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To cite this article:
Fabian Gaessler; , Dietmar Harhoff; , Stefan Sorg; , Georg von Graevenitz (2025) Patents, Freedom to Operate, and Follow-on Innovation: Evidence from Post-Grant Opposition. Management Science 71(2):1315-1334. https://doi.org/10.1287/mnsc.2019.02294

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https://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Vol. 71, No. 2, February 2025, pp. 1315–1334
ISSN 0025-1909 (print), ISSN 1526-5501 (online)



# Patents, Freedom to Operate, and Follow-on Innovation: Evidence from Post-Grant Opposition

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**Received:** August 26, 2019
**Revised:** April 5, 2021; July 3, 2022; August 28, 2023
**Accepted:** September 4, 2023
**Published Online in Articles in Advance:** May 8, 2024

**https://doi.org/10.1287/mnsc.2019.02294**



**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.

**History:** Accepted by Ashish Arora, entrepreneurship and innovation.



**Funding:** This work was supported by the Deutsche Forschungsgemeinschaft [Collaborative Research Center TRR 190]. F. Gaessler acknowledges financial support from the Spanish Agencia Estatal de Investigación through the Severo Ochoa Programme for Centres of Excellence in R&D [Barcelona School of Economics CEX2019-000915-S].

**Supplemental Material:** The online appendices and data files are available at https://doi.org/10.1287/mnsc.2019.02294.

**Keywords:** follow-on innovation • freedom to operate • licensing • patents • opposition

## 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 (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 nonexclusive 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 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 (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 nonexclusive licensing postvalidity 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). 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 use 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 with 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 Galasso and Schankerman (2015) for patents challenged within U.S. 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 (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, intellectual property (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 (Moreira et al. 2020, de Bettignies et al. 2023).

Finally, we establish FTO as a key consideration in a firm's decision to innovate. Although the literature on innovation and IP strategy sporadically refers to FTO (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 Online 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. 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 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, that is, "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" (Kowalski 2007, p. 1329).[2] Firms without FTO are discouraged from pursuing follow-on innovation due to the risk of patent infringement, costly litigation, and damage payments.[3]

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, and (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 $\rho$ 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 use 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.

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 (Leone and Reichstein 2012, Ambashi et al. 2019). 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.

### 2.2.1. Stage 2: Licensing and Follow-on Innovation.

In the decision to license out, the patentee considers expected profits from three mutually exclusive outcomes: (i) with probability $\rho$, the patentee innovates and obtains $\pi_p$, (ii) with probability $n \cdot \rho$, one of $n$ licensees innovates and the patentee obtains $\pi_l$, or (iii) with probability $1-[n+1]\cdot\rho$, there is no follow-on innovation and the patentee obtains $\pi_s$. 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.

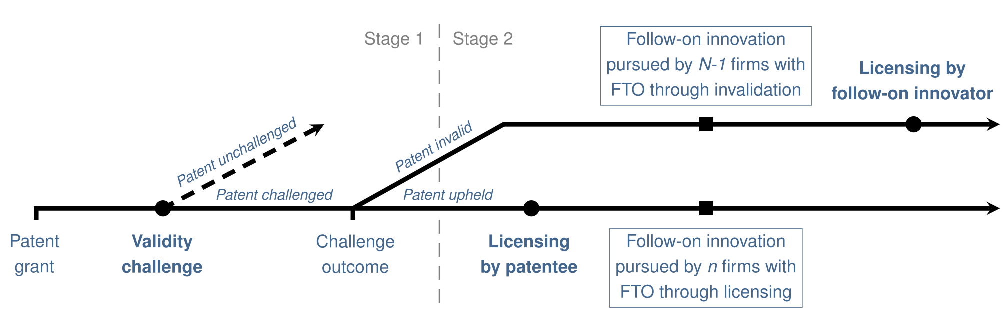
The patentee selects the number of licenses, $n$, that maximize the expected value of licensing, $V$:

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

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

**Figure 1.** (Color online) Structure of the Licensing Model with Validity Challenge




*Notes.* This figure illustrates the structure of a model of nonexclusive 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 nodes 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: $n$. The patentee has FTO in either scenario. We focus on the change in FTO as a result of invalidation.

licensing:

$$V = \underbrace{\pi_s(n, v^o) - nT}_{\textit{static return}} + \underbrace{\begin{matrix}\rho \cdot ([\pi_p(n, v^f) - \pi_s(n, v^o)] \\ + n[\pi_l(n, v^o, v^f) - \pi_s(n, v^o)])\end{matrix}}_{\textit{dynamic return}} - H.$$

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 2(a) 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 $v^o$.

