Knowledge Spillover Absorption and Corporate Innovation*

Michael Woeppel and M. Deniz Yavuz†

March 2025

Abstract

Understanding firms' ability to absorb external information is crucial for identifying firms that benefit most from knowledge spillovers. We introduce a novel measure of this ability – absorption intensity – based on external information contained in firms' patents. Using the American Inventor's Protection Act as an exogenous shock, we show that firms with higher absorption intensity increase their patent output more in response to knowledge spillovers. These firms also produce higher-quality patents and experience greater growth in capital, labor, profit, and output. Our measure can be used in research on innovation policy and corporate decisions that involve acquisition of knowledge.

Keywords: Innovation, knowledge spillovers, information absorption, patent disclosure
JEL: D83, G38, O3

*We thank Heitor Almeida (discussant), Mara Faccio, Yongseok Kim, Song Ma, Filippo Mezzanotti, Marina Niessner, Noah Stoffman, and seminar participants at Chicago Entrepreneurship Workshop at Northwestern University (2024), Illinois State University, Indiana University, Purdue University, and the Wabash River Finance Conference (2024) for helpful comments.

†Woeppel is at the Kelley School of Business at Indiana University, Bloomington, IN, 47405 (mwoeppel@iu.edu). Yavuz is at the Daniels School of Business at Purdue University, West Lafayette, IN 47907 (myavuz@purdue.edu).

1 Introduction

Knowledge spillovers play a pivotal role in fostering innovation (Bloom, Schankerman, and Van Reenen, 2013; Akcigit and Kerr, 2018; Akcigit and Ates, 2023). While it is commonly assumed that all firms within a given geographic (Jaffe, Trajtenberg, and Henderson, 1993) or technological proximity (Jaffe, 1986) benefit equally from knowledge spillovers, a foundational literature, beginning with Cohen and Levinthal (1989), argues that firms likely vary substantially in their ability to absorb spillovers. Understanding this variation is essential for identifying which firms are best positioned to leverage spillovers and achieve superior innovation outcomes (Aghion and Jaravel, 2015). However, since this ability depends on many factors (Cohen and Levinthal, 1990), empirically measuring it has proven challenging.

Prior research has predominantly relied on R&D-based proxies to measure a firm's ability to absorb external information.[1] This approach, however, has several fundamental limitations. First, R&D influences innovation output not only through information absorption but also directly, complicating the identification of the specific impact that absorption has on innovation. Second, although any firm can invest in R&D, the effectiveness of converting this investment into improved information absorption likely varies across firms. We address these issues by directly quantifying firms' use of external information.

We propose that a firm's ability to internalize external information affects not only a firm's productivity but also the characteristics of its innovation. Intuitively, firms with greater ability to absorb external information are more likely to incorporate external information into their own innovation. We therefore measure this ability by counting the number of recent patents granted to other firms cited in a firm's own patents. Since we scale this sum by the number of a firm's patents, we call our measure "absorption intensity." Our measure captures the essence of absorptive capacity, which is defined by Cohen and Levinthal (1989, 1990) as the ability to recognize the value of external information, assimilate it, and apply

[1] See Zahra and George (2002), Lane, Koka, and Pathak (2006), Volberda, Foss, and Lyles (2010), and Song, Gnyawali, Srivastava, and Asgari (2018) for comprehensive reviews.

it to commercial ends.

As discussed below, absorption intensity is likely endogenously determined by several firm-level factors. Indeed, it is moderately persistent within firms over time but varies significantly across firms within the same industry. Since it is endogenously determined, there could be omitted firm-level factors that are correlated with both absorption intensity and innovation output but are unrelated to the ability to absorb information. To determine whether firms with higher absorption intensity can more effectively leverage external information for innovation output, we exploit an exogenous shock to knowledge spillovers.

The shock we use is the American Investor Protection Act of 1999 (AIPA), which significantly changed the patent disclosure process and had a causal impact on knowledge spillovers (Hegde, Herkenhoff, and Zhu, 2023). AIPA requires that most patent applications filed at the United States Patent and Trademark Office (USPTO) after November 28, 2000 be published 18 months after the application date. Prior to AIPA, the information in a patent application was revealed only when the patent was granted, which was often years after the application date. If an application was never granted, the information therein was never revealed.

We first show that firms with higher absorption intensity are more likely to use information that became available only after AIPA. Specifically, firms with higher pre-AIPA absorption intensity cite more external patent *applications* in the post-AIPA period. This finding aligns with the expectation that firms exhibiting higher absorption intensity are more likely to effectively leverage knowledge spillovers.

Next, we examine whether changes in innovation output around AIPA vary predictably with absorption intensity. Using a difference-in-differences approach in which we carefully control for time-varying effects of various inputs to patent production, we find that firms with higher pre-AIPA absorption intensity increase their innovation output significantly more in the post-AIPA period. For example, average annual patent output across all firms is 12% higher in the post-AIPA period. However, firms in the 75^{th} percentile of absorption intensity experience a 61% larger increase in annual patent output in the post-AIPA period than firms

in the 25^{th} percentile.

To eliminate the possibility that our results are confounded by contemporaneous events that may have differently influenced the patenting behavior of high absorption intensity firms, we leverage variation in the treatment effect. Before AIPA, the average time between the patent application date and the patent grant date (i.e., grant lag) varied significantly across patent classifications. Since AIPA requires that most applications be published 18 months after the application date, AIPA resulted in variation in treatment intensity, which we estimate using a weighted average of the grant lags of patents cited in the focal firm's pre-AIPA patents. Using a triple differences setup, we show that the relation between absorption intensity and the difference between pre-AIPA and post-AIPA innovation output is stronger for firms that were exposed to larger information shocks. These results are especially pronounced in high-tech, R&D-intensive, and patent-rich industries, where knowledge spillovers play a crucial role in driving innovation (Bloom et al., 2013).[2] Placebo tests show that in non-AIPA years, the relation between absorption intensity and the difference between pre-event and post-event innovation output does not vary with the placebo treatment.

A remaining concern is that firms may respond to AIPA for reasons unrelated to their ability to incorporate information, and such a response may affect both patent output and patent characteristics. For instance, firms might increase the number of patent filings after AIPA while narrowing their scope, thereby reducing their average value. Such a strategy could be used to avoid disclosing all details in a single application due to the concern that parts of the application might be deemed unpatentable, yet the entire application would still become public. However, we show that neither the relation between absorption intensity and patent scope nor its relation to patent value change in response to AIPA.

There may also be concerns with using external patent citations as a proxy for a firm's

[2]We also find similar results when accounting for the possibility that firms with high absorption intensity increase output simply by increasing R&D investment after AIPA. Furthermore, our results remain robust when we use variations of absorption intensity and when we control for factors such as originality (Trajtenberg, Henderson, and Jaffe, 1997), technological obsolescence (Ma, 2025) and various versions of scaled R&D.

ability to absorb information. First, firms do not always select their own external citations. Patent examiners often require additional citations during the patent approval process, which can add noise to the measure. This is not a major concern because after the enactment of AIPA, we can distinguish whether citations are added by applicants or examiners. We also show that our results around AIPA are robust when using a future version of absorption intensity constructed using only applicant-added citations but weaken or disappear when doing the same with examiner-added citations. Second, firms may strategically exclude citations for various reasons, potentially introducing bias into our measure. Omitted variables may explain both strategic patent exclusions and patent productivity but not be related to the firm's ability to absorb information. However, such concerns are mitigated by using AIPA as an exogenous shock to knowledge spillovers. Finally, our measure cannot be calculated for firms that have not yet innovated or choose not to patent their innovations.

We externally validate our findings by demonstrating that absorption intensity is significantly and positively correlated with future innovation output in panel regressions covering the sample period from 1975 to 2019. During this period, firms with higher absorption intensity also tend to produce higher-quality patents. Moreover, absorption intensity is strongly correlated with future growth in R&D capital, profitability, and labor, and weakly correlated with future growth in physical capital and output. These correlations highlight absorption intensity as a potential predictor of firm growth.

Various fundamental factors – both known and unknown – can influence a firm's ability to absorb information (Cohen and Levinthal, 1989, 1990). Many of these factors (e.g., human capital, management practices, organizational structure) are difficult to directly observe and may contribute only marginally to a firm's overall absorption intensity. This is why an output-based measure is advantageous – it captures the cumulative effect of both known and unknown factors. Consistent with this argument, we find that absorption intensity is correlated with several firm-level factors (i.e., inventor skill, organizational practices conducive to innovation, proximity to highly ranked academic institutions, fraction of college-educated

employees) but outperforms each in explaining future innovation.

Our paper contributes to the literature on firms' absorptive capacity (Cohen and Levinthal, 1989, 1990) by introducing a novel, observable measure that reliably predicts which firms benefit most from knowledge spillovers. As noted, prior research has primarily used R&D-based proxies to estimate firms' ability to absorb external information.[3] However, none of these measures predict firms' innovation output response to AIPA in our sample.

Our paper also contributes to the literature on knowledge spillovers and innovation policy by demonstrating that firms vary predictably in their ability to capitalize on spillovers. Since the impacts of innovation policy are highly dependent on the multiplier effects of the innovation process, gaining a clearer understanding of how the effects of knowledge spillovers vary across firms is critical for any debate on innovation policy (Aghion and Jaravel, 2015).

Our measure is also relevant for the literature on firm boundaries and innovation, where incentive problems (Robinson, 2008; Seru, 2014) and accessing expertise and information from other firms is often a key motivation for forming alliances (Hamel, 1991; Kumar and Nti, 1998; Gomes-Casseres, Hagedoorn, and Jaffe, 2006), engaging in corporate venture capital (Siegel, Siegel, and MacMillan, 1988; Benson and Ziedonis, 2010; Ma, 2020), establishing joint ventures (Kogut, 1988; Lane, Salk, and Lyles, 2001), and pursuing mergers and acquisitions (Phillips and Zhdanov, 2013; Bena and Li, 2014; Frésard, Hoberg, and Phillips, 2020). These decisions are frequently influenced by significant information frictions (Howell, 2020; Celik, Tian, and Wang, 2022), and the benefits that firms derive from such activities and the trade-offs they face may depend on their ability to absorb external information.

In summary, we propose a novel, patent-based measure to capture a firm's ability to absorb external information, grounded in the notion that firms with higher absorption ability are more likely to integrate external information into their patents. Using the American

[3]These proxies include, but are not limited to, different versions of R&D intensity (Tsai, 2009; Zou, Ertug, and George, 2018), raw R&D expenses (Dushnitsky and Lenox, 2005; Nambisan, 2013), dummy variable for any positive R&D activity (de Faria, Lima, and Santos, 2010), number of R&D employees (Huang, Lin, Wu, and Yu, 2015), and R&D employees as a percent of all employees (Estrada, de la Fuente, and Martín-Cruz, 2010).

Inventor's Protection Act of 1999 as an exogenous shock to knowledge spillovers, we demonstrate that firms with higher absorption intensity more effectively convert spillovers into innovation. Our measure reflects several fundamental factors such as human capital, management practices, and organizational practices and structures into a single indicator. We encourage future research to explore these foundational elements in greater depth.

2 Absorption intensity

To understand how the effects of knowledge spillovers vary across firms, we develop a measure of a firm's ability to internalize these spillovers. This measure is constructed using patent citations, which are widely considered indicators of knowledge spillovers (Jaffe et al., 1993; Jaffe, Trajtenberg, and Fogarty, 2000). In this section, we describe our measure and discuss its strengths and shortcomings.

We define a firm's ability to internalize spillovers as *Absorption intensity*, which is calculated in four steps. First, we identify all new patents firm i applied for in the five years through the current year (i.e., year *t-4* through year t) that were eventually granted. Second, we identify the unique external citations of patents granted in the five years prior to the application of each granted patent. An external citation refers to a patent granted to another firm $j \neq i$. The number of unique backward external citations is going to naturally scale with the number of patents, which itself is largely a function of firm size (Kogan, Papanikolaou, Seru, and Stoffman, 2017). However, we want to focus on a firm's ability to internalize external information irrespective of firm size. Thus, in step three, we divide the sum of citations by the number of new patents. The distribution of this ratio is heavily right-skewed, so in our fourth step, we take the natural logarithm of it. In alternative versions of our measure, we use a three-year or a ten-year prior horizon to identify patent grants and citations.

Absorption intensity reflects the concept of absorptive capacity, which is a firm's ability to recognize, assimilate, and apply external information for commercial purposes (Cohen

and Levinthal, 1989, 1990). Our measure focuses on the characteristics of a firm's innovation output, which we argue provides a more direct way to assess a firm's ability to absorb external information. This approach contrasts with previous research that attempts to capture a firm's ability to internalize external information, which often relies on R&D-based proxies. Examples of these R&D-bases proxies include R&D expenses scaled by sales or total assets, R&D expenses scaled by number of employees, raw R&D expenses, dummy variable indicating any positive R&D activity, number of R&D employees, and the proportion of employees working in R&D relative to total employees.

However, using a direct input to patent production as a proxy for a firm's ability to utilize external information is problematic. R&D influences future innovation in two ways: indirectly by enhancing a firm's ability to internalize external information, and directly as the primary input to innovation (Cohen and Levinthal, 1989, 1990). Distinguishing between these two effects on future innovation is challenging. Our measure is less likely to face this issue. Incorporating information from other firms' patents signals productivity through an absorption channel but is not necessarily indicative of a direct investment in a firm's innovation process. Indeed, as we show below, correlations between different versions of our measure and R&D-based proxies are close to zero.

Moreover, a conceptual issue with using R&D-based proxies to measure a firm's ability to internalize information is that these proxies implicitly assume that all firms translate R&D investments into absorption ability in the same way. While any firm can invest in R&D, the effectiveness of converting this investment into an enhanced ability to absorb information likely varies across firms. Furthermore, different types of R&D may affect firms' absorption ability in different ways. As a result, indirect measures are less suitable for analyzing cross-sectional differences in firms' ability to absorb external information.

A potential limitation of absorption intensity is that it can only be calculated for firms with recently granted patents. However, this is not a significant issue for firms that innovate regularly. A similar challenge exists for R&D-based measures, for many small firms have

recent patent grants but do not report R&D expenses (Koh and Reeb, 2015).

