Recombining Knowledge after Patent Eligibility Tightening

Danfeng YUE*

August 17, 2026

Abstract

When the returns to an existing use of knowledge decline, innovators may respond not only by reallocating innovation activities, but also by changing how that knowledge is used. We study knowledge recombination as a margin of adjustment using the 2014 *Alice Corp. v. CLS Bank International* decision, which tightened patent eligibility for abstract ideas and reduced patent protection in affected technologies. We find that innovators respond by increasing cross-technology recombination: patent applications in more exposed technologies recombine knowledge from a broader set of technological components and shift toward combinations that are less exposed to the new eligibility standard. This response is stronger for technologies with greater recombination opportunities, measured using historical patterns of technological compatibility. At the firm level, technological boundaries determine which of these opportunities can be accessed at relatively low cost. Firms with greater recombination capacity sustain more innovation in affected technologies and experience smaller declines in economic performance after Alice.

*Toulouse School of Economics. Email: danfeng.yue@tse-fr.eu. I am deeply grateful to Ulrich Hege for his guidance and supervision. I thank Nicola Bianchi, James Bessen, Nicolas Crouzet, Joan Farre-Mensa, Lee Fleming, Marek Giebel, César A. Hidalgo, Ryan Hill, Doh-Shin Jeon, Benjamin Jones, Yassine Lefouili, Filippo Mezzanotti, Sophie Moinas, Felix Poege, Gordon M. Phillips, Bryan Elwin Seegmiller, Dashun Wang, Xizhao Wang, and M. Deniz Yavuz for valuable comments and discussions. I also thank participants at the Northwestern Kellogg FINC Brown Bag, the TPRI Workshop, the Chicago Entrepreneurship Workshop, and the TSE Finance Workshop for valuable feedback. All remaining errors are my own.

1 Introduction

What determines the direction of innovation is a longstanding question in economics. Since the early work collected in *The Rate and Direction of Inventive Activity* (NBER, 1962), economists have studied how economic incentives shape which innovations are pursued. A central insight of this literature is that changes in relative returns can redirect innovative effort toward more rewarding activities (Acemoglu, 2002; Bryan and Lemus, 2017). This provides a natural benchmark for understanding how innovation adjusts when its economic environment changes.

The 2014 Supreme Court decision in *Alice Corp. v. CLS Bank International* provides a useful setting for studying how innovation adjusts to a sharp change in incentives. The decision tightened patent eligibility for abstract ideas and substantially weakened patent protection for innovation in a subset of technologies. A natural response to such a shock would be to reduce innovative activity in the affected areas and reallocate resources toward activities where patent protection remained relatively stronger. Yet the evolution of patenting after *Alice* suggests a more nuanced adjustment. Patent grants in highly exposed technologies fell sharply following the decision, but the decline was temporary and grants subsequently recovered. At the same time, patenting activity in these technologies remained substantial, raising the question of how innovators continued to build on knowledge whose economic returns had declined.

We show that an important margin of this adjustment is knowledge recombination. Innovators respond to the decline in returns by increasingly combining affected knowledge with knowledge from other technological domains, allowing them to continue building on affected knowledge while redirecting innovation toward new combinations. This response highlights a distinctive feature of innovation production: existing knowledge is not tied to a single use, but can be recombined to produce new knowledge. Changes in economic incentives can therefore redirect innovation not only by changing how innovators allocate resources across activities, but also by changing how existing knowledge is used. We document this recombination margin and study the factors that shape innovators' ability to use it.

Our empirical strategy exploits variation in exposure to *Alice* across technologies. To measure this exposure, we combine USPTO patent examination records with detailed information on statutory rejection grounds. We identify applications filed before *Alice* but examined after the decision and use their examination outcomes to estimate technology-level exposure to the new eligibility standard. Because these applications were filed before the decision, the resulting measure captures differential exposure across technologies without reflecting post-*Alice* changes in innovators' technological choices. We then use this predetermined measure to examine how the composition of subsequent innovation changed after *Alice*.

Our first set of results establishes knowledge recombination as an important margin of adjustment following *Alice*. Using a difference-in-differences design, we find that patent applications in more exposed technologies recombine knowledge across a broader set of technology classes after the decision. At the same time, the overall exposure of these applications declines, indicating that the resulting technological combinations become less exposed to the new eligibility standard. We find consistent changes in inputs to innovation production. Inventor teams in more exposed technologies draw on more diverse technological backgrounds after *Alice*, and backward citations span a broader and more diverse set of technological knowledge. Together, these results show that the response to *Alice* extends beyond changes in the amount of innovative activity: innovators also change how affected knowledge is combined with other knowledge.

How extensively innovators adjust through cross-technology recombination depends on the recombination opportunities surrounding affected technologies. Such opportunities differ across technologies because some technology classes have historically been combined with a broader set of other technological components than others. To capture this variation, we construct a technology network from historical patterns of cross-technology recombination, where stronger links connect technology classes that have more frequently appeared together in prior innovations. We use this network to measure the recombination opportunities associated with each technology before *Alice*. We find that the increase in cross-technology recombination following the decision is substantially stronger in exposed technologies with greater recombination opportunities. This result shows that the existing structure of technological compatibility shapes the extent to which innovators adjust through knowledge recombination.

Technology-level recombination opportunities, however, need not be equally accessible to individual firms. Whether a firm can exploit a potential combination depends on the knowledge already contained in its technological portfolio. We therefore construct firm-specific recombination opportunities by restricting the technology-level opportunities identified above to knowledge components within each firm's pre-existing technological boundary. We find that, among firms exposed to *Alice*, those with greater access to recombination opportunities sustain more innovation in affected technologies following the decision. Their adjustment relies primarily on the reuse of technologies already present in their knowledge portfolios, consistent with the redeployment of accumulated knowledge through new combinations. Greater access to recombination opportunities is also associated with smaller declines in operating performance and market valuation. These results show that firms' technological boundaries shape their ability to exploit recombination opportunities and preserve the economic value of affected knowledge.

Taken together, these findings broaden the way we think about the direction of innovation. Changes in economic incentives can redirect innovation not only by reallocating resources across innovation activities, but also by changing how existing knowledge is used within innovation production. Knowledge recombination provides a distinct margin of adjustment through which innovators can continue building on affected knowledge by combining it in new ways. The extent to which this margin can be used depends on the technological opportunities for recombination and on whether the relevant knowledge lies within firms' existing technological boundaries. Although we document this margin in the context of patent eligibility, its implications extend more broadly to how changes in economic incentives shape the direction of innovation.

Our paper therefore contributes to empirical research showing that changes in patent protection, market incentives, and research funding can redirect innovative activity across technological areas and alter the composition of innovation outputs (Moser, 2005; Aghion et al., 2016; Babina et al., 2023). We highlight a distinct margin that arises from the combinatorial nature of innovation. Because existing knowledge can be recombined in different ways, changes in relative returns can alter not only which innovation activities innovators pursue or which types of outputs they produce, but also how existing knowledge is used to produce new innovation. Our findings provide empirical evidence for this recombination margin of directed innovation.

Second, our paper builds on the recombinant view of innovation, which emphasizes that new knowledge is produced by combining existing knowledge components (Weitzman, 1998; Fleming, 2001; Griffith et al., 2017). While this literature primarily studies how knowledge combinations shape innovative outcomes, we study recombination itself as an endogenous response to economic incentives. We show that when the returns to existing knowledge decline, innovators increasingly recombine affected knowledge with other technological components. Our findings therefore show that economic incentives can shape not only which innovations are pursued, but also the combinations of existing knowledge through which new innovation is produced.

Third, our paper contributes to the literature on firm-level determinants of innovation, including firms' capabilities to utilize external knowledge (Cohen et al., 1990; Griffith et al., 2017; Woeppel and Yavuz, 2026) and organize knowledge within the firm (Kogut and Zander, 1992). We show that the ability to exploit knowledge recombination depends on both the technological opportunities available for recombination and firms' access to the relevant knowledge. While technological compatibility determines the potential for recombination, firms' existing technological boundaries determine which of these opportunities they can access. Our findings thus show how technological opportunities and firms' accumulated knowledge jointly shape their ability to recombine knowledge and sustain innovation.

Fourth, our paper contributes to the literature on intellectual property protection and innovation (Galasso and Schankerman, 2018; Mezzanotti, 2021), and particularly to recent studies of the economic consequences of *Alice* (Acikalin et al., 2026; Feng and Williams, 2026). Existing work examines how the decision affected patenting, competition, firm performance, and entrepreneurial financing. We complement this literature by studying how innovators reorganize the use of knowledge following the decline in patent protection. We show that affected knowledge is increasingly recombined with other technological components, identifying knowledge recombination as an additional margin through which changes in intellectual property protection shape innovation.

2 Institutional Background

On June 19, 2014, the U.S. Supreme Court issued its decision in *Alice Corp. v. CLS Bank International*, a landmark ruling concerning the patent eligibility of inventions involving abstract ideas implemented through computer technology. The Court held that merely implementing an abstract idea using a generic computer does not make an invention eligible for patent protection under Section 101 of the U.S. Patent Act.

The decision tightened the patent eligibility standard for computer-implemented inventions, with particularly important consequences for software and business methods (Chien and Wu, 2018).

The case involved patents held by Alice Corporation that covered a computerized escrow system for facilitating financial transactions. The Supreme Court held that the claims were directed to the abstract idea of intermediated settlement and that implementing this idea on a generic computer did not provide an inventive concept sufficient for patent eligibility. The decision established a two-step framework under Section 101, under which courts and patent examiners first assess whether a claim is directed to an abstract idea and, if so, whether it contains additional elements that transform it into a patent-eligible application.

Unlike legislative reforms that are typically accompanied by public discussion and implementation periods, the Alice decision immediately altered the eligibility standard applied by courts and patent examiners. Alice therefore represented a sudden reinterpretation of an existing patent eligibility standard rather than a legislative change introducing new patent rules. Importantly, the impact of Alice was not uniform across technologies. Technologies differed in the extent to which their inventions relied on information-processing methods and abstract computational concepts, generating substantial heterogeneity in exposure to the new eligibility standard.

Alice was incorporated into USPTO examination procedures almost immediately after the ruling. On June 25, 2014, the USPTO issued preliminary examination instructions directing patent examiners to apply the Alice framework when evaluating subject-matter eligibility under Section 101 (USPTO, 2014). The USPTO subsequently released additional guidance clarifying the implementation of the new eligibility standard. Consistent with this rapid institutional response, Figure 1 shows a sharp increase in Section 101 rejection activity following Alice.

Alice also had implications for the perceived strength and enforceability of existing patent portfolios. Although issued patents enjoy a presumption of validity, patent eligibility can still be challenged during litigation and administrative review. Consequently, the tightening of patent eligibility standards following Alice influenced not only newly filed applications but also the expected value of existing patent assets. Importantly, however, Alice affected the legal protection available for these technologies rather than the underlying technological value of the knowledge they embodied. By reducing innovators' expected ability to appropriate returns through patent protection, the decision lowered the economic returns associated with affected uses of this knowledge.

3 Conceptual Framework

3.1 Knowledge Recombination as a Margin of Innovation Adjustment

Innovation builds on existing knowledge. A new innovation can draw on one or multiple knowledge components and combine them in different ways to generate new technological applications (Weitzman, 1998; Fleming, 2001). This combinatorial nature of innovation creates an additional margin of adjustment beyond reallocating innovative effort across existing activities: innovators can change how existing knowledge is used by recombining it with other knowledge components.

Consider a knowledge component A that is used in innovation. A decline in the economic return associated with its current use reduces the attractiveness of continuing to use A in the same way. Innovators may respond along multiple margins, including reducing innovative effort involving A, reallocating effort toward other activities, or changing how A is used. We focus on the latter margin. If A can be combined with another knowledge component B, the innovator may continue building on A through a new combination AB. Knowledge recombination thus provides a way to redeploy affected knowledge toward alternative uses rather than abandoning it altogether.

Whether recombination increases following a decline in returns depends on the relative returns and costs associated with different uses of knowledge. A combination such as AB need not have been preferred before the shock. Once the return to the existing use of A declines, however, previously less attractive combinations may become relatively more attractive. Changes in economic incentives can therefore affect not only which innovation activities innovators pursue, but also how existing knowledge is combined in innovation production.

3.2 Recombination Opportunities and Technological Compatibility

The extent to which innovators respond through recombination depends on the alternative combinations available for affected knowledge. Knowledge components differ in their technological compatibility with other components, so the set of potential recombination opportunities varies across technologies. For a knowledge component A, denote its set of potential combinations with other knowledge components by

$$\Omega(A) = \{AB, AC, \ldots\}.$$

A richer $\Omega(A)$ provides more ways to continue using A when the return to its existing use declines. We therefore expect innovators to increase cross-technology recombination more extensively following a decline in returns when affected knowledge has greater recombination opportunities.