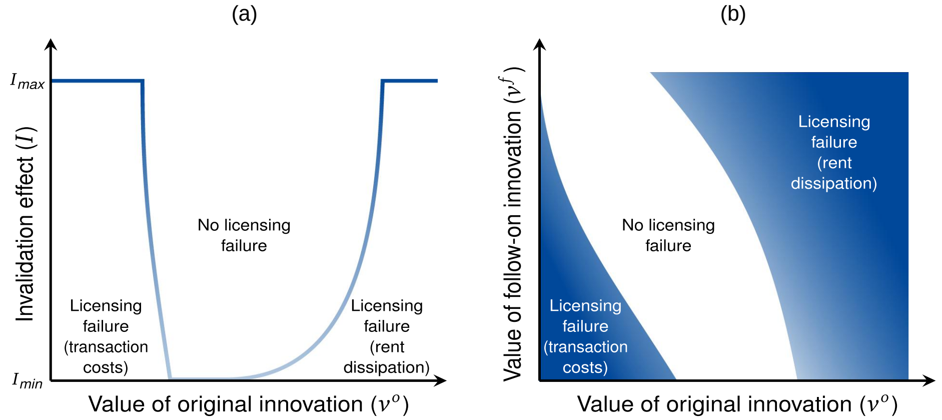
Figure 2(b) illustrates how the strength of the invalidation effect $I$ varies with $v^o$ and $v^f$ in combination. It shows that a higher $v^f$ makes licensing failure due to transaction costs less likely, as the dynamic return compensates for a negative static return. This weakens $I$ at low $v^o$.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

#### 2.2.1.1. 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]

##### 2.2.1.1.1. 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. Although 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]

##### 2.2.1.1.2. (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 the patentee's product market revenues. However, it still influences the patentee's

**Figure 2.** (Color online) Licensing Failure and Invalidation Effect




*Notes.* (a) By value of original innovation. (b) By value of original and follow-on innovation. These figures illustrate the relationship between the invalidation effect ($I$) and the value of the original innovation ($v^o$) (panel (a)) and between $I$, $v^o$, and the value of the follow-on innovation ($v^f$) (panel (b)). $I$ increases with the number of unlicensed firms that would obtain FTO only through patent invalidation (Equation (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 shadings indicate a stronger invalidation effect.

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 $v^o$.

**2.2.2. 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 tradeoffs. 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 tradeoffs 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]

### 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.

**2.3.1. 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 2(a), Prediction 2 follows from Figure 2(b), and Prediction 3 follows from the extensions discussed previously. 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.

**2.3.2. 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. Last, we will use 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, and 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 EPO. Within the first nine 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. 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.

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. Online 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 United States (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 Online 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 (Galasso and Schankerman 2015, 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, 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 semielasticities. 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]

**3.5.1. Invalidation.** We create a binary variable ("invalidated") equaling one for the opposition outcomes "invalid" and "valid but in amended form" and zero for "valid" with a mean of 0.71. This operationalization follows Galasso and Schankerman (2015). Our main results are robust to alternative operationalizations.

**3.5.2. 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]

**3.5.3. 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 previous 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.

**3.5.4. 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 Online Appendix B, 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]

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, due to *confirmation bias*, may be more inclined to reaffirm the patent's validity, making it challenging for the opponent to convince the examiner 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*, leading to a tendency to adhere 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 biannual 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 versus number of correct granting decisions), it is possible that the examiner 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 Online 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 demonstrate the robustness of our main results to the inclusion of technology class-year, examiner, and examiner-year fixed effects.

