012	0.012	0.008
		(0.009)	(0.009)	(0.010)
Accelerated examination (d)			0.022***	0.020**
			(0.008)	(0.008)
Examined in Munich (d)			0.083***	0.083***
			(0.007)	(0.007)
Duration of examination (yr)			0.013**	0.012**
			(0.006)	(0.006)
Duration of wait (yr)			0.020***	0.019***
			(0.006)	(0.006)
No of applicants				0.002
				(0.008)
Applicant EU (d)				−0.020
				(0.016)
Applicant GB (d)				−0.019
				(0.019)
Applicant US (d)				−0.015
				(0.016)
Applicant JP (d)				−0.006
				(0.017)
Corporate applicant (d)				−0.015
				(0.011)
Small applicant (d)				0.003
				(0.006)
Medium-sized applicant (d)				0.010
				(0.007)
No of opponents				−0.002
				(0.004)
Opponent EU (d)				0.016
				(0.024)
Opponent GB (d)				0.016
				(0.026)
Opponent US (d)				0.002
				(0.025)
Opponent JP (d)				−0.010
				(0.030)
Corporate opponent (d)				0.010
				(0.015)
Small opponent (d)				0.004
				(0.006)
Medium-sized opponent (d)				0.004
				(0.006)
Year effects	Yes	Yes	Yes	Yes
Age effects	Yes	Yes	Yes	Yes
Technology effects	No	Yes	Yes	Yes
Dep Var mean	0.58	0.58	0.58	0.58
Model degrees of freedom	588	601	605	621
Adjusted-R^2	0.115	0.116	0.119	0.119
Observations	38,365	38,365	38,365	38,365

Notes: This table shows linear regressions of the "Examiner participation" dummy on exogenous variables. Marginal effects are reported. One is added to all citation variables before taking the logarithm to include patents without citations. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table D-8: Effect of patent invalidation on follow-on innovation – exclusion of cases by examination characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Dep var	log(Citations)					
Excluded examinations:	Accelerated	40% earliest	40% latest	40% slowest	40% fastest	not in Muc
Invalidated (d)	0.142*	0.053	0.160*	0.161**	0.121	0.128*
	(0.075)	(0.081)	(0.091)	(0.081)	(0.088)	(0.074)
Covariates set	Full	Full	Full	Full	Full	Full
Dep var mean	0.71	0.74	0.69	0.72	0.71	0.71
Underidentification test	172.3	220.6	113.2	170.1	169.9	190.8
Weak identification test	392.3	306.7	275.4	338.8	247.5	400.9
Observations	33,752	23,951	22,870	22,859	22,840	30,896

Notes: Columns (1) to (6) correspond to the 2SLS regression specification in Table 2, column (4). One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table D-9: Effect of patent invalidation on follow-on innovation – exclusion of cases by opposition duration

	(1)	(2)	(3)	(4)	(5)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS
Dep var	log(Citations)				
Excluded oppositions by length:	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
Invalidated (d)	0.163**	0.156**	0.136**	0.152**	0.122*
	(0.077)	(0.077)	(0.068)	(0.071)	(0.070)
Covariates set	Full	Full	Full	Full	Full
Dep var mean	0.74	0.72	0.71	0.71	0.70
Underidentification test	200.5	240.4	220.2	200.6	167.7
Weak identification test	333.4	357.0	424.5	399.3	409.3
Observations	30,606	30,565	30,599	30,563	30,597

Notes: Columns (1) to (5) correspond to the 2SLS regression specification in Table 2, column (4). One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table D-10: LATE discussion – Complier shares

	Binary instrument			
	Exam. part.	$\hat{p}$(Inv) < q(.25)	$\hat{p}$(Inv) < q(.5)	$\hat{p}$(Inv) < q(.75)
P(Invalidated)	0.7143	0.7143	0.7143	0.7143
P(Instrument = 1)	0.5803	0.2491	0.4982	0.7474
P(Complier)	0.0719	0.2290	0.2033	0.2098
P(Complier | Invalidated)	0.0423	0.2407	0.1428	0.0742
P(Complier | Not Inv.)	0.1461	0.1997	0.3546	0.5490

