Intangible Capital and Leverage*

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Abstract

This study investigates the causal effect of intangible capital on leverage. We use court invalidations of patents by the U.S. Court of Appeals for the Federal Circuit as a proxy for reductions in intangible capital and mitigate endogeneity concerns by exploiting random assignment of judges to court cases. Using an instrumental variable research design, we show that a loss of intangible capital causes a reduction in a firm's leverage. The effect is stronger for firms with low interest coverage, high proximity to default and small firm size, and if an invalidated patent is pledged as collateral.

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Introduction

How do intangible assets affect firms' capital structure? Addressing this question is crucial for a thorough understanding of corporate financing behavior given the growing importance of intangible capital such as human capital, patents or brands in today's developed economies[1]. While existing empirical and theoretical work documents a positive (negative) association between asset (in)tangibility and leverage (see e.g., Falato, Kadyrzhanova and Sim, 2013; Frank and Goyal, 2009; Graham and Leary, 2011; Rajan and Zingales, 1995; Rampini and Viswanathan, 2013; Shleifer and Vishny, 1992), Graham, Leary and Roberts (2015) note that the tangibility-leverage relationship is incomplete[2]. Motivated by the growing importance of intangible capital, this paper aims at improving our understanding of how intangible assets shape leverage by studying how firms adjust leverage after a loss of intangible capital.

Endogeneity is a major obstacle that any investigation of the effect of intangible capital on leverage must deal with. Firms choose their amount of intangible capital by investing in research and development (R&D) or employee training. An unobservable variable (such as managerial risk aversion) affecting a firm's choice of intangible capital could potentially also affect a firm's choice of leverage, thereby challenging a causal interpretation of an empirically documented correlation between intangible capital and leverage. Causal inference is also troubled by a potential reverse effect of leverage on intangible capital. For instance, firms might raise debt to purchase intangible assets. In addition to endogeneity, our study also needs to address the measurement challenge inherent to intangible capital. Measuring a firm's intangible capital is non-trivial because the values of firms' intangible assets are generally unknown. Accounting assets do not appropriately reflect firms' intangible assets (Barth,

[1] For evidence on how business investment in the United States has continuously moved away from tangible capital towards intangible capital since the end of World War II, see for instance Corrado and Hulten (2010).
[2] Graham et al. (2015: 669-670) note: "Asset tangibility, despite large fluctuations in the 1940s and 1950s, generally declined over the century. Not only does this pattern miss some of the important turning points in leverage, it is also difficult to reconcile with existing empirical evidence (e.g., Frank and Goyal, 2009) and theory (e.g., Shleifer and Vishny, 1992), which suggests that decreasing asset tangibility decreases debt capacity because there is less collateral to secure debt."

Kasznik and McNichols, 2001; Corrado and Hulten, 2010; Myers, 1984). Proxies based on R&D expenses contain significant measurement errors, since firms which do not report R&D can still be highly innovative (Koh and Reeb, 2015), and studies using fair values of intangible assets disclosed in M&A transactions might be prone to selection bias (e.g., Lim, Macias and Moeller, 2016).

To overcome these endogeneity and measurement issues, we exploit an approach proposed by Galasso and Schankerman (2015a). We use patent invalidations at the United States Court of Appeals for the Federal Circuit (CAFC) as negative shocks to firms' intangible capital and study how firms adjust leverage subsequent to such a decrease in intangible capital. The CAFC has the nationwide jurisdiction to hear patent case appeals, including cases of patent validity. Patent validity is usually challenged by alleged patent infringers as a defense. For instance, an alleged infringer might claim that a patent violates the novelty condition for patentability (35 U.S. Code, section 102). If a patent is invalidated[3], the patentee loses the commercial privileges previously conferred to her by the patent. Since the patents whose validity is disputed before the CAFC are more valuable than average patents (Galasso and Schankerman, 2015a), and given the legal expenses from litigation which firms are willing to incur when escalating cases to the CAFC, it is reasonable to assume that losing a patent before the CAFC represents a substantial loss of intangible capital for a firm.

The instrumental variable (IV) we use for patent invalidation exploits institutional circumstances at the CAFC. According to court rules, three judges are randomly assigned to a case by a computer program. Since the judges have different attitudes towards patent validity, the probability that a patent is invalidated can be predicted from the judges' historical patent

[3] Technically, the CAFC only invalidates specific claims of a patent, not a patent in its entirety. For ease of exposition, we use the terms "patent validity" and "patent invalidation" instead of "patent claim validity" and "patent claim invalidation".

validity votes, once the three judges are known[4]. Since judges are randomly assigned to cases, the predicted invalidation represents an exogenous instrument for patent invalidation (Galasso and Schankerman, 2015a). The instrument, judges' invalidation propensity (*JIP*), meets both conditions needed for a valid instrument. It satisfies the relevance condition following the tests of Staiger and Stock (1997) and Stock and Yogo (2005). It also satisfies the exclusion restriction, which requires that *JIP* affects leverage only through its effect on patent invalidation: Since *JIP* is computed from the individual patent invalidation probabilities of the three judges randomly assigned to a court case, *JIP* is a random variable itself, and should therefore only correlate with patent invalidation. Our use of *JIP* as an instrument for patent invalidation allows us to investigate the causal impact of patent invalidation on leverage.

Our main result shows that across our sample of US-listed public firms which engage in patent litigation at the CAFC, the loss of a patent causes a statistically significant reduction in subsequent leverage. The result is robust to the inclusion of industry and year fixed effects, to the use of a variety of alternative definitions of leverage encountered in the literature, to the inclusion of different control variables and to changes in the model specification. Since our research design allows us to capture the variation in invalidation arising from the random assignment of judges, the results from this test allow for a causal interpretation of the effect of patent invalidation on leverage. When we compare the results obtained using the IV research design with the result from a naïve OLS regression that simply correlates patent invalidation with leverage, the importance of appropriately dealing with endogeneity is striking. In the naïve OLS specification, which assumes that the patent validity decision is exogenous, the regression coefficient for patent invalidation is small and not significantly different from zero.

[4] There is evidence suggesting that the CAFC itself beliefs that panel composition could predict case outcome: In a pilot program from December 2004 to February 2006, panel composition was announced on Thursdays before the week of the court hearing. The goal of the early panel composition announcement was to reduce case load by encouraging out of court settlement (Jordan, 2007). Except during the 15-month period of the pilot program, the firms in our sample could not predict case outcome from panel composition, as the CAFC announced panel composition only on the day of the court hearing. Note that our findings persist if we exclude the 29 court decisions made during the mentioned pilot program from the analysis.

Of course, endogeneity likely leads to a biased regression coefficient of patent invalidation, masking the causal negative effect of patent invalidation on leverage.

We also exploit heterogeneity in various firm characteristics among our sample firms to better understand how patent invalidation causes lower leverage. We find that the leverage-reducing effect of patent invalidation is stronger for firms with lower interest coverage and lower distance to default. For firms which find it more difficulty to finance debt, intangible capital seems to be a more important support for leverage. The leverage ratio of small firms decreases more after a patent invalidation, possibly because a patent invalidation represents a relatively larger shock to intangible assets. Lastly, the negative effect of patent invalidation on leverage is more pronounced for firms which actively use patents as loan collateral.