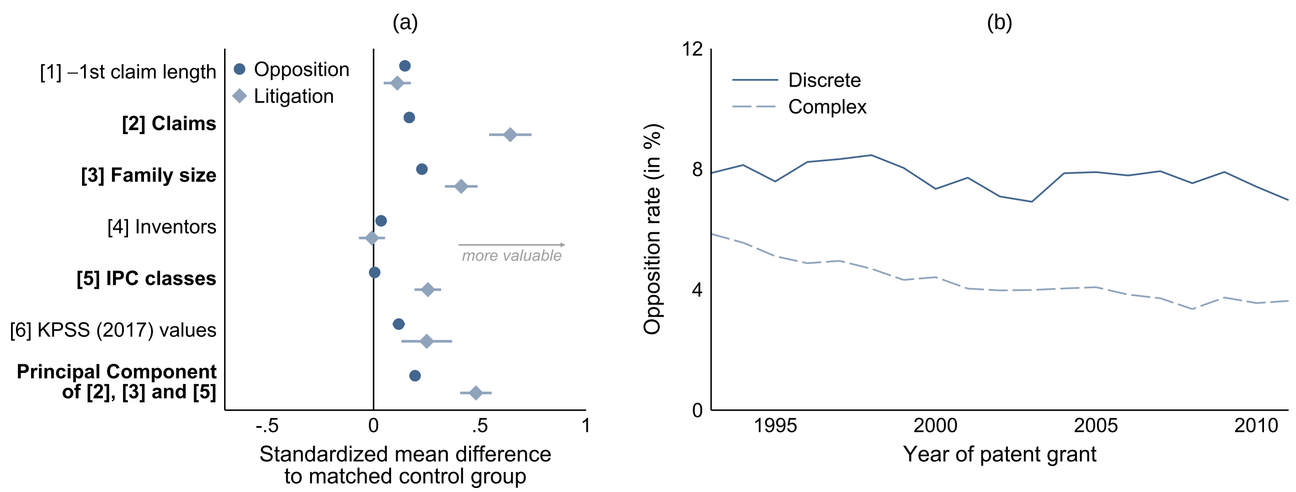
### 3.7. Sample

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 3(a), 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' first 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 3(a), we

**Figure 3.** (Color online) Patents Selected into Opposition




*Notes.* (a) Patent value. (b) Opposition rates over time. Panel (a) shows the standardized mean differences between EPO opposition (and U.S. 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 Online Appendix E, 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. Panel (b) 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).

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 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.

Opposition rates differ noticeably between discrete and complex technologies (Figure 3(b)). 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% versus 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 are a cross section where the unit of observation is the unique patent $p$. Our basic empirical specification is

$$\begin{aligned}\log(Citations_p) &= \beta_0 + \beta_1\,Invalidated_p + \beta_2\,Patent\ thicket\ density_p \\ &\quad + \boldsymbol{\beta_3}\,\boldsymbol{Patent_p} + \boldsymbol{\beta_4}\,\boldsymbol{Patentee_p} + \boldsymbol{\beta_5}\,\boldsymbol{Opponent_p} \\ &\quad + \boldsymbol{\beta_6}\,\boldsymbol{Age_p} + \boldsymbol{\beta_7}\,\boldsymbol{Year_p} + \boldsymbol{\beta_8}\,\boldsymbol{Tech_p} + \epsilon_p. \qquad (3)\end{aligned}$$

The dependent variable captures the number of citations within the first five years after the opposition outcome. The coefficient $\beta_1$ 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 $\boldsymbol{x}$:

$$Invalidated_p = \alpha_1\,Predicted\ probability_p + \boldsymbol{\alpha x}_p + u_p$$

$$\log(Citations_p) = \beta_1\,\widehat{Invalidated}_p + \boldsymbol{\beta x}_p + \epsilon_p. \qquad (4)$$

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 (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).

Although 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 10 years before the decision outcome. Online Appendix D provides further details.

## 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 ordinary least squares (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

**Table 1.** Examiner Participation and Patent Invalidation

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Estimation method | Probit | Probit | Probit | Probit |
| Dependent variable | | | *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 × year | Exam. × year |
| Dependent variable mean | 0.71 | 0.71 | 0.70 | 0.61 |
| Model degrees of freedom | 1 | 588 | 3,458 | 4,998 |
| $\chi^2$ 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 Online Appendix B, Table B.1. Robust standard errors are presented in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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) 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

**Table 2.** Effect of Patent Invalidation on Follow-on Innovation

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Estimation method | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| Dependent variable | | | *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 |
| Dependent variable 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 five-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 Online Appendix B, Table B.1. Robust standard errors are presented in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