Notes: This table shows the share of complier patents in the full sample, P(Complier), the share among invalidated patents, P(Complier | Invalidated), and the share among non-invalidated patents, P(Complier | Not Inv.), with respect to different binary instruments. The first column uses the examiner participation indicator variable, the remaining columns transform the probit-predicted invalidation probability instrument $\hat{p}$ of Equation (4) into binary instruments by splitting at the 25th, 50th, and 75th percentile, respectively. For the examiner participation instrument, the population share of compliers lies at around 7.2%, which is comprised of a share of 4.2% for invalidated patents and 14.6% for non-invalidated patents. Following the notation of Angrist and Pischke (2009, Section 4.4.4), we can write a patent i's potential treatment status as D_{1i} when the instrument is $Z = 1$ and as D_{0i} when $Z = 0$. "Complier" patents are then defined as those whose treatment status is sensitive to the instrument, i.e., $D_{1i} = 0$ (no invalidation) and $D_{0i} = 1$ (invalidation) in the above context. In a potential outcomes framework, the Wald estimand can be interpreted as a local average treatment effect (LATE) on the subpopulation of compliers (Imbens and Angrist, 1994). They have to be distinguished from "always-takers" with $D_{1i} = D_{0i} = 1$, and "never-takers" with $D_{1i} = D_{0i} = 0$. The calculations of this table rely, inter alia, on the monotonicity assumption $D_{0i} \geq D_{1i} \forall i$, i.e., on excluding the existence of "defiers" with $D_{1i} = 1$ and $D_{0i} = 0$.

Table D-11: LATE discussion – Complier characteristics

Binary characteristic x	E[x]	E[x | complier]	E[x | complier] / E[x]		p(Ratio = 1)
Cites (3yrs, other) > 0.00	0.390	0.338	0.865	(0.079)	0.088
Cites (3yrs, self) > 0.00	0.229	0.160	0.699	(0.116)	0.010
DOCDB family size > 8.00	0.471	0.471	1.002	(0.067)	0.982
EP family size > 0.50	0.246	0.278	1.128	(0.113)	0.258
No of claims > 11.00	0.473	0.495	1.048	(0.067)	0.471
No of IPC classess > 2.00	0.630	0.628	0.995	(0.050)	0.926
Principal Component > -0.26	0.501	0.487	0.972	(0.065)	0.664
No of applicants > 1.00	0.060	0.009	0.158	(0.262)	0.001
No of inventors > 2.00	0.427	0.375	0.878	(0.074)	0.098
No of PL refs > 4.00	0.492	0.511	1.039	(0.065)	0.547
PCT application (d)	0.455	0.450	0.989	(0.069)	0.878
Appeal (d)	0.469	0.471	1.003	(0.067)	0.960

Notes: This table explores in how far the complier subpopulation differs from the full sample of opposed patents with respect to a series of patent characteristics, conditional on IPC4 technology class and year fixed effects. Since the underlying calculation relies on binary characteristics, count variables are split at their indicated median. The first column indicates the share $E[x] = P(x = 1)$ of patents with $x = 1$ in the entire population, the second column indicates the corresponding share $E[x \mid \text{complier}]$ among complier patents. The third column shows the relative likelihood that complier patents have the binary characteristic x indicated on the left. The corresponding robust standard errors shown in parentheses are derived using seemingly unrelated estimation. Almost all characteristics occur among complier patents with similar rates as in the full sample. Compliers are defined as in the notes of Table D-10.

E Replication of GS2015

The study most similar to ours is GS2015. Based on a sample of 1,357 patents litigated at the US Court of Appeals for the Federal Circuit (CAFC), GS2015 also find that invalidation increases follow-on innovation by others. They observe invalidations as an outcome of infringement disputes at an appellate court in the United States, whereas our study focuses on post-grant validity challenges at the European Patent Office. In Table E-2, we provide a detailed institutional and econometric comparison between GS2015 and our study. Despite substantial differences in the empirical setting, GS2015 and our study share several findings: the overall positive effect of patent invalidation on citations by others, the timing of the effect, and the direction of the endogeneity bias.