3.3 Firm Technological Boundaries and Accessible Recombination Opportunities

Potential recombination opportunities at the technology level need not be equally accessible to individual firms. Firms accumulate different stocks of technological knowledge, and exploiting a potential combination may depend on whether the complementary knowledge required for that combination is available within the firm's existing knowledge base. Accessing knowledge outside the firm's existing technological portfolio may require additional search, learning, coordination, or acquisition, making such knowledge more costly to deploy than knowledge already accumulated within the firm (Cohen et al., 1990; Kogut and Zander, 1992).

Let K_i denote the set of knowledge components contained in firm i's technological portfolio. For an affected knowledge component A, define the firm's within-boundary recombination opportunities as

$$\Omega_i(A) = \{AB \in \Omega(A) : B \in K_i\}.$$

These opportunities represent combinations for which the complementary knowledge is already available within the firm's existing technological portfolio and can therefore be accessed with relatively lower organizational and acquisition frictions.

This distinction separates the technological potential for recombination from the opportunities that can be exploited using knowledge already accumulated within the firm. Two firms exposed to the same affected technology may therefore face the same set of potential recombination opportunities $\Omega(A)$ but differ substantially in $\Omega_i(A)$ because of differences in their existing technological portfolios.

We therefore expect firms with greater within-boundary recombination opportunities to be better positioned to continue building on affected knowledge following a decline in its returns and, consequently, to sustain more innovation in affected technologies. To the extent that maintaining these innovation activities generates economic value, greater access to recombination opportunities may also mitigate the effects of the shock on firm performance.

4 Data

4.1 Data Sources

We combine several administrative and financial datasets to study how innovators respond to changes in patent eligibility standards. Our primary data source is the universe of U.S. patent applications and granted patents provided by PatentsView. These data contain detailed information on patent characteristics, including application and grant dates, inventors, backward citations, and Cooperative Patent Classification (CPC) assignments. The CPC classification system allows us to measure the technological composition of patents and construct technology-level exposure measures.

To examine how patent examination outcomes changed following the Alice decision, we combine the Patent Examination Research Dataset (PatEx) with the Office Action Research Dataset (OARD). PatEx provides detailed information on patent prosecution histories, including office actions issued during examination, while OARD identifies the statutory grounds associated with each rejection. Together, these datasets allow us to identify Section 101 patent eligibility rejections and characterize changes in examination outcomes after Alice.

For the firm-level analysis, we link patents to publicly traded firms using the patent–firm matching data developed by Kogan et al. (2017). We then merge patent information with firm financial data from Compustat using the CRSP–Compustat link table. This matched dataset enables us to construct firm-level measures of technological portfolios, recombination capacity, investment, and firm performance.

4.2 Measuring Alice Exposure

A challenge in measuring exposure to Alice is that the Supreme Court decision did not provide a clear definition of which inventions constitute unpatentable "abstract ideas." Because the application of this standard depends on examiner interpretation, we measure exposure using observed USPTO examination outcomes rather than ex ante technological characteristics. Specifically, technology-level Alice exposure captures the extent to which inventions in a technology field were affected by Alice-related rejections during examination.

A further challenge is that post-Alice patent filings may reflect applicants' strategic responses to the new eligibility standard. To avoid this concern, we construct our measure using applications filed before the Alice decision but examined afterward. These applications were submitted under the pre-Alice regime but evaluated after the change in examination standards, providing a cleaner measure of technology-specific exposure.

We first estimate an illustrative exposure measure using a simple OLS framework. This analysis reveals two important empirical patterns: Alice exposure is largely concentrated at the technology-class level, and patent-level exposure reflects a weighted contribution of both primary and secondary CPC classifications. Motivated by these patterns, we construct a generalized linear mixed model (GLMM) that estimates latent exposure across technology classes while accounting for the contribution of multiple CPC classifications. The detailed estimation procedure and alternative specifications are reported in Appendix B. As a descriptive validation, patents assigned to higher-exposure technologies have lower grant rates, consistent with the interpretation that these technologies were more adversely affected by Alice.

We present high-exposure technology classes (exposure level $\geq 5\%$) in Panel A of Table 1 and report the estimated weights assigned to primary and secondary classifications by the number of CPC classes in Panel B. The results generated by OLS and GLMM are highly comparable, and we use the GLMM-based measure throughout the paper.

Finally, we construct patent-level exposure as the weighted average of the exposure levels of all CPC subclasses assigned to a patent using the estimated classification weights. This approach follows the empirical relationship identified in the OLS analysis and incorporated into the GLMM framework, allowing the measure to capture the overall exposure embedded in an invention rather than relying only on its primary classification.

4.3 Measuring Recombination Opportunities

Technologies differ in the opportunities they provide for recombination with other knowledge components. To measure these opportunities, we use historical patterns of technological combinations as an empirical proxy for technological compatibility. Technologies that have been combined more frequently in previous inventions are treated as more compatible and therefore as providing stronger potential opportunities for future recombination.

We measure the compatibility between technologies using historical co-occurrence patterns among CPC subclasses. Following the literature (Jaffe, 1986; Breschi et al., 2003; Alstott et al., 2017), we construct a pairwise relatedness measure based on the frequency with which two technologies appear together in the same patent application. The relatedness measure is estimated using patent applications filed between 2001 and 2013, ensuring that it captures the technological landscape before the Alice shock. We use cosine similarity to normalize co-occurrence intensity by the overall prevalence of each technology:

$$R_{ij} = \frac{N_{ij}}{\sqrt{N_i N_j}}.$$

where N_i denotes the depreciated number of patent applications containing CPC subclass i, and N_{ij} denotes the depreciated number of applications containing both subclasses i and j. Unlike a structural estimate of future recombination probabilities, this reduced-form measure does not require specifying the underlying recombination process or the distribution of potential technological matches.

The pairwise relatedness measures naturally form a technology compatibility network, where nodes represent technologies and edges capture the strength of their historical connections. Because relatedness describes the relationship between a pair of technologies, we aggregate these pairwise measures to construct a technology-level measure of recombination opportunities. Specifically, for each technology subclass i, we calculate:

$$Recombination\ Opportunities_i = \sum_{j \neq i} R_{ij}.$$

A higher value indicates that technology i has stronger overall compatibility with other technologies and therefore greater potential for recombination. Although this measure can increase either because a technology has many related technologies or because it has particularly strong connections with a few technologies, our empirical setting shows that variation in this measure is primarily driven by the breadth of technological connections.

This measure is closely related to weighted degree centrality in network analysis, which captures the total strength of a node's connections (Jackson et al., 2008).

Our interpretation, however, differs from the traditional network interpretation of centrality: rather than measuring technological importance, influence, or prominence, we interpret weighted degree as a measure of a technology's potential recombination opportunities.

The technology-level measures constructed above are summarized in Table A3, and the distribution of class exposure and recombination opportunities is shown in Figure A1. We then assign these measures to individual patent applications and granted patents based on their CPC primary classes. Table A4 reports the summary statistics of the resulting patent-level sample used in our empirical analyses.

4.4 Measuring Firm-Level Exposure and Recombination Capacity

We first define each firm's technological portfolio using all patent applications filed between 2001 and 2013. We use applications rather than granted patents to ensure that the portfolio captures firms' technological activities before the Alice decision and is not affected by subsequent changes in patent eligibility. Earlier patent applications are depreciated using a 20% annual depreciation rate to reflect the gradual decline in the relevance of accumulated knowledge.

We then construct firm-level Alice exposure by aggregating patent-level exposure measures across each firm's pre-Alice patent portfolio. Specifically, firm-level exposure is calculated as:

$$Exposure_f = \sum_{p \in P_f} Exposure_p,$$

where P_f denotes the set of patent applications in firm f's pre-Alice portfolio and $Exposure_p$ is the patent-level Alice exposure measure constructed from the weighted exposure of its assigned CPC subclasses. This measure captures the extent to which a firm's accumulated technological knowledge was exposed to the change in patent eligibility standards.

Firms differ in their access to potential recombination opportunities because they hold different technological portfolios. Building on the conceptual framework, we measure firm-level access by restricting the complementary knowledge components available for recombination to those already present in the firm's pre-Alice technological portfolio.

For each technology class i in firm f's portfolio, we define accessible recombination opportunities as:

$$RO_{fi} = \sum_{j \neq i} R_{ij} \mathbb{I}(j \in K_f),$$

where R_{ij} denotes the relatedness between technology classes i and j, and $\mathbb{I}(j \in K_f)$ equals one if technology j is present in firm f's pre-Alice portfolio. Firm-level recombination capacity is then calculated as the portfolio-weighted average of accessible recombination opportunities:

$$Recombination\ Capacity_f = \sum_{i} w_{fi} RO_{fi},$$

where w_{fi} represents the share of technology class i in firm f's depreciated patent portfolio. Multi-class patents are fractionally allocated across their assigned technology classes. This measure captures the extent to which a firm's existing technological portfolio provides access to potential recombination opportunities.

We thus summarize the firm-level sample in Table A5, and the distribution of firm exposure and recombination capacity is shown in Figure A2.

5 Knowledge Recombination after Alice

This section examines how innovators respond to the Alice shock through knowledge recombination. We define knowledge components as technology classes in the main analysis. Under this definition, cross-technology recombination occurs when innovators combine multiple technology classes within a single patent, and it may reduce the patent-level exposure according to the contribution structure discovered in Section 4.2. The first four subsections analyze the response to Alice within this framework. In Section 5.5, we discuss the empirical strategy and provide complementary evidence using an alternative definition of knowledge components that allows us to trace how pre-existing knowledge is subsequently reused and recombined.

5.1 Stylized Facts

Before presenting our empirical analysis, we document two stylized facts that motivate our study of knowledge recombination after Alice. The first fact shows that patent grants in high-exposure technology classes experienced only a temporary decline after Alice and subsequently recovered, suggesting that innovation in affected technologies remained substantial after the shock. The second fact shows that applications involving a single technology class were more likely to receive Alice-related rejections, while broader technological combinations were less affected by the shock. Together, these patterns motivate our analysis of knowledge recombination as a margin through which innovators respond to appropriation shocks.

Fact 1: Patent grants in high-exposure technologies recovered after the initial post-Alice disruption.

Figure 2 documents the evolution of patent grants in technologies highly exposed to Alice-related eligibility risk, defined as CPC subclasses with estimated exposure greater than or equal to 0.05. Patent grants in these technologies declined sharply following the 2014 Alice decision and reached a trough around 2015. However, the decline was temporary: patent grants gradually recovered afterward and returned close to their pre-Alice peak by the end of the sample period. The recovery is also evident in the share of high-exposure patents among all granted patents, suggesting that the pattern is not driven solely by aggregate changes in patenting activity. Since the legal standard remained largely unchanged after Alice, this recovery suggests that innovators adapted their innovation activities to the stricter eligibility environment.

Fact 2: Broader technological combinations are associated with lower Alice-related rejection risk.

Figure 3 examines the relationship between cross-class technological combinations and Alice-related rejection risk among applications filed before Alice but examined afterward in high-exposure technology classes. This sample minimizes concerns that the observed patterns are driven by post-Alice changes in innovators' application decisions, and instead captures how the technological composition of inventions was associated with vulnerability to Alice-related rejections. Applications with more CPC subclasses are systematically less likely to receive Alice-related rejections. While most patent applications involve a single technology subclass, the likelihood of an Alice-related rejection declines substantially as the number of technological components increases. This pattern suggests that broader technological combinations were less vulnerable to Alice-related eligibility challenges even before innovators could adapt to the post-Alice environment, motivating our analysis of whether innovators subsequently increased knowledge recombination in response to the shock.

5.2 Knowledge Recombination to Reduce Alice Exposure

We examine whether innovators respond to the Alice decision through knowledge recombination by analyzing changes in the technological composition of patents associated with technology classes facing different levels of Alice exposure. Specifically, we exploit the cross-sectional variation in Alice exposure across technology classes and estimate a difference-in-differences framework with continuous treatment in a repeated cross-sectional setting (Wooldridge, 2026).

The treatment intensity is defined as the Alice exposure of the primary CPC subclass assigned to each patent. This allows us to examine how innovators change the use of knowledge in technologies differentially affected by Alice. If innovators respond to a decline in the returns to affected knowledge through recombination, patents associated with more exposed primary technology classes should recombine knowledge from a broader set of technology classes after Alice. Moreover, if innovators recombine affected knowledge with less exposed components, the resulting inventions should exhibit lower patent-level exposure. We therefore examine both the number of technology classes combined within a patent and its overall Alice exposure.