Another potential limitation of our measure is that patent citations are determined by both applicants and examiners. During the patent approval process, examiners may require applicants to cite additional external patents. These citations reflect the examiner's preferences rather than the applicant's ability to absorb external information. For patents granted before 2002, citation data do not distinguish between citations added by applicants and those added by examiners. However, for patents granted from 2002 onward, citation data specify who added the citation. As a result, examiner-added citations are not a concern when using our measure in more recent time periods. We provide evidence below that our results are driven by applicant-added citations, not examiner-added citations.

Firms may also strategically exclude citations, which could make absorption intensity a noisy or even biased measure of absorption ability. Patent law requires applicants to disclose all relevant citations, and failure to do so can render the patent unenforceable (Cotropia, Lemley, and Sampat, 2013).[4] However, since citations limit the breadth of property rights awarded, excluding citations allows applicants to potentially claim ownership over technologies reflected in the excluded citation. Given the potential benefits of excluding citations, it is estimated that applicants withhold an estimated 21% to 33% of relevant citations (Lampe, 2012). This practice introduces noise into our estimate of firms' ability to absorb information and may make it harder to detect significant results.

It is possible that the tendency to strategically exclude citations is correlated with an omitted firm-level factor that influences patent production. In fact, other omitted variables that are unrelated to the firm's ability to absorb information could also explain both citation practices and patent productivity. However, as discussed below, we address these concerns by using AIPA as an exogenous shock to knowledge spillovers.

In summary, absorption intensity offers the key advantage of directly measuring a firm's ability to absorb external information. The main limitations are that our measure cannot

[4]See `https://www.uspto.gov/web/offices/pac/mpep/s2001.html` for more details.

be applied to firms without recently granted patents, and strategic or institutional factors that influence patent citations may introduce noise.

3 American Inventors Protection Act of 1999

We use AIPA as an exogenous shock to knowledge spillovers. As such, it is important to understand how AIPA changed patent disclosure requirements and to consider potential caveats when using it as a shock in our analysis.

Patent applications include details and drawings of the underlying invention. Before the passage of AIPA, the information in an application was private until the application was granted. In 2001, the year after AIPA went into effect, the average time between application and grant was 38 months (Graham and Hegde, 2015). For applications that were never granted, the information remained private. The passage of AIPA significantly changed the patent disclosure process: AIPA requires that most patents filed at the USPTO after November 28, 2000 be published 18 months after the earliest application date.[5] As a result, the information in patent applications that were eventually granted had to be disclosed, on average, in less than half the time it had been before AIPA. Information from applications that were never granted, which was previously kept private, began to almost always be disclosed. Consequently, AIPA led to a sudden increase in information about other firms' innovation activities.[6]

Even before AIPA, U.S. patent applications filed in foreign countries were published 18 months after the filing date in those countries. Therefore, the enactment of AIPA may not have represented a major information shock for firms active in technological sectors in which international patent filings are common. However, AIPA's impact as an information shock

[5]There is one exception to the early mandated disclosure of patent applications. A patent application could be kept private if the patent did not pursue foreign protection and if the applicant specifically requested privacy until the application was granted. Less than 10% of all patent applications were kept private in the years immediately after AIPA (Graham and Hegde, 2015).

[6]See Ergenzinger (2006) for a complete legislative history of the American Inventor's Protection Act, whose passage has been described as contentious and uncertain (Saidi and Žaldokas, 2021).

is still significant for these firms for two reasons. First, accessing foreign patent applications was challenging due to language barriers and a lack of public records linking U.S. patents to their foreign counterparts (Hegde and Luo, 2018). Second, knowledge spillovers tend to be geographically localized (Jaffe et al., 1993; Jaffe and Trajtenberg, 1999), suggesting that foreign patent information had limited dissemination into the U.S.

Consistent with these arguments, there is significant evidence that AIPA resulted in a significant increase in information. Hegde et al. (2023) report that U.S. patents received more and quicker follow-on citations after AIPA than their twin European patents. They also note greater knowledge spillovers for U.S. patents also filed in Japan, supporting the language barrier argument. Overall, Hegde et al. (2023) conclude that AIPA had a causal impact on knowledge spillovers. This conclusion is further corroborated by other work on AIPA (e.g., Kim and Valentine, 2021; Saidi and Žaldokas, 2021).

4 Sample

We obtain patent data from PatentsView, which is maintained by the Office of the Chief Economist at the USPTO. These data include patent numbers, assignee names, application dates, grant dates, and citations, which reference prior patents that the focal patent builds upon. Since the application date is the closest observable date to when the innovation is created, we include granted patents as of the application date (Griliches, Pakes, and Hall, 1988). To link patents to firms, we use patent-permco matches from Stoffman, Woeppel, and Yavuz (2022) to merge the patent data with firms in the Compustat/CRSP Merged file. We exclude financial firms (SIC codes 6000 to 6799), utility firms (SIC codes 4900 to 4949), and public administration firms (SIC codes 9000 to 9999). Additionally, we drop observations with missing or non-positive total assets or sales and are missing any of our independent variables as of the year 2000 (i.e., the year AIPA went into effect).

4.1 Summary statistics

AIPA went into effect on November 29, 2000. Consistent with other studies that focus on the firm-level effects of AIPA (e.g., Kim and Valentine, 2021, Saidi and Žaldokas, 2021), we define the pre-AIPA period as 1996 through 2000. To be included in this period, a firm must have non-missing data for all independent variables in the year 2000 and at least one observation between 2003 and 2007. We exclude 2001 and 2002 from most of our analysis because AIPA took effect at the end of 2000, and the first information disclosures mandated by AIPA became publicly available in May 2002. In other words, we exclude the years when AIPA was in effect but had not yet produced publicly available information.

Table 1 presents summary statistics for different versions of *Absorption intensity* in the pre-AIPA period. Since logged variables can be difficult to interpret economically, Panel A reports various versions of *Absorption intensity* before taking the log. On average, firms cite unique external patents 2.63, 3.64, and 5.37 times per patent in windows of three, five, and ten years, respectively. Panel B presents summary statistics for the logged versions of *Absorption intensity*, which are the versions we use in our analysis.

Table 2 presents correlations between different versions of *Absorption intensity* and previously-developed R&D-based proxies for the ability to internalize external information. All correlations are close to zero, which provide evidence that our measure is not only conceptually distinct from R&D-based measures but also empirically so.

4.2 Variation in absorption intensity

To provide some color on our measure, Figure 1 presents the average and standard deviation of the five-year version of *Absorption intensity* for the 20 industries (SIC3) with the most observations in our sample in the pre-AIPA period. These industries account for over 60% of all observations in this period. There are two main takeaways from this figure. The first is that there is substantial variation in our measure across industries, as evidenced by the different industry-level averages. For example, *Absorption intensity* is nearly 1.5 in

Computer and Data Processing Services but just above 0.5 in Petroleum Refining. The second is that there is also substantial variation within industries, as evidenced by the industry-level standard deviations. Again, focusing on Petroleum Refining, the standard deviation is about the same as the average.

Given the substantial variation both across and within industries, we analyze two decompositions of the five-year version of *Absorption intensity*. In both decompositions, we focus on observations in the pre-AIPA period. The first decomposition in Table 3 shows variation across industries, across firms within an industry, and within firms over time. Most of variation here is within industries, which is consistent with the results in Figure 1. The relatively low variation within firms suggests that *Absorption intensity* is somewhat stable over time.[7] Taken together, these two statistics imply that there is significant within industry by year variation. The second decomposition confirms this implication; 75% of all variation in *Absorption intensity* occurs within industry-year pairs. This finding suggests that our measure is driven by firm-level differences rather than industry-wide citation practices.

4.3 Control variables

In our main specifications, we include a battery of firm-level characteristics that are plausibly associated with firm-level innovation. *R&D capital* is accumulated and depreciated R&D expenses (Peters and Taylor, 2017), deflated by CPI (in millions). *Physical capital* is gross property, plant, and equipment adjusted for the age of the capital (İmrohoroğlu and Tüzel, 2014), deflated by the NIPA price of equipment (in millions). *Labor* is the number of employees (in thousands). *Profit* is sales minus cost of goods sold, deflated by CPI (in millions). *Patent count* is the total number of active patents. *Firm age* is the number of years since entering the Compustat database. *Tangibility* is net property, plant, and equipment divided by total assets. *Market-to-book* is the market value of assets divided by total

[7] In unreported tests, we find that in the pre-AIPA period, Absorption intensity exhibits 89% autocorrelation at lag of one year and 55% autocorrelation at lag of four years. Higher autocorrelation at shorter lags is partially due to overlapping measurement windows.

assets. *Leverage* is the sum of current debt and long-term debt divided by total assets. Importantly, we find that correlations between all versions of *Absorption intensity* and all control variables are close to zero. The low correlations with measures of direct investment in innovation and measures of firm size (i.e., *R&D capital*, *Physical capital*, *Labor*, *Profit*, and *Patent count*) are especially helpful for ruling out the possibility that our results are driven by direct measures of investment in R&D or firm size. Summary statistics of our control variables and correlations between them and *Absorption intensity* can be found in Tables IA1 and IA2 in the Internet Appendix.

5 Main results

As described above, we use AIPA as a shock to the amount of external information available to firms. We begin this section by showing that firms with higher absorption intensity before AIPA are more likely to use the information that became available after AIPA. We then use a difference-in-differences approach to demonstrate that firms with higher absorption intensity experienced a relatively greater increase in innovation output after AIPA. We conclude the section by showing that our results are stronger for firms that experienced a larger information shock and for firms that are in more innovative industries.

5.1 External application citations

AIPA requires most patent applications filed after November 28, 2000 to be published 18 months after the earliest filing date. To understand whether firms with higher absorption intensity before AIPA use the patent application information made available by AIPA's passage, we estimate Poisson regressions with the number of citations of external patent applications (added by the applicant) scaled by the number of patents in a given year as the dependent variable. The main independent variable is *Absorption intensity* (as of the year 2000). Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*,

Firm age, *Tangibility*, *Market-to-book*, and *Leverage*. To ensure we are comparing similar firms, we bin each control variable into quintiles as of the year 2000 (Bau and Matray, 2023). Binning also helps avoid issues with non-linear relations between independent and dependent variables. Since each regression uses a single cross-section of firms, we expect standard errors to be most correlated within industries, and thus, we cluster errors at the industry level.

Table 4 shows that firms with higher pre-AIPA *Absorption intensity* were much more likely to cite external patent applications after AIPA. For instance, the first column shows that a one unit increase in *Absorption intensity*, which is akin to moving from the 20$^{\text{th}}$ percentile to the 75$^{\text{th}}$ percentile, is associated with an 84% increase (i.e., ($e^{0.61}$-1)×100%) in external patent application citations per patent filed in 2003. The remaining four columns show that the relation between *Absorption intensity* and citations of future external patent applications is also strong in subsequent years.

Since information on patent applications became available only after AIPA's implementation, we cannot use difference-in-differences regressions for improved identification. Nevertheless, the correlations in Table 4 suggest that firms with higher absorption intensity are more likely to effectively leverage knowledge spillovers.[8]

5.2 Innovation output

Our primary prediction is that firms with a higher absorption intensity prior to AIPA are better positioned to leverage knowledge spillovers from AIPA, leading to a greater increase in post-AIPA innovation output. To test this prediction, we estimate the following difference-in-differences Poisson regression:

$$\log\big(Patents_{it}\big) = \alpha + \beta_1 Absorption\ intensity_i \times Post_t + \eta_i + \gamma_i \times \delta_t + \zeta_i \times \delta_t \qquad (1)$$

in which $Patents_{it}$ is the number of new patents applied for by firm i in year t that are

[8]Table IA3 in the Internet Appendix shows that our results are qualitatively similar when using three-year or ten-year versions of our measure.

eventually granted. *Absorption intensity*$_i$ is the five-year version of our measure as of the year 2000. $Post_t$ is one for years 2003 through 2007 and zero otherwise. η_i is firm fixed effects, and γ_i is a vector of controls. As before, we bin controls into quintiles as of the year 2000. ζ_i is industry fixed effects, and δ_t is year fixed effects. The information shock provided by AIPA could affect control variables in the post period, and in turn, bias the coefficient of interest. To avoid this "bad controls" issue (Angrist and Pischke, 2009), each control variable in each year is also as of the year 2000. The inclusion of firm fixed effects and year fixed effects absorb the main effects of *Absorption intensity*$_i$ and $Post_t$.

Table 5 presents results from estimating different versions of Equation 1. In the first column, we include only firm fixed effects and year fixed effects. The coefficient of 0.78 (t-stat of 5.62) implies that when increasing *Absorption intensity* by one unit results in an 118% higher change in average annual patents in the post-AIPA period, relative to the pre-AIPA period. In the second column, we replace year fixed effects with industry by year fixed effects, and the coefficient remains largely unchanged. In the third column, we exclude industry by year fixed effects and include control by year fixed effects. The coefficient on the interaction term declines slightly but remains highly significant. In the fourth column, we include both industry by year fixed effects and control by year fixed effects. The coefficient again declines slightly, but it still implies a relative 75% increase in innovation output.

In the first four columns, we double cluster standard errors at the firm and year levels. Firm-level clustering accounts for the persistence of absorption intensity. However, given the limited years around the AIPA, the necessity of year-level clustering is less clear. Additionally, industry-level shocks may introduce within-industry correlation. To address these concerns, we explore alternative clustering strategies in the last three columns of Table 5. Clustering by firm, industry, or by industry and year yields slightly lower standard errors. To remain conservative, we adopt double clustering by firm and year in subsequent tables unless otherwise specified.

Overall, Table 5 shows that firms with higher absorption intensity before AIPA exhibit

larger increases in their innovation output after AIPA.[9]

5.3 Innovation output: Treatment intensity

A potential concern with the above analysis is that other, perhaps unobservable, events occurring simultaneously with AIPA could also affect innovation output. To alleviate this concern, we take advantage of the variation in changes in knowledge spillovers resulting from AIPA's passage. Since AIPA reduced the time of patent disclosure from the time between application date and grant date to 18 months, the size of the treatment varied significantly across technological classifications. We estimate this treatment intensity using a variable we call *Grant lag*, which we calculate in four steps.

First, we identify all new patents firm i applied for in the five years through the current year that were eventually granted. Second, we identify the external citations of patents granted in the five years prior to the application of each granted patent. Third, we calculate the average grant lag for all patents granted in the same technological classification and year as the cited patents identified in the second step.[10] Fourth, we calculate a firm-year grant lag by averaging all grant lags from the third step for the focal firm prior to AIPA.