Specifically, GS2015 find that patent invalidation increases citations by others by about 0.41. This average effect is more than twice as large as the one we observe in our study (0.15). They also report an OLS estimate of −0.05, which, when we interpret the coefficients directly, is almost ten times larger than the corresponding one in our study (−0.007). As a first step, we seek to replicate these large estimates by factoring in the arguably stronger selection present in their sample.

To accomplish this, we focus on particular subsets of our sample: i) opposed patents of particularly high value and ii) opposed patents that can be linked to infringement disputes before courts.[55] The rationale for focusing on these two sets of patents is the following. Patents selected into expensive US patent litigation are highly valuable, as already shown in Section 3.7. Moreover, the predominant share of all CAFC cases is linked to infringement allegations, indicating the patents' considerable commercial value (see Appendix Figure E-3).

We find that the estimates derived from OLS and instrumental variable regression amplify in magnitude when focusing on particularly valuable opposed patents (Appendix Table E-1). For instance, in the infringement subsample, the OLS estimate yields a coefficient practically identical to that in GS2015. Similarly, the invalidation effect derived from the subsample using our composite patent value indicator stands at 0.33, approximating 80% of the effect magnitude found in GS2015. Hence, we infer that the average invalidation effect in GS2015 can be replicated with our data by emulating the selection into costly infringement disputes.

Based on the results of several heterogeneity analyses, GS2015 come to the conclusion that licensing failure due to transaction costs causes the observed invalidation effect in their sample. Notably, they locate the largest effect in complex technology fields and argue that this reflects licensing

[55] We create the infringement sample by matching the opposed patents to infringement disputes filed before European courts or—via their patent family—before US courts. To this end, we match patents with litigation data from Cremers et al. (2017) and Darts-IP. Altogether, we link 2,369 patents to infringement disputes (6% of the sample).

Table E-1: Effect of patent invalidation on follow-on innovation – high-value and infringement subsamples of opposed patent

	(1)	(2)	(3)	(4)	(5)
Estimation method	OLS	OLS	OLS	OLS	OLS
Dep var			log(Citations)		
Sample: High-value patents based on:	Claims	IPC classes	EP family size	Value (PC1)	Infringement
Invalidated (d)	−0.003	−0.022	−0.002	−0.018	−0.050
	(0.015)	(0.014)	(0.014)	(0.015)	(0.036)
Covariates	Full	Full	Full	Full	Full
Dep var mean	0.50	0.50	0.48	0.53	0.60
Adjusted-R^2	0.113	0.116	0.098	0.111	0.145
Observations	8,800	9,359	9,464	9,354	2,369
	(6)	(7)	(8)	(9)	(10)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS
Dep var			log(Citations)		
Sample: High-value patents based on:	Claims	IPC classes	EP family size	Value (PC1)	Infringement
Invalidated (d)	0.267*	0.225*	0.295**	0.327**	0.263
	(0.143)	(0.116)	(0.124)	(0.136)	(0.239)
Covariates	Full	Full	Full	Full	Full
Dep var mean	0.50	0.50	0.48	0.53	0.60
Underidentification test	90.5	104.1	116.3	104.2	41.7
Weak identification test	108.6	172.9	145.8	139.3	38.3
Observations	8,767	9,347	9,431	9,324	2,354

Notes: Columns (1) to (5) and (6) to (10) correspond to the OLS and 2SLS regression specifications in Table 2, columns (3) and (4), respectively. The subsamples in columns (1) to (4) and (6) to (9) are restricted to patents that are in the top quartile of the respective patent value indicator variable. The patent value distribution is stratified by technology field and year to account for time- and technology-specific variation. The sample in columns (5) and (10) are patents that could be linked to infringement disputes. One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