The main innovation of our paper is to provide evidence of a causal effect of intangible capital on capital structure. In doing so, we contribute to four streams of the existing literature. First, we extend the growing area of capital structure research studying how capital structure decisions are shaped by specific factors such as corporate taxes (e.g., Heider and Ljungqvist, 2015), unemployment benefits (e.g., Agrawal and Matsa, 2013) or firing costs (Serfling, 2016). More generally, we extend previous research on the determinants of capital structure (e.g., Frank and Goyal, 2009; Graham et al., 2015; Leary and Roberts, 2014; Lemmon, Roberts and Zender, 2008; Rajan and Zingales, 1995; Titman and Wessels, 1988) by showing that variation in intangible capital can explain some of the variation in leverage. By documenting that, at least for firms valuing their intangible capital in the form of patents enough to go to court to defend them, intangible capital affects leverage in a way similar to tangible capital, our result presents one possible explanation for the incomplete tangibility-leverage relationship mentioned in Graham et al. (2015). To overcome the endogeneity concerns inherent in an analysis of leverage determinants, we exploit an identification strategy that allows us to draw plausibly causal conclusions regarding the effect of a loss of intangible capital on leverage. In doing so, our paper also contributes to the results of Lim et al. (2016), who document a positive correlation between intangible capital and leverage among a group of acquired companies. We also add to Larkin (2013), who presents a negative link between brand value and cash flow volatility, using proprietary survey-based data on customers' brand perception. Her paper provides evidence that brands, another type of intangible assets, can increase debt capacity and leverage.

Second, we extend the literature on how patents affect firms' access to financing. Farre-Mensa, Hegde and Ljungqvist (2016) show that for start-up firms, obtaining a patent for the first time increases the likelihood of securing funding from professional investors by 53% over the three years following patent approval. The contribution of our paper is to show that for mature (i.e. non-start-up) firms with an existing patent portfolio, the exogenous loss of a patent has a negative causal effect on leverage. Mann (2016) exploits four federal court decisions on patent ownership rights during bankruptcy as a source of exogenous variation in creditor rights, to study how changes in the extent to which patents can be used as loan collateral affect leverage. He documents a positive effect of the degree of patent "pledgeability" on the use of patents as collateral and on leverage. In contrast, our paper investigates how the exogenous loss of a patent (as a proxy for intangible capital), not a change to existing patent pledgeability, affects subsequent capital structure. By documenting how intangible capital affects firms' use of debt, we also add to a recent study by Chava, Nanda and Xiao (2016) who show that increases in patent protection and creditor rights over collateral result in cheaper bank loans, possibly because lenders value innovative activity.

Third, by exploiting the random assignment of judges to cases at the CAFC, we expand the number of empirical studies using an identification strategy based on the random assignment of experts with heterogeneous beliefs, like judges (e.g., Bernstein, Colonnelli, Giroud and Iverson, 2016; Dahl, Kostøl and Mogstad, 2014; Di Tella and Schargrodsky, 2013; Galasso and Schankerman, 2015a, 2015b), patent examiners (Farre-Mensa, et al., 2016; Sampat and Williams, 2015) or disability insurance specialists (Maestas, Mullen and Strand, 2013).

Finally, we extend the limited number of papers using hand-collected data from CAFC patent cases to study economic outcomes. Galasso and Schankerman (2015a) use patent invalidations to examine the effect of patent rights on cumulative innovation in the economy. Their paper finds that patents get cited 50% more after invalidation. In a different paper, the same authors study how patent protection affects innovation at the firm level, and find a negative impact of patent invalidation on patenting activity (Galasso and Schankerman, 2015b). In a contemporaneous corporate finance study, Caskurlu (2016) finds that alleged patent infringers increase acquisition activity after losing an infringement lawsuit, possibly to acquire substitute patents. His paper is based on patent infringement decisions and focuses on acquisition behavior, whereas our paper uses patent validity decisions to explain capital structure.

The remainder of this paper is organized as follows: Section 1 outlines the identification challenge and presents the identification strategy used in this paper. Section 2 describes the data collection process and the sample. Section 3 presents our main results, along with various robustness tests. Section 4 presents the results from tests of heterogeneous treatment effects. Section 5 concludes.

1. Identification Challenge and Identification Strategy

A simple way to study the effect of intangible capital on leverage would be to run an OLS regression with leverage as dependent variable and a proxy for intangible capital as independent variable, for instance

$$Leverage_i = \beta \; Intangible\ Capital_i + \gamma' X_i + \varepsilon_i \;, \tag{1}$$

where i indexes firms, *Intangible Capital* denotes a proxy for intangible capital, and X is a vector of control variables. The coefficient β measures the relation between leverage and intangible capital after controlling for other determinants of leverage as captured by X. But, an estimate of β is unlikely to reflect a causal effect of intangible capital on leverage as the specification might suffer from endogeneity. An unobservable omitted variable might simultaneously influence both leverage and intangible capital. For instance, a comparatively small level of managerial risk appetite could be associated with low leverage and might also be reflected in low levels of investments in intangible capital. This situation leads to a positive correlation between the error term and intangible capital, thus biasing any estimate of β upward. Reverse causality is yet another challenge to a causal interpretation of an estimate of β. In equation (1), we cannot rule out that the level of intangible capital is itself a function of the level of leverage. Consider a firm that raises a significant amount of debt with the intention of buying intangible assets. In this scenario, there will be a positive correlation between intangible capital and leverage, since the firm increases both leverage and intangible capital, but causality runs from leverage to intangible capital. To cleanly identify the causal impact of intangible capital on leverage, we need an identification strategy that rules out omitted variables and reverse causality explanations. In addition to the omitted variables and reverse causality issues, the lack of reliable measures for intangible capital poses another challenge to identification in the form of measurement error. In corporate balance sheets, many intangible assets are not shown under current accounting rules (see for instance Barth et al. 2001; Corrado and Hulten, 2010; Myers, 1984), and in income statements, R&D expenses do not necessarily reflect actual innovation (Koh and Reeb, 2015).

To target these concerns and to identify the causal effect of intangible capital on leverage, we use patent invalidations as a source of negative shocks to firms' intangible capital, and examine how firms' leverage reacts to such shocks. Our identification strategy is an instrumental variable (IV) research design introduced by Galasso and Schankerman (2015a). This research design provides a prediction of patent invalidations and exploits the fact that at the CAFC, a computer program randomly assigns three judges to court cases. The three judges decide by majority vote whether a patent should be invalidated. The instrument we use, judges' invalidation propensity (*JIP*), predicts the outcome of this vote. *JIP* is computed per patent validity decision p as

$$JIP_p = f_p^1 f_p^2 f_p^3 + f_p^1 f_p^2 \left(1 - f_p^3\right) + f_p^1 \left(1 - f_p^2\right) f_p^3 + (1 - f_p^1) f_p^2 f_p^3. \tag{2}$$

The variable f_p^X is the judge-specific patent invalidation rate for the three judges randomly assigned to each case. For every judge, f_p^X is computed as the ratio of votes in favor of patent invalidation divided by the total number of votes on patent validity during the judge's CAFC career. Following Galasso and Schankerman (2015a), we exclude the patent validity decision p itself from the computation of the ratio f_p^X to ensure that the patent validity decision p does not affect its own instrument. Thus, *JIP* is the predicted probability that the three judges will invalidate the patent.

We believe that this research design (based on the work of Galasso and Schankerman, 2015a) is suitable to investigate whether there is a causal effect of intangible capital on leverage. The random assignment of judges to validity decisions provides an instrument for invalidation which in turn represents an exogenous negative shock to firms' intangible capital. We show in Section 3 that this instrument meets both the validity and the exclusion restriction. Moreover, it is reasonable to assume that patent invalidations represent a meaningful decrease of intangible capital. The costs associated with litigation at the CAFC lead to a situation where a patentee (plaintiff) firm will only choose to defend (challenge) the validity of a patent that is considered valuable. The litigated patent is therefore economically important for at least the two litigating firms (if not for entire industries). Consistently, empirical evidence provided by

Galasso and Schankerman (2015a) shows that only more valuable patents (e.g., in terms of citations) are disputed before the CAFC.[5]