Table 2 presents the empirical results. Panel A reports estimates using the continuous exposure measure. Columns (1) and (2) examine changes in the number of CPC subclasses, while Columns (3) and (4) examine changes in patent-level exposure. Results are reported for both published patent applications and granted patents, with both samples showing highly consistent patterns. This consistency suggests that the observed changes in technological composition are not driven solely by changes in the examination process.

The results show that innovators increased knowledge recombination after Alice, with stronger responses in more exposed technology classes. In Column (1), the coefficient on the interaction term is 0.523. In the PPML specification, this implies that a 0.1 increase in Alice exposure is associated with approximately a 5.4 percent increase in the expected number of technology classes after Alice. Since exposure is below 0.4 in our sample, effects at the upper end of the exposure distribution represent extrapolations under the linear continuous-treatment specification. Columns (3) and

(4) show that this increase in knowledge recombination is accompanied by a reduction in patent-level exposure, consistent with innovators recombining affected knowledge with less exposed technological components and thereby producing inventions that are less exposed to the new eligibility standard.

To examine the timing of these responses, Figures 4a and 4b report event-study estimates corresponding to Columns (1) and (3). Both outcomes exhibit no apparent pre-trend, with the effects emerging gradually after Alice. This pattern is consistent with the idea that identifying and developing compatible technological combinations requires time after an appropriation shock.

Panel B provides a non-parametric comparison across exposure groups. Using low-exposure technologies as the reference category, high-exposure technologies exhibit the largest increase in knowledge recombination and the greatest reduction in patent-level exposure after Alice. The smaller magnitude relative to the continuous specification reflects that the grouped specification compares average differences across exposure categories rather than exploiting the full continuous variation.

Overall, these findings show that innovators responded to the Alice decision by increasing knowledge recombination in more exposed technologies and combining affected knowledge with less exposed technological components. These results provide evidence that knowledge recombination constitutes an important margin of adjustment when the returns to existing knowledge decline.

5.3 Recombination Opportunities and Heterogeneous Responses

The ability to respond through knowledge recombination may depend on the availability of compatible technological components. We therefore examine whether recombination opportunities shape heterogeneous responses to Alice. As defined in Section 4.3, recombination opportunities capture the extent to which a focal technology has compatible technological components available for recombination. We interact this measure with Alice exposure to examine whether more exposed technologies respond more strongly when more recombination opportunities are available.

Table 3 presents the results. Panel A reports estimates using continuous measures of Alice exposure and recombination opportunities. The positive interaction between Class Exposure and Recombination Opportunities indicates that more exposed technologies exhibit stronger increases in knowledge recombination when they have greater recombination opportunities. A similar pattern appears for exposure reduction in Columns (3) and (4), showing that the resulting combinations also become less exposed to Alice when greater recombination opportunities are available.

Figure 5 shows that these heterogeneous responses emerge gradually after Alice corresponding to Columns (1) and (3) in Panel A. The difference between high- and low-opportunity technologies widens over time, consistent with the idea that identifying and developing compatible technological combinations requires time.

Panel B provides a non-parametric comparison across exposure groups. High-exposure technologies exhibit the strongest response when recombination opportunities are abundant, while responses among less exposed technologies are limited. This pattern suggests that access to compatible technologies is particularly important when innovators face a substantial appropriation shock.

Overall, these findings show that recombination opportunities shape the extent to which innovators respond to Alice through knowledge recombination. When the returns to affected knowledge decline, innovators increase recombination more strongly when that knowledge has greater opportunities for combination with other technological components. These results highlight technological compatibility as an important determinant of the recombination margin.

5.4 Changes of Inputs in Innovation Production

The technological composition of patents captures the outcome of the innovation process, but does not directly reveal changes in the inputs used to produce these inventions. To provide complementary evidence that knowledge recombination also involves changes in the innovation production process, we examine two key inputs: human capital, represented by inventor teams, and knowledge inputs, represented by backward citations.

Table 4 presents the results. The results show that patents in more Alice-exposed technology classes are associated with broader and more diverse innovation inputs after Alice. On the human capital side, inventor teams exhibit broader historical knowledge bases, greater knowledge dispersion, and larger technological distance across inventors. On the knowledge input side, patents rely on cited knowledge drawn from a broader and more diverse set of technological classes.

These measures should be interpreted as complementary evidence rather than direct measures of knowledge recombination. The advantage of technology classes in our main analysis is that CPC classifications provide a consistent and externally assigned measure of technological composition across inventions. In contrast, inventor- and citation-based measures provide insights into the innovation process but are subject to important limitations. Inventor measures cannot directly observe each inventor's contribution to a specific invention or fully recover an inventor's knowledge base, while citation measures may reflect legal requirements, examiner practices, and applicant strategies in addition to technological knowledge flows (Kuhn et al., 2020). Therefore, these outcomes complement the technology-class evidence by showing that the increase in knowledge recombination was accompanied by corresponding changes in the inputs underlying innovation production.

5.5 Alternative Definition of Knowledge Components

The previous analysis defines knowledge components as technology classes, with knowledge recombination captured by the combination of multiple technology classes within a patent. This approach provides a transparent and consistent measure of technological composition because CPC classifications are assigned according to a standardized classification system. However, technology classes represent relatively broad knowledge components and do not allow us to directly trace how knowledge embodied in individual pre-Alice inventions is subsequently reused and recombined. Moreover, applicants may anticipate classification rules and strategically shape patent descriptions in ways that affect observed technology assignments.

To provide complementary evidence, we consider an alternative definition in which individual inventions represent knowledge components. Under this definition, we can directly trace how knowledge embodied in pre-Alice inventions is used in subsequent innovation and examine whether Alice changes the way this existing knowledge is recombined with other knowledge components. We implement this approach using citation and continuation relationships, which provide two distinct links between existing inventions and subsequent innovation.

Table A6 first examines cited-citing patent pairs. We compare patents citing the same pre-Alice patent before and after Alice. Panel A shows that, after Alice, citing patents associated with more exposed cited patents expand their technological scope and reduce their overall Alice exposure. They are also more likely to introduce new technology classes and modify their primary technology class. Panel B further shows that the additional patents cited together with the focal cited patent have lower Alice exposure after Alice. These patterns suggest that Alice changed how affected pre-existing knowledge was used in subsequent innovation: more exposed knowledge was recombined with a broader and less exposed set of knowledge components after the shock.

Table A7 provides stronger evidence by focusing on continuation applications. Compared with citations, continuation applications represent adjustments made by the same applicant within the same inventive lineage. Because the parent application already embodies the original invention, continuation applications allow us to more directly examine whether innovators change how existing knowledge is used by recombining it with new technological components. Importantly, continuation applications can only be filed while the parent application remains pending. We therefore exploit whether pre-Alice applications were still pending at the time of the Alice decision, which determines whether applicants retained the option to file continuation children under the post-Alice eligibility environment.

We find that more exposed inventions generated more continuation-in-part (CIP) applications and introduced more new technology classes in CIPs. In contrast, we do not find significant adaptation in regular continuation applications, suggesting that merely modifying claims within the same technological scope may not have been sufficient to overcome Alice-related eligibility challenges. This contrast provides further evidence that innovators responded to Alice by recombining affected existing knowledge with new technological components.

Together, these results complement the technology-class evidence by showing that the post-Alice increase in recombination is not merely a change in observable technological classifications. Instead, innovators changed how previously developed knowledge was used in subsequent innovation, recombining more affected knowledge with a broader and less exposed set of knowledge components. These findings provide additional evidence that changes in economic returns can reshape how existing knowledge is recombined in innovation production.

6 Firm Technological Boundaries and Adaptation

In this section, we move from the technology-level perspective to the firm-level perspective and examine how firms' technological boundaries shape their ability to adapt to the Alice shock. While the previous analysis shows that technological compatibility determines the availability of potential recombination opportunities, firms can access only a subset of these opportunities at relatively low cost. This subset depends on the knowledge already contained in their technological portfolios. We therefore examine whether firms with greater recombination capacity are better able to sustain innovation in affected technologies following Alice and whether this advantage translates into differences in firm performance.

6.1 Innovation Responses through Recombination Capacity

Similar to the patent-level analysis, we apply a difference-in-differences design to examine how Alice affected firms' innovation activities. The treatment intensity is firm exposure, which measures the extent to which firms' pre-Alice patent portfolios were exposed to Alice-related eligibility risk. Recombination capacity is constructed in Section 4.4 and captures the recombination opportunities that firms can access at relatively low cost through knowledge already contained in their existing technological portfolios.

Table 5 examines firms' patenting responses by firm exposure and recombination capacity. The heterogeneous effect of recombination capacity is concentrated in high-exposure technologies and is not significant for low-exposure technologies. This pattern is consistent with recombination capacity facilitating firms' continued use of knowledge most affected by Alice. More specifically, Column (3) shows that a one-standard-deviation increase in firm exposure is associated with an average decrease of 2.8% in the number of patent applications in high-exposure technologies. When considering heterogeneity in recombination capacity in Column (4), a firm with average recombination capacity experiences a decline of 25.2% in patenting when firm exposure increases by one standard deviation, while a one-standard-deviation increase in recombination capacity attenuates this decline from 25.2% to 18.2%. Figure 6 further illustrates the dynamic effects.

To distinguish the role of firms' technological boundaries from the broader availability of recombination opportunities, we construct an alternative measure of recombination potential that ignores firm boundaries. This measure assigns firms the recombination opportunities available in the broader technology space, regardless of whether the complementary knowledge is already contained in their existing technological portfolios. We repeat the regressions in Table A8. This unconstrained measure does not significantly predict heterogeneous innovation responses after Alice. The contrast suggests that technology-level recombination opportunities alone are insufficient to explain differences in firms' responses. What matters is whether compatible knowledge is already available within firms' technological boundaries and can therefore be accessed at relatively low cost.

6.2 Technological Scope and Knowledge Reuse

If recombination capacity facilitates firms' adaptation by providing relatively low-cost access to compatible knowledge within their technological boundaries, firms with greater recombination capacity should be better able to sustain their technological scope after Alice. More importantly, this adjustment should rely primarily on technologies already contained in firms' existing knowledge portfolios rather than requiring entry into entirely new technological domains.

Table 6 examines how firms adjust their technological scope after Alice. We define technology scope as the number of technology classes in which a firm is active in a given year, and define existing technology reuse as the number of active technology classes that were also active in the firm's portfolio during the previous five years. Columns (2) and (4) show that, conditional on firm exposure, firms with greater recombination capacity maintain a broader technological scope and reuse more of their previously developed technology classes after Alice. The stronger reuse of existing technologies is consistent with the idea that recombination capacity facilitates adaptation by allowing firms to draw on compatible knowledge already contained within their technological boundaries.

Greater recombination capacity is also associated with entry into new technological domains, although this effect is weaker than that for existing technology reuse. Thus, while firms with greater recombination capacity expand into some new technological areas after Alice, their adjustment relies more strongly on the reuse of knowledge already contained in their existing technological portfolios.

6.3 Economic Consequences of Firm Adaptation

The previous results show that firms with greater recombination capacity are better able to sustain innovation in affected technologies after Alice. We next examine whether these differences in firms' innovation responses are accompanied by differences in economic performance.

Table 7 examines how firm performance responds to Alice exposure and whether recombination capacity mitigates the adverse consequences of the shock. Similar to the previous analyses, although the average effects of firm exposure are not significant, substantial heterogeneity emerges with respect to recombination capacity. For sales, Column (2) shows that firms with average recombination capacity experience a decline of approximately 8.2% in sales following a one-standard-deviation increase in exposure. However, the positive triple interaction indicates that this negative effect is significantly weaker for firms with greater recombination capacity. The pattern is similar for sales per employee and market value of equity, suggesting that firms with greater recombination capacity experience smaller declines in economic performance after the appropriation shock.

Taken together, these results show that the advantages associated with recombination capacity extend beyond firms' innovation responses. Firms with greater recombination capacity not only sustain more innovation in affected technologies after Alice, but also experience smaller declines in operating performance and market valuation. This pattern is consistent with the idea that access to recombination opportunities helps firms preserve the economic value generated from affected knowledge when its existing uses become less valuable.

7 Discussion and Further Study

7.1 Knowledge Recombination and the Consequences of Appropriation Shocks

The Alice decision affected not only patent eligibility but also the expected returns to knowledge in exposed technology areas. Our analysis identifies knowledge recombination as one margin through which innovators respond to this change in returns. This perspective complements other margins studied in the literature and provides a way to understand how recombination may interact with broader changes in innovation activities, firm performance, and market structure following appropriation shocks.

Existing studies have examined several consequences of weaker intellectual property protection, including changes in market competition, entry, and firm performance (Feng and Williams, 2026; Guler et al., 2026; Galasso and Schankerman, 2018; Acikalin et al., 2026). Our analysis highlights a complementary margin: incumbent innovators can respond by changing how they use affected knowledge. Rather than focusing only on whether innovation activity expands or contracts following an appropriation shock, we show that innovators recombine affected knowledge with other technological components and that firms differ substantially in their ability to use this margin.