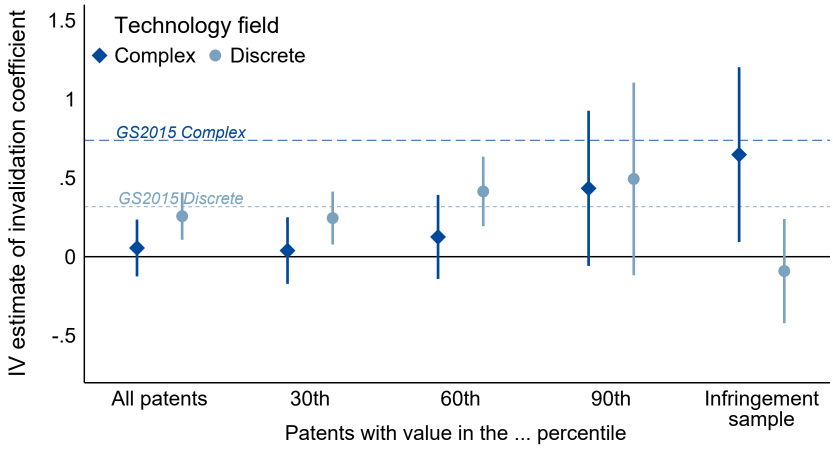
failure due to the high transaction costs of finding licensing agreements when multiple parties have a stake in the original innovation.[56]

We therefore estimate as a second step the invalidation effect on citations by others for patents in complex and discrete technology fields separately (Appendix Figure E-1).[57] For patents in discrete technology fields, the invalidation effect is significant and only slightly smaller than the corresponding one in GS2015. In contrast, for patents in complex technology fields, we find an insignificant invalidation effect close to zero. This result resonates well with our earlier finding that the high density of patent thickets in complex technology fields lowers the invalidation effect on citations in Table 2. It stands, however, in stark contrast to the large corresponding estimate in GS2015.

[56]They further observe a more pronounced invalidation effect when large patentees face smaller follow-on innovators compared to small patentees facing large follow-on innovators. We are not able to replicate this specific effect differential. The underlying factors accounting for this discrepancy warrant further investigation.

[57]The time-invariant classification of technologies into discrete and complex fields follows Von Graevenitz et al. (2013).

Figure E-1: Effect of patent invalidation on follow-on innovation – discrete and complex technologies



Notes: The figure provides the point estimates and 90% confidence intervals for the invalidation coefficient on other citations in distinct subsamples. The value subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated percentile range. The value distribution is stratified by year and technology field. The infringement subsample consists of patents that could be linked to infringement disputes. The classification of technology areas into discrete and complex follows Von Graevenitz et al. (2013). The corresponding regression results can be found in Appendix Table E-4.

We find that the invalidation effect for patents in complex technologies increases with patent value. Narrowing down the set of patents unavoidably decreases the precision of the estimates, especially in the subsample above the 90th percentile of the value distribution. Notwithstanding, among these high-value patents, the invalidation effect in complex technology fields reaches a considerably larger magnitude. We further examine the invalidation effects in the infringement subsample. For these infringement patents, the invalidation effect is large and significant in complex technology fields but statistically indistinguishable from zero in discrete technology fields—mirroring the ordering of the estimates in GS2015.

Several reasons may explain why the invalidation effect in complex technology fields increases with innovation value. First, patentees likely face considerable rent dissipation effects as these patents protect particularly valuable original innovations. This results in many firms in the market without FTO through licensing. Second, the invalidated patents likely protect aspects of the original innovation with an asymmetric (i.e., disproportionately large) share of the combined innovation value. This implies that many firms gain FTO through invalidation despite the possible existence of other patentees holding complementary patent rights. Relatedly, the CAFC patents, which are significantly older with validity decisions made between 1983 and 2008, may not be surrounded by as many patent thickets compared to the patents in our sample.

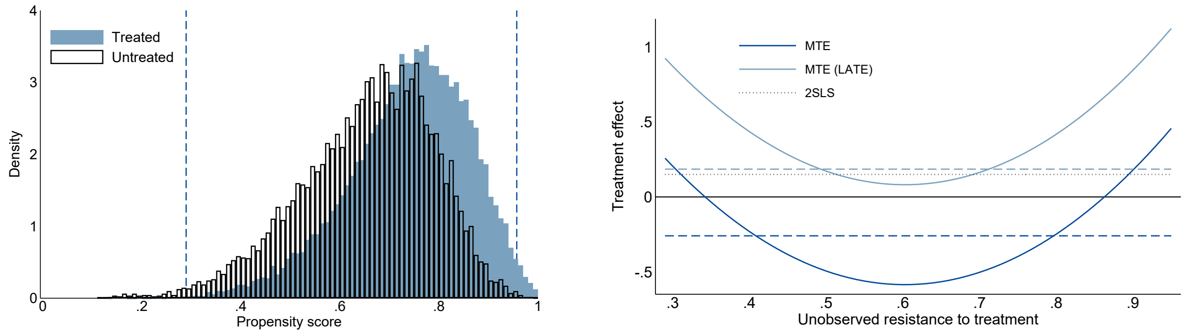
Finally, GS2015 argue that the distribution of the marginal treatment effect (MTE) of invalidation provides additional evidence for licensing failure due to transaction costs. We therefore compare the MTE in our study with the MTE reported by GS2015. The MTE is based on patents that are invalidated because of the instrument. This concerns patents with common support, which ranges from a predicted probability of invalidation of about 0.35 to 0.95 (see Appendix Figure E-2a).