We implement the identification strategy as follows. Our final data set is an unbalanced panel where the unit of observation is a firm-validity decision[6]. The patent invalidation dummy, $Invalidated_{i,p}$, is one if the patent validity decision p invalidates a patent owned by patentee firm i, and zero otherwise. We follow Angrist and Pischke (2009) and Wooldridge (2010) and account for the binary nature of the instrumented endogenous variable by instrumenting $Invalidated_{i,p}$ with the predicted invalidation probability obtained from the probit model

$$\hat{P}_{i,p} = P(JIP_{i,p}, X_{i,p}), \tag{3}$$

where $X_{i,p}$ is a vector of control variables including industry indicators, year indicators and a set of lagged firm-level control variables. We implement our IV research design by estimating the following two-stage model with a two-stage least squares estimate (equation (4) denotes the first stage, equation (5) denotes the second stage):

$$Invalidated_{i,p} = \alpha\, \hat{P}_{i,p} + \delta' X_{i,p} + u_{i,p}, \tag{4}$$

$$Leverage_{i,p} = \beta\, \widehat{Invalidated}_{i,p} + \gamma' X_{i,p} + \varepsilon_{i,p}. \tag{5}$$

Equation (4) is an OLS regression of $Invalidated_{i,p}$, the patent invalidation dummy, on $\hat{P}_{i,p}$, the patent invalidation propensity predicted from the probit model shown in Equation (3). From this first-stage regression, we predict $\widehat{Invalidated}_{i,p}$ (i.e. instrumented patent invalidation), which we use as an independent variable in the second-stage leverage regression (Equation (5)). We measure leverage in the period following the patent validity

[5] Another concern might be that the CAFC's patent validity decision is not necessarily a final verdict, as litigants can appeal to the Supreme Court if they disagree with the CAFC's judgment. Since this option exists, it is thinkable that a firm does not actively react to the CAFC's validity decision until a final decision is taken by the Supreme Court. However, less than 1% of CAFC patent validity decisions ever reach the Supreme Court (Galasso and Schankerman, 2015a), and therefore the validity decisions by the CAFC can be considered final.

[6] We choose this unit of observation as we feel it offers the most accurate measure of patent invalidation. More aggregated units of observation lead to a noisier patent invalidation measure, because in multi-patent cases, these units of observation will rely on (somewhat arbitrarily) defined rules for aggregating validity decisions. We show in Section 3 below that our results are robust to running our analyses on firm-cases as an example of a more aggregated unit of observation.

decision because we study whether and how firms adjust their leverage in the wake of a patent invalidation. The coefficient β in equation (5) captures the causal effect of a loss of intangible capital on leverage. A negative estimate of β indicates that a loss of intangible capital leads to a reduction in leverage.

The vector of control variables $X_{i,p}$ is the same for all regressions. We control for financial variables found to be significant predictors of leverage in earlier empirical studies, such as firm size, market-to-book ratio, profitability and asset tangibility (e.g., Frank and Goyal, 2009; Leary and Roberts, 2014; Rajan and Zingales, 1995). We also include lagged leverage to control for serial correlation in leverage, following Lemmon et al. (2008). To control for industry-dependent differences across firms, we add industry fixed effects based on the Fama and French 48 industry classification. We also include year fixed effects to control for time-dependent trends in leverage affecting all firms. Since some companies experience multiple patent validity decisions, we cluster standard errors at the firm level in all regressions.

2. Data and Sample

We search the Federal Court Cases database from LexisNexis for all court opinions published between 1982 (the year the CAFC was established) and 2015 which contain the keywords "Court of Appeals for the Federal Circuit", "patent or patents" and "invalid or invalidity or unenforceable". We download the full text of the resulting 3.201 court opinions. These present the court’s official decision in a case and describe the legal principles and rationale applied by the judges. We study each court opinion and apply the following filters: 1) We only keep cases where the CAFC explicitly revisits the lower court’s decision regarding patent validity, i.e. cases where the validity of one or more patent claims is discussed and a decision is reached. 2) We eliminate opinions issued by judge panels consisting of more or less than three judges because our IV relies on judge trinomials[7]. 3) We drop opinions where the patent validity decision is unclear, for instance if the CAFC sends the case back to the lower court without instructions regarding patent validity. We compile a list of patent validity decisions contained in the remaining court opinions. For every patent validity decision, we record the following information: the patent number, the names of the three judges on the panel, whether the patent was invalidated, the name of the legal entity asserting patent validity and the date of the court opinion. Following Galasso and Schankerman (2015a), we consider a patent validity decision as invalidation if it invalidates at least one patent claim.

We merge our dataset of patent validity decisions with firm financials by manually matching the names of the legal entities asserting patent validity in the court opinions with the variable *conm* from the Annual Compustat North America database. This matching procedure results in a match for the majority of our sample, but it does not account for changes in firm names over time, because *conm* is backdated. Also, it is possible that only the parent company of a legal entity disputing patent validity at the CAFC is covered by Compustat, in which case the validity decision should be matched to the Compustat entry of the parent company. To further increase sample size, we therefore use online searches of all legal entities asserting patent validity in the validity decisions which could not be matched to Compustat entries via the *conm* variable. If a newer company name of the legal entity in the court opinion exists in Compustat, we assign the validity decision to the respective firm's Compustat entry. If we find that a legal entity in the court opinion is a subsidiary of a firm covered by Compustat, we assign the validity decision to the parent company's Compustat entry. For each matched validity decision, we add the financial information reported in the three year window around the year in which the court decision was published [-1;+1]. We use the firm financials from year *t+1* to compute the dependent variable, a measure of leverage, at the end of the first year

[7] Although the CAFC by default uses panels of three, two judges may decide in rare cases of conflicts of interest, illness or death of one judge. Other cases are decided per curiam, i.e. by all twelve judges.

after the validity decision. We require firm financials from year *t-1* to compute the lagged firm-level control variables. The one-year lag ensures that the control variables are not affected by the court decision, because the court decision is not yet known at the time when control variables are measured. Following the empirical capital structure literature, we exclude banks, insurance companies and regulated utility firms from our sample by dropping observations with four-digit SIC (*sich*) codes between 4000 and 4999 and between 6000 and 6999.

Our final sample contains 579 patent validity decisions. They are the result of 347 CAFC court cases held between 1983 and 2014. Half of the cases were heard after 2004. The validity decisions affirm or remove the validity of 518 distinct patents (514 utility patents, 4 design patents). Some patents are disputed more than once before the CAFC. Overall, 205 distinct firms are affected by the validity decisions in our sample. The firms are mainly from the pharmaceutical, electronic equipment, medical equipment and chemicals industries, which together account for 48% of sample firms. Firms in our sample experience 2.8 patent validity decisions on average.

The main variables of this paper are defined as follows. We define book leverage and market leverage, our two primary leverage indicators, as in Leary and Roberts (2014). Book leverage is total debt (long term debt (Compustat item *dltt*) plus debt in current liabilities (*dlc*)) divided by the book value of assets (*at*). Market leverage is total debt divided by the market value of assets (MVA), where MVA equals the sum of the market value of equity (common shares outstanding (*cshpri*) multiplied by the stock price at the end of the fiscal year (*prcc_f*)), total debt and the liquidating value of preferred stock (*pstkl*), minus deferred tax credits (*txditc*).

We also follow Leary and Roberts (2014) for the computation of our main set of firm-level control variables. The main control variables are firm size (defined as the natural logarithm of net sales (*sale*)), the market-to-book ratio (MVA divided by *at*), profitability (EBITDA (*oibdp*) divided by *at*) and tangibility (property, plant and equipment (*ppent*) divided by *at*). For one set of robustness tests, we compute a number of alternative dependent variables. We follow Rampini and Viswanathan (2013) by adding 10 times the value of outstanding rental expenses to both the numerator and the denominator of book and market leverage, respectively, to obtain lease-adjusted leverage ratios. Following Leary and Roberts (2014), we compute net debt issuance as the first difference in total debt divided by lagged *at*, and define firms as debt issuers if net debt issuance is above 1%. For another set of robustness tests, we compute a number of additional control variables. We compute the modified Altman (1968) Z-Score as in Leary and Roberts (2014) as the sum (normalized by *at*) of 330% of pretax income (*pi*), 100% of *sale*, 140% of retained earnings (*re*) and 120% of working capital (current assets (*act*) minus current liabilities (*lct*)). We define a firm as a dividend-payer if it pays a common dividend during the fiscal year, i.e. if the variable *dvc* is positive (see e.g., Serfling, 2016). We compute firm age as the year of the validity decision minus the first year the firm appears in Compustat (Yim, 2013).