Figure 2 presents the distribution of *Grant lag* in the year 2000. We winsorize *Grant lag* at the 0.1% percentile on both sides for presentation purposes. Panel A presents the distribution after subtracting its mean, which is 720 days. The distribution is slightly right-skewed, and the standard deviation is 64 days. Panel B presents the distribution after subtracting the within-industry mean. Although this distribution is noticeably tighter, there is still significant variation in *Grant lag* within industries. Indeed, the standard deviation of *Grant lag* within industries is 45 days. Consistent with the results in Figure 2, an unreported decomposition of *Grant lag* shows that about half of the variation is between industries and

[9] Table IA4 in the Internet Appendix shows that our results are qualitatively similar when using three-year or ten-year versions of our measure.

[10] We define technological classifications at the three-digit Cooperative Patent Classification (CPC) level, of which there are over 120. See `https://www.uspto.gov/web/patents/classification/cpc/html/cpc.html` for more details.

the other half is within industries.

If the increase in innovation output after AIPA is driven by the knowledge spillovers it provides, we expect the positive relation between absorption intensity and change in innovation output to strengthen with the level of treatment. To explore this prediction, we estimate the following Poisson regression:

$$\begin{aligned} \log\big(Patents_{it}\big) = \alpha + \beta_1 Absorption\ intensity_i \times Post_t + \\ \beta_2 Grant\ lag\ (ordinal)_i \times Post_t + \\ \beta_3 Absorption\ intensity_i \times Grant\ lag\ (ordinal)_i \times Post_t + \\ \eta_i + \gamma_i \times \delta_t + \zeta_i \times \delta_t \end{aligned} \tag{2}$$

in which *Grant lag* $(ordinal)_i$ is an ordinalized value of *Grant lag*. This transformation facilitates easier economic interpretation of coefficient estimates and ensures that outliers do not disproportionately influence our results (results are similar if we use *Grant lag*). The variable *Grant lag* $(ordinal)_i$ is defined by sorting *Grant lag* into percentiles (0.01 through 1.00) as of the year 2000.

Table 6 presents results from estimating the treatment intensity specification. As in Table 5, we begin by including just firm fixed effects and year fixed effects. Consistent with our expectations, the coefficient on the triple interaction term is positive and highly significant. The economic interpretation is that the positive relation between firms' *Absorption intensity* and change in innovation output strengthens with the intensity of treatment of knowledge spillovers. For example, the coefficient on the triple interaction term in the first column implies that a one-unit increase in *Absorption intensity* is associated with a 1.67% increase in future innovation output, conditional on a one percentile increase in *Grant lag*.

In the second, third, and fourth columns, we progressively add industry by year fixed effects, control by year fixed effects, and both sets of fixed effects. In the second and third column, the coefficient on the triple interaction term either increases or remains roughly the same. The fourth column shows that when both sets of fixed effects are included, the

coefficient declines slightly but remains both economically and statistically significant.

After adding the triple interaction with *Grant lag*, the coefficient on the interaction of *Absorption intensity* and *Post* becomes slightly negative and mostly insignificant. This result implies that for firms that do not experience information shocks, higher absorption intensity does not lead to a larger increase in post-AIPA innovation output. This result supports the idea that the information made public by AIPA, rather than some contemporaneous event, affected the relation between *Absorption intensity* and future innovation.

Moreover, the double interactions of *Grant lag (ordinal)* and *Post* are negative and highly significant. This result implies that firms that cite patents in technological classifications with longer grant lags patent less after AIPA. This finding is in line with Kim and Valentine (2021), who also find that firms patent less after AIPA in technological classifications with longer grant lags. The intuition is that firms value the delay in the disclosure of information about their patents to other firms. Since AIPA accelerated the disclosure of information more for firms with higher pre-AIPA grant lags, these firms were less likely to patent after AIPA. Our results align with Kim and Valentine (2021) because the grant lag of a firm's patents is highly correlated with the average grant lag of the patents that the firm cites.

Overall, the results in Table 6 show that the positive relation between absorption intensity and changes in post-AIPA innovation strengthens with the magnitude of knowledge spillovers. This result is consistent with our argument that absorption intensity positively affects future innovation.[11]

5.4 Pre-event and post-event trends

In Panel A of Figure 3, we plot the coefficient of the interaction of *Absorption intensity* × *Grant lag* (*ordinal*) for each of the years surrounding AIPA. To do so, we replace *Post* in our treatment intensity specification (i.e., Equation 2) with indicator variables for each year around AIPA. The plotted coefficients therefore represent the interaction of *Absorption intensity*×

[11] Table IA5 in the Internet Appendix shows that we obtain similar results when using three-year or ten-year versions of our measure.

Grant lag (*ordinal*) $\times$ *Year* for each of year between 1996 and 2007. The lack of an upward trend in these coefficients in the years prior to AIPA suggests that our results are not driven by pre-event trends.

Panel A of Figure 3 also reveals two notable post-event trends. First, the coefficient estimates begin to increase in 2003, and they are not significantly different from zero before 2003. As discussed above, AIPA did not affect the external information environment until May 2002. The insignificant coefficients in 2001 and 2002 are consistent with this patent disclosure timeline. Second, the effect of AIPA is progressive over time. This progressive effect may be due to the time required to internalize external information and produce new patents, or it may reflect the accumulation of information on patent applications over time.

To formally test whether our results are driven by pre-event trends, Panel B of Figure 3 presents confidence intervals for the average treatment effect on the treated in the post-treatment period after adjusting for potential pre-treatment trends (Roth, 2022). The confidence intervals are adjusted to limit post-treatment violations of parallel trends to M times the maximum pre-treatment violation of parallel trends. For example, Panel B shows that the confidence interval includes zero when M exceeds 0.5, meaning that post-treatment violations are no larger than 50% of the maximum pre-treatment violations across consecutive periods. Overall, the results in Figure 3 provide evidence that our results are unlikely to be driven by pre-event trends.

5.5 Innovation output: Response heterogeneity

Since spillovers are especially important in innovative industries (Bloom et al., 2013), we expect our results to be stronger in such industries. To test this conjecture, we divide industries into more and less innovative categories using various definitions, and re-estimate our treatment intensity specification.

In the first two columns of Table 7, we present results for firms in high-tech and low-tech industries. High-tech industries have SIC codes 283, 357, 366, 367, 382, 384, or 737

(Brown, Fazzari, and Petersen, 2009), and low-tech industries include all other industries. The coefficient on the triple interaction term is positive and highly significant for high-tech firms but close to zero and insignificant for low-tech firms.

In the middle two columns, we categorize firms into high-patent and low-patent industries. High-patent industries are those in which the average patent count (as of the year 2000) is in the top two deciles, which include 43% of firms. All other industries are low-patent industries. Using this alternative delineation for innovation, the coefficients on the triple interaction term are again positive and significant for firms in highly innovative industries and insignificant for firms in other industries.

In the last two columns, we classify firms into high-R&D and low-R&D industries. High R&D industries are those in which the average R&D/assets ratio (as of the year 2000) is in the top decile, which includes 60% of firms. All other industries are low-R&D industries. Consistent with the results using the other two categorizations, the last two columns show that the coefficient of interest for firms in high-R&D industries is positive and significant but insignificant for firms in low-R&D industries.

In summary, Table 7 shows that the relation between pre-AIPA absorption intensity and changes in innovation output is stronger in more innovative industries. These results are consistent with our prior that the causal relation between absorption intensity and future innovation is stronger for firms in more innovative industries.

6 Robustness and validity

In this section, we show that our results obtain in a number of robustness tests, do not obtain in several falsification tests, and are not driven by a trade off between patent output and patent quality.

6.1 Robustness checks

Panel A of Table 8 presents results from several alternative specifications designed to test the robustness of our results. The first row in Panel A presents the coefficient estimate of the triple interaction term from our treatment intensity specification with full industry by year and controls by year fixed effects (i.e., fourth column of Table 6).

In our main results, we use *R&D capital* control for R&D. It is possible that our results would not obtain if we controlled for a different R&D-based variable. However, the second through sixth rows of Panel A show that our results are largely unchanged after swapping *R&D capital* for *R&D expenses*, *R&D dummy*, *R&D/Sales*, *R&D/Assets*, or *R&D/Labor*.

One might worry that firms with high absorption intensity react to AIPA by increasing their R&D expenses and this increase in R&D is what is actually driving our results. To alleviate concerns over this alternative explanation, we set aside the aforementioned "bad controls" issue and re-estimate our treatment intensity specification after including lagged R&D expenses as a time-varying control variable. The seventh row of Panel A shows that our results are again largely unchanged when doing so.

Our measure, like established measures such as *Originality* (Trajtenberg et al., 1997) and *Technological obsolescence* (Ma, 2025), relies on citations to other firms' patents. However, these measures capture different aspects of innovation: *Originality* reflects the diversity of technological sources cited, and *Technological obsolescence* reflects how a firm's technology becomes less valuable as newer innovations emerge. To ensure our results are not driven by these related citation-based measures, we re-estimate our specification while controlling for each. Despite the positive correlation between *Absorption intensity* and *Originality* (11%) and its negative correlation with *Technological obsolescence* (18%), the last two rows of Panel A in Table 8 show that our results remain similar when controlling for *Originality* and become even stronger when controlling for *Technological obsolescence*.[12]

[12] In unreported tests, we find that the increase in the magnitude of the coefficient estimate is due in part to controlling for *Technological obsolescence* and due in part to differences in samples.

6.2 Falsification tests

Panel B of Table 8 presents results from falsification tests in which we swap *Absorption intensity* for a different variable.

It is possible that our measure is not capturing anything about a firm's ability to internalize spillovers. Perhaps it is instead capturing the fact that some firms cite a lot of patents, and this propensity to cite a lot of patents is correlated with future innovation. If this alternative explanation is indeed correct, we expect similar results after substituting *Absorption intensity* with a measure that uses citations of internal patents, or patents granted to the same firm, rather than the citations of external patents. We do just that with a variable we call *Self-citations intensity*. The first row in Panel B of Table 8 shows that the coefficient on this alternative triple interaction is close to zero and insignificant.

We also test whether our results would obtain if we swapped *Absorption intensity* for R&D-based proxies for the ability to absorb external information. In these tests, we exclude *R&D capital* as a control variable. The last six columns of Panel B show that the positive relation between R&D (as determined by the measure used in that specification) and innovation output does not increase with the treatment in spillovers. This null result could be due to R&D's direct effect on innovation being more important than its effect on a firm's ability to absorb external information.

6.3 Placebo event years

An alternative explanation is that treatment intensity is correlated with some unobservable, firm-specific characteristic that predicts more future innovation when interacted with absorption intensity. If that is the case, our results would not depend on information shocks, and we should obtain similar results when using years other than the AIPA enactment year.

To rule out this alternative explanation, we run a placebo test. In this test, rather than estimate Equation 2 from the period 1996 through 2007 and use 2000 as the event year, we use 15 different sample periods and 15 different hypothetical event years. For each hypothetical

event year, we construct the sample following the same procedure as in our main test. For example, when the hypothetical event year is 1995, our sample spans 1991 through 2002, with the pre-period being 1991 through 1995, the post-period being 1998 through 2002, and the excluded period being 1996 and 1997.

Figure 4 presents the results of this placebo test. The solid line links together each of the triple interaction coefficients we obtain from the 15 regressions we estimate (i.e., one for each hypothetical event year from 1981 through 1995). The dashed lines represent the 95% confidence interval of the associated coefficient estimates. Consistent with our main results being driven by a shock to knowledge spillovers and not the aforementioned unobserved relation, none of the coefficients are positive and significant.

6.4 Absorption intensity: Applicant-added citations

As discussed above (Section 2), both patent applicants and patent examiners add citations to patents. Citations added by the examiner do not reflect an applicant's ability to internalize spillovers. Therefore, their inclusion in our measure adds noise and likely biases us toward not finding a result.

While we would ideally construct our measure using only applicant-added citations, the data preclude us from identifying whether citations were added by applicants or examiners for patents granted before January 2002. Regardless, the two measures are likely to be very highly correlated because the number of examiner citations constitutes a smaller fraction of overall citations and is positively correlated with the number of applicant citations. For patents filed between 2003 and 2005, examiner-added citations from patents in our sample ranged from 24% to 29% of all external citations. During each of those same years, the log number of examiner-added citations (at the firm-year level) was 75% correlated with the log number of applicant-added citations. As a result, we find that between 2003 and 2005, correlations between the base version of absorption intensity and a version of absorption intensity that includes only applicant-added citations are very high (84% to 90%).

To understand the role played by applicant citations versus that played by examiner citations, we use the feature that absorption intensity is relatively persistent over time to generate a proxy for pre-AIPA absorption intensity by using a version of absorption intensity constructed from applicant-added citations in patents granted beginning January 2002. We use applicant-added citations to calculate absorption intensity in years 2003, 2004 and 2005.[13] Although this test uses future information, it is useful as a robustness test to understand whether examiner-added citations bias our results in any way.

We present the results in Table 9. The first three columns employs applicant-added citations versions of *Absorption intensity* from 2003, 2004, and 2005. In all cases, the coefficient on the triple interaction term is positive and significant. The last three columns of Table 9 presents results from a falsification test in which we construct *Absorption intensity* using only examiner-added citations. Interestingly, all coefficients on the triple interaction term are insignificant and mostly close to zero.

In summary, the results from Table 9 suggest that the inclusion of examiner-added citations in our main measure adds noise and may be biasing us away from finding a result.

6.5 Innovation output: Patent scope and patent value

After developing an invention, firms face a decision: apply for patent protection and publicly disclose the invention or not apply for patent protection and keep the invention a trade secret (Hall, Helmers, Rogers, and Sena, 2014). The main change introduced by AIPA was the accelerated disclosure of nearly all patent applications. In response to this change, firms may choose to file multiple narrow patents, rather than a single broad patent, on a

[13]The 2003 version of *Absorption intensity* uses only applicant-added citations from patent grants that were filed between 1999 through 2003. It is important to note that because we can only identify who added a given citation for patents granted beginning January 2002, this version of *Absorption intensity* will necessarily exclude patents that were applied for between 1999 through 2001 and granted before January 2002. In our base version of *Absorption intensity*, citations from these types of patents would be included. However, since there is, on average, about a three year lag between application date and grant date, this issue should not result in many excluded citations. In the years after 2003, while we are able to identify whether citations were added by the applicant or examiner for a higher share of patents, our measures are further removed from 2000.

given innovation. The rationale behind this strategy is to avoid disclosing all aspects of the innovation in a single patent application due to the concern that parts of the application might be deemed unpatentable, yet the entire application would still become public.