In Appendix Figure E-2b, we plot the estimates of the MTE (dark blue line) and the weighted MTE (light blue line) against the predicted probability of invalidation, which can also be described as the *unobserved resistance to treatment*. The estimates emerge from patents that are at the margin of getting invalidated despite their predicted probability of invalidation based on observables. The mean of the weighted MTE (light blue dashed line) is close to our 2SLS coefficient, which indicates that the MTE curve is well-specified. The estimated MTE is particularly pronounced at both extremes of unobservable resistance to treatment. While the large MTE at the high end is consistent with GS2015, the elevated MTE at the lower end supports our contention that two distinct reasons for licensing failure exist within our sample.

Figure E-2: Common support and marginal treatment effect

(a) Common support

(b) Marginal treatment effect



Notes: The MTE is calculated based on the specification in Table 2, column (4).

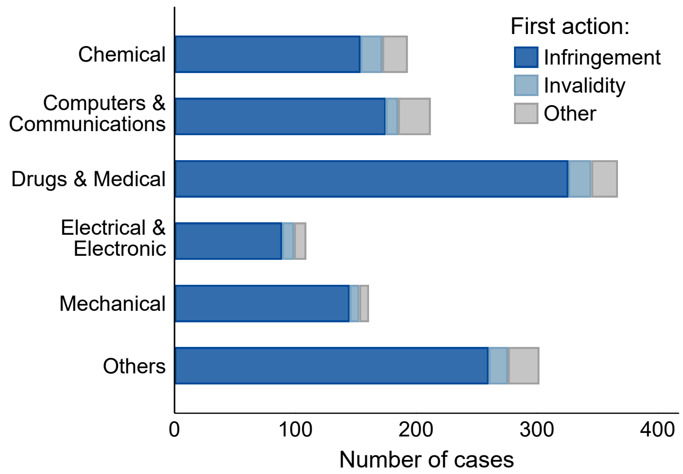
In summary, despite the markedly different setting, we successfully replicate several key findings from GS2015.

Table E-2: Institutional and econometric comparison with GS2015

	GS2015	This study
Institutional context		
Institution	Court of Appeals for the Federal Circuit (CAFC)	European Patent Office (EPO)
Geographical jurisdiction	United States	EPC member states (Europe)
Patents	Granted by USPTO	Granted by EPO
Type of proceeding	Civil proceeding	Administrative proceeding
Timing of action	No restriction	Within first 9 months after patent grant
Initiator	Patentee (82%)§	Third party (100%)§
First action	Infringement action (85%)§	Validity challenge (100%)§
Prior decision	Yes (District court/USPTO)	Yes (EPO)
Decision made by	Three judges	Three patent examiners (+ one legally qualified examiner)
Appeal possible	Yes	Yes
Litigation costs	650,000 to 5.5 million USD†	6,000 to 50,000 EUR‡
Settlement rate	$\sim$ 90% (lower court)†† / $\sim$ 20% (CAFC)‡‡	$\sim$ 12%§
Sample		
Patents	1,258	38,405
Share of granted patents	$\sim$ 0.05%	$\sim$ 6%§
Court decisions	1982-2008	1993-2013
Case to patent relationship	m:n	1:1
Econometric model		
Model	Two-stage least squares estimation	Two-stage least squares estimation
Instrumental variable	Predicted probability of invalidation	Predicted probability of invalidation
Exclusion restriction	Judge invalidity propensity	Participation of granting examiner
Citation measure		
Citation source	USPTO	EPO/WIPO
Citation origin	Applicant / examiner	Applicant / examiner
Citing patents	Granted patents and applications (post AIPA)	Granted patents and applications
Citing patent applicants	Domestic applicants	All applicants
Citation date	Filing year	(Priority) filing year
Pre-decision citation window	From grant to decision	First three years from (priority) filing
Post-decision citation window	First five years from decision	First five years from decision
Invalidation measure		
Operationalization	At least one claim invalidated	At least one claim invalidated
Invalidation rate	39%	71%
Control variables		
Patent characteristics	Claims, pre-cites, age	Claims, pre-cites, age, + various
Patentee characteristics	No	Various
Other party characteristics	No	Various
Technology fields	6 categories (Hall et al., 2001) or 36 subcategories (Hall et al., 2001)	567 categories (IPC4 classes) or 34 categories (Schmoch, 2008)
Complexity definition	Electronics, computers, medical instruments	See Von Graevenitz et al. (2013)
Time fixed effects	Outcome year	Grant year, outcome year