For tests of heterogeneous treatment effects, we compute a number of additional variables. We compute interest coverage as in Agrawal and Matsa (2013), by setting negative operating income before depreciation (*oibdp*) to zero and computing the logarithm of one plus the ratio of operating income before depreciation to interest expense (*xint*). We obtain data on patent collateral from the USPTO, where lenders can publicly register the patents assigned to them under security agreements. This signals to other lenders that the patent is encumbered. For each patent in our final sample, we collect the assignment history. We identify patent collateral by scanning the assignment description for the keywords "security", "collateral", "lien" and "mortgage", following Hochberg, Serrano and Ziedonis (2014). The assignment recording date shows whether a patent was used as collateral at the time of the Federal Circuit decision. We create a dummy variable to indicate whether a patent was assigned to a lender as collateral under a security agreement at the time of the validity decision. We provide detailed variable definitions in Appendix A.

Table 1 presents summary statistics of the validity decision variables, the leverage variables and all other variables used in this paper. Panel A reports descriptive statistics of the validity decision variables. The CAFC invalidates a patent in 45% of observations. This invalidation rate is comparable to previous studies: Between 1982 and 1994, our rate is 34%, compared to 33% found in Dunner, Jakes and Karceski (1995). For the period from 1983 to 2008, 42% of validity decisions in our sample are invalidations, compared to 39% in Galasso and Schankerman (2015a). *JIP*, the invalidation rate predicted from randomly assigned three-judge panels, is 42% on average. Panel B reports descriptive statistics of various measures of firm leverage. Panel C presents summary statistics for further variables.

3. Results

Table 2 presents the main results of our empirical investigation of the effect of intangible capital on leverage. As a benchmark, we first present the results of simple OLS regressions that correlate leverage with a dummy variable equal to one if a patent is invalidated. This dummy is a proxy for a reduction in a firm's intangible capital. In Column (1), we present the result from regressing book leverage in the year after the court decision on the invalidation dummy as well as year and industry fixed effects. The coefficient of invalidation is small (0.00546) and not statistically significant, suggesting no significant correlation between patent invalidation and leverage. It could be, however, that other known determinants of leverage obscure a significant estimate of the coefficient of invalidation. In Column (2), we thus include control variables to account for observable differences in determinants of leverage across firms. The coefficient of invalidation continues to be small and statistically insignificant. This estimate confirms the result from Column (1) that the invalidation of a patent (as a proxy for a reduction in intangible capital) does not significantly affect leverage.

However, as discussed above, these OLS estimates are likely troubled by omitted variables and reverse causality issues and can thus not be interpreted causally.

To address these endogeneity concerns and move towards a causal estimate of the effect of intangible capital on leverage, we apply the 2SLS specification described in Section 1. We instrument the invalidation dummy with the predicted probability that a patent is invalidated. This instrument is computed from the individual invalidation rates of the three CAFC judges randomly assigned to each court case. The results from the second-stage regression shown in Column (3) reveal a negative and statistically significant relationship between instrumented patent invalidation and leverage. As we did for the OLS specification, we also add firm-level control variables to account for other determinants of leverage. The coefficient on the instrumented invalidation variable is slightly smaller but remains statistically significant (at the 5% level). The results presented in Column (4) document that after controlling for observable firm-level determinants of leverage, industry and year fixed effects, the invalidation of a patent leads a firm to decrease its leverage. This effect is also economically meaningful: A patent invalidation leads to a decrease in leverage by 14% in the subsequent year, which corresponds to a decrease in leverage of about one sample standard deviation.

The difference between our OLS estimates and our 2SLS estimates highlights the importance of addressing the endogeneity of patent invalidation. The invalidation dummy appears to positively correlate with the OLS error term, leading to a significant upward bias of the regression coefficient if we treat patent invalidation as an exogenous variable. From the OLS results, one would conclude that patent invalidation does not affect leverage at all. Our identification strategy applies an instrument that strongly predicts invalidation while plausibly affecting leverage only through its impact on patent invalidation. This permits us to uncover the significantly negative causal effect of patent invalidation on leverage.

One concern might be that the 14 percentage points decrease in leverage, which we identified as a causal reaction to patent invalidation, appears large at first, given that other studies which identify causal effects of exogenous factors on leverage find substantially smaller impacts (e.g., Agrawal and Matsa, 2013; Serfling, 2016). It is important to note, however, that our 2SLS estimates document local average treatment effects (LATEs, see Imbens and Angrist, 1994), and care is thus required when extrapolating them to the population of firms at large. The causal effect we estimate pertains to those firms which could have experienced a different patent validity decision had their case been assigned to a different three-judge panel. This excludes firms, which, for whatever reason, do not defend patent validity before the CAFC. The LATE we document is valid in a group of firms which chose to engage in costly litigation at the appellate court to defend their intangible capital. Due to the substantial costs associated with such litigation, it is reasonable to assume that the effect of patent invalidation will be relatively large.

Our main finding of our empirical investigation is that a reduction in intangible capital leads to lower leverage. This suggests that intangible capital can play a supporting role for firms' debt financing. The literature has so far concluded that tangible assets, not intangible assets, support debt. First, investments in tangible capital are believed to contain little information asymmetry and thus debt-related agency problems are reduced (Harris and Raviv, 1991). Second, most tangible assets are easy to value. They add to liquidation value, which decreases expected distress costs (Frank and Goyal, 2009; Harris and Raviv, 1991). However, as noted in the Introduction, Graham et al. (2015) point out that asset tangibility decreased over time, while leverage ratios increased. Our result presents one possible explanation for the incomplete tangibility-leverage relationship: Intangible capital can affect leverage in a way similar to tangible capital, at least for firms valuing their intangible capital in the form of patents enough to go to court to defend them.

In a next step, we discuss the results of the first-stage regression from our instrumental variables research design used in Table 2. An instrument needs to meet the relevance and exclusion conditions to be a valid instrument (see e.g., Roberts and Whited, 2012; Wooldridge, 2010). The relevance condition requires that the instrument reliably explains the endogenous variable. In the context of our paper, the relevance condition is fulfilled if the partial correlation of *JIP* with the CAFC's patent validity decision is strong. The first-stage regression shows whether the relevance condition is fulfilled. We present results from estimating three variants of the first-stage regression in Table 3. Column (1) shows the results from the OLS regression of the invalidation dummy on JIP, year and industry fixed effects. We find that JIP is a statistically strong predictor of the Federal Circuit's patent validity decision. The Kleibergen-Paap (2006) F-statistic is 10.90, which indicates that JIP is a strong instrument (Staiger and Stock, 1997; Stock and Yogo, 2005). In Column (2), we replace JIP with the invalidation probability predicted from a probit regression of the invalidation dummy on JIP and control variables. For a binary endogenous variable, this estimator is more efficient (Wooldridge, 2010), and thus as expected, the F-statistic increases to 14.82. In Column (3), we add firm-level control variables to the first-stage regression. We find that while none of the firm-level variables correlate with the Federal Circuit decision, our instrument continues to predict it positively and strongly. The results of our first-stage regression estimation show that JIP meets the relevance condition required for a valid instrument. These results also mitigate another concern regarding our instrument. It could be that CAFC judges could share homogeneous attitudes towards patent validity, which would result in a narrow distribution of judges' individual invalidation propensities (f_p^X) across judges. This could ultimately lead to low variance in *JIP*, which might decrease *JIP*'s statistical power in predicting the patent validity decision. However, for our sample, we find that f_p^X is heterogeneously distributed across judges. Appendix B shows that f_p^X ranges from 18% to 63%. *JIP* is 42% on average and shows substantial variation (range from 10% to 74%).