Our firm-level results further identify technological boundaries as one source of this heterogeneity. Firms with greater recombination capacity have relatively low-cost access to a richer set of compatible knowledge components and are better able to sustain innovation in affected technologies after Alice. Other firm characteristics, such as size, diversification, financial resources, or organizational capabilities, may also shape responses to appropriation shocks. Our results isolate a specifically knowledge-based dimension of this heterogeneity: the opportunities for recombination made accessible by firms' accumulated technological portfolios.

More broadly, weaker intellectual property protection may change not only how existing innovators use affected knowledge, but also who can build on that knowledge. While existing innovators may respond by recombining affected knowledge and developing alternative uses, weaker protection may simultaneously create opportunities for other innovators to build on knowledge that was previously more strongly protected (Galasso and Schankerman, 2015; Sampat and Williams, 2019). Our study focuses on the former margin by examining how innovators continue to build on affected knowledge after Alice. An important complementary question is which firms are better positioned to exploit knowledge made more accessible by weaker intellectual property protection, which may depend on their ability to absorb and integrate external knowledge (Cohen et al., 1990; Woeppel and Yavuz, 2026).

Furthermore, appropriation shocks may also reshape the organization of innovation production by affecting the market for knowledge. When abstract ideas themselves become difficult to protect through patents, transforming such ideas into patentable and commercially valuable inventions may require greater investment in complementary R&D activities. Firms specializing in generating intermediate knowledge components may therefore face greater challenges in commercializing their outputs through market transactions, potentially increasing incentives for firms to expand their boundaries and internalize complementary innovation activities. This possibility suggests another direction for future research: how changes in patent protection reshape firms' boundaries and the organization of knowledge production.

7.2 Knowledge Recombination beyond Appropriation Shocks

The recombination margin studied in this paper is not specific to changes in intellectual property protection. More generally, if the value of an innovation depends on the knowledge components used to produce it and on how those components are combined, changes in the value of existing knowledge can alter the combinations through which that knowledge is used. Following an adverse shock, as long as affected knowledge retains some value as an input to innovation, innovators may continue to build on it by recombining it with other knowledge components. Knowledge recombination can therefore provide a more general margin through which innovation responds when the economic value of existing knowledge declines.

An important limitation is that we do not fully characterize how the value of individual knowledge components maps into the value created by their combinations. Existing theories of recombinant innovation emphasize that new knowledge is produced by combining existing knowledge components and that the outcomes of such combinations can be highly uncertain (Weitzman, 1998; Fleming, 2001). Yet the production process through which the characteristics and value of individual knowledge components map into the value of their combinations remains relatively underexplored. It is therefore possible that even knowledge whose existing uses lose most or all of their economic value could become valuable again when combined with other knowledge components in sufficiently different ways. Our framework does not establish when such possibilities arise, but they point to a broader question about how the value of knowledge depends on the combinations in which it is deployed.

The same recombination logic may also apply to other changes in the innovation environment. Positive shocks that increase the value of particular knowledge components may make new combinations involving that knowledge more attractive, while changes in search and integration costs may alter which combinations are economically feasible. One example is the emergence of artificial intelligence, which may reduce the costs of searching for and integrating knowledge across technological domains (Cockburn et al., 2019). Whereas Alice changes the returns to particular uses of knowledge, AI may change the costs of identifying and forming new knowledge combinations. By making previously difficult combinations easier to identify and develop, AI could expand the range of knowledge that innovators can effectively recombine. An important question is whether such technologies disproportionately benefit firms whose existing knowledge portfolios already provide rich recombination opportunities or instead reduce the importance of technological boundaries by making knowledge outside those boundaries easier to access.

8 Conclusion

This paper studies knowledge recombination as a margin through which innovators respond to changes in the economic returns to existing knowledge. Because innovation builds on combinations of existing knowledge components, a decline in the return to one use of knowledge need not lead innovators to abandon that knowledge altogether. Instead, innovators may continue building on affected knowledge by recombining it with other knowledge components and redirecting it toward alternative uses.

We study this margin using the 2014 *Alice Corp. v. CLS Bank International* decision, which tightened patent eligibility for abstract ideas and disproportionately reduced patent protection in affected technologies. We show that innovators respond to greater Alice exposure by increasing cross-technology recombination. Patent applications in more exposed technologies recombine knowledge from a broader set of technology classes after Alice, and the resulting inventions become less exposed to the new eligibility standard. Consistent changes in inventor teams and knowledge inputs, together with evidence from citation and continuation relationships, further show that innovators change how affected knowledge is used in innovation production rather than merely changing observable patent classifications.

The extent of this response depends on the opportunities available for recombination. Using historical patterns of technological combinations, we show that affected technologies with greater recombination opportunities exhibit stronger increases in knowledge recombination after Alice. Technological compatibility therefore shapes the extent to which innovators can redeploy affected knowledge through alternative combinations. At the firm level, these opportunities are further constrained by technological boundaries. Firms differ in the complementary knowledge already contained in their technological portfolios and therefore in the recombination opportunities they can access at relatively low cost. Firms with greater recombination capacity sustain more innovation in affected technologies, rely more extensively on knowledge already contained in their portfolios, and experience smaller declines in economic performance following Alice.

More broadly, our findings show that changes in economic incentives can shape innovation not only by changing which knowledge innovators pursue, but also by changing how existing knowledge is used. The combinatorial nature of innovation allows the same knowledge to contribute to different innovations depending on the other knowledge with which it is combined. Recombination therefore provides a margin through which innovators can redeploy accumulated knowledge as its economic environment changes. Which alternative uses are available, and which of them can be accessed at relatively low cost, depend on both technological compatibility and the knowledge already accumulated within firm boundaries.

References

Acemoglu, Daron, "Directed Technical Change," *The Review of Economic Studies*, 2002, *69* (4), 781–809.

Acikalin, Utku U., Tolga Caskurlu, Gerard Hoberg, and Gordon M. Phillips, "Intellectual Property Protection Lost and Competition: An Examination Using Large Language Models," *Journal of Financial Economics*, 2026, *182*, 104306.

Aghion, Philippe, Antoine Dechezleprêtre, David Hémous, Ralf Martin, and John Van Reenen, "Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry," *Journal of Political Economy*, 2016, *124* (1), 1–51.

Alstott, Jeff, Giorgio Triulzi, Bowen Yan, and Jianxi Luo, "Mapping technology space by normalizing patent networks," *Scientometrics*, 2017, *110* (1), 443–479.

Babina, Tania, Sabrina T. He, Sabrina T. Howell, Elisabeth Perlman, and Joseph Staudt, "Cutting the Innovation Engine: How Federal Funding Shocks Affect University Patenting, Entrepreneurship, and Publications," *The Quarterly Journal of Economics*, 2023, *138* (2), 895–954.

Breschi, Stefano, Francesco Lissoni, and Franco Malerba, "Knowledge-relatedness in firm technological diversification," *Research policy*, 2003, *32* (1), 69–87.

Bryan, Kevin A. and Jorge Lemus, "The Direction of Innovation," *Journal of Economic Theory*, 2017, *172*, 247–272.

Chien, Colleen V and Jiun Ying Wu, "Decoding patentable subject matter," *Patently-O Patent Law Journal*, 2018, *1.*

Cockburn, IM, R Henderson, and S Stern, "The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis. Chap. 4 in The Economics of Artificial Intelligence, edited by AK Agrawal, J. Gans and A. Goldfarb," 2019.

Cohen, Wesley M, Daniel A Levinthal et al., "Absorptive capacity: A new perspective on learning and innovation," *Administrative science quarterly*, 1990, *35* (1), 128–152.

Feng, Josh and Peyton Williams, "Abstract patents and startup funding: Evidence from Alice v. CLS Bank," *Research Policy*, 2026, *55* (5), 105462.

Fleming, Lee, "Recombinant uncertainty in technological search," *Management science*, 2001, *47* (1), 117–132.

— **and Olav Sorenson**, "Technology as a complex adaptive system: evidence from patent data," *Research policy*, 2001, *30* (7), 1019–1039.

Galasso, Alberto and Mark Schankerman, "Patents and cumulative innovation: Causal evidence from the courts," *The Quarterly Journal of Economics*, 2015, *130* (1), 317–369.

— **and** — , "Patent rights, innovation, and firm exit," *The RAND Journal of Economics*, 2018, *49* (1), 64–86.

Griffith, Rachel, Sokbae Lee, and Bas Straathof, "Recombinant Innovation and the Boundaries of the Firm," *International Journal of Industrial Organization*, 2017, *50*, 34–56.

Guler, Elif N, Alexander Montag, and Michael Woeppel, "How Does Patent Protection Affect Venture Capital Investment?," *Available at SSRN 5755942*, 2026.

Jackson, Matthew O et al., *Social and economic networks*, Vol. 3, Princeton university press Princeton, 2008.

Jaffe, Adam B, "Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value," 1986.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, "Technological innovation, resource allocation, and growth," *The quarterly journal of economics*, 2017, *132* (2), 665–712.

Kogut, Bruce and Udo Zander, "Knowledge of the firm, combinative capabilities, and the replication of technology," *Organization science*, 1992, *3* (3), 383–397.

Kuhn, Jeffrey, Kenneth Younge, and Alan Marco, "Patent citations reexamined," *The RAND Journal of Economics*, 2020, *51* (1), 109–132.

March, James G, "Exploration and exploitation in organizational learning," *Organization science*, 1991, *2* (1), 71–87.

Mezzanotti, Filippo, "Roadblock to innovation: The role of patent litigation in corporate R&D," *Management Science*, 2021, *67* (12), 7362–7390.

Moser, Petra, "How Do Patent Laws Influence Innovation? Evidence from Nineteenth-Century World's Fairs," *American Economic Review*, 2005, *95* (4), 1214–1236.

NBER, *The Rate and Direction of Inventive Activity: Economic and Social Factors*, Princeton, NJ: Princeton University Press, 1962.

Sampat, Bhaven and Heidi L Williams, "How do patents affect follow-on innovation? Evidence from the human genome," *American Economic Review*, 2019, *109* (1), 203–236.

USPTO, "Preliminary Examination Instructions in View of the Supreme Court Decision in Alice Corporation Pty. Ltd. v. CLS Bank International," Memorandum, United States Patent and Trademark Office June 2014.

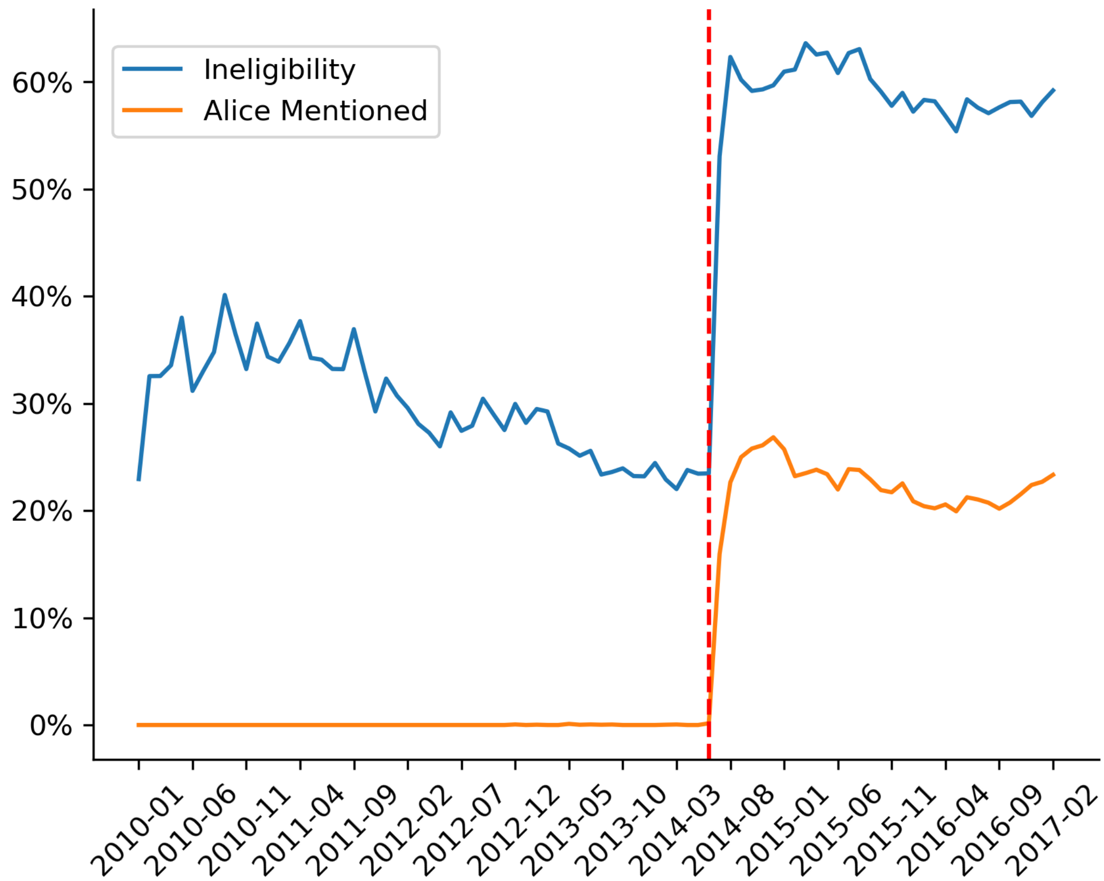
Uzzi, Brian, Satyam Mukherjee, Michael Stringer, and Ben Jones, "Atypical combinations and scientific impact," *Science*, 2013, *342* (6157), 468–472.