Notes: AIPA: American Inventor's Protection Act of 1999. EPC: European Patent Convention. USPTO: United States Patent and Trademark Office. WIPO: World Intellectual Property Office. Sources: §own data, †AIPLA (2009), ‡Mejer and van Pottelsberghe de la Potterie (2012), ††Galasso and Schankerman (2010); Moore (2001), ‡‡CAFC Year Statistics.

Figure E-3: Distribution of first action types (CAFC)



Notes: The figure shows the distribution of cases by first action type and technology field (NBER technology categories). Information on the first action type was collected from Darts-IP.

Table E-3: Comparison between characteristics of EPO opposition (CAFC litigation) patents and matched controls

	Opposed (N = 36,661)			Controls (N = 183,305)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
−1st claim length	−143.30	−126.00	92.78	−159.62	−139.00	110.68	−16.33	0.000***
Claims	13.59	11.00	10.14	12.14	10.00	8.62	−1.45	0.000***
Family size	10.76	8.00	11.10	8.93	7.00	8.03	−1.83	0.000***
Inventors	2.64	2.00	1.78	2.57	2.00	1.78	−0.06	0.000***
IPC classes	2.61	2.00	2.35	2.60	2.00	2.30	−0.01	0.379
KPSS (2017) values	24.36	6.22	56.16	18.78	4.75	47.04	−5.57	0.000***
Principal component	0.18	−0.14	1.37	−0.04	−0.29	1.11	−0.22	0.000***

	CAFC (N = 1,330)			Controls (N = 6,200)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
−1st claim length	−159.43	−139.00	100.35	−174.19	−154.00	132.36	−14.76	0.001***
Claims	21.97	14.00	39.27	13.42	10.00	13.29	−8.55	0.000***
Family size	7.41	3.00	15.99	4.40	2.00	7.30	−3.01	0.000***
Inventors	2.00	1.00	1.76	2.01	2.00	1.48	0.01	0.809
IPC classes	3.03	2.00	2.95	2.44	2.00	2.31	−0.59	0.000***
KPSS (2017) values	23.02	6.36	57.96	13.47	4.50	38.16	−9.54	0.000***
Principal component	0.39	−0.07	1.70	−0.09	−0.31	1.00	−0.48	0.000***

Notes: This table presents summary statistics of patent characteristics of EPO opposition (CAFC litigation) patents and matched control patents. Patents are matched on the (priority) filing year and the IPC4 technology class. Only granted patents are considered. Claims information for US patents before 1976 is not available. Patents with fewer than five controls in the respective strata are excluded. The unit of observation is at the patent level. Reported p-values are based on an unpaired t-test. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table E-4: Effect of patent invalidation on follow-on innovation – discrete and complex technology fields