The exclusion restriction requires the correlation between the error term and the instrument to be zero. In the context of this paper, the exclusion restriction is fulfilled if *JIP* (the instrumental variable) affects a firm's leverage ratio (the outcome variable) exclusively through the influence *JIP* has on the patent validity decision (the endogenous independent variable). Whether the exclusion restriction is met cannot be formally tested because the error term is unobservable (Angrist and Pischke, 2009). In our setting, the random nature of the assignment of judges to court cases by a computer program supports the exclusion restriction. It is reasonable to expect the exclusion restriction to be met as *JIP* is computed from three randomly assigned variables (f_p^X) and is therefore a random variable by itself and as such uncorrelated with firm leverage.

We next present the results from additional tests to demonstrate that our main result shown in Column (4) of Table 2 is not particular to the specific leverage measure, the specific control variables, or the specific empirical specification we use. We first show that the negative effect of a loss in intangible capital on leverage is not particular to the leverage measure based on book leverage we use in Table 2. Financial leverage can be measured in various ways. While book leverage is more relevant for managers when making capital structure decisions (Graham and Harvey, 2002) and is a cleaner measure of debt policy (Heider and Ljungqvist, 2015), market leverage, where debt is divided by the market value of a firm, could be closer to theoretical predictions of target leverage ratios (Serfling, 2016). We find that the effect of patent invalidation on market leverage is significant and nearly identical to book leverage (Column 1 of Table 4). In Columns (2) and (3), we add the value of outstanding operating lease payments to total debt before computing book and market leverage, respectively. Not accounting for operating leases may result in the underestimation of a firm's true magnitude of leverage (Eisfeldt and Rampini, 2009; Rampini and Viswanathan, 2013; Rauh and Sufi, 2012). We find that using these lease-adjusted leverage ratios does not change the inference from our main results in Table 2. In Columns (4) and (5), we use net leverage (computed by subtracting cash and cash equivalents from total debt) as dependent variables. In Column (4), we use book debt in the denominator when calculating net leverage, and in Column (5), we use market debt in the denominator when calculating net leverage. Our main finding of a significantly negative influence of a loss of intangible capital on leverage is again confirmed. In Column (6), the dependent variable is a debt issuance dummy which we define as in Leary and Roberts (2014). This dummy variable captures firms' active debt financing decisions, as it equals one when the change in total book debt from one year to the next surpasses 1% of total lagged book assets. We find that the likelihood that a firm issues new debt after a patent invalidation decreases substantially. The estimated coefficient of -0.587 is significant at the 5% level. We obtain a comparable estimate if we normalize the change in total book debt by the market value instead of the book value of assets (not reported).

We next extend the set of control variables to ensure that our finding is not driven by our choice of control variables we have included so far. Table 5 presents the results of estimating Column (4) of Table 2 with additional control variables. In Columns (1) and (2), we control for industry-year median and industry-year mean book leverage, respectively. The empirical capital structure literature has found that firms' capital structure is substantially determined by the leverage ratios of peer firms (e.g., Frank and Goyal, 2009; Leary and Roberts, 2014; MacKay and Phillips, 2005). Since the industry fixed effects we include in all regressions capture only time-invariant, persistent differences between industries, it is possible that industry-wide developments in leverage over time, such as gradual deleveraging in a specific industry, could explain the identified negative effect of a patent invalidation on subsequent leverage. In Column (1), we control for peer firms' leverage ratio by adding the industry-year median of book leverage, which we compute from the full Compustat database, to our regression specification from Column (4) in Table 2. The coefficient on instrumented invalidation is estimated as -0.124 and statistically significant at the 5% level. In Column (2), we replace the industry-year median of book leverage with the industry-year mean of book leverage. The estimated coefficient is barely affected by this change. In Column (3), we use the modified Altman (1968) Z-Score to account for heterogeneity in firms' distance to default. We also include a dividend payer dummy and a firm age indicator, both of which were previously found to significantly correlate with leverage (Frank and Goyal, 2009). The results show that adding these additional firm-level control variables does not affect our main finding. In Column (4), we control for the cost of debt by adding the term spread and the credit spread to the analysis. Also for this set of control variables, we find a significantly negative effect of patent invalidation on subsequent leverage.

We next study whether our main finding is robust to changes to our empirical implementation of the instrumental variable research design. We present these results in Table 6. First, we test whether our result depends on measuring firm-level control variables at *t-1*. One could worry that other developments occurring between then and *t+1* (when the dependent variable is measured) could contribute to the effect we document. We reduce the lag between the control variables and the outcome variable by shifting the control variables closer to the validity decision. In Column (1), we present the results of measuring control variables at *t=0*, i.e. in the year of the Federal Circuit decision. We again find that patent invalidation leads to lower leverage. Column (2) presents results of a model where both the control variables and the dependent variable are measured in the year after the validity decision. In this model, we eliminate the book leverage ratio from the control variables in order to avoid running a regression where the dependent variable is completely explained by a single explanatory variable. Our main finding is confirmed and the choice of when control variables are measured does not seem to critically affect our results. We next show that our finding is not dependent on the econometric refinement of running a probit regression before the first-stage regression. In Column (3) of Table 6, we directly use *JIP* as the instrumental variable. We showed in Column (1) of Table 3 that the relevance condition for a valid instrument is fulfilled (as the F-Statistic is 10.90) if we skip the step of running the probit regression from Equation (3) before the first-stage regression, and instead directly use *JIP* as instrumental variable in the first-stage regression. We find that the coefficient on instrumented invalidation is estimated as -0.178 when we use *JIP* as the instrumental variable. The coefficient is still significant at the 5% level. The identified negative effect of a loss in intangible capital on leverage is therefore not contingent on our choice to use the econometrically more efficient method which specifically accounts for the binary nature of the endogenous variable. In Column (4), we vary our choice of outlier treatment and winsorize the top and bottom 5% of all financial variables, instead of the top and bottom 1%. This different outlier treatment does not change our results, and we continue to find a significantly negative effect of instrumented patent invalidation on leverage. The same holds if we do not winsorize our data at all or if we winsorize at the top and bottom 10% (not reported). In Column (5), we follow recent empirical research by running a regression of changes in leverage on changes in control variables (e.g., Heider and Ljungqvist, 2015; Leary and Roberts, 2014). This specification addresses concerns over omitted firm-level characteristics, and it is comparable to a levels specifications which uses firm fixed effects (Leary and Roberts, 2014; Lemmon et al., 2008). The dependent variable is the one-year change in the book leverage ratio, computed as the first difference from year *t=0* to year *t+1*. The control variables are the first differences measured between year *t-1* and year *t=0*. The estimated coefficient (-0.0986, t-value -2.387) suggests a significant negative effect of patent invalidation on the change in leverage. This finding suggests that unobserved firm-specific variables do not unduly influence our results. We further examine whether the negative effect of patent invalidation on leverage persists when we modify unit of observation of our analysis. For this test, we collapse our sample from the firm-validity decision level used in the analyses presented so far to the firm-case level. Sample size decreases, as some Federal Circuit court opinions present multiple patent validity decisions (i.e., they provide validity decisions for several patents). We define case-level *JIP* as the mean *JIP* per case and set the invalidation dummy to one if at least one patent is invalidated during the case. In Column (6), we show that we continue to find a significantly negative effect of patent invalidation on leverage when using this alternative unit of observation.

4. Heterogeneous effects of intangible capital on leverage

Our main result shows that patent invalidation leads to a reduction in leverage. Next, we investigate whether the treatment effect from losing intangible capital is heterogeneous across sample companies. In particular, we study whether the treatment effect varies depending on financing needs of companies, firm size or whether firms use patents as collateral.