Weitzman, Martin L, "Recombinant growth," *The quarterly journal of economics*, 1998, *113* (2), 331–360.

Woeppel, Michael and M Deniz Yavuz, "Measuring firms' capability to absorb external knowledge," *Journal of Financial Economics*, 2026, *183*, 104322.

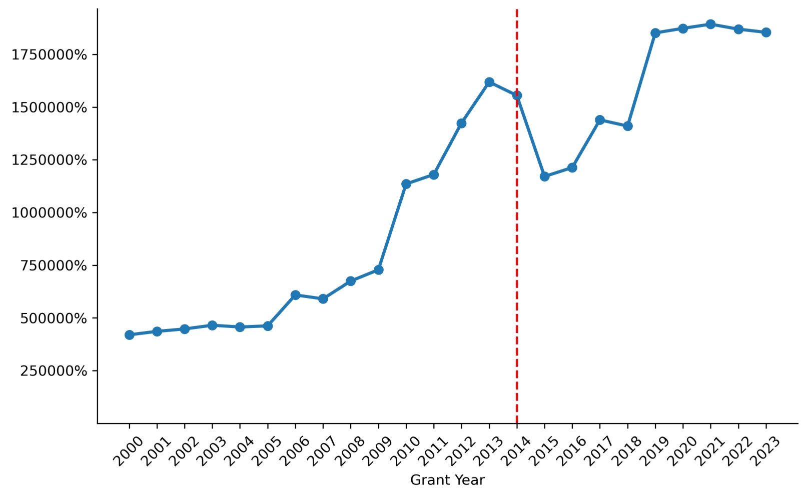
Wooldridge, Jeffrey M, "Nonlinear Difference-in-Differences with Repeated Cross Sections," in "AEA Papers and Proceedings," Vol. 116 American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425 2026, pp. 75–80.

Figure 1: The Immediate Increase in Patent Examination Rejections (High-Exposure Technologies)

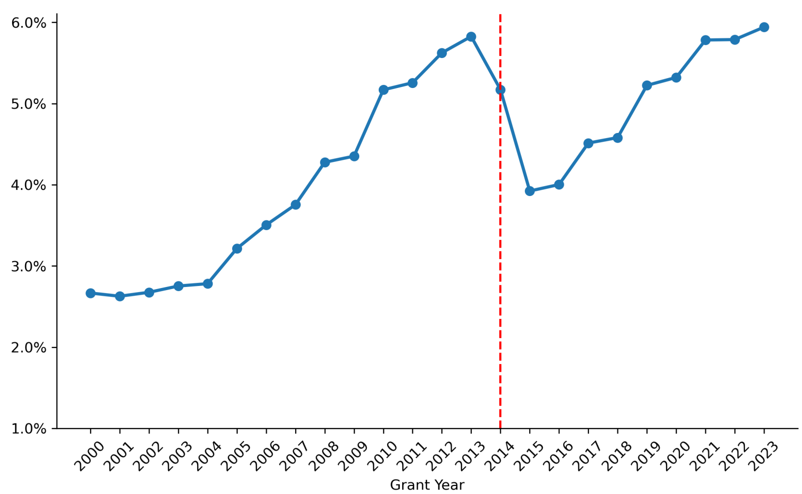


Notes: This figure reports the monthly share of recorded patent examination rejections within high-exposure technologies that fall into two categories. High-exposure technologies are defined as CPC technology subclasses with Alice exposure of at least 5%. The blue line represents the fraction of all recorded rejections classified as subject-matter ineligibility rejections under Section 101. The orange line represents the fraction of all recorded rejections that explicitly reference the Alice decision. Alice-referenced rejections constitute a subset of subject-matter ineligibility rejections. The vertical dashed line indicates June 19, 2014, the date of the Supreme Court decision.

Figure 2: Patent Grants in High-Exposure Technologies



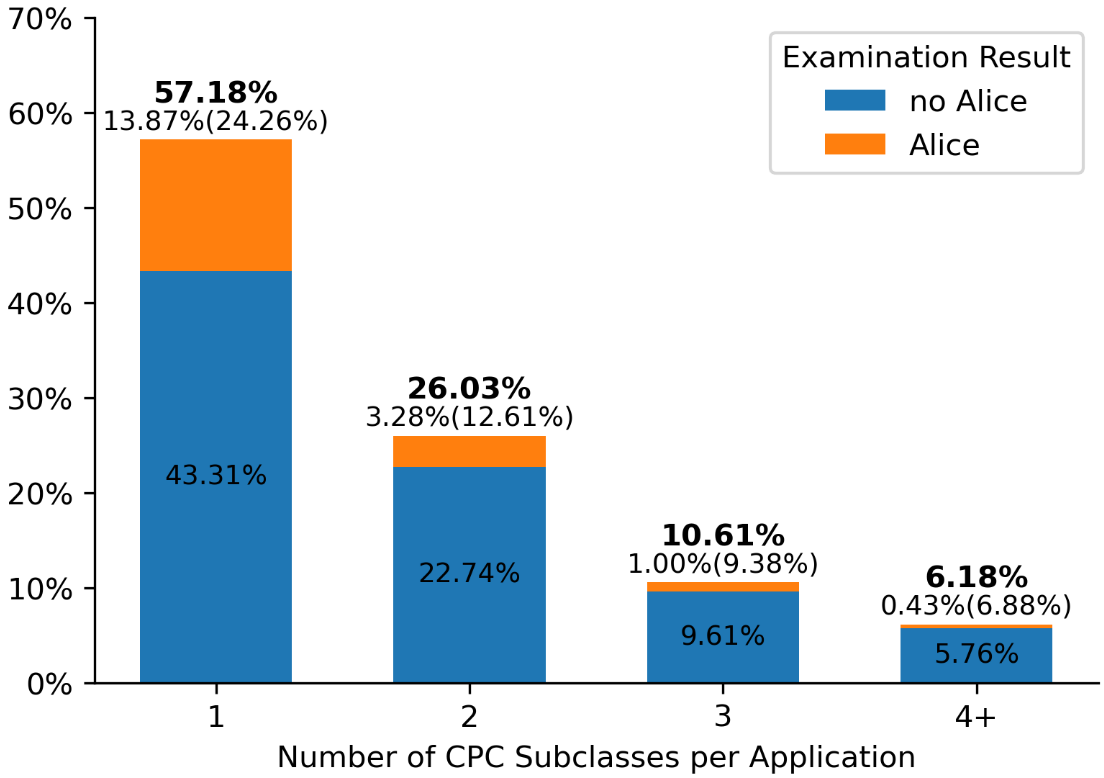
(a) Number of Patent Grants in High-Exposure Technologies



(b) Proportion of Patent Grants in High-Exposure Technologies

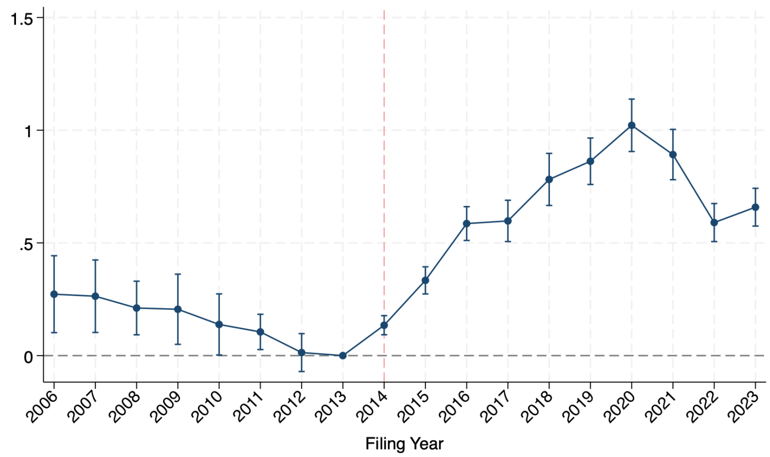
Notes: This figure illustrates patent grants in high-exposure technologies over time. High-exposure technologies are defined as CPC subclasses whose estimated class exposure to Alice-related rejection risk is greater than or equal to 0.05. Class exposure is constructed using the GLMM-based exposure measure described in the paper. Panel (a) reports the annual number of patent grants whose primary CPC subclass belongs to the high-exposure category. Panel (b) reports the share of patent grants in high-exposure technologies relative to the total number of patent grants in each year. The vertical dashed line indicates the *Alice Corp. v. CLS Bank* decision in June 2014.

Figure 3: Cross-Technology Recombination and Alice-Related Rejection Risk

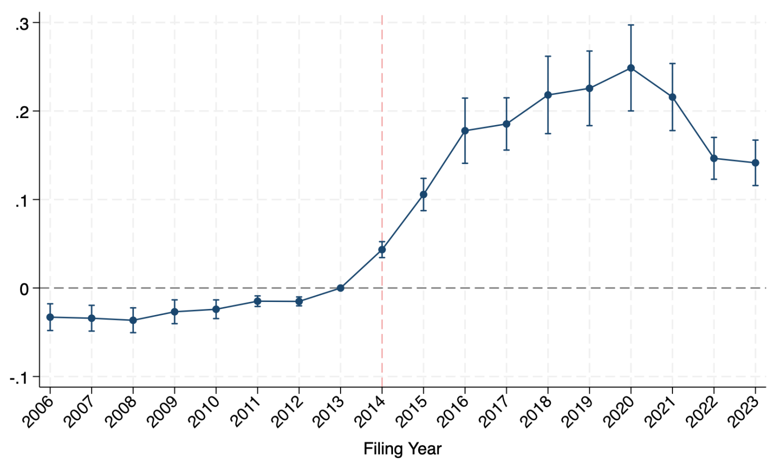


Notes: This figure shows the relationship between technological combinations and Alice-related rejection risk. The sample consists of patent applications whose primary CPC subclass belongs to the high-exposure category. Applications are grouped according to the number of CPC subclasses assigned to the application (1, 2, 3, and 4 or more). Within each bar, the orange segment represents applications that received an Alice-related rejection during examination, while the blue segment represents applications that did not receive an Alice-related rejection. These applications may have received other types of rejections or no rejection. The bold percentage above each bar indicates the share of applications in the sample belonging to that subclass-count category. The percentage before the parentheses reports the share of applications in that category receiving an Alice-related rejection relative to the full sample, while the percentage in parentheses reports the share of Alice-related rejections within that subclass-count category.