Indeed, there is some evidence that patent applications became narrower in scope right after AIPA (Hegde et al., 2023). This decline in scope is a potential concern for our analysis if firms with high absorption intensity have a higher tendency to file for narrower, and therefore less valuable, patents after AIPA. If that is the case, the interpretation of our results becomes complicated, for these firms may trade patent output for patent quality, as proxied by patent scope and patent value, after AIPA.

To explore this possibility, we employ two proxies for patent scope and three proxies for patent value. The proxies for patent scope are used in Hegde et al. (2023) and developed by Marco, Sarnoff, and deGrazia (2019). The first proxy is the number of words in the shortest independent claim. Claims with more words have narrower scope because each additional word imposes some additional restriction.[14] The second proxy is the number of independent claims. Each independent claim is a variation to the core inventive idea that is identified in the patent, so more independent claims implies broader patent scope and legal protection.

For our three proxies for patent value, we focus on one proxy for private economic value and two proxies for scientific value. The private economic value of patents is estimated by the stock market response to news about patents (Kogan et al., 2017). The first proxy for the scientific value of patents is the number of future citations a patent receives after publication. We include citations of both granted patents, whose publication date is the grant date, and applications of patents that are eventually granted, whose publication date is 18 months after the filing date. The number of future citations has long been considered a proxy for scientific value (e.g., Hall, Jaffe, and Trajtenberg, 2005). The second proxy for the scientific value of patents is generality, which is estimated as the dispersion of citations across different

[14]Kuhn and Thompson (2019) focus on the number of words in the first independent claim, rather than the shortest patent claim. The two numbers are over 80% correlated. In unreported tests, we find that our results are qualitatively similar when using the number of words in the first independent claim.

technological classifications a patent receives after being granted (Trajtenberg et al., 1997). Generality indicates the extent to which the knowledge described in a patent applies beyond its original domain. For both proxies for scientific value, we include only ten years of future patent citations so that we can make a valid comparison across time. Lastly, we aggregate all patent-level measures to the firm-year level by averaging across all patents for each firm-year.

Table 10 shows that when we estimate Equation 2 but swap patent output for patent scope or patent value, the coefficient on the triple interaction is insignificant and close to zero. These results imply that any differences in patent scope or patent value between firms with high absorption intensity and firms with low absorption intensity were not any different before AIPA than they were after AIPA. In other words, we do not find evidence that higher absorption intensity firms traded patent output for patent scope or patent value after AIPA.

Overall, the results in Table 10 alleviate concerns that the larger post-AIPA increase in innovation output for higher absorption intensity firms was accompanied by narrower or less valuable patents.

7 External validity

7.1 Patent count

One might be concerned that the positive relation between absorption intensity and future innovation output is confined to the period around AIPA. We show that this relation generalizes to other periods by estimating a panel regression of future patent grants on absorption intensity using a sample spanning 1975 through 2019. Panel A of Table 11 shows that absorption intensity is positively associated with innovation output through at least five years in the future. These results suggest that regardless of the sample period, absorption intensity likely plays a role in the production of innovation output.

7.2 Patent quality

Although we previously show that high absorption intensity firms do not change patent scope or patent value in response to AIPA, such firms may have broader patents and more valuable patents to begin with. We find that to indeed be the case. Panel B of Table 11 shows that firms with higher absorption intensity generate patents with broader scope, higher economic value, more citations, and greater generality. These findings indicate that firms with higher absorption intensity tend to produce higher-quality patents.

7.3 Firm growth

We have shown that absorption intensity has a causal effect on patent output. Patents, in turn, can influence firm-level outcomes through various mechanisms. Patents may drive the development of new products, which ultimately enhances sales, investment, and growth (Kogan et al., 2017). Patents may focus on improving process efficiency and automation (Bena, Ortiz-Molina, and Simintzi, 2022). Patents can serve defensive purposes, such as blocking competitors or enhancing monopolistic power, which can further boost profitability (Ziedonis, 2004). Patents can also provide revenue through licensing agreements (Arora, Fosfuri, and Gambardella, 2004).

Given the multiple channels through which patents can affect firm-level outcomes, we investigate how absorption intensity is associated with firm growth. Following previous work (Kogan et al., 2017; Ma, 2025), our measures of firm growth are defined as log changes in physical capital, labor, profit, output, and total factor productivity (TFP). Given the large and growing importance of intangible capital to the modern economy (Haskel and Westlake, 2018), we also examine how absorption intensity is associated with growth in R&D capital. We present the results in Panel C of Table 11.

We find that absorption intensity is strongly correlated with changes in R&D capital, which likely reflects the role of patenting in increasing resources for further R&D (Hsu and Ziedonis, 2013). Absorption intensity is also strongly correlated with growth in profit

and labor. The correlations between our measure and both output and physical capital are positive but economically and statistically weaker. The lack of correlation between absorption intensity and TFP could be driven by the idea that process-related patents can improve productivity, whereas product-related patents may not (Scherer, 1982).

The relationships between absorption intensity and firm growth are undoubtedly complex. We present initial correlations and leave the exploration of underlying mechanisms and causality to future research.

8 Antecedents of absorption intensity

Absorption intensity serves as an output-based proxy for a firm's ability to assimilate external information and effectively summarizes the fundamental factors that influence this ability. In this section, we examine several key factors that may impact a firm's ability to absorb information. Specifically, we show that firms with higher absorption intensity tend to have more skilled inventors, organizational practices that are more conducive to innovation, closer proximity to highly ranked academic institutions, and higher rates of college-educated employees. Coupled with the fact that absorption intensity outperforms each of these antecedents in explaining future innovation output (Table IA6), the results in this section support our arguments (i) that each antecedent may contribute only marginally to a firm's overall absorption intensity and (ii) that absorption intensity reflects both known and unknown factors that contribute to the ability to absorb information.

8.1 Human capital: Inventor quality

Quality of human capital is vital for the development and utilization of a firm's ability to use external information (Zahra and George, 2002). Due to their role as producers of innovation, inventors are perhaps the most important type of skilled employees in this context. To that end, we expect inventor quality to be positively related to absorption intensity.

We measure inventor quality using *Inventor citation rank*$_{t\text{-}5}$, which is the average citation rank of all inventors on patents granted in the past five years as of five years ago. We use the USPTO inventor disambiguation file to identify inventors and estimate rankings using all inventors, not just inventors employed at firms in our sample. Due to data constraints and the need for five years of data to construct our variable, the sample for this test is 1980 through 2019. Consistent with our expectation, the first column of Table 12 shows that *Absorption intensity* is indeed highly positively correlated with *Inventor citation rank*$_{t\text{-}5}$.

8.2 Organizational structure: Inventor distance

An organizational structure that promotes communication between various units within firms helps firms develop their ability to assimilate external information (Cohen and Levinthal, 1990). Such communication between executives, who develop firm strategy, and inventors, who generate new ideas, is an essential form of communication in this context. Furthermore, other work has shown the importance of spatial proximity in effective communication (Akerlof, 1997). Taken together, we expect firms with a shorter physical distance between their inventors and their headquarters to have higher absorption intensity.

We identify inventor locations from patent grants, and we obtain information on firm headquarters from Gao, Leung, and Qiu (2021). To develop our variable *Inventor distance*$_{t\text{-}5}$, we calculate the average distance at the patent level before aggregating to the firm level. As before, we use patents granted over the past five years as of five years ago. Due to data constraints and the need for five years of data to construct *Inventor distance*$_{t\text{-}5}$, the sample for this test begins in 2008. The second column of Table 12 shows a strong negative correlation between *Absorption intensity* and *Inventor distance*$_{t\text{-}5}$. That is, firms with inventors located closer to headquarters have higher absorption intensity.

8.3 Culture of innovation

A firm's "learning culture" or "knowledge-friendly culture" is necessary for knowledge to be gained and effectively used within an organization (Davenport, De Long, and Beers, 1998; Harvey, Palmer, and Speier, 1998; Harrington and Guimaraes, 2005). For example, tolerance for failure may affect incentives to innovate (Manso, 2011; Tian and Wang, 2014). We therefore expect firms with a culture that fosters innovation to exhibit higher absorption intensity.

We measure innovation culture using the natural log of the corporate cultural value of innovation from Li, Mai, Shen, and Yan (2021) (*Innovation culture*$_{t\text{-}5}$). This measure is estimated using machine learning techniques from earnings call transcripts. The sample for this test begins in 2006. Again, consistent with our expectations, the third column of Table 12 shows a positive relation between *Absorption intensity* and *Innovation culture*$_{t\text{-}5}$.

8.4 Proximity to academic institutions

Academic institutions can play a vital role in the development of a firm's ability to internalize external information. First, university research programs are often at the technological frontier (Furman and MacGarvie, 2007), and being closer to this frontier contributes to the development of a firm's ability to internalize outside information (Cohen and Levinthal, 1990). Second, academic scientists may contribute to a firm's ability not only through their human capital but also through their social capital (Murray, 2004). Third, informal relationships and networking through academic institutions may also help a firm develop this ability (Owen-Smith and Powell, 2004). Given these channels through which academic institutions may aid the development of a firm's ability to absorb external information, we expect firms closely located to highly-ranked institutions to have higher absorption intensity.

We obtain rankings of U.S.-based academic institutions from SCImago Institution Rankings. These rankings are determined by three factors: research (50%), innovation (30%), and societal (20%). Research rankings are determined mostly by various indicators associ-

ated with research publications. Innovation rankings are determined by patent application counts and the number of research publications cited by patents. Societal impact rankings are determined by factors that measure general public awareness of the institution and its associated research.[15]

We test our expectation by regressing *Absorption intensity* on *Academic research rank*$_{t\text{-}5}$, which is the average rank of universities located within 100 miles of firm headquarters as of five years ago. Our sample for this test begins in 2014. The fourth column of Table 12 shows a positive and significant relation between *Absorption intensity* and average research rank of closely-located academic institutions.[16]

8.5 Prior knowledge: Education

Cohen and Levinthal (1990) argue that the ability to internalize external information is largely a function of prior knowledge, for prior knowledge enhances learning and increases the ability to use new knowledge. An important source of prior knowledge is education. Thus, we expect firms with higher absorption intensity to have more educated employees.

To test this expectation, we obtain data on employee education levels from the World Management Survey (WMS).[17] Specifically, we use two variables from this data set: the percent of managers with a college degree and the percent of non-managers with a college degree. Data from the WMS are drawn from both public and private medium-sized manufacturing firms located all over the world (Bloom and Van Reenen, 2007; Bloom, Sadun, and Van Reenen, 2013). After matching these data to our sample and lagging the education variables by five years, we have fewer than 65 observations. Therefore, we analyze scatter plots and simple correlations between lagged education and *Absorption intensity*.

We present the scatter plots in Figure 5. Panels A and B show positive relations between the raw values of *Absorption intensity* and percent of college educated employees. The

[15] See `https://www.scimagoir.com/methodology.php` for more details on the methodology.

[16] In unreported tests, we obtain similar results when using different distances from firm headquarters (e.g., 50 miles, 150 miles, 200 miles).

[17] We thank Nicholas Bloom and the team at the World Management Survey for kindly providing us the data.

fitted lines are upward sloping, and the relations do not appear to be driven by outliers. Furthermore, in unreported tests, we find that the correlation between the two variables is 18% in Panel A and 30% in Panel B.

To control for industry-specific characteristics and time trends, we also analyze the relation between *Absorption intensity* and education after demeaning each variable within industry and within year. Panels C and D show that the relations between the demeaned variables are even stronger. Indeed, we find that the correlation between the two variables is 63% in Panel C and 32% in Panel D. However, since these findings are based on a limited number of observations, it is important to interpret these results with caution.[18]

9 Discussion

Our measure has broad applicability across various research areas. In this section, we discuss how our measure fits into some of these areas and make suggestions for future research.

Our measure is particularly relevant to innovation policy research, where economists have long argued that firms underinvest in innovation relative to the socially optimal level because firms do not account for the positive effects of knowledge spillovers (e.g., Arrow, 1962; Aghion and Howitt, 1992; Bloom et al., 2013). Specifically, since absorption intensity is observable and relatively persistent, it can aid in the implementation of innovation policy. For example, our measure could be used to assess which sectors are likely to experience a more pronounced underinvestment in innovation. Given that the effect of knowledge spillovers is more significant in industries with higher absorption intensity, it may make sense to focus on these sectors. Additionally, the literature suggests that firm efficiency (or type) in innovation production (e.g., Akcigit, Hanley, and Stantcheva, 2022) could be used to help determine optimal innovation policies; absorption intensity could be a determinant of firm

[18] In unreported tests, we find a positive, but small, correlation between *Absorption intensity* and the main management variable in the WMS data (about 3%). This lack of a strong relation between the two variables is unsurprising, for the questions used to estimate the management variable are likely too general to be relevant for what we are trying to capture.

type. Lastly, our results suggest that policies designed to enhance firms' ability to absorb external information – through initiatives like organizational development, employee training, or partnerships with universities and research institutions – could potentially increase the multiplier effects of innovation.

Our measure could also be used in research areas that focus on how firms integrate external information acquired through various means. For example, a primary motivation for alliances (Hamel, 1991; Kumar and Nti, 1998; Gomes-Casseres et al., 2006), corporate venture capital (Siegel et al., 1988; Benson and Ziedonis, 2010; Ma, 2020), joint ventures (Kogut, 1988; Lane et al., 2001), and mergers and acquisitions (Phillips and Zhdanov, 2013; Bena and Li, 2014; Frésard et al., 2020) is to benefit from outside firms' innovation and technological expertise. These types of investments are subject to significant information frictions (Howell, 2020; Celik et al., 2022). Since our measure captures firms' ability to absorb external information, it can serve as an indicator of how well a firm might succeed in such investments.

Our measure can also be calculated at the individual inventor level. This measure could serve as a tool to examine how individuals contribute to knowledge spillovers, an area of critical importance for future empirical research, as emphasized by Aghion and Jaravel (2015).