	(1)	(2)	(3)	(4)	(5)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS
Dep var			log(Citations)		
Sample: Complex tech	All	Value (PC1) ≥ p30	Value (PC1) ≥ p60	Value (PC1) ≥ p90	Infringement
Invalidated (d)	0.055	0.039	0.125	0.434	0.648*
	(0.110)	(0.128)	(0.162)	(0.299)	(0.337)
Covariates	Full (TF34)	Full (TF34)	Full (TF34)	Full (TF34)	Full (TF34)
Dep var mean	0.42	0.46	0.51	0.62	0.63
Underidentification test	68.1	58.9	69.6	27.7	21.6
Weak identification test	203.2	159.8	99.5	34.7	22.4
Observations	17,624	12,521	7,212	1,955	1,259
	(6)	(7)	(8)	(9)	(10)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS
Dep var			log(Citations)		
Sample: Discrete tech	All	Value (PC1) ≥ p30	Value (PC1) ≥ p60	Value (PC1) ≥ p90	Infringement
Invalidated (d)	0.257***	0.245**	0.414***	0.494	−0.091
	(0.091)	(0.102)	(0.134)	(0.372)	(0.201)
Covariates	Full (TF34)	Full (TF34)	Full (TF34)	Full (TF34)	Full (TF34)
Dep var mean	0.40	0.43	0.47	0.55	0.56
Underidentification test	162.5	146.4	97.3	16.2	57.5
Weak identification test	268.8	232.0	148.5	21.3	65.0
Observations	20,781	14,666	8,419	2,197	1,098

Notes: Columns (1) to (5) and (6) to (10) correspond to the 2SLS regression specifications in Table 2, column (4), with technology field fixed effects. The value subsamples are restricted to patents with a patent value (based on the principal component of claims, IPC classes, and family size) in the stated percentile range. The value distribution is stratified by year and technology field. The infringement subsample consists of patents that could be linked to infringement disputes. The classification of technology areas into discrete and complex follows Von Graevenitz et al. (2013). One is added to all citation variables before taking the logarithm to include patents without citations. In each 2SLS regression, the "Invalidated" dummy is instrumented with the corresponding probability predicted by a probit regression on the "Examiner participation" dummy and all other exogenous variables. The underidentification and weak identification tests are the heteroskedasticity-robust Kleibergen and Paap (2006) rk LM and Wald F statistics, respectively, as reported by Stata's ivreg2 command (Baum et al., 2010). A comprehensive list of the control variables can be found in Appendix Table B-1. Robust standard errors are presented in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

F Institutional Details

F.1 Examination

The majority of patent applications at the EPO are based on national first filings or international PCT filings (see Harhoff and Wagner (2009) for a detailed description). Only a small share of filings takes the EPO as its priority office. Publication of patent applications occurs at the EPO (as in many other patent authorities) almost exactly 18 months after the priority date; the publication of the patent document is usually accompanied by the EPO Search Report. In the case of PCT filings, which are published by the World Intellectual Property Organization (WIPO), an International Search Report is generated by an International Search Authority (ISA). Most International Search Reports are actually generated by the EPO. While the patent application may contain many references to prior art inserted by the applicant, only the prior art listed in the search report is relevant for the examination process. The examiner controls the selection of prior art references, including those already listed by the applicant, but also generates references via her own search efforts.

Within six months after the publication of the search report compiled by the patent office, the patent applicant has to request examination of the patent application. If the applicant fails to do so, the application is deemed to be withdrawn. With the end of the search procedure, the responsibility for examining the application passes internally from the receiving section to an appointed examining division, which consists of a primary examiner, a secondary examiner, and the chairman. The primary examiner assesses whether the application and the invention meet the requirements of the European Patent Convention and whether the invention is patentable based on the search report. The primary examiner then either grants the patent directly, contingent on the approval by the other two members of the division, or requests a reply from the applicant that addresses the objections raised in the search report. If the objections are successfully overcome by the applicant, the primary examiner sends the version in which he intends to grant the patent, including his own amendments, to the applicant. After the applicant's approval and the completion of formalities (e.g., fee payments, the provision of translations), the grant of the patent is published. The publication date of the B1 document is the official grant date of the patent.

Currently, it takes on average more than four years from the filing of the application to the final decision on the grant of the patent (Harhoff and Wagner, 2009). Since the grant comes along with validation fees and costly translations into national languages, some applicants deliberately delay the examination process. Other applicants are interested in fast resolution of the patent examination and file a request for accelerated examination (about 12% of opposed patents).