Figure 4: Dynamic Effects of Alice Exposure



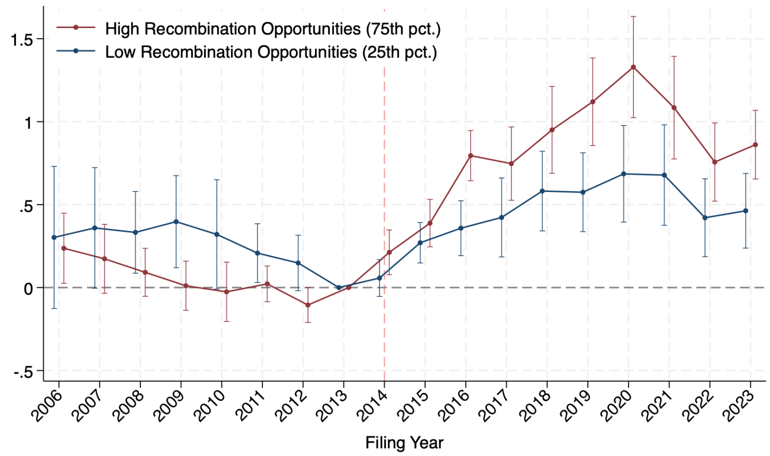
(a) Treatment Effect on Knowledge Recombination



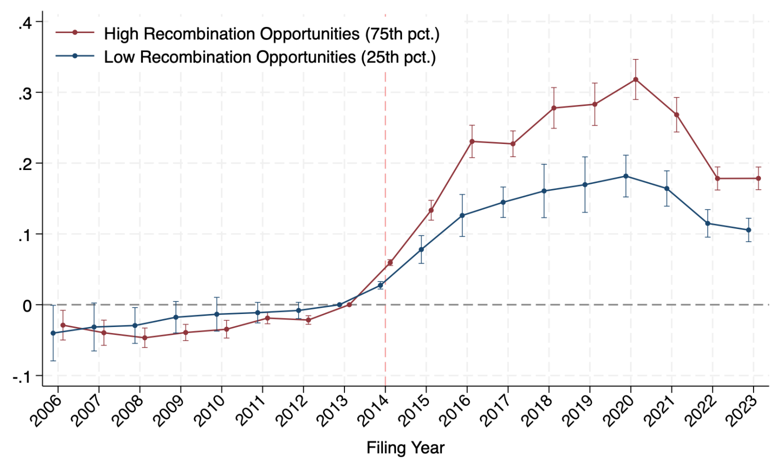
(b) Treatment Effect on Exposure Reduction

Notes: This figure presents dynamic treatment effects of Alice exposure on knowledge recombination and exposure reduction. The estimates are obtained from event-study specifications corresponding to Columns (1) and (3) of Panel A in Table 2. Panel (a) reports coefficients where the dependent variable is the number of CPC subclasses assigned to a patent application. Panel (b) reports coefficients where the dependent variable is exposure reduction, defined as the difference between the exposure of the primary technology class and the predicted Alice-related exposure of the patent. The omitted reference year is 2013. The vertical dashed line indicates the Alice Corp. v. CLS Bank decision in June 2014. All specifications include primary CPC class fixed effects and year fixed effects. Confidence intervals represent 95% confidence intervals.

Figure 5: Dynamic Effects of Alice Exposure by Recombination Opportunities



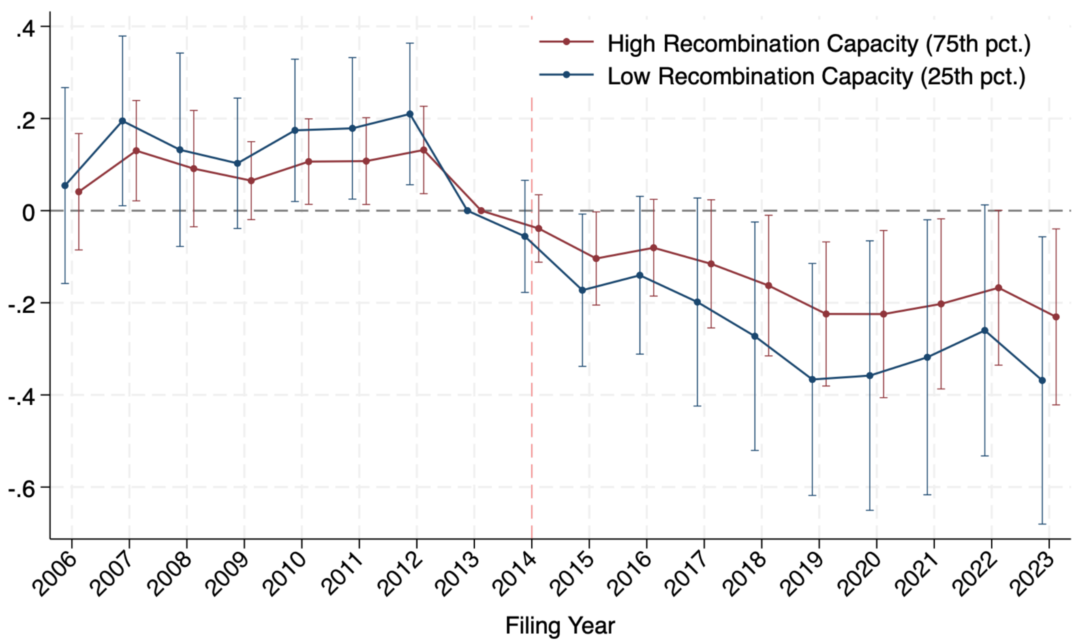
(a) Treatment Effect on Knowledge Recombination



(b) Treatment Effect on Exposure Reduction

Notes: This figure presents dynamic effects of Alice exposure by recombination opportunities. The estimates are obtained from event-study specifications corresponding to Columns (1) and (3) of Panel A in Table 2. The specifications use continuous measures of class exposure and recombination opportunities. For illustration, the figure plots the estimated effects evaluated at the 25th and 75th percentiles of recombination opportunities. Panel (a) reports coefficients from specifications where the dependent variable is the number of CPC subclasses assigned to a patent application. Panel (b) reports coefficients from specifications where the dependent variable is exposure reduction, defined as the difference between the exposure of the primary technology class and the predicted Alice-related exposure of the patent. Recombination Opportunities captures the availability of complementary knowledge components based on historical co-occurrence patterns among technology classes in the knowledge network described in the paper. The omitted reference year is 2013. The vertical dashed line indicates the Alice Corp. v. CLS Bank decision in June 2014. All specifications include primary CPC class fixed effects and year fixed effects. Confidence intervals represent 95% confidence intervals.

Figure 6: Dynamic Effects on Patenting in High-Exposure Technologies



Notes: This figure presents dynamic effects of firm exposure on patenting in high-exposure technologies. The estimates are obtained from the event-study specification corresponding to Column (4) of Table 5. The specification uses continuous measures of firm exposure and recombination capacity. For illustration, the figure plots the estimated effects evaluated at different levels of recombination capacity. High and low recombination capacity correspond to the 75th and 25th percentiles of the recombination capacity distribution, respectively. The dependent variable is the number of patent applications filed by firms in high-exposure technologies. The omitted reference year is 2013. The vertical dashed line indicates the Alice Corp. v. CLS Bank decision in June 2014. All specifications include firm fixed effects and industry-by-year fixed effects. Confidence intervals represent 95% confidence intervals.

Table 1: Construction of Alice Exposure Measures

Panel A: CPC Subclasses with High Alice Exposure

CPC Subclass	Short Description	Exposure (%)	
		OLS	GLMM
G06Q	ICT for administrative or business purposes	28.14	34.36
G07F	Coin or payment-operated apparatus	25.25	27.85
G16B	Bioinformatics and computational genomics	18.43	25.91
A63F	Games and amusement devices	20.51	24.81
G16C	Computational chemistry and molecular informatics	14.68	23.08
G07B	Ticketing, fare collection, and access control	18.07	18.06
G09B	Educational or demonstration apparatus	13.16	15.75
G16Z	ICT applied to specific fields	5.63	12.98
G01W	Meteorology-related measurement and forecasting	10.83	10.61
G07G	Registering cash registers, point-of-sale systems, and related devices	3.64	9.77
C12Q	Measuring or testing processes involving enzymes, nucleic acids, or microorganisms	4.87	6.28
G09C	Cryptography and secure communication	3.23	6.10
G01V	Geophysics; detection of underground structures or resources	4.87	5.82
G16H	Healthcare informatics	5.64	5.81
G01C	Measuring distances, navigation, and positioning	4.70	5.65
G10L	Speech analysis, recognition, and processing	4.50	5.42
G07C	Time or attendance registers; time recording devices	3.77	5.33

Panel B: Estimated Contributions of Primary and Secondary CPC Subclasses

$N_{\text{subclasses}}$	$N_{\text{applications}}$ (Share)	OLS Estimates (%)		GLMM Weights (%)	
		Primary	Secondary	Primary	Secondary
1	313,143 (45.18)	118.91	–	100.00	0.00
2	222,836 (32.15)	65.93	24.67	70.28	29.72
3	102,798 (14.83)	53.61	31.07	54.18	45.82
4	38,470 (5.55)	43.12	40.22	44.08	55.92
5	12,883 (1.86)	29.12	58.63	37.16	62.84
6	4,336 (0.63)	22.22	88.63	32.11	67.89
7+	2,870 (0.41)	-3.49	51.33	28.27	71.73

Notes: This table summarizes the construction and properties of the Alice exposure measures. Panel A reports CPC subclasses with high Alice exposure, defined as subclasses with a GLMM-based exposure measure greater than or equal to 5%. Panel B reports the estimated contributions of primary and secondary CPC classifications in determining patent-level exposure. The OLS estimates in Panel B are obtained from regressions relating patent-level Alice-related rejections to the exposure of primary and secondary CPC subclasses, while the GLMM weights represent the estimated contributions of primary and secondary classifications used to construct the main exposure measure.

Table 2: Baseline: Knowledge Recombination and Exposure Reduction

Panel A: Continuous Exposure Intensity				
	Num. of Classes		Exposure Reduction	
	(1)	(2)	(3)	(4)
Class Exposure × Post	0.523***	0.530***	0.191***	0.193***
	(7.30)	(5.92)	(9.82)	(7.36)
Primary Class FE	Yes	Yes	Yes	Yes
Filing Year FE	Yes	Yes	Yes	Yes
Clustering	Primary Class	Primary Class	Primary Class	Primary Class
Pseudo/Adj. R^2	0.0325	0.0327	0.4477	0.5112
Num. of Observations	6586138	4772492	6586138	4772492
Sample	Pub Apps	Grants	Pub Apps	Grants
Model	PPML	PPML	OLS	OLS
Panel B: Discrete Exposure Level				
	Num. of Classes		Exposure Reduction	
	(1)	(2)	(3)	(4)
Med. Exposure × Post	0.0570***	0.0589***	0.000521**	0.000540**
	(2.85)	(3.27)	(2.04)	(2.53)
High Exposure × Post	0.137***	0.138***	0.0416***	0.0397**
	(3.36)	(3.33)	(2.65)	(2.40)
Primary Class FE	Yes	Yes	Yes	Yes
Filing Year FE	Yes	Yes	Yes	Yes
Clustering	Primary Class	Primary Class	Primary Class	Primary Class
Pseudo/Adj. R^2	0.0326	0.0328	0.4321	0.4968
Num. of Observations	6586138	4772492	6586138	4772492
Sample	Pub Apps	Grants	Pub Apps	Grants
Model	PPML	PPML	OLS	OLS

Notes: This table examines whether innovators respond to the Alice decision through knowledge recombination. Panel A reports estimates using continuous class exposure, while Panel B reports estimates using discrete exposure categories. In Panel B, high exposure technologies are defined as technology classes with exposure levels greater than or equal to 0.05, medium exposure technologies are defined as technology classes with exposure levels below 0.05 and greater than or equal to 0.005, and low exposure technologies are defined as technology classes with exposure levels below 0.005. The dependent variables are the number of CPC subclasses assigned to a patent application and exposure reduction, defined as the difference between the exposure of the primary technology class and the predicted Alice-related exposure of the patent. A higher value of exposure reduction indicates that additional technological components reduce the patent's exposure relative to its primary technology class. Class exposure is measured using the GLMM-based exposure measure described in the paper. The sample consists of patent applications filed between 2006 and 2023 and granted patents in the corresponding grant sample. All specifications include primary CPC class fixed effects and year fixed effects. Standard errors are clustered at the primary CPC class level. t statistics are reported in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 3: Heterogeneity: The Role of Recombination Opportunities

Panel A: Continuous Exposure Intensity				
	Num. of Classes		Exposure Reduction	
	(1)	(2)	(3)	(4)
Class Exposure × Post	0.542***	0.545***	0.197***	0.199***
	(9.59)	(7.22)	(24.36)	(18.10)
Recombination Opportunities × Post	-0.0269***	-0.0283***	-0.000512*	-0.000675**
	(-2.74)	(-2.75)	(-1.67)	(-2.02)
Class Exposure × Recombination Opportunities × Post	0.454**	0.521***	0.0719***	0.0827***
	(2.33)	(2.62)	(2.88)	(3.27)
Primary Class FE	Yes	Yes	Yes	Yes
Filing Year FE	Yes	Yes	Yes	Yes
Clustering	Primary Class	Primary Class	Primary Class	Primary Class
Pseudo/Adj. R^2	0.0326	0.0328	0.4479	0.5114
Num. of Observations	6586138	4772492	6586138	4772492
Sample	Pub Apps	Grants	Pub Apps	Grants
Model	PPML	PPML	OLS	OLS
Panel B: Discrete Exposure Level				
	Num. of Classes		Exposure Reduction	
	(1)	(2)	(3)	(4)
Med. Exposure × Post	0.0560***	0.0602***	0.000554**	0.000561***
	(3.12)	(3.61)	(2.26)	(2.62)
High Exposure × Post	0.157***	0.162***	0.0545***	0.0540***
	(4.48)	(4.68)	(4.81)	(4.52)
Recombination Opportunities × Post	-0.0273***	-0.0294***	0.0000354**	0.0000412***
	(-3.31)	(-3.29)	(2.24)	(2.59)
Med. Exposure × Recombination Opportunities × Post	0.0167	0.0152	-0.000209	-0.000151
	(0.70)	(0.79)	(-1.02)	(-0.85)
High Exposure × Recombination Opportunities × Post	0.0939**	0.0981**	0.0369***	0.0369***
	(2.36)	(2.40)	(3.37)	(3.36)
Primary Class FE	Yes	Yes	Yes	Yes
Filing Year FE	Yes	Yes	Yes	Yes
Clustering	Primary Class	Primary Class	Primary Class	Primary Class
Pseudo/Adj. R^2	0.0326	0.0328	0.4321	0.5142
Num. of Observations	6586138	4772492	6586138	4772492
Sample	Pub Apps	Grants	Pub Apps	Grants
Model	PPML	PPML	OLS	OLS