We welcome further research that delves deeper into the firm-level characteristics and organizational practices that enhance absorption intensity. Such research can provide valuable insights into how firms can better position themselves to take advantage of knowledge spillovers. Developing this understanding can also help researchers and policymakers craft more nuanced and effective innovation policies that target improving firms' ability to absorb and use external information.

In summary, our study highlights the significance of absorption intensity in determining how firms benefit from external knowledge. We believe our measure can be applied across a wide range of research areas.

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Figure 1. Absorption intensity

This figure presents the mean and standard deviation of *Absorption intensity* (five-year version) in the 20 most prevalent SIC3 industries (by observation count) in the pre-AIPA period (1996 through 2000).

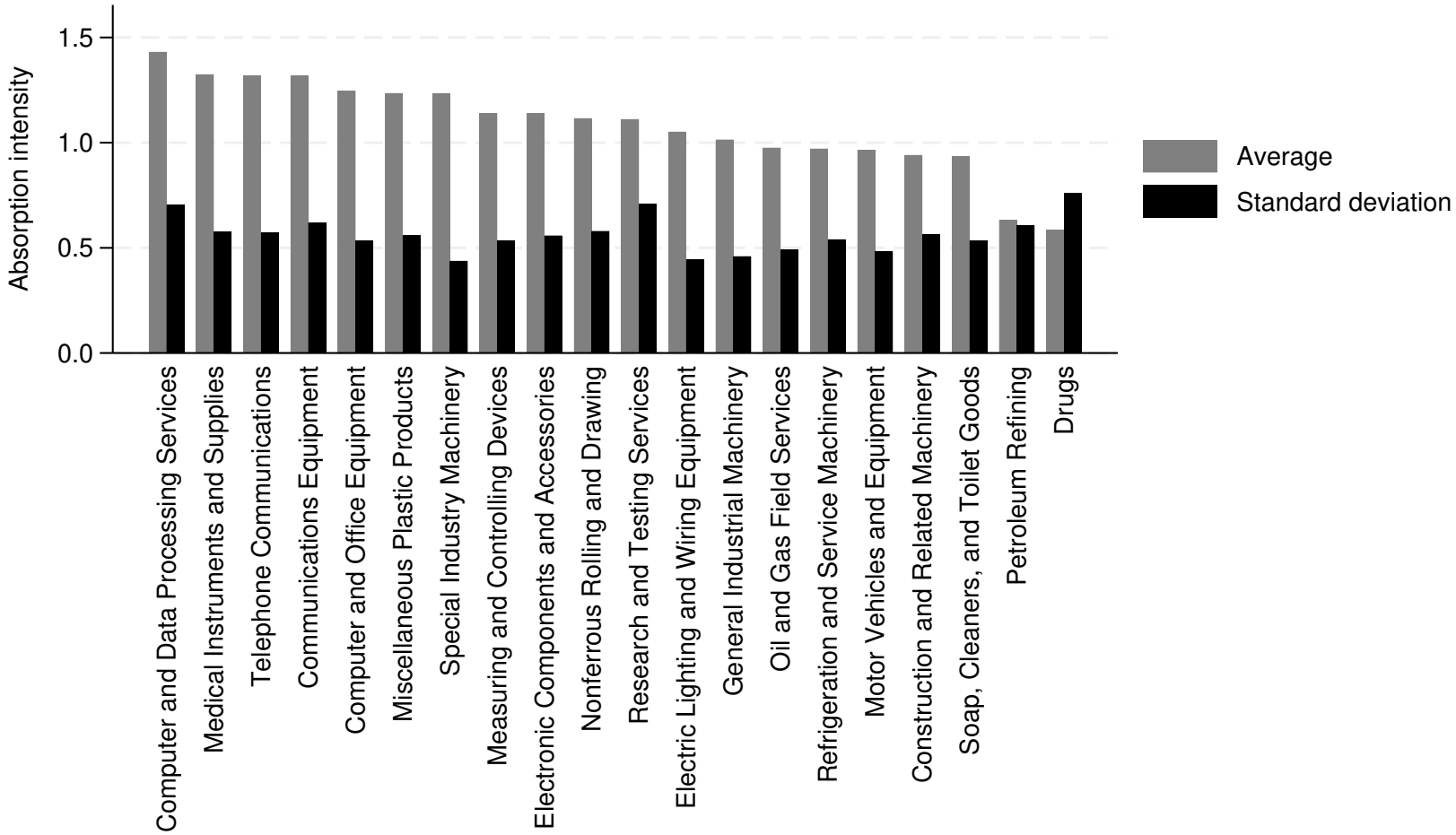


Figure 2. Grant lag

This figure presents the distribution of *Grant lag* in the year 2000. *Grant lag* is calculated in four steps. First, we identify patents applied for by a firm in the five years through the current year that are eventually granted. Second, in each of those patents, we identify the citations of external patents in the five years prior to citing them. Third, for the external patents identified in the second step, we calculate the average grant lag of all patents granted in the same technological classification and in the same year. Fourth, we take the average of all grant lags in the third step to calculate a firm-year grant lag of the focal firm prior to AIPA. In Panel A, we demean *Grant lag* using all observations. In Panel B, we demean *Grant lag* within each SIC3 industry. *Grant lag* is winsorized at the 0.1% and 99.9% in each panel.

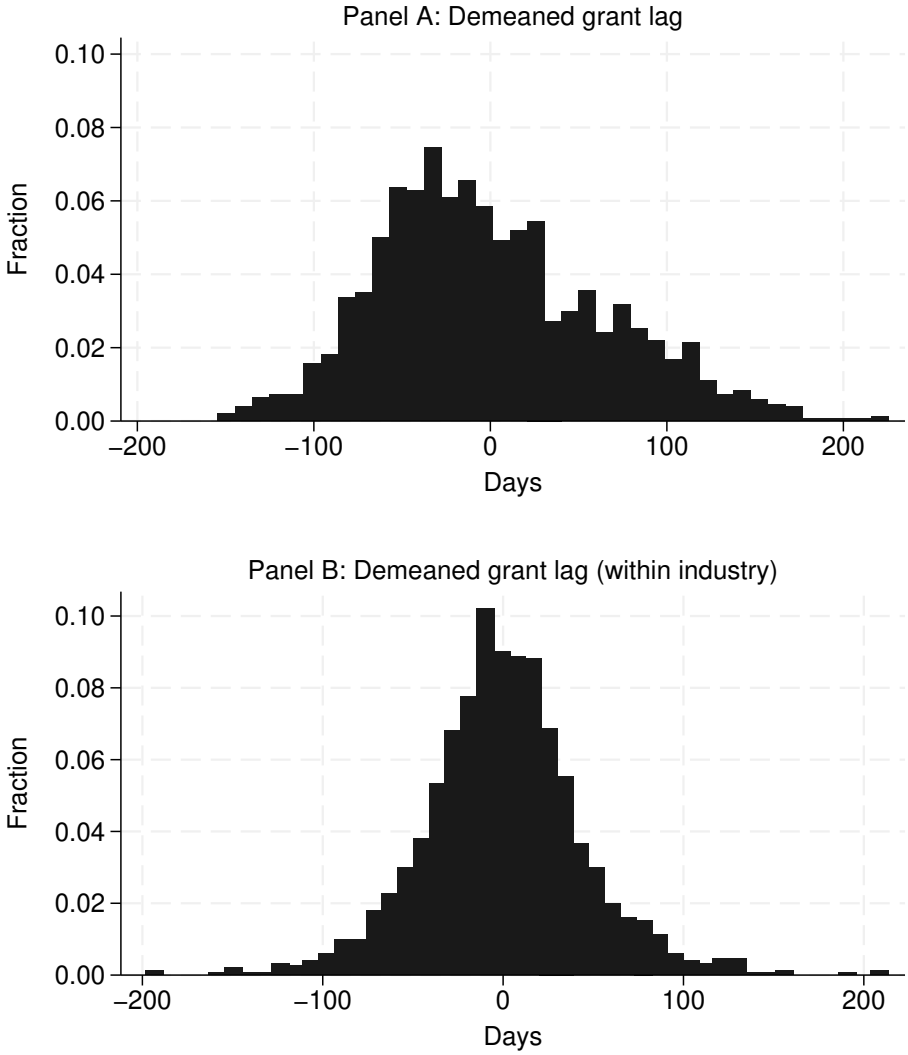
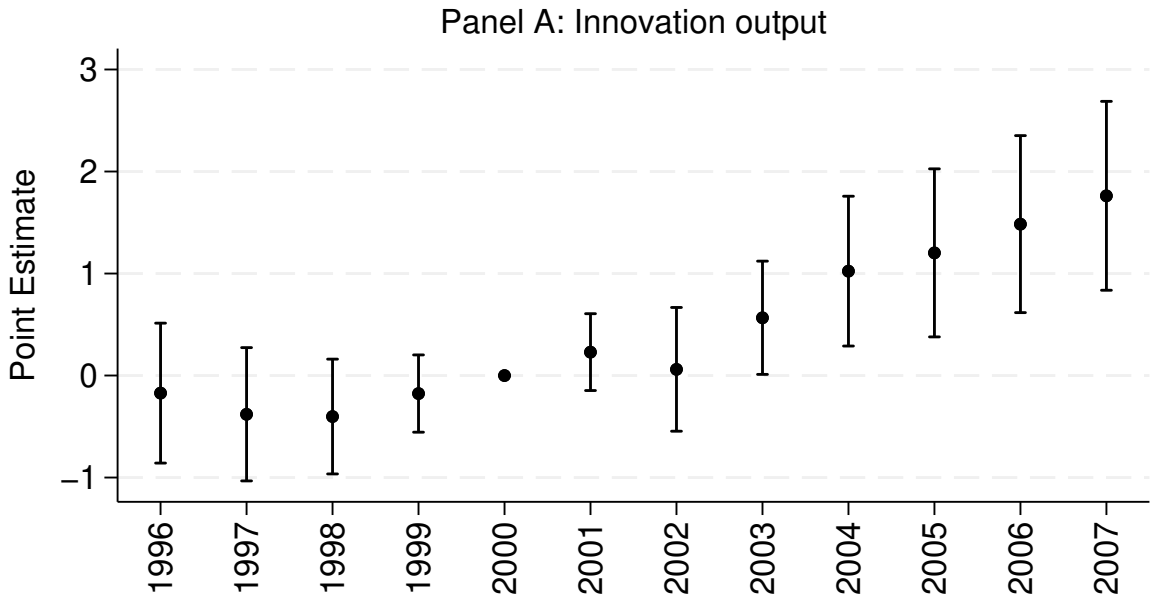


Figure 3. Innovation output and absorption intensity: Variation in treatment

This figure shows the pre-AIPA and post-AIPA trends in the relation between *Absorption intensity* and innovation output. Panel A shows the annual effect of the interaction of the variation in treatment of AIPA and *Absorption intensity* on innovation output. The associated Poisson model is as follows:

$$\log\left(Patents_{it}\right) = \alpha + \beta_1 Absorption\ intensity_i \times Year_t + \beta_2 Grant\ lag\ (ordinal)_i \times Year_t + \beta_3 Absorption\ intensity_i \times Grant\ lag\ (ordinal)_i \times Year_t + \eta_i + \gamma_i \times \delta_t + \zeta_i \times \delta_t$$

The dependent variable is the number of patents applied for in a given year that are eventually granted. This number is winsorized at the 99% level of the non-zero observations each year. *Absorption intensity* is as of the year 2000 and winsorized at the 1% and 99% levels. *Grant lag (ordinal)* spans 0.01 through 1.00 and is defined by sorting *Grant lag* into percentiles as of the year 2000. $Year_t$ is a vector of indicator variables that equals one for year t and zero otherwise. η_i is firm fixed effects. Control variables (γ_i) include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage*. All control variables are binned into quintiles as of the year 2000. δ_t is year fixed effects, and ζ_i is industry fixed effects. Industry is at the SIC3 level as of 2000. Panel B presents confidence intervals of the average treatment effect on the treated in the post period after adjusting for potential trends in the pre-treatment period. As in our main specification, the post period includes just 2003 through 2007 (i.e., 2001 and 2002 are excluded). Confidence intervals are adjusted for restricting the post-treatment violations of parallel trend by M times the maximum pre-treatment violation of parallel trends. Standard errors are clustered at the firm level.


Panel A: Innovation output
Point Estimate
3
2
1
0
−1
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007

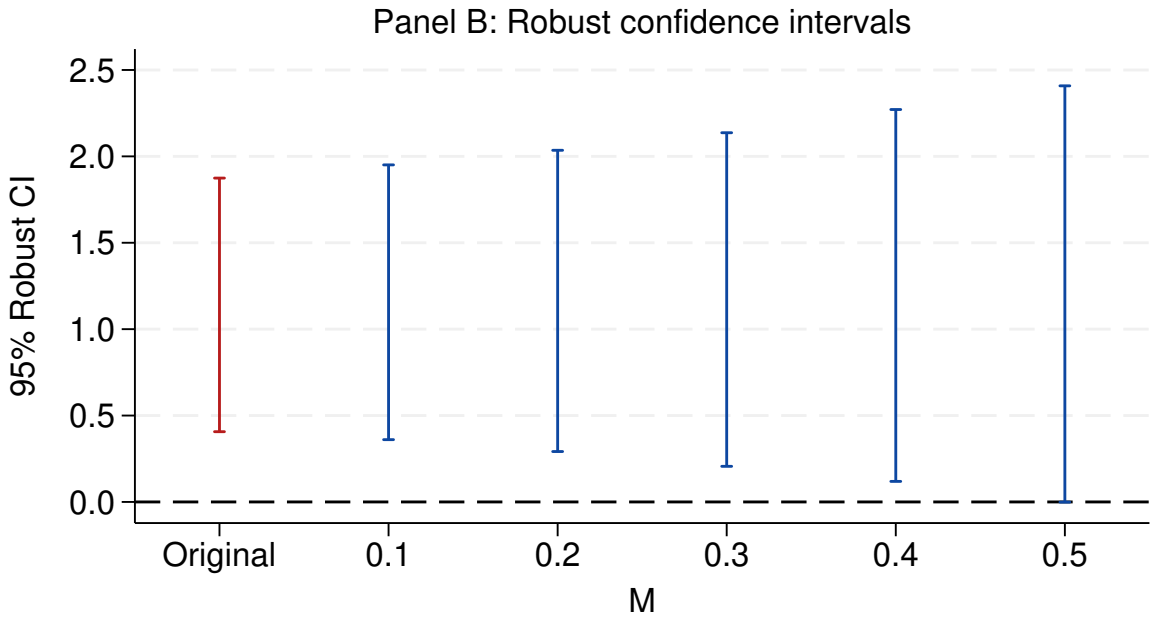

Panel B: Robust confidence intervals
95% Robust CI
2.5
2.0
1.5
1.0
0.5
0.0
Original
0.1
0.2
0.3
0.4
0.5
M

Figure 4. Innovation output: Placebo test

This figure presents the coefficient estimates and 95% confidence intervals of the triple interaction term for 15 different hypothetical event years from the following Poisson model:

$$\log\left(Patents_{it}\right) = \alpha + \beta_1 Absorption\ intensity_i \times Post_t + \beta_2 Grant\ lag\ (ordinal)_i \times Post_t + \beta_3 Absorption\ intensity_i \times Grant\ lag\ (ordinal)_i \times Post_t + \eta_i + \gamma_i \times \delta_t + \zeta_i \times \delta_t$$

The dependent variable is the number of patents applied for in a given year that are eventually granted. This number is winsorized at the 99% level of the non-zero observations each year. *Absorption intensity* is as of the hypothetical event year and winsorized at the 1% and 99% levels. *Grant lag (ordinal)* spans 0.01 through 1.00 and is defined by sorting *Grant lag* into percentiles as of the hypothetical event year. η_i is firm fixed effects. Control variables (γ_i) include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage*. All control variables are binned into quintiles as of the hypothetical event year. δ_t is year fixed effects, and ζ_i is industry fixed effects. Industry is at the SIC3 level as of the hypothetical event year. For each hypothetical event year, the sample is *t-4* through *t+7* and excludes *t+1* and *t+2*. Standard errors are double clustered at the firm and year levels.