F.2 Opposition

The examiner's decision to grant the patent can be opposed by any party except the patentee herself. The opposition may be filed on the grounds that the subject matter is not new or inventive, the invention is not sufficiently disclosed, or the granted patent extends beyond the application's content as filed. In the case of multiple independently filed oppositions, all objections are dealt with in one combined proceeding.

The opposition division, which consists of three technically qualified examiners, hears the case. Case law has established that the patentee and the opponent cannot object to the appointment of a particular examiner in the opposition division. The opposition division's decision can, in principle, be appealed on the ground of a suspected lack of impartiality among the division members. However, there are only very few cases where this has occurred, and these cases typically refer to different allegations than the involvement in the previous grant decision. If appointed, the granting examiner participates as one of the three members of the opposition division with an equal vote on the patent's validity.

The opposition proceeding involves the exchange of communications between the patentee and the opponent. The patentee can propose amendments to the description, claims, and drawings of the patent. An oral proceeding is summoned if requested by one of the parties, including the opposition division itself. Despite being optional, the oral proceeding before the opposition division is a rarely omitted part of the opposition procedure. About 90% of all oppositions conclude in a decision by the opposition division.

On average, about three years after the grant, the opposition division rules the opposed patent as either fully valid, valid but in amended form (i.e., with a narrowed scope), or invalid. Amended patents typically have a reduced number of claims, which narrows their scope. The patentee and the opponent can appeal the opposition division's decision at the EPO's Boards of Appeal. Almost half of all opposition decisions are appealed, but the reversal rate is low (7%).

G Collection of Examiner Information

As explained in Section 3, we use the presence or absence of the primary examiner in the opposition division as an instrument to allow for causal inference concerning follow-on innovation for the sample of all opposed EP patents between 1993 and 2012. For this purpose, we first identify the relevant set of patents by the EPO PATSTAT Register – 2015 Autumn Edition. Second, to determine the names of the examination and opposition division's members, we download three types of (scanned) pdf-documents from the European Patent Register for each of the identified patents: the grant decision for the examination division and the minutes of the oral proceedings as well as the opposition outcome decision for the opposition division.[58] We use two types of documents for the latter to reduce the likelihood of errors. Third, we extract and pre-process the image files included in the pdf-files and read the contained information to txt-files using optical character recognition (OCR) software. Fourth, using a keyword search specific to each document type and language, we identify and parse the names of the respective division's members to a standardized format with first and last names separated. Fifth, we check whether one person is a member of both the examination and the opposition division by comparing the names of both divisions with different string similarity measures.

Two aspects are worth noting. First, using both the minutes of the oral proceedings and the opposition decision document to identify the opposition division is justified since the division holding the oral proceedings must be the same as the opposition division rendering the decision in writing. Otherwise, the decision is deemed to be void.[59] Second, in some cases, we are unable to identify all relevant members, for example, because the EPO database holds the wrong document under the specific link, and in some cases, we might erroneously identify the substantive examiner as being present or absent, for example, because the scanned document and thus the OCR is of poor quality. However, the read-out quality and success do not depend on the outcome of the opposition since the corresponding decision document has the same format across all three outcomes and thus does not affect identification.

[58]The European Patent Register provides access to digital documents in the public part of a patent file (also known as online file inspection or "file wrapper"). The documents are grouped by procedural stage and include the full written correspondence between the EPO, the applicant, and the opponent. Outgoing communications become available online on the day after the date of dispatch. Incoming communications become available once the filed document has been coded by the EPO.

[59]See for instance T 390/86 with a decision from 17 November 1987.

Table G-1: Overview and definition of samples

Sample definition	N	%
All patents with filed opposition and grant date 1993-2012	54,023	100.00%
− destroyed files	8	0.01%
− unavailable files	150	0.28%
⇒ **available in online file inspection register**	53,865	99.71%
− no readable examiner information	1,203	2.23%
⇒ **with examiner information**	52,662	97.48%
− patent holder requests revocation	2,221	4.11%
− patent holder withdraws patent	514	0.95%
− opponent withdraws opposition	4,057	7.51%
− no readable opposition information	362	0.67%
− opposition proceeding still pending	1,130	2.09%
⇒ **with opposition division information**	44,378	82.15%
− first decision after 2013	5,913	10.95%
⇒ **sample of analysis**	38,405	71.09%

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