Notes: This table examines whether recombination opportunities shape innovators' ability to adapt to the Alice decision through knowledge recombination. Panel A reports estimates using continuous class exposure, while Panel B reports estimates using discrete exposure categories. In Panel B, high exposure technologies are defined as technology classes with exposure levels greater than or equal to 0.05, medium exposure technologies are defined as technology classes with exposure levels below 0.05 and greater than or equal to 0.005, and low exposure technologies are defined as technology classes with exposure levels below 0.005. The dependent variables are the number of CPC subclasses assigned to a patent application and exposure reduction, defined as the difference between the exposure of the primary technology class and the predicted Alice-related exposure of the patent. Recombination Opportunities captures the availability of complementary knowledge components based on historical co-occurrence patterns among technology classes in the knowledge network described in the paper. The sample consists of patent applications filed between 2006 and 2023 and granted patents in the corresponding grant sample. All specifications include primary CPC class fixed effects and year fixed effects. Standard errors are clustered at the primary CPC class level. t statistics are reported in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 4: Structural Changes of Innovation Inputs

Panel A: Inventor Team (Input of Human Capital)						
	Team Knowledge Breadth		Team Knowledge Dispersion		Member Knowledge Distance	
	(1)	(2)	(3)	(4)	(5)	(6)
Class Exposure × Post	0.189*	0.220**	0.0829**	0.0954***	0.0832***	0.0942***
	(1.88)	(2.24)	(2.32)	(5.91)	(2.59)	(6.78)
Recombination Opportunities × Post		-0.000840		-0.00602***		0.000327
		(-0.07)		(-2.90)		(0.26)
Class Exposure × Recombination Opportunities × Post		0.325		0.162*		0.123***
		(1.10)		(1.75)		(3.23)
Primary Class FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Primary Class	Primary Class	Primary Class	Primary Class	Primary Class	Primary Class
Pseudo/Adj. R^2	0.0760	0.0760	0.0364	0.0365	0.0587	0.0588
Num. of Observations	6586135	6586135	5801352	5801352	3760282	3760282
Model	PPML	PPML	OLS	OLS	OLS	OLS

Panel B: Backward Citations (Input of Knowledge)				
	Citation Breadth		Citation Dispersion	
	(1)	(2)	(3)	(4)
Class Exposure × Post	0.129	0.129**	0.00331	0.0157
	(1.63)	(2.57)	(0.09)	(0.97)
Recombination Opportunities × Post		-0.0359***		-0.0172***
		(-3.64)		(-4.40)
Class Exposure × Recombination Opportunities × Post		0.403**		0.217***
		(2.46)		(3.23)
Primary Class FE	Yes	Yes	Yes	Yes
Filing Year FE	Yes	Yes	Yes	Yes
Clustering	Primary Class	Primary Class	Primary Class	Primary Class
Pseudo/Adj. R^2	0.0890	0.0892	0.1070	0.1077
Num. of Observations	4511111	4511111	4511111	4511111
Model	PPML	PPML	OLS	OLS

Notes: This table examines whether innovators adjusted the inputs used in innovation production after the Alice decision. The treatment intensity is defined as the Alice exposure of the primary CPC subclass assigned to each patent. Panel A uses a sample of patent applications filed between 2006 and 2023, while Panel B uses a sample of granted patents filed between 2006 and 2023 because citation information is only available for granted patents. Inventor-based outcomes capture changes in the human capital inputs of innovation. For each inventor, we construct a historical knowledge set based on CPC subclasses appearing in the inventor's previous patents. Team knowledge breadth is the number of unique CPC subclasses across all inventors in a team, knowledge dispersion is measured by the entropy of the team's historical knowledge distribution, and inventor distance is the average pairwise technological distance between inventors based on their historical knowledge sets. Citation-based outcomes capture changes in knowledge inputs. Citation knowledge breadth is the number of unique CPC subclasses among backward-cited patents, and citation knowledge dispersion is measured by the entropy of cited technological knowledge. Citation distance is not reported due to computational constraints.

Table 5: Firm-Level Patenting Responses across Technology Exposure

	Number of Patent Applications					
	Total		High-Exposure Tech		Low-Exposure Tech	
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Exposure × Post	-0.0184**	-0.0908	-0.0283***	-0.290***	-0.00141	-0.0616
	(-2.30)	(-1.43)	(-3.79)	(-3.34)	(-0.13)	(-0.67)
Recombination Capacity × Post		0.0558		0.0923		0.0300
		(1.02)		(1.18)		(0.50)
Firm Exposure × Recombination Capacity × Post		0.0244		0.0888***		0.0216
		(1.14)		(3.15)		(0.69)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Pseudo R^2	0.9636	0.9636	0.8853	0.8868	0.9568	0.9569
Num. of Observations	29998	29998	16234	16234	26365	26365

Notes: This table examines firm-level patenting responses following the Alice decision. Columns (1) and (2) use the total number of patent applications filed by each firm as the dependent variable. Columns (3) and (4) examine patent applications in high-exposure technologies (technology classes with Alice exposure levels greater than or equal to 0.05), while Columns (5) and (6) examine patent applications in low-exposure technologies (technology classes with Alice exposure levels below 0.005). Firm Exposure captures the extent to which a firm's pre-Alice patent portfolio was exposed to Alice-related eligibility risk. Recombination Capacity measures the availability of technologically compatible knowledge components accessible within a firm's existing technology portfolio based on the knowledge network described in the paper. The sample consists of publicly listed U.S. firms observed annually from 2006 to 2023. All specifications include lagged firm-level controls (Firm Size, Tobin's Q, Leverage, Cash, and R&D Expenses), firm fixed effects, and industry-by-year fixed effects. All regressions are estimated by PPML. Standard errors are clustered at the firm level. t statistics are reported in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 6: Changes in Firm Technology Portfolios

	Technology Scope		Existing Technology Reuse		New Technology Entry	
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Exposure × Post	-0.00726**	-0.0869**	-0.0134***	-0.109***	-0.0181**	-0.101**
	(-1.96)	(-2.49)	(-3.03)	(-2.73)	(-2.23)	(-2.11)
Recombination Capacity × Post		-0.0393*		-0.0689***		-0.110***
		(-1.84)		(-2.72)		(-5.32)
Firm Exposure × Recombination Capacity × Post		0.0301***		0.0368***		0.0349**
		(2.67)		(2.88)		(2.17)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Pseudo R^2	0.8772	0.8775	0.8831	0.8836	0.5557	0.5570
Num. of Observations	29998	29998	28511	28511	28775	28775

Notes: This table examines how firms adjust their technological portfolios following the Alice decision. The dependent variables characterize different dimensions of firms' technology usage. Technology Scope measures the number of unique CPC subclasses appearing in a firm's patent applications, including both primary and secondary technology classes. Existing Technology Reuse measures the number of technology classes appearing in a firm's patent applications that have also been used in the firm's patent portfolio during the previous five years. New Technology Entry measures the number of technology classes newly introduced relative to the firm's patent portfolio during the previous five years. Firm Exposure captures the exposure of a firm's pre-Alice patent portfolio to Alice-related rejection risk. Recombination Capacity measures the availability of complementary knowledge components within a firm's technology portfolio based on the knowledge network described in the paper. The sample consists of publicly listed U.S. firms observed annually from 2006 to 2023. All specifications include lagged firm-level controls (Firm Size, Tobin's Q, Leverage, Cash, and R&D Expenses), firm fixed effects, and industry-by-year fixed effects. All regressions are estimated by PPML. Standard errors are clustered at the firm level. t statistics are reported in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

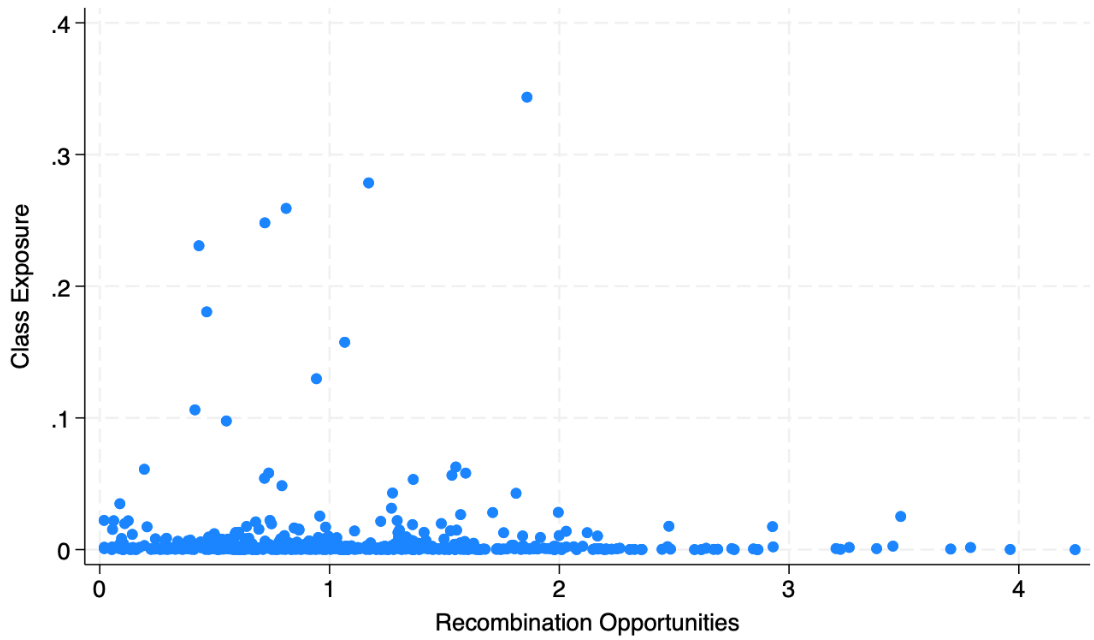
Table 7: Firm-Level Economic Consequences of Adaptation

	log(Sales)		Sales/Employees		Log(MVE)	
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Exposure × Post	-0.0102	-0.0853**	-0.949	-41.02**	-0.0171	-0.160***
	(-1.14)	(-2.56)	(-0.38)	(-2.04)	(-1.32)	(-3.53)
Recombination Capacity × Post		0.0161		34.81***		0.0630***
		(1.00)		(2.98)		(3.22)
Firm Exposure × Recombination Capacity × Post		0.0268**		12.23*		0.0486***
		(2.36)		(1.90)		(3.06)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Adj. R^2	0.9606	0.9606	0.6955	0.6958	0.9285	0.9286
Num. of Observations	29655	29655	29274	29274	30666	30666

Notes: This table examines firm-level economic outcomes following the Alice decision and their heterogeneity with respect to recombination capacity. The dependent variables are measures of firm performance, including log sales, sales per employee, and log market value of equity (MVE). Firm Exposure captures the exposure of a firm's pre-Alice patent portfolio to Alice-related rejection risk. Recombination Capacity measures the availability of complementary knowledge components within a firm's technology portfolio based on the knowledge network described in the paper. The sample consists of publicly listed U.S. firms observed annually from 2006 to 2023. All specifications include lagged firm-level controls (Firm Size, Tobin's Q, Leverage, Cash, and R&D Expenses), firm fixed effects, and industry-by-year fixed effects. All regressions are estimated by PPML. Standard errors are clustered at the firm level. t statistics are reported in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

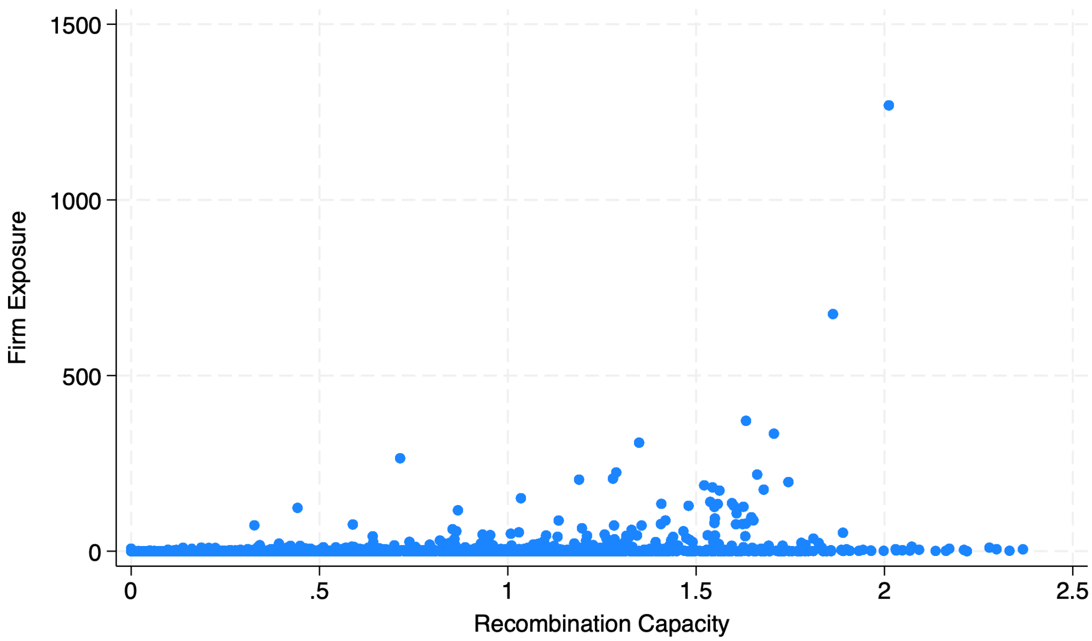
A Additional Figures and Tables

Figure A1: Distribution of Class Exposure and Recombination Opportunities



Notes: This figure shows the distribution of technology-class-level Alice exposure and recombination opportunities. Class exposure measures the exposure of each technology class to the Alice decision, estimated using the GLMM approach in Section 4.2 and Appendix B. Recombination opportunities are defined in Section 4.3.