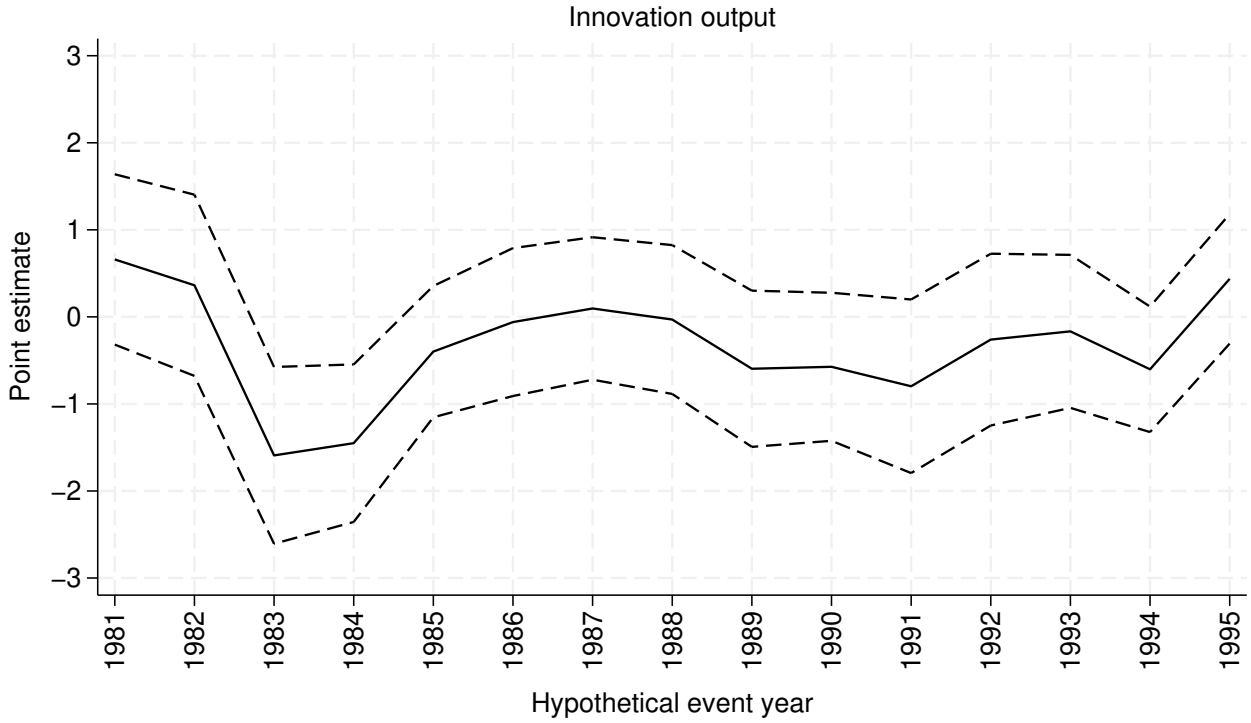


Figure 5. Prior knowledge: Education

This figures presents scatter plots of the relation between *Absorption intensity* and either the percent of managers with a college degree or the percent of non-managers with a college degree. Education variables are lagged five years. In Panels A and B, we present the relations between the raw values. In Panels C and D, we present the relations after demeaning the variables within SIC3 industry and within year.

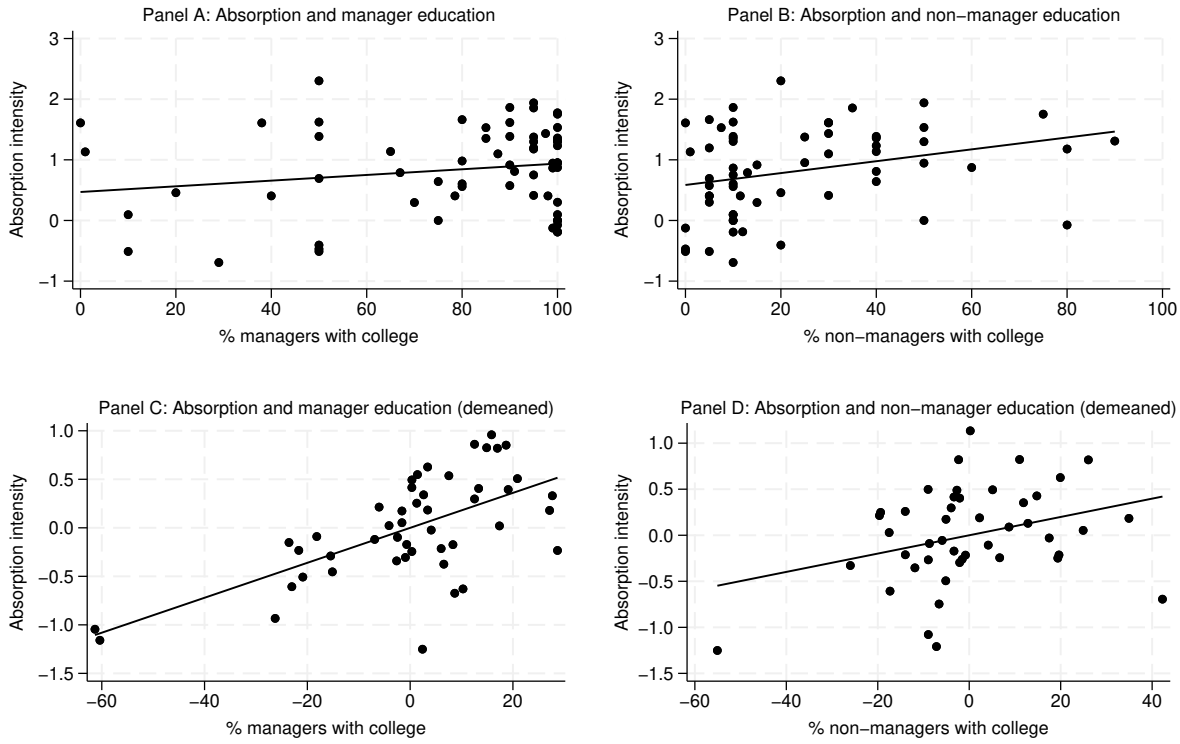


Table 1. Summary statistics: Absorption intensity

This table presents summary statistics of different versions of *Absorption intensity* in the pre-AIPA period (1996 through 2000). *Absorption intensity* is calculated in four steps. First, we identify patents applied for in the five years (for the five-year version) through the current year that are eventually granted. Second, in the patents identified in step one, we identify unique external citations of patents that were granted in the five years prior to applying for the eventually-granted patent. Third, we divide the sum of unique external citations in step two by the number of new patents in step one. Fourth, we take the natural logarithm of the quotient. For the versions of *Absorption intensity* in Panel A, we stop at the third step. All variables are winsorized at the 1% and 99% levels.

Panel A: Absorption intensity (unlogged)

	Mean	Std. dev.	10%	25%	50%	75%	90%	Obs.
Three-year version	2.63	2.20	0.83	1.31	2.00	3.10	5.00	6,577
Five-year version	3.64	2.70	1.17	2.00	3.00	4.43	6.67	7,534
Ten-year version	5.37	3.93	2.00	3.00	4.37	6.50	9.50	8,357

Panel B: Absorption intensity

	Mean	Std. dev.	10%	25%	50%	75%	90%	Obs.
Three-year version	0.70	0.72	-0.18	0.27	0.69	1.13	1.61	6,577
Five-year version	1.07	0.67	0.15	0.69	1.10	1.49	1.90	7,534
Ten-year version	1.47	0.65	0.69	1.10	1.47	1.87	2.25	8,357

Table 2. Correlations: Absorption intensity and R&D-based variables

This table presents correlations between each version of *Absorption intensity* and previously-developed R&D-based proxies for the ability to absorb external information in the pre-AIPA period (1996 through 2000). *R&D capital* is the natural log of cumulated and depreciated R&D expenses (Peters and Taylor, 2017), deflated by CPI (in millions). *R&D expenses* is the natural log of annual R&D expenses, deflated by CPI (in millions) (Nambisan, 2013). *R&D dummy* is one if the firm reports any positive R&D and zero otherwise (de Faria et al., 2010). *R&D/sales* is the natural log of the quotient of R&D expenses and sales. *R&D/assets* is the natural log of the quotient of R&D expenses and book assets (Zou et al., 2018). *R&D/labor* is the natural log of the quotient of the three-year sum of R&D expenses (deflated by CPI and in millions) and the number of thousands of employees (Tsai, 2009). All variables are winsorized at the 1% and 99% levels.

	R&D capital	R&D expenses	R&D dummy	R&D/sales	R&D/assets	R&D/labor
Three-year version	-0.14	-0.10	0.01	0.01	0.06	0.02
Five-year version	-0.16	-0.11	0.00	-0.06	0.00	-0.07
Ten-year version	-0.16	-0.15	-0.02	-0.13	-0.08	-0.15

Table 3. Decomposition of absorption intensity

This table presents two decompositions of *Absorption intensity* (five-year version) in the pre-AIPA period (1996 through 2000). The first decomposition shows variation across industries, across firms within an industry, and within firms over time. The second decomposition shows variation across industries, within industries across different years, and across firms in the same industry by year combination (Ma, 2025). See the Internet Appendix for details on each decomposition.

	Decomposition (1)		Decomposition (2)	
	Variation	% of total variation	Variation	% of total variation
Total	3,089.2	100.0	3,089.2	100.0
Between industries	674.0	21.8	674.0	21.8
Within industries	1,958.8	63.4	99.7	3.2
Within firm	457.3	14.8		
Within industries × year			2,315.4	75.0

Table 4. External citations of patent applications

This table presents results from Poisson regressions of *Application citations* on *Absorption intensity* (five-year version) and controls. *Application citations* is the number of citations of external applications (made by the applicant) per patent filed in a particular year (i.e., 2003, 2004, 2005, 2006, 2007) and is winsorized at the 99% level of the non-zero observations. *Absorption intensity* is as of the year 2000 and winsorized at the 1% and 99% levels. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage*. *R&D capital* is cumulated and depreciated R&D expenses (Peters and Taylor, 2017), deflated by CPI (in millions). *Physical capital* is gross property, plant, and equipment adjusted for the age of the capital (İmrohoroğlu and Tüzel, 2014), deflated by the NIPA price of equipment (in millions). *Labor* is the number of employees (in thousands). *Profit* is sales minus cost of goods sold, deflated by CPI (in millions). *Patent count* is the natural log of the total number of active patents. *Firm age* is the number of years since entering the Compustat database. *Tangibility* is net property, plant, and equipment divided by total assets. *Market-to-book* is the market value of assets divided by total assets. *Leverage* is the sum of current debt and long-term debt divided by total assets. All control variables are binned into quintiles as of year 2000. Industry is defined at the SIC3 level. z-scores below coefficients are adjusted for clustering at the industry level. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

	2003	2004	2005	2006	2007
	(1)	(2)	(3)	(4)	(5)
Absorption intensity	0.61***	0.75***	0.72***	0.67***	0.49***
	(3.12)	(5.09)	(3.85)	(4.20)	(3.86)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	22.3%	26.2%	20.9%	23.2%	21.5%
Observations	1,694	1,610	1,497	1,370	1,235

Table 5. Innovation output

This table shows the effect of the interaction of AIPA and *Absorption intensity* (five-year version) on innovation output. The dependent variable is the number of patents applied for in a given year that are eventually granted. This number is winsorized at the 99% level of the non-zero observations each year. *Absorption intensity* is as of the year 2000 and winsorized at the 1% and 99% levels. *Post* is a dummy that equals one for years 2003 through 2007 and zero otherwise. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table 4 for definitions). All control variables are binned into quintiles as of year 2000. Sample is from 1996 through 2007 but excludes 2001 and 2002. Industry is at the SIC3 level as of 2000. z-scores below coefficients are adjusted for clustering at the level indicated in that column. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Absorption intensity × Post	0.78***	0.80***	0.64***	0.56***	0.56***	0.56***	0.56***
	(5.62)	(5.39)	(5.81)	(4.85)	(6.15)	(6.69)	(5.22)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No	No
Industry × Year FE	No	Yes	No	Yes	Yes	Yes	Yes
Controls × Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Clustering	Firm + Year	Firm + Year	Firm + Year	Firm + Year	Firm	Industry	Industry + Year
Pseudo R^2	92.9%	93.9%	94.1%	95.1%	95.1%	95.1%	95.1%
Observations	16,798	16,164	15,273	14,593	14,593	14,593	14,593