We proxy for financing needs using interest coverage and distance to default. As a proxy for distance to default we use the modified Altman Z-Score (e.g., Graham and Leary, 2011). Firm size is measured as the log of market capitalization. To test the effect of patent collateralization, we obtain the patent assignment history for all patents in our sample from the USPTO patent assignment database. Following Hochberg, Serrano and Ziedonis (2014), we identify 45 observations (1.7% of our sample) where a patent was pledged as collateral under a lending agreement at the time of the patent validity decision. For these observations, we create a patent collateral indicator and set it to one. For all other observations, the patent collateral indicator is set to zero. See Appendix A for more details on how the variables are measured.

We split our sample using the median of the respective variable. To split our sample, we use data from the fiscal year prior to the validity decision to ensure that the sample split is not affected by the outcome of the validity decision. We then implement the heterogeneous treatment effects analysis as follows: We multiply the endogenous independent variable, *Invalidated*, with the interaction dummy. We then estimate a probit regression of *Invalidated* on *JIP*, the interaction dummy and the control variables. We use this estimate to predict instrumented invalidation, the primary instrumental variable. We then multiply the instrumented patent invalidation with the interaction dummy to obtain a second instrument. Finally, we run a 2SLS regression, where two endogenous variables, *Invalidated* and *Invalidated* multiplied by the interaction dummy, are instrumented by instrumented invalidation and instrumented invalidation multiplied by the interaction dummy.

Table 7 presents the results from our tests of heterogeneous treatment effects. Column (1) shows that the negative effect of patent invalidation is significantly stronger for firms with low interest coverage (estimate is -0.169). This result is supported when we examine how differences in firms' distance to default affect the uncovered negative effect of patent invalidation on leverage (Column 2). The coefficient on interacted instrumented patent invalidation is -0.151 and significant. This indicates that for firms close to default, patent invalidation leads to a stronger decrease in leverage. Taken together, the results from Column (1) and Column (2) suggest that our documented reduction in leverage as a response to patent invalidation is more pronounced for firms with more difficulty to finance their debt.

We expect the negative influence of patent invalidation on leverage to be more pronounced for small firms because the loss of one patent represents a larger relative loss of intangible capital. Column (3) shows the results from estimating the second-stage regression of our 2SLS research design when instrumented invalidation is interacted with the small firm dummy. The coefficient on the interacted variable is negative (-0.148) and statistically significant at the 10% level. This finding indicates that for small firms which experience an exogenous loss in intangible capital, the following leverage decrease is significantly more pronounced than for large firms.

The frequency of firms assigning intangible capital as collateral has steadily grown over the past decades (Loumioti, 2015). Mann (2016) estimates that about 40% of all patenting firms in the U.S. have pledged a patent as collateral at some point in time. If patents are actively used by firms to obtain debt financing, this could potentially explain the negative effect of patent invalidation on leverage. The invalidation of a patent pledged as collateral could represent a covenant breach triggering a margin call from the lender. Instead of replacing the former security value of the patent, the borrower patentee might repay the loan early (resulting in lower leverage). Consistent with this hypothesis, Column (4) shows that the negative effect of patent invalidation is significantly more pronounced if a firm's patent is invalidated while the patent served as loan collateral. Our finding suggests that a patent's status as loan collateral at the time of a patent validity decision explains some of the negative effect a patent invalidation has on leverage. In addition, Column 4 shows that the negative effect of patent invalidation remains significant even for firms that do not pledge the invalidated patent as collateral (the coefficient is -0.106, 10% significance).

5. Conclusion

In this paper, we empirically analyse the causal effect of intangible capital on leverage. Exploiting shocks to firms' intangible capital from patent invalidations by a U.S. court, and instrumenting for the potentially endogenous validity decision, we provide empirical evidence that losing intangible assets leads to lower leverage. Our IV research design, which exploits random assignment of judges with heterogeneous attitudes regarding patent validity to court cases at the CAFC, permits this causal interpretation. The main finding of this paper, that a loss of intangible capital leads to a significant reduction in leverage in firms which value their intangible capital highly, sheds a new light on our current understanding of the relationship between asset tangibility and leverage. Whereas existing research generally suggests a negative correlation between intangible capital and leverage, we show that in a sample of firms willing to incur high costs to defend their intangible capital before court, losing intangible capital leads to lower leverage.

In addition to the negative average treatment effect of a patent loss at the CAFC on leverage uncovered in this paper, we document heterogeneity in the treatment effect. We find that the leverage ratios of firms with the largest financing needs – firms facing financial difficulties when serving interest payments and firms close to default – rely the most on intangible capital, as in these firms, the leverage drop following patent invalidation is especially pronounced. The importance of intangible capital as a leverage-supporting device thus seems to increase with firms' financing needs. Furthermore, when isolating the treatment effect of patent invalidation for small firms, we find that if the lost patent represents a relatively larger fraction of the firm's assets, leverage decreases further after patent invalidation. The capital structure of large firms might thus rely less on intangible capital, while for small firms, intangible capital is a more important leverage support. Lastly, we show that if a patent pledged as loan collateral is invalidated by the CAFC, the subsequent drop in leverage is larger than average. This is in line with the notion that collateral is pledged to increase debt. However, we find that leverage falls after a patent invalidation even if the invalidated patent was not explicitly pledged as collateral.

Overall, our findings are consistent with the view that the role intangible capital plays in explaining capital structure might be more comparable to tangible capital than previously assumed. Observable leverage ratios depend strongly on the presence of intangible capital. As intangible capital continues to gain importance for modern economies, we believe that our results provide important insights.

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Appendix A. Variable Definitions.

Variable	**Definition (using Compustat variable names)**
Validity decision variables	
Invalidated	equals 1 if the CAFC invalidates at least 1 patent claim, 0 otherwise
JIP (Judges' Invalidation Propensity)	predicted propensity of the judge panel randomly assigned to a court case at the CAFC to invalidate a patent, based on judges' historical invalidation votes observed in other patent validity cases
Leverage variables	
Book leverage	(dltt + dlc) / at
Adj. book leverage	(dltt + dlc + xrent*10) / (at + xrent*10)
Net book leverage	(dltt + dlc - che) / at
Market leverage	(dltt + dlc) / (prcc_f * cshpri + dltt + dlc + pstkl - txditc)
Adj. market leverage	(dltt + dlc + xrent*10) / ((prcc_f * cshpri + dltt + dlc + pstkl - txditc) + xrent*10)
Net market leverage	(dltt + dlc - che) / (prcc_f * cshpri + dltt + dlc + pstkl - txditc)
New debt issuer	equals 1 if (dltt + dlc - (l1.dltt + l1.dlc))/l1.at > 0.01
Other variables	
Size	log(sale)
Market-to-book ratio	(prcc_f * cshpri + dltt + dlc + pstkl - txditc) / at
Profitability	oibdp / at
Tangibility	ppent / at
Interest coverage	log(1 + (oibdp_ic / xint)) [where oibdp reset to 0 if oibdp < 0]
Modified Altman Z-Score	(3.3 * pi + sale + 1.4 * re + 1.2 * (act - lct)) / at
Patent is collateral at decision	equals 1 if patent is assigned as collateral in a loan agreement at the time of the validity decision (data from USPTO assignment database)
Patent is collateral at some time	equals 1 if patent is assigned as collateral in a loan agreement at any time (data from USPTO assignment database), 0 otherwise
Dividend payer	equals 1 if dvc > 0, 0 otherwise
Firm age	current year minus first year the firm appears in Compustat
Term spread	difference between 10 year yield and 1 year yield (constant maturity, data from the Federal Reserve)
Credit spread	difference between annual yield on BAA rated corporate bond and AAA rated corporate bond (data from the Federal Reserve)

Appendix B. Judges' Individual Patent Invalidation Propensities.

This table summarizes judges' individual patent invalidation propensities for the 25 CAFC judges most frequently present in our sample of 579 hand-collected patent validity decisions. A judge's individual patent invalidation propensity is computed per patent validity decision as the ratio of votes in favor of patent invalidation (excluding the focal validity decision itself) by that judge divided by all votes on patent validity (excluding the focal validity decision itself) by her. Following Galasso and Schankerman (2015a), we record a patent validity decision as a patent invalidation if the three-judge panel invalidates at least one claim of a focal patent.