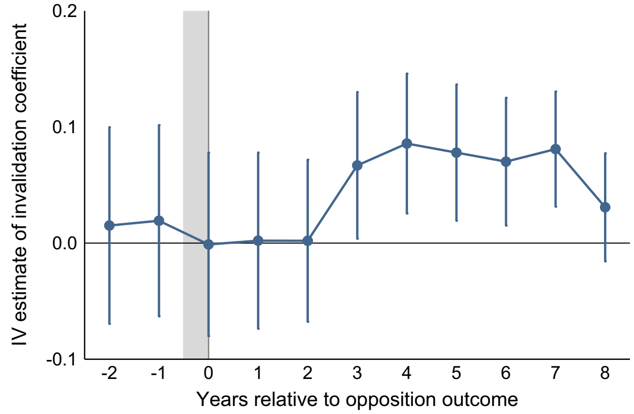
2SLS regression, an increase of one standard deviation in the patent thicket density lowers the invalidation effect on citations by about 0.16. The negative coefficient of the thickets interaction is in line with our reasoning that, in the case of overlapping patent rights, firms do not necessarily obtain 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 Online 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 United States Patent and Trademark Office (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 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 citations 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 (Galasso and Schankerman 2015). 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.

**Figure 4.** (Color online) 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).

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.

### 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.

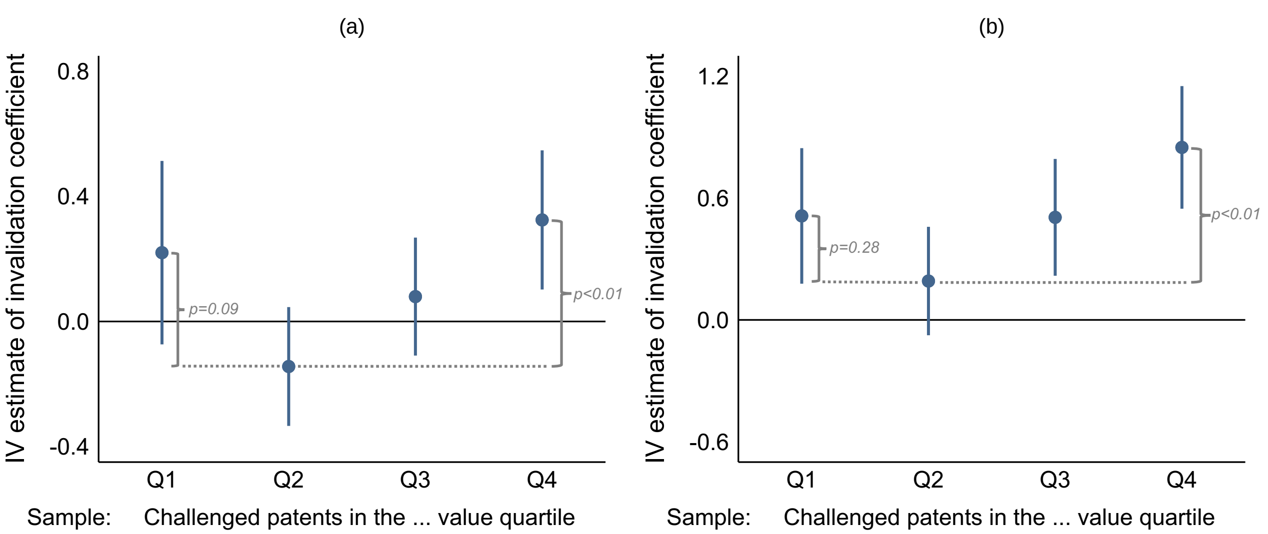
To discern whether the invalidation effect in our sample can be explained by licensing failure due to transaction costs or rent dissipation, we probe the relationship between the invalidation effect and the value of the original innovation. For this purpose, we leverage our sample's substantial heterogeneity 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 5(a), 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 (Galasso and Schankerman 2015). 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 5(b)). 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 versus 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 Online Appendix C.2). First, we find a similar albeit less marked pattern when measuring patent value through other (noncomposite) 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 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

**Figure 5.** (Color online) Effect of Patent Invalidation on Follow-on Innovation: Original Innovation Value




*Notes.* (a) IV estimates. (b) IV estimates with patent thicket interaction. 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 Online Appendix C, Table C.8). The corresponding regression results are in Online Appendix C, Table C.7.