Table 6. Variation in treatment

This table shows the effect of the interaction of AIPA and *Absorption intensity* (five-year version) on innovation output after considering heterogeneity in knowledge spillover treatment intensity. The dependent variable is the number of patents applied for in a given year that are eventually granted. This number is winsorized at the 99% level of the non-zero observations each year. *Absorption intensity* is as of the year 2000 and winsorized at the 1% and 99% levels. *Grant lag (ordinal)* spans 0.01 through 1.00 and is defined by sorting grant lag into percentiles as of the year 2000. *Post* is a dummy that equals one for years 2003 through 2007 and zero otherwise. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table 4 for definitions). All control variables are binned into quintiles as of year 2000. Sample is from 1996 through 2007 but excludes 2001 and 2002. z-scores below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

	(1)	(2)	(3)	(4)
Absorption intensity × Post	-0.29	-0.50*	-0.40*	-0.23
	(-1.21)	(-1.79)	(-1.72)	(-1.01)
Grant lag (ordinal) × Post	-1.50***	-1.88***	-2.16***	-1.85***
	(-3.25)	(-3.11)	(-4.50)	(-3.46)
Absorption intensity × Grant lag (ordinal) × Post	1.67***	1.93***	1.68***	1.15***
	(3.83)	(3.87)	(3.76)	(2.98)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Industry × Year FE	No	Yes	No	Yes
Controls × Year FE	No	No	Yes	Yes
Pseudo R^2	93.0%	94.1%	94.3%	95.3%
Observations	13,532	12,943	12,305	11,711

Table 7. Response heterogeneity

This table shows the effect of the interaction of AIPA and *Absorption intensity* (five-year version) on innovation output in innovative industries after considering heterogeneity in knowledge spillover treatment intensity. The dependent variable is the number of patents applied for in a given year that are eventually granted. This number is winsorized at the 99% level of the non-zero observations each year. *Absorption intensity* is as of the year 2000 and winsorized at the 1% and 99% levels. *Grant lag (ordinal)* spans 0.01 through 1.00 and is defined by sorting grant lag into percentiles as of the year 2000. *Post* is a dummy that equals one for years 2003 through 2007 and zero otherwise. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table 4 for definitions). All control variables are binned into quintiles as of year 2000. In the first two columns, high-tech firms are firms in industries with SIC codes 283, 357, 366, 367, 382, 384, and 737 (Brown et al., 2009). All other industries are low-tech industries. In the middle two columns, high-patent industries are industries in which the average patent count (as of the year 2000) is in the top two deciles. All other industries are low-patent industries. In the last two columns, high R&D industries are industries in which the average R&D/assets ratio (as of the year 2000) is in the top decile. All other industries are low-R&D industries. Sample is from 1996 through 2007 but excludes 2001 and 2002. z-scores below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

	(1)	(2)	(3)	(4)	(5)	(6)
Absorption intensity × Post	-0.39	0.42	-0.55	0.18	-0.06	0.18
	(-1.54)	(1.40)	(-1.62)	(0.77)	(-0.27)	(0.66)
Grant lag (ordinal) × Post	-2.36***	0.07	-3.20***	-0.54	-1.65**	-0.68
	(-3.90)	(0.12)	(-3.23)	(-1.05)	(-2.53)	(-1.40)
Absorption intensity × Grant lag (ordinal) × Post	1.72***	-0.10	2.13***	0.25	1.23**	0.25
	(3.46)	(-0.17)	(3.26)	(0.66)	(2.46)	(0.54)
Industry type	High-tech	Low-tech	High-patent	Low-patent	High-R&D	Low-R&D
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	95.6%	95.8%	96.5%	89.7%	95.7%	96.1%
Observations	6,039	5,595	5,050	6,528	6,904	4,707

Table 8. Robustness and falsification tests

This table presents results from robustness checks of our treatment intensity specification (Equation 2) and results from falsification tests. The dependent variable is the number of patents applied for in a given year that are eventually granted. This number is winsorized at the 99% level of the non-zero observations each year. Panel A presents results from specifications that include small changes to our treatment intensity specification. Panel B presents results from falsification tests in which we swap *Absorption intensity* (five-year version) for the variable listed in the particular row. Unless otherwise stated, control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* and are binned into quintiles as of year 2000. See Table 4 for definitions of control variables. In rows two through seven of Panel B, we do not control for *R&D capital*. Sample is from 1996 through 2007 but excludes 2001 and 2002. See Table 2 for definitions of R&D-based variables. *Technological obsolescence* is calculated as in Ma (2025) and is binned into quintiles as of year 2000. *Self-citations intensity* is calculated as *Absorption intensity* except that we use unique self citations rather than unique external citations in the second calculation step. *Originality* is the Herfindahl Index of a patent's backward citations across technological fields (averaged to the firm level). *Self-citations intensity* is as of the year 2000 and winsorized at the 1% and 99% levels. z-scores below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

Panel A: Robustness checks

	Change to specification	Triple Interaction	z-score	Observations
(1)	None (column 4 of Table 6))	1.15***	(2.98)	11,711
(2)	Swap R&D capital for R&D expense	1.11***	(2.97)	11,711
(3)	Swap R&D capital for R&D dummy	1.19***	(3.11)	11,711
(4)	Swap R&D capital for R&D/sales	1.05***	(2.95)	11,711
(5)	Swap R&D capital for R&D/assets	1.10***	(2.80)	11,711
(6)	Swap R&D capital for R&D/labor	0.82**	(2.14)	10,723
(7)	Control for time-varying R&D expense	0.99***	(2.19)	8,655
(8)	Control for originality	1.00**	(2.35)	8,975
(9)	Control for technological obsolescence	1.73***	(3.77)	9,460

Panel B: Falsification tests

	Alternative measure	Triple Interaction	z-score	Observations
(1)	Self-citations intensity	0.12	(0.70)	6,875
(2)	R&D expense	-0.12	(-1.18)	9,991
(3)	R&D capital	-0.17*	(-1.70)	10,757
(4)	R&D dummy	0.34	(0.38)	11,989
(5)	R&D/sales	-0.28	(-1.39)	9,991
(6)	R&D/assets	-0.43*	(-1.71)	9,991
(7)	R&D/labor	-0.52**	(-2.19)	9,160

Table 9. Absorption intensity using applicant versus examiner added citations

This table shows the effect of the interaction of AIPA and *Absorption intensity* on innovation output after considering heterogeneity in knowledge spillover treatment intensity and using future versions of *Absorption intensity*. The dependent variable is the number of patents applied for in a given year that are eventually granted. This number is winsorized at the 99% level of the non-zero observations each year. In the first three columns, we use an applicant-added citations version of *Absorption intensity*. In the last three columns, we use an examiner-added citations version of *Absorption intensity*. Each version is constructed exactly as the main version except that we only use citations added by the applicant (in the first three columns) or by the examiner (in the last three columns). As indicated by the 'Absorption year' row, each version of *Absorption intensity* used in these tests is from some future year. *Grant lag (ordinal)* spans 0.01 through 1.00 and is defined by sorting grant lag into percentiles as of the year 2000. *Post* is a dummy that equals one for years 2003 through 2007 and zero otherwise. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table 4 for definitions). All control variables are binned into quintiles as of year 2000. Sample is from 1996 through 2007 but excludes 2001 and 2002. z-scores below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

	Applicant-only citations			Examiner-only citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Absorption intensity × Post	-0.24	-0.34**	-0.32*	0.67***	0.09	-0.28
	(-1.42)	(-1.98)	(-1.89)	(3.29)	(0.43)	(-1.14)
Grant lag (ordinal) × Post	-0.84**	-0.77**	-0.75*	-0.74**	-0.55	-0.67*
	(-2.31)	(-2.05)	(-1.92)	(-2.15)	(-1.58)	(-1.77)
Absorption intensity × Grant lag (ordinal) × Post	0.86***	0.88***	0.66**	-0.15	0.35	0.56
	(2.76)	(2.66)	(2.18)	(-0.47)	(1.01)	(1.47)
Absorption year	2003	2004	2005	2003	2004	2005
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	95.28%	95.20%	95.33%	95.28%	95.23%	95.28%
Observations	9,850	9,666	9,071	10,061	9,679	9,135

Table 10. Does patent scope or patent value change?

This table shows the effect of the interaction of AIPA and *Absorption intensity* (five-year version) on proxies for patent scope and patent value after considering heterogeneity in knowledge spillover treatment intensity. *Words* is the number of words in the shortest independent claim per patent. *Claims* is the number of independent claims per patent. *Value* is the estimated economic value per patent. *Citations* is the number of future external citations received within ten years of publication date per patent. *Generality* is the dispersion of citations across different technological classifications a patent receives within ten years of publication date per patent. *Words*, *Claims*, and *Generality* are winsorized at the 1% and 99% levels each year. *Value* and *Citations* are winsorized at the 99% level of the non-zero observations each year. *Absorption intensity* is as of the year 2000 and winsorized at the 1% and 99% levels. *Grant lag (ordinal)* spans 0.01 through 1.00 and is defined by sorting grant lag into percentiles as of the year 2000. *Post* is a dummy that equals one for years 2003 through 2007 and zero otherwise. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table 4 for definitions). All control variables are binned into quintiles as of year 2000. We estimate Poisson regressions in columns (1) through (4) and an ordinary least squares regression in column (5). Sample is from 1996 through 2007 but excludes 2001 and 2002. z-scores and t-statistics below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

	(1)	(2)	(3)	(4)	(5)
Absorption intensity × Post	-0.02	-0.10	-0.18	-0.22	-0.01
	(-0.51)	(-1.53)	(-0.79)	(-1.48)	(-0.25)
Grant lag (ordinal) × Post	0.04	-0.17	-0.15	-0.01	0.00
	(0.27)	(-1.17)	(-0.46)	(-0.05)	(0.02)
Absorption intensity × Grant lag (ordinal) × Post	-0.04	0.07	0.04	-0.17	0.00
	(-0.40)	(0.75)	(0.13)	(-0.81)	(0.04)
Proxy	Words	Claims	Value	Citations	Generality
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	45.2%	8.42%	83.8%	61.7%	
Adjusted R^2					32.4%
Observations	7,340	7,340	7,340	7,347	7,364

Table 11. Panel regressions

This table presents coefficient estimates on *Absorption intensity* (five-year version) from regressions of measures of innovation output, patent quality, or firm growth on *Absorption intensity*, controls, and industry by year fixed effects. In Panel A, we focus on innovation output. *Count* is the number of patents. In Panel B, we focus on proxies for patent quality (as described in Table 10). Control variables include the levels of *R&D capital*, *Profit*, *Labor*, *Physical capital*,*Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table 4 for definitions). We also control for the levels *Output* and *TFP*, respectively when focusing on growth rates in *Output* and *TFP*. Besides *Leverage*, all independent variables are logged. Aside from *Count*, which is winsorized at the 99% level of non-zero observations each year, all variables (dependent and independent) are winsorized at the 1% and 99% levels each year. The sample is from 1975 through 2019. We estimate Poisson regressions in Panels A and B and ordinary least squares regressions in Panel C. z-scores and t-statistics below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

Panel A: Patent output

	t+1	t+2	t+3	t+4	t+5
Count	0.14**	0.19***	0.23***	0.27***	0.30***
	(2.53)	(3.01)	(3.19)	(3.35)	(3.44)

Panel B: Patent quality

	t+1	t+2	t+3	t+4	t+5
Words	-0.012**	-0.017**	-0.018**	-0.013*	-0.011
	(-2.00)	(-2.51)	(-2.43)	(-1.65)	(-1.48)
Claims	0.056***	0.045***	0.038***	0.028***	0.021***
	(6.70)	(6.84)	(5.44)	(4.10)	(2.68)
Value	0.23***	0.25***	0.25***	0.24***	0.21***
	(5.78)	(5.87)	(5.18)	(4.62)	(4.13)
Citations	0.305***	0.282***	0.260***	0.234***	0.194***
	(9.43)	(8.11)	(7.76)	(6.24)	(5.00)
Generality	0.094***	0.095***	0.075***	0.078***	0.063***
	(7.66)	(6.47)	(5.74)	(5.60)	(4.41)

Panel C: Firm growth

	t+1	t+2	t+3	t+4	t+5
R&D capital	0.006***	0.014***	0.023***	0.034***	0.044***
	(3.39)	(3.77)	(4.08)	(4.60)	(4.61)
Profit	0.006**	0.013**	0.017**	0.022***	0.029***
	(2.21)	(2.53)	(2.56)	(2.71)	(2.96)
Labor	0.003*	0.006*	0.011**	0.016**	0.021**
	(1.92)	(1.91)	(2.32)	(2.39)	(2.44)
Physical capital	0.001	0.003	0.007	0.011	0.017*
	(0.69)	(0.64)	(1.18)	(1.47)	(1.92)
Output	0.003	0.006	0.010*	0.013*	0.016*
	(1.20)	(1.22)	(1.74)	(1.78)	(1.69)
TFP	-0.002	-0.002	-0.001	-0.002	0.002
	(-0.53)	(-0.52)	(-0.28)	(-0.39)	(0.21)

Table 12. Antecedents of absorption intensity

This table presents results from ordinary least squared regressions of *Absorption intensity* (five-year version) on its cross-sectional determinants and controls. *Inventor citation rank* is the average lagged citation rank of inventors on patents granted in the past five years. *Inventor distance* is the average distance between headquarters and inventors of patents granted in the past five years. *Innovation culture* is the corporate cultural value of innovation from Li et al. (2021). *Academic research rank* is the average ranking of academic institutions located within 100 miles of headquarters. All variables of interest are lagged five years. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table 4 for definitions). Besides *Leverage*, all independent variables are logged. All independent variables are winsorized at the 1% and 99% levels. t-statistics below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

	(1)	(2)	(3)	(4)
Inventor citation rank$_{t-5}$	0.190***			
	(4.24)			
Inventor distance$_{t-5}$		-0.046***		
		(-3.47)		
Innovation culture$_{t-5}$			0.067**	
			(2.34)	
Academic research rank$_{t-5}$				0.243***
				(2.98)
Controls	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	35.7%	29.9%	31.5%	18.2%
Observations	21,152	5,866	8,761	4,774

Internet Appendix

In Table 3, we present two decompositions of *Absorption intensity*. We follow Ma (2025) in our decomposition calculations. The first decomposition shows variation across industries, across firms within an industry, and within firms over time:

$$\begin{aligned}
\Sigma_i\Sigma_j\Sigma_t\left(Absorb_{ijt} - \overline{\overline{\overline{Absorb}}}\right)^2 &= \Sigma_i\Sigma_j\Sigma_t\Big[(Absorb_{ijt} - \overline{Absorb}_{ij}) + (\overline{Absorb}_{ij} - \overline{\overline{Absorb}}_j) \\
&\quad + (\overline{\overline{Absorb}}_j - \overline{\overline{\overline{Absorb}}})\Big]^2 \\
&= \Sigma_i\Sigma_j\Sigma_t\left(Absorb_{ijt} - \overline{Absorb}_{ij}\right)^2 \text{ within firm} \\
&= \Sigma_i\Sigma_j\Sigma_t\left(\overline{Absorb}_{ij} - \overline{\overline{Absorb}}_j\right)^2 \text{ within industries} \\
&= \Sigma_i\Sigma_j\Sigma_t\left(\overline{\overline{Absorb}}_j - \overline{\overline{\overline{Absorb}}}\right)^2 \text{ between industries}
\end{aligned}$$

in which $Absorb_{ijt}$ is *Absorption intensity* for firm i in industry j in year t, $\overline{Absorb}_{ij}$ is the within-firm mean for firm i, $\overline{\overline{Absorb}}_j$ is the industry mean for industry j, and $\overline{\overline{\overline{Absorb}}}$ is the overall mean.