Judge	Patent Validity Decisions	Individual Patent Invalidation Propensity
Newman	142	18%
Bryson	134	57%
Rader	131	39%
Lourie	114	47%
Prost	111	54%
Dyk	104	61%
Mayer	99	49%
Gajarsa	91	48%
Michel	83	40%
Linn	72	49%
Clevenger	67	46%
Schall	64	45%
Archer	50	36%
Plager	49	51%
Moore	48	63%
Wallach	36	22%
Markey	36	50%
Rich	31	26%
Friedman	31	42%
Omalley	29	48%
Davis	25	48%
Reyna	21	38%
Smith	21	24%
Nies	19	32%
Cowen	17	41%

Table 1. Summary Statistics.

This table reports summary statistics of validity decision variables (Panel A), leverage variables (Panel B) and other variables used in this paper (Panel C). To reduce the effects of outliers, financial ratios are winsorized at the 1% and 99% level. We obtain the validity decision variables from a hand-collected set of 579 patent validity court decisions issued by the CAFC between 1983 and 2014. Following Galasso and Schankerman (2015a), *Invalidated* equals one if the CAFC judges invalidate at least one claim of a patent. *Judges' invalidation propensity (JIP)* is the predicted probability that the three-judge panel randomly assigned to the validity decision invalidates the focal patent. Variables are defined in Appendix A.

	n	mean	median	s. d.
Panel A: Validity decision variables				
Patent invalidated (*Invalidated* = 1)	579	0.45	0	0.50
Judges' invalidation propensity (*JIP*)	579	0.42	0.43	0.11
Panel B: Leverage variables				
Book leverage	579	0.21	0.20	0.14
Market leverage	554	0.16	0.13	0.14
Book leverage, adj. for op. leases	511	0.28	0.28	0.13
Market leverage, adj. for op. leases	491	0.22	0.20	0.15
Book leverage, net of cash	579	0.04	0.08	0.25
Market leverage, net of cash	554	0.06	0.05	0.18
New debt issuer = 1	579	0.39	0	0.49
Industry-year median book leverage	579	0.14	0.10	0.09
Industry-year mean book leverage	579	0.31	0.29	0.07
Δ Book leverage (1st difference)	579	0	0	0.08
Panel C: Other variables				
Size	579	8.33	8.93	2.48
Market-to-book	579	2.03	1.55	1.46
Profitability	579	0.15	0.15	0.12
Tangibility	579	0.23	0.20	0.16
Modified Altman Z-Score	569	1.27	1.87	2.75
Dividend payer	579	0.71	1	0.46
Firm age	579	31.48	28	18.32
Term spread	579	1.71	1.83	0.97
Credit spread	579	1.07	0.92	0.34
Interest coverage	522	2.71	2.71	1.24
Patent is collateral = 1	579	0.08	0	0.27

Table 2. Second Stage: Effect of Patent Invalidation on Book Leverage.

This table summarizes the results from OLS (Columns (1) and (2)) and 2SLS (Columns (3) and (4)) regressions of book leverage on patent invalidation and control variables. In Columns (1) and (2), the patent validity decision (*Invalidated*) is used as an explanatory variable. In Columns (3) and (4), the patent validity decision (*Invalidated*) is instrumented with the predicted invalidation obtained from a probit regression of the invalidation dummy on *JIP* and control variables. The dependent variable is measured at *t+1*, at the end of the fiscal year following the patent validity decision. All control variables are measured at *t-1*, at the end of the fiscal year before the patent validity decision. Heteroskedasticity-robust standard errors clustered at the firm-level are reported in parentheses below the coefficients. All financial variables are winsorized at 1% and 99%. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Variables are defined in Appendix A.

	Dependent variable: Book leverage			
	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	2SLS	2SLS
Invalidation	0.00546	0.00300	-0.212***	-0.141**
	(0.0171)	(0.00896)	(0.0816)	(0.0599)
Book leverage		0.705***		0.718***
		(0.0591)		(0.0645)
Size		-0.00457		-0.00381
		(0.00484)		(0.00553)
Market-to-book		-0.00258		0.00255
		(0.00599)		(0.00747)
Profitability		0.0526		0.0367
		(0.0821)		(0.0986)
Tangibility		-0.0591		-0.103
		(0.0677)		(0.0778)
Year fixed effects	Yes	Yes	Yes	Yes
FF 48 industry fixed effects	Yes	Yes	Yes	Yes
Number of observations	579	579	579	579

Table 3. First Stage: Predicting Patent Invalidation from Judges' Voting Behavior.

This table summarizes the results from OLS first stage regressions of the patent validity decision (*Invalidated*) on two instruments of patent invalidation. *JIP* is the judges' invalidation propensity. Predicted invalidation is obtained from a probit regression of the invalidation dummy on *JIP* and control variables. The probit approach is recommended in 2SLS regressions where the endogenous variable is binary (see e.g., Angrist and Pischke, 2009). The estimate in Column (3) represents the first stage upon which Column (4) in Table 2 is based. The reported IV test is the Kleibergen-Paap (2006) Wald rk F-statistic for weak identification. All control variables are measured at *t-1*, at the end of the fiscal year before the patent validity decision. Heteroskedasticity-robust standard errors clustered at the firm-level are reported in parentheses below the coefficients. All financial variables are winsorized at 1% and 99%. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Variables are defined in Appendix A.

	Dependent variable: *Invalidated*		
	(1)	(2)	(3)
Instruments for invalidation			
JIP	0.990***		
	(0.300)		
Predicted invalidation		1.088***	1.116***
		(0.283)	(0.297)
Control variables			
Book leverage			-0.0165
			(0.218)
Size			-0.000709
			(0.0164)
Market-to-book			-0.00315
			(0.0271)
Profitability			0.00953
			(0.320)
Tangibility			-0.00859
			(0.257)
Year fixed effects	Yes	Yes	Yes
FF 48 industry fixed effects	Yes	Yes	Yes
IV test	10.90	14.82	14.14
Number of observations	579	579	579

Table 4. Second Stage: Effect of Patent Invalidation on Alternative Leverage Measures.

This table summarizes the results from 2SLS regressions of alternative leverage measures on patent invalidation and control variables. As in Table 2, Column (4), the patent validity decision (*Invalidated*) is instrumented with the predicted invalidation obtained from a probit regression of the invalidation dummy on *JIP* and control variables. The dependent variable is measured at *t+1*, at the end of the fiscal year following the patent validity decision. All control variables are measured at *t-1*, at the end of the fiscal year before the patent validity decision. Heteroskedasticity-robust standard errors clustered at the firm-level are reported in parentheses below the coefficients. All financial variables are winsorized at 1% and 99%. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Variables are defined in Appendix A.

	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
	Market leverage	Adj. book leverage	Adj. market leverage	Net book leverage	Net market leverage	New debt issuer
Invalidation	-0.132**	-0.161**	-0.179**	-0.140*	-0.180**	-0.587**
	(0.0573)	(0.0787)	(0.0848)	(0.0787)	(0.0738)	(0.262)
Lagged dependent var.	0.629***	0.748***	0.673***	0.667***	0.517***	0.128*
	(0.0693)	(0.0663)	(0.0670)	(0.0550)	(0.0691)	(0.0708)
Size	-0.00114	-0.00225	0.00433	0.0133*	0.000670	0.0194
	(0.00473)	(0.00527)	(0.00538)	(0.00718)	(0.00566)	(0.0202)
Market-to-book	0.000150	0.00116	0.00379	-0.00468	-0.0132	0.0595**
	(0.00760)	(0.00753)	(0.00884)	(0.0107)	(0.00881)	(0.0298)
Profitability	-0.0118	-0.00913	-0.0537	-0.0853	-0.0632	-0.162
	(0.0868)	(0.1000)	(0.105)	(0.131)	(0.123)	(0.406)
Tangibility	-0.0261	-0.103	-0.0287	-0.0398	-0.0130	-0.0520
	(0.0604)	(0.0834)	(0.0766)	(0.0899)	(0.0750)	(0.290)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
FF 48 industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	554	503	483	579	554	577

Table 5. Second Stage: Controlling for Additional Determinants of Leverage.