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

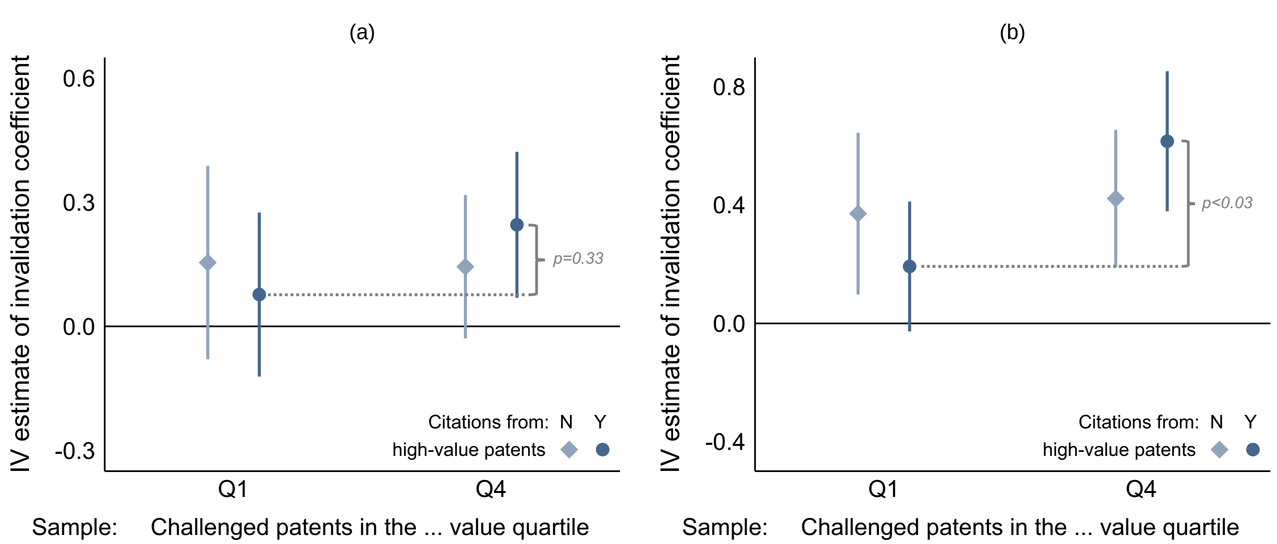
In our theoretical framework, we posit that not only the value of the original innovation but also the prospect of a valuable follow-on innovation influences the extent of licensing failure and, consequently, the invalidation effect. Specifically, we predict that for high-value follow-on innovations, 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 Online 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 6(a)). When controlling for patent thickets surrounding the challenged patents, we find a substantially larger difference in effect sizes (Figure 6(b)). 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 versus 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 versus 0.37).

Although 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 Online Appendix C.3). Using different patent value indicators (patent family size, patent claims, IPC classes) to measure the

**Figure 6.** (Color online) Effect of Patent Invalidation on Follow-on Innovation: Original and Follow-on Innovation Value




*Notes.* (a) IV estimates. (b) IV estimates with patent thicket interaction. 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 Online Appendix C, Table C.16). The corresponding regression results are in Online Appendix C, Table C.15.

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.

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

Last, 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.

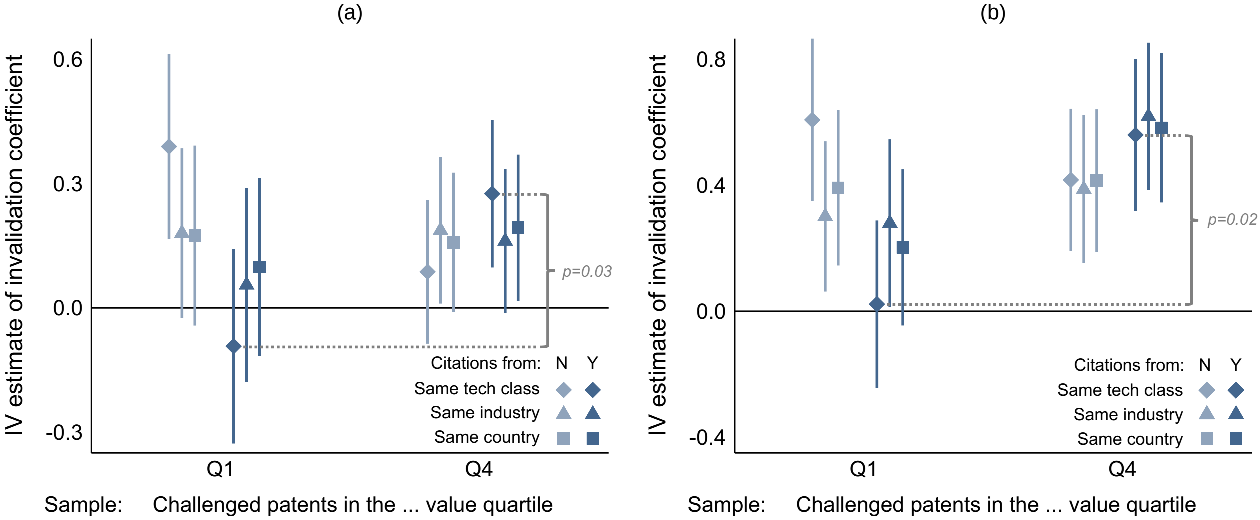
We find that the invalidation effect on citations, in the presence of product market competition between the patentee and follow-on innovators, is distinctly stronger for patents in the top value quartile than those in the bottom value quartile. Citations from the same technology class exhibit a noticeably larger invalidation effect (0.28 versus $-0.1$, $p = 0.03$). 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 7(a)). That said, the differences become substantially larger across all three indicators when controlling for patent thicket density (Figure 7(b)). 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 versus 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 Online 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 if transaction costs erode the surplus of licensing; that is, where innovation value is low compared with 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 previous 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