The second decomposition of *Absorption intensity* shows variation across industries, within industries across different years, and across firms in the same industry by year combination:

$$\begin{aligned}
\Sigma_i\Sigma_j\Sigma_t\left(Absorb_{ijt} - \overline{\overline{\overline{Absorb}}}\right)^2 &= \Sigma_i\Sigma_j\Sigma_t\Big[(Absorb_{ijt} - \overline{Absorb}_{jt}) + (\overline{Absorb}_{jt} - \overline{\overline{Absorb}}_j) \\
&\quad + (\overline{\overline{Absorb}}_j - \overline{\overline{\overline{Absorb}}})\Big]^2 \\
&= \Sigma_i\Sigma_j\Sigma_t\left(Absorb_{ijt} - \overline{Absorb}_{jt}\right)^2 \text{ within industry} \times \text{year} \\
&= \Sigma_i\Sigma_j\Sigma_t\left(\overline{Absorb}_{jt} - \overline{\overline{Absorb}}_j\right)^2 \text{ within industries} \\
&= \Sigma_i\Sigma_j\Sigma_t\left(\overline{\overline{Absorb}}_j - \overline{\overline{\overline{Absorb}}}\right)^2 \text{ between industries}
\end{aligned}$$

in which $\overline{Absorb}_{jt}$ is the within-industry by year mean for industry j in year t.

Table IA1. Summary statistics: Control variables

This table presents summary statistics for all controls variables in the pre-AIPA period (1996 through 2000). *R&D capital* is cumulated and depreciated R&D expenses (Peters and Taylor, 2017), deflated by CPI (in millions). *Physical capital* is gross property, plant, and equipment adjusted for the age of the capital (İmrohoroğlu and Tüzel, 2014), deflated by the NIPA price of equipment (in millions). *Labor* is the number of employees (in thousands). *Profit* is sales minus cost of goods sold, deflated by CPI (in millions). *Patent count* is the natural log of the total number of active patents. *Firm age* is the number of years since entering the Compustat database. *Tangibility* is net property, plant, and equipment divided by total assets. *Market-to-book* is the market value of assets divided by total assets. *Leverage* is the sum of current debt and long-term debt divided by total assets. All variables are winsorized at the 1% and 99% levels.

	Mean	Std. dev.	10%	25%	50%	75%	90%	Obs.
R&D capital	471	1,818	0	5	30	122	590	7,490
Physical capital	1,815	6,088	4.3	14	72	512	3,508	7,486
Labor	10.47	28.38	0.08	0.22	1.02	6.00	24.90	7,389
Profit	1,171	3,550	0.6	19	97	532	2,380	7,490
Patent count	2.95	2.01	0.69	1.39	2.71	4.06	5.84	7,033
Firm age	14.0	13.1	2	4	9	22	34	7,490
Tangibility	0.24	0.18	0.05	0.10	0.20	0.33	0.51	7,487
Market-to-book	2.66	3.02	0.70	0.97	1.58	3.00	5.78	7,352
Leverage	0.18	0.18	0.00	0.01	0.14	0.29	0.43	7,480

Table IA2. Correlations: Absorption intensity and control variables

This table presents correlations between each version of *Absorption intensity* and control variables in the pre-AIPA period (1996 through 2000). *R&D capital* is cumulated and depreciated R&D expenses (Peters and Taylor, 2017), deflated by CPI (in millions). *Physical capital* is gross property, plant, and equipment adjusted for the age of the capital (İmrohoroğlu and Tüzel, 2014), deflated by the NIPA price of equipment (in millions). *Labor* is the number of employees (in thousands). *Profit* is sales minus cost of goods sold, deflated by CPI (in millions). *Patent count* is the natural log of the total number of active patents. *Firm age* is the number of years since entering the Compustat database. *Tangibility* is net property, plant, and equipment divided by total assets. *Market-to-book* is the market value of assets divided by total assets. *Leverage* is the sum of current debt and long-term debt divided by total assets. All variables are winsorized at the 1% and 99% levels.

Absorption intensity	R&D capital	Physical capital	Labor	Profit	Patent count	Firm age	Tangibility	Market-to-book	Leverage
Three-year version	-0.14	-0.15	-0.09	-0.15	-0.22	-0.19	-0.15	0.06	-0.08
Five-year version	-0.16	-0.10	-0.05	-0.13	-0.21	-0.16	-0.09	0.02	-0.06
Ten-year version	-0.16	-0.08	-0.03	-0.13	-0.22	-0.10	-0.04	-0.07	-0.02

Table IA3. External application citations: Alternative versions of absorption intensity

This table presents results from Poisson regressions of *Application citations* on *Absorption intensity* and controls. *Application citations* is the number of citations of external applications (made by the applicant) per patent filed in a particular year. *Application citations* is winsorized at the 99% level of the non-zero observations each year. *Absorption intensity* is as of the year 2000 and winsorized at the 1% and 99% levels. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table IA2 for definitions). All control variables are binned into quintiles as of year 2000. Industry is defined at the SIC3 level. z-scores below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

Panel A: Absorption version: Three-year

	2003	2004	2005	2006	2007
	(1)	(2)	(3)	(4)	(5)
Absorption intensity	0.67***	0.68***	0.56***	0.66***	0.42***
	(3.43)	(4.76)	(2.86)	(4.68)	(3.41)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	22.6%	24.3%	19.8%	22.5%	21.3%
Observations	1,528	1,458	1,353	1,241	1,129

Panel B: Absorption version: Ten-year

	2003	2004	2005	2006	2007
	(1)	(2)	(3)	(4)	(5)
Absorption intensity	0.66***	0.59***	0.68***	0.60***	0.49***
	(3.47)	(4.11)	(5.35)	(4.34)	(3.92)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	25.0%	26.9%	23.3%	26.0%	23.8%
Observations	1,833	1,741	1,626	1,493	1,346

Table IA4. Alternative versions of absorption intensity

This table shows the effect of the interaction of AIPA and *Absorption intensity* on innovation output. The dependent variable is the number of patents applied for in a given year that are eventually granted. This number is winsorized at the 99% level of the non-zero observations each year. *Absorption intensity* is as of the year 2000 and winsorized at the 1% and 99% levels. *Post* is a dummy that equals one for years 2003 through 2007 and zero otherwise. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table IA2 for definitions). All control variables are binned into quintiles as of year 2000. Sample is from 1996 through 2007 but excludes 2001 and 2002. Industry is at the SIC3 level. z-scores below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

Panel A: Absorption version: Three-year

	(1)	(2)	(3)	(4)
Absorption intensity × Post	0.73***	0.76***	0.56***	0.55***
	(5.59)	(5.67)	(5.27)	(5.61)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Industry × Year FE	No	Yes	No	Yes
Controls × Year FE	No	No	Yes	Yes
Pseudo R^2	92.7%	93.7%	94.0%	95.0%
Observations	15,246	14,614	13,817	13,146

Panel B: Absorption version: Ten-year

	(1)	(2)	(3)	(4)
Absorption intensity × Post	0.74***	0.79***	0.80***	0.69***
	(5.17)	(4.93)	(5.92)	(5.31)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Industry × Year FE	No	Yes	No	Yes
Controls × Year FE	No	No	Yes	Yes
Pseudo R^2	93.0%	94.0%	94.2%	95.2%
Observations	18,177	17,588	16,526	15,884

Table IA5. Variation in treatment with alternative versions of absorption intensity

This table shows the effect of the interaction of AIPA and *Absorption intensity* on innovation output after considering heterogeneity in knowledge spillover treatment intensity. The dependent variable is the number of patents applied for in a given year that are eventually granted. This number is winsorized at the 99% level of the non-zero observations each year. *Absorption intensity* is as of the year 2000 and winsorized at the 1% and 99% levels. *Grant lag (ordinal)* spans 0.01 through 1.00 and is defined by sorting grant lag into percentiles as of the year 2000. *Post* is a dummy that equals one for years 2003 through 2007 and zero otherwise. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table IA2 for definitions). All control variables are binned into quintiles as of year 2000. Sample is from 1996 through 2007 but excludes 2001 and 2002. z-scores below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

Panel A: Absorption version: Three-year

	(1)	(2)	(3)	(4)
Absorption intensity × Post	-0.23	-0.37	-0.26	-0.07
	(-1.12)	(-1.48)	(-1.25)	(-0.32)
Grant lag (ordinal) × Post	-1.10***	-1.28***	-1.78***	-1.29***
	(-3.43)	(-2.62)	(-5.09)	(-2.80)
Absorption intensity × Grant lag (ordinal) × Post	1.58***	1.66***	1.46***	0.84**
	(3.96)	(3.60)	(3.46)	(2.20)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	No	Yes	No	Yes
Controls × Year FE	No	No	Yes	Yes
Pseudo R^2	92.9%	94.0%	94.2%	95.3%
Observations	12,330	11,716	11,199	10,604

Panel B: Absorption version: Ten-year

	(1)	(2)	(3)	(4)
Absorption intensity × Post	-0.25	-0.53	-0.44*	-0.49*
	(-0.91)	(-1.63)	(-1.79)	(-1.65)
Grant lag (ordinal) × Post	-1.65**	-2.25***	-2.60***	-2.60***
	(-2.39)	(-2.82)	(-4.09)	(-3.54)
Absorption intensity × Grant lag (ordinal) × Post	1.54***	1.90***	1.73***	1.50***
	(3.16)	(3.44)	(3.90)	(3.22)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry × Year FE	No	Yes	No	Yes
Controls × Year FE	No	No	Yes	Yes
Pseudo R^2	93.0%	94.1%	94.4%	95.3%
Observations	13,829	13,239	12,572	11,971

Table IA6. Antecedents of absorption intensity and innovation output

This table presents results from regressions of innovation output on *Absorption intensity* (five-year version), antecedents of *Absorption intensity*, and controls. In all panels, we estimate Poisson regressions in which the dependent variable is *Patents*, which is winsorized at the 99% level of the non-zero observations each year. *Inventor citation rank* is the average lagged citation rank of inventors on patents granted in the past five years. *Inventor distance* is the average distance between headquarters and inventors of patents granted in the past five years. *Innovation culture* is the corporate cultural value of innovation from Li et al. (2021). *Academic research rank* is the average ranking of academic institutions located within 100 miles of headquarters. Control variables include *R&D capital*, *Physical capital*, *Labor*, *Profit*, *Patent count*, *Firm age*, *Tangibility*, *Market-to-book*, and *Leverage* (see Table IA2 for definitions). Besides *Leverage*, all independent variables are logged. All independent variables are winsorized at the 1% and 99% levels. The sample is from 1975 through 2019. z-scores below coefficients are adjusted for double clustering at the firm and year levels. Statistical significance at the 90%, 95%, and 99% levels is denoted by *, **, and ***.

Panel A: Output and inventor citation rank

	t+1	t+2	t+3	t+4	t+5
	(1)	(2)	(3)	(4)	(5)
Absorption intensity	0.14**	0.19***	0.23***	0.27***	0.31***
	(2.22)	(2.68)	(2.91)	(2.92)	(3.03)
Inventor citation rank	-0.002	-0.001	0.000	0.001	0.001
	(-0.97)	(-0.29)	(0.02)	(0.29)	(0.53)
Controls	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	91.8%	90.8%	89.8%	88.9%	88.2%
Observations	35,608	32,677	29,946	27,427	25,118

Panel B: Output and inventor distance

	t+1	t+2	t+3	t+4	t+5
	(1)	(2)	(3)	(4)	(5)
Absorption intensity	0.15**	0.21***	0.24***	0.28***	0.31***
	(2.46)	(2.98)	(3.27)	(3.37)	(3.48)
Inventor distance	-0.04	-0.05	-0.05	-0.06	-0.07
	(-1.40)	(-1.51)	(-1.58)	(-1.55)	(-1.55)
Controls	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	91.7%	90.9%	90.2%	89.7%	89.3%
Observations	9,861	8,864	7,835	6,864	5,959

Panel C: Output and innovation culture

	t+1	t+2	t+3	t+4	t+5
	(1)	(2)	(3)	(4)	(5)
Absorption intensity	0.18***	0.24***	0.27***	0.31***	0.34***
	(3.22)	(3.77)	(3.82)	(3.83)	(3.87)
Innovation culture	0.01	0.02	0.03	0.07	0.09
	(0.22)	(0.34)	(0.41)	(0.95)	(1.38)
Controls	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	91.5%	90.7%	89.9%	89.0%	88.5%
Observations	14,758	13,081	11,515	10,119	8,869

Panel D: Output and academic research rank

	t+1	t+2	t+3	t+4	t+5
	(1)	(2)	(3)	(4)	(5)
Absorption intensity	0.13***	0.20***	0.24***	0.28***	0.31***
	(2.74)	(3.31)	(3.53)	(3.67)	(3.75)
Academic research rank	0.0001	-0.0002	-0.0005	-0.0006	-0.0007
	(0.10)	(-0.16)	(-0.32)	(-0.37)	(-0.40)
Controls	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	91.9%	90.9%	90.0%	89.0%	88.3%
Observations	50,288	46,262	42,406	38,871	35,610