This table summarizes the results from 2SLS regressions of book leverage on patent invalidation and additional determinants of leverage. As in Table 2, Column (4), the patent validity decision (*Invalidated*) is instrumented with the predicted invalidation obtained from a probit regression of the invalidation dummy on *JIP* and control variables. The dependent variable is measured at *t+1*, at the end of the fiscal year following the patent validity decision. All control variables are measured at *t-1*, at the end of the fiscal year before the patent validity decision. Heteroskedasticity-robust standard errors clustered at the firm-level are reported in parentheses below the coefficients. All financial variables are winsorized at 1% and 99%. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Variables are defined in Appendix A.

	Dependent variable: Book leverage			
	(1)	(2)	(3)	(4)
Invalidation	-0.124**	-0.129**	-0.140**	-0.140**
	(0.0616)	(0.0620)	(0.0615)	(0.0615)
Book leverage	0.718***	0.722***	0.728***	0.728***
	(0.0626)	(0.0633)	(0.0713)	(0.0713)
Size	-0.00411	-0.00420	-0.000298	-0.000298
	(0.00537)	(0.00530)	(0.00557)	(0.00557)
Market-to-book	0.00124	0.000764	0.00259	0.00259
	(0.00749)	(0.00746)	(0.00796)	(0.00796)
Profitability	0.0424	0.0438	0.0309	0.0309
	(0.0955)	(0.0945)	(0.128)	(0.128)
Tangibility	-0.0961	-0.104	-0.0760	-0.0760
	(0.0760)	(0.0757)	(0.0756)	(0.0756)
Industry-year med. leverage	-0.168			
	(0.220)			
Industry-year mean leverage		-0.169		
		(0.170)		
Modified Altman (1968) Z-Score			0.000714	0.000714
			(0.00457)	(0.00457)
Dividend payer			-0.00977	-0.00977
			(0.0232)	(0.0232)
Firm age			-0.000661	-0.000661
			(0.000467)	(0.000467)
Term spread				0.0685
				(0.0519)
Credit spread				0.00643
				(0.131)
Year fixed effects	Yes	Yes	Yes	Yes
FF 48 industry fixed effects	Yes	Yes	Yes	Yes
Number of observations	579	579	569	569

Table 6. Second Stage: Alternative Empirical Specifications.

This table summarizes the results from 2SLS regressions of book leverage on patent invalidation and control variables, under alternative empirical specifications. As in Table 2, Column (4), the patent validity decision (*Invalidated*) is instrumented with the predicted invalidation obtained from a probit regression of the invalidation dummy on *JIP* and control variables (except for Column (3), where *Invalidated* is directly instrumented by *JIP*, so that the first stage estimate equals Column (1) in Table (3)). The dependent variable is measured at *t+1*, at the end of the fiscal year following the patent validity decision. All control variables are measured at *t-1*, at the end of the fiscal year before the patent validity decision (except in Columns (1) and (2), where they are measured at *t=0* and at *t+1*, respectively). In Column (5), the dependent variable is the one-year change in the book leverage ratio, computed as the first difference from year *t=0* to year *t+1*. The control variables are the first differences measured between year *t-1* and year *t=0*. In Column (6), we collapse the sample from the firm-validity decision level to the firm-case level. We define case-level JIP as the mean JIP per case and set the invalidation dummy to one if at least one patent is invalidated during the case. In all specifications, heteroskedasticity-robust standard errors clustered at the firm-level are reported in parentheses below the coefficients. All financial variables are winsorized at 1% and 99% (except for Column (4), where the corresponding levels are 5% and 95%). ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Variables are defined in Appendix A.

	Dependent variable: Book leverage					
	(1)	(2)	(3)	(4)	(5)	(6)
Test:	Control variables at *t=0*	Control variables at *t+1*	First stage regression without probit	Financials winsorized at 5% and 95%	Change on changes regression	Unit of observation: firm-case
Invalidation	-0.118***	-0.167**	-0.178**	-0.116**	-0.0682**	-0.0986**
	(0.0445)	(0.0741)	(0.0759)	(0.0529)	(0.0335)	(0.0413)
Book leverage	0.499***		0.721***	0.761***	-0.170*	0.711***
	(0.134)		(0.0688)	(0.0534)	(0.0911)	(0.0652)
Size	0.00232	-0.00397	-0.00362	-0.00412	0.0407**	-0.00312
	(0.00563)	(0.00733)	(0.00592)	(0.00439)	(0.0186)	(0.00453)
Market-to-book	-0.00462	-0.0180**	0.00387	0.00370	-0.0115***	-0.00369
	(0.00318)	(0.00890)	(0.00833)	(0.00757)	(0.00255)	(0.00605)
Profitability	-0.0188	-0.0570	0.0326	0.0456	-0.0155	0.0322
	(0.0598)	(0.0807)	(0.107)	(0.104)	(0.0425)	(0.0832)
Tangibility	-0.0173	0.00944	-0.114	-0.0893	0.109	-0.0336
	(0.0660)	(0.0911)	(0.0832)	(0.0686)	(0.151)	(0.0658)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
FF 48 industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	563	542	579	579	563	372

Table 7. Second Stage with Interactions: Additional Results.

This table summarizes the results from interacted 2SLS regressions of book leverage on patent invalidation and control variables. We interact 2SLS regressions with interaction terms as follows: We multiply the endogenous independent variable, *Invalidated,* with the interaction dummy. We then estimate a probit regression of *Invalidated* on *JIP*, the interaction dummy and the control variables. We use this estimate to predict instrumented invalidation, the primary instrumental variable. We then multiply the instrumented patent invalidation with the interaction dummy to obtain a second instrument. Finally, we run a 2SLS regression, where two endogenous variables, Invalidated and Invalidated multiplied by the interaction dummy, are instrumented by instrumented invalidation and instrumented invalidation multiplied by the interaction dummy. The dependent variable is measured at *t+1*, at the end of the fiscal year following the patent validity decision. All control variables are measured at *t-1*, at the end of the fiscal year before the patent validity decision. Heteroskedasticity-robust standard errors clustered at the firm-level are reported in parentheses below the coefficients. All financial variables are winsorized at 1% and 99%. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Variables are defined in Appendix A.

	Dependent variable: Book leverage			
	(1)	(2)	(3)	(4)
Interaction term:	Low interest coverage	Low Z-score	Small firm	Patent is collateral
Invalidation	-0.0485	-0.0620	-0.0708	-0.106*
	(0.0621)	(0.0576)	(0.0518)	(0.0621)
Invalidation x Interaction term	-0.169**	-0.151**	-0.148*	-0.284*
	(0.0781)	(0.0732)	(0.0781)	(0.167)
Interaction term	0.112***	0.0573	0.0772*	0.114*
	(0.0414)	(0.0383)	(0.0423)	(0.0689)
Book leverage	0.671***	0.707***	0.706***	0.715***
	(0.0846)	(0.0723)	(0.0711)	(0.0628)
Size	-0.00796	-0.00482	-0.00166	-0.00544
	(0.00560)	(0.00569)	(0.00806)	(0.00528)
Market-to-book	-0.00297	0.000674	0.00503	0.00286
	(0.00739)	(0.00754)	(0.00818)	(0.00747)
Profitability	0.193*	0.0191	-0.00162	0.0452
	(0.108)	(0.105)	(0.113)	(0.0923)
Tangibility	-0.165*	-0.121	-0.0742	-0.0908
	(0.0889)	(0.0843)	(0.0811)	(0.0758)
Year fixed effects	Yes	Yes	Yes	Yes
FF 48 industry fixed effects	Yes	Yes	Yes	Yes
Number of observations	522	569	579	579