**Figure 7.** (Color online) Effect of Patent Invalidation on Follow-on Innovation: Original Innovation Value and Product Market Competition




*Notes.* (a) IV estimates. (b) IV estimates with patent thicket interaction. 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 patents share the same primary IPC4 technology code. Citations from the same industry are defined as those where both patentees share the same three-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 Online Appendix C, Table C.20). The corresponding regression results are in Online Appendix C, Tables C.18 and C.19.

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 Galasso and Schankerman (2015), 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 with Galasso and Schankerman (2015). Although 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 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.

## Acknowledgments

The authors thank Ashish Arora for invaluable guidance throughout the review process; the associate editor and three reviewers for constructive comments and suggestions; Alberto Galasso, Klaus Gugler, Peter Haan, Christian Helmers, Jussi Heikkilä, Robin Mamrak, Yassine Lefouili, Yann Ménière, Maikel Pellens, Bhaven Sampat, Mark Schankerman, Tetsuo Wada, and Stefan Wagner for feedback on the paper; and participants for comments at the 16th Roundtable for Engineering Entrepreneurship Research (REER) Conference, the Annual Meeting of the Committee for Industrial Economics, the ZEW/MaCCI Conference on the Economics of Innovation and Patenting, the Strategy, Entrepreneurship and Innovation (SEI) Faculty Workshop, the Munich Summer Institute, the Annual Meeting of the Academy of Management, the Searle Center/United States Patent and Trademark Office Conference on Innovation Economics, the Boston University IP Day, the Intellectual Property Statistics for Decision Makers (IPSDM) Conference, and the Centre for Competition Policy (CCP) Annual Conference. Earlier versions of this paper circulated under the title "Patents and Cumulative Innovation–Evidence from Post-Grant Patent Oppositions" and "Bargaining Failure and Freedom to Operate: Re-evaluating the Effect of Patents on Cumulative Innovation."

## Endnotes

[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." In 2015, SAP announced a broad cross-licensing agreement with Google that should "increase freedom to operate and prevent distractions from unnecessary patent litigation."

[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] 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.

[4] For simplicity, we assume that $\rho$ is exogenous here. This excludes potential externalities that might arise from firms' decisions to pursue follow-on innovation, as suggested by "prospect theory" (Kitch 1977, Merges and Nelson 1994). In the Online Appendix, we allow that $\rho$ 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.

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

[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 ($\rho$) has to decrease in $n$, as discussed in Online Appendix A. This implies that $n$ also decreases the probability that the patentee innovates. Our results encompass this dependency.

[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.

[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 (Galasso and Schankerman 2015).

[16] In practice, it is likely that the overall probability of follow-on innovation, $\rho$, 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.

[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%).

[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 three digits and relate to manufacturing activities. The NACE codes are a European Industry standard classification system with a four-digit hierarchy.

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

[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. Although 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 Online 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.

[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.

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

[26] This reduces our sample by about 17% per year (see Online Appendix G, 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 Online Appendix B, 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 (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 Online Appendix B, Table B.2).

[30] This sample approximates the one used by Galasso and Schankerman (2015). It is based on patent litigation cases at the U.S. Court of Appeals for the Federal Circuit (CAFC) with a decision between 1983 and 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. Because 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.

[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.

[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.

[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 5(b).

[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.

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

[38] In fact, Galasso and Schankerman (2015) 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 Online 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.

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