Figure A2: Distribution of Firm Exposure and Recombination Capacity



Notes: This figure shows the distribution of firm-level Alice exposure and recombination capacity. Both variables are defined in Section 4.4.

Table A1: Definition of Patent-Level Variables

Variable	Definition	Source
Class Exposure	Technology-level exposure of primary class to Alice-related patent eligibility risk.	USPTO
Patent Exposure	Weighted average of exposure across all CPC subclasses assigned to a patent.	USPTO
Number of Technology Classes	The number of CPC subclasses assigned to a patent application or granted patent. Used to measure the technological breadth of an invention.	USPTO
Exposure Reduction	Class Exposure - Patent Exposure	USPTO
Recombination Opportunity	The sum of cosine similarities between the primary CPC subclass of a patent and all other CPC subclasses in the pre-Alice technology network. Higher values indicate a larger set of technologically compatible alternatives.	USPTO
Team Knowledge Breadth	The average number of technology classes previously associated with inventors participating in a patent.	USPTO
Team Knowledge Dispersion	The entropy of the team's historical knowledge distribution.	USPTO
Member Knowledge Distance	The average technological distance among inventors based on their historical patent portfolios.	USPTO
Citation Breadth	The number of CPC subclasses represented among backward citations of a patent.	USPTO
Citation Dispersion	The entropy of cited technological knowledge.	USPTO

Table A2: Definition of Firm-Level Variables

Variable	Definition	Source
Firm Exposure	The sum of patent-level Alice exposure of a firm's pre-Alice technological portfolio. The portfolio includes patent applications filed between 2001 and 2013 and applies a 20% annual depreciation rate.	PatentsView; Kogan et al. (2017)
Recombination Capacity	A firm-level measure of accessible recombination opportunities. Calculated as the portfolio-weighted average of technology-level recombination opportunities where potential recombination partners are restricted to technologies previously developed by the firm.	USPTO; Kogan et al. (2017)
Total Number of Patent Applications	The annual number of patent applications filed by a firm.	USPTO; Kogan et al. (2017)
Number of High-Exposure Patent Applications	The annual number of patent applications assigned to CPC subclasses with Alice exposure above the high-exposure threshold (0.05).	USPTO; Kogan et al. (2017)
Number of Low-Exposure Patent Applications	The annual number of patent applications assigned to CPC subclasses with Alice exposure below the low-exposure threshold (0.005).	USPTO; Kogan et al. (2017)
Technology Scope	The number of CPC subclasses in which a firm is active in a given year.	USPTO; Kogan et al. (2017)
Existing Technology Reuse	The number of CPC subclasses in which a firm reuse in a given year that have also been used in the firm's patent portfolio during the previous five years.	USPTO; Kogan et al. (2017)
New Technology Entry	The number of technology classes newly introduced relative to the firm's patent portfolio during the previous five years.	USPTO; Kogan et al. (2017)
log(Sales)	Log value of annual firm sales.	Compustat
Sales per Employee	Annual sales divided by the number of employees.	Compustat
log(MVE)	Log value of Market capitalization of the firm.	Compustat
Firm Size	Natural logarithm of total assets.	Compustat
Tobin's Q	Market value of assets divided by book value of assets, measuring firm growth opportunities.	Compustat
Leverage	Total debt divided by total assets.	Compustat
Cash	Cash and short-term investments divided by total assets.	Compustat
R&D Expenses	Research and development expenditures scaled by total assets.	Compustat

Table A3: Summary Statistics of Technology Classes based on Measurement Sample

	N	Mean	S.D.	Min	P.25	Median	P.75	Max
Num. of Apps	649	1074	3530	0	55	221	839	62389
Class Exposure	646	.0067	.028	.000031	.00043	.00097	.0027	.34
Recombination Opportunities	649	1	.67	.0022	.58	.87	1.4	4.2

Notes: This table reports summary statistics based on the measurement sample, which includes patent applications filed before the Alice decision but examined after the decision. Number of applications is the number of applications assigned to each technology class, where technology classes are defined by the primary classification of each application. Class exposure measures the exposure of each technology class to the Alice decision, estimated using the GLMM approach in Section 4.2 and Appendix B. Recombination opportunities are defined in Section 4.3.

Table A4: Summary Statistics of Patent-Level Sample

	N	Mean	S.D.	Min	P.25	Median	P.75	Max
Panel A: Published Applications								
Predetermined Variables								
Class Exposure	6586139	.021	.063	.000031	.00051	.0025	.017	.34
High Exposure (Class)	6586139	.062	.24	0	0	0	0	1
Medium Exposure (Class)	6586139	.36	.48	0	0	0	1	1
Low Exposure (Class)	6586139	.58	.49	0	0	1	1	1
Recombination Opportunities	6586139	1.8	.79	.0022	1.2	1.7	2.3	4.2
Std. Recombination Opportunities	6586139	2.2e-09	1	-2.3	-.72	-.15	.58	3.1
Time-Varying Variables: Pre-Alice period (post=0)								
Number of Tech Classes	2630094	1.7	1	1	1	1	2	23
Patent Exposure	2630094	.019	.058	.000031	.00051	.0025	.013	.34
Exposure Reduction	2630094	.0023	.021	-.088	-8.1e-07	0	0	.34
Team Knowledge Breadth	2630094	5.8	8.3	0	1	3	7	156
Team Knowledge Dispersion	2265894	.8	.37	0	.9	.97	1	1
Member Knowledge Distance	1375830	.49	.29	-2.2e-16	.29	.48	.7	1
Time-Varying Variables: Post-Alice period (post=1)								
Number of Tech Classes	3956045	2.1	1.2	1	1	2	3	41
Patent Exposure	3956045	.016	.045	.000031	.0006	.0031	.014	.34
Exposure Reduction	3956045	.0047	.03	-.088	-.00015	0	.00018	.34
Team Knowledge Breadth	3956045	7.5	10	0	2	4	9	197
Team Knowledge Dispersion	3535463	.82	.34	0	.91	.96	1	1
Member Knowledge Distance	2384454	.49	.28	-2.2e-16	.29	.48	.7	1
Panel B: Granted Patents								
	N	Mean	S.D.	Min	P.25	Median	P.75	Max
Predetermined Variables								
Class Exposure	4772495	.018	.054	.000031	.00053	.0028	.017	.34
High Exposure (Class)	5116283	.11	.32	0	0	0	0	1
Medium Exposure (Class)	5116283	.36	.48	0	0	0	1	1
Low Exposure (Class)	5116283	.52	.5	0	0	1	1	1
Recombination Opportunities	4772495	1.7	.76	.0022	1.1	1.6	2.2	4.2
Std. Recombination Opportunities	4772495	-2.5e-09	1	-2.3	-.81	-.15	.55	3.3
Time-Varying Variables: Pre-Alice period (post=0)								
Number of Tech Classes	1867011	1.7	1	1	1	1	2	23
Patent Exposure	1867011	.015	.048	.000031	.00054	.0026	.013	.34
Exposure Reduction	1867011	.0022	.02	-.088	0	0	0	.34
Citation Breadth	1677052	5.3	6.2	1	2	4	6	223
Citation Dispersion	1677052	.7	.34	0	.63	.83	.94	1
Time-Varying Variables: Post-Alice period (post=1)								
Number of Tech Classes	2905484	2.1	1.2	1	1	2	3	41
Patent Exposure	2905484	.014	.038	.000031	.00062	.0034	.015	.34
Exposure Reduction	2905484	.0042	.028	-.084	-.00014	0	.0002	.34
Citation Breadth	2834063	8.2	11	1	3	5	9	317
Citation Dispersion	2834063	.75	.26	0	.7	.83	.92	1

Notes: This table reports summary statistics for the repeated cross-sectional patent sample used in analysis based on all patents filed between 2006 and 2023. Panel A reports statistics for patent applications, while Panel B reports statistics for granted patents. Variables are grouped into three categories: predetermined variables, variables measured before Alice, and variables measured after Alice. Predetermined variables, such as treatment intensity, are time-invariant by construction. All other time-varying variables are reported separately for the pre-Alice and post-Alice periods.

Table A5: Summary Statistics of Firm-Level Sample

	N	Mean	S.D.	Min	P.25	Median	P.75	Max
Predetermined Variables								
Firm Exposure	2750	3.8	31	6.2e-06	.01	.07	.52	1165
Std. Firm Exposure	2750	-9.8e-10	1	-.12	-.12	-.12	-.11	38
Recombination Capacity	2750	.54	.48	0	.15	.41	.85	2.4
Std. Recombination Capacity	2750	-1.8e-10	1	-1.1	-.82	-.28	.64	3.8
Pre-Alice period (post=0)								
Outcomes								
Total Num. of Apps	15882	58	340	0	0	2	13	11372
Num. of Apps in High-Exposure	15882	3.4	24	0	0	0	0	992
Num. of Apps in Low-Exposure	15882	31	186	0	0	1	7	7233
Technology Scope	15882	11	30	0	0	3	8	449
Existing Technology Reuse	15882	8.8	27	0	0	2	6	418
New Technology Entry	15882	2.5	5.2	0	0	0	3	80
log(Sales)	15496	6.1	2.8	-4.1	4.4	6.3	8.1	11
Sales/Employees	14828	430	631	3.8	192	288	457	11814
log(MVE)	15070	6.7	2.3	-1.6	5.1	6.7	8.4	11
Controls								
lagged Firm Size	15507	6.5	2.6	-4	4.6	6.3	8.3	12
lagged Tobin's Q	14616	2.8	9.9	.33	1.2	1.6	2.6	364
lagged ROA	15450	-.056	.82	-17	-.002	.096	.16	.5
lagged Leverage	15507	.23	.52	0	.002	.13	.3	10
lagged Cash	15505	.28	.26	0	.068	.19	.44	.99
lagged log(R&D)	15507	.12	.22	0	.0018	.039	.13	1.9
Post-Alice period (post=1)								
Outcomes								
Total Num. of Apps	17422	99	552	0	0	4	22	13990
Num. of Apps in High-Exposure	17422	5.5	32	0	0	0	1	1115
Num. of Apps in Low-Exposure	17422	50	301	0	0	2	10	6983
Technology Scope	17422	18	42	0	0	4	14	477
Existing Technology Reuse	17422	15	38	0	0	4	11	464
New Technology Entry	17422	2.5	4.6	0	0	0	3	58
log(Sales)	16570	6.4	3	-3.8	4.6	6.8	8.6	11
Sales/Employees	16120	507	908	3	207	317	525	16775
log(MVE)	16931	7.3	2.5	-1.1	5.4	7.4	9.2	12
Controls								
lagged Firm Size	17196	6.9	2.7	-3.8	4.9	6.9	8.9	13
lagged Tobin's Q	16494	3	7.4	.29	1.3	1.9	3.1	340
lagged ROA	17134	-.097	.8	-25	-.095	.078	.14	.47
lagged Leverage	17196	.27	.5	0	.033	.2	.37	16
lagged Cash	17196	.3	.28	0	.072	.19	.48	1
lagged log(R&D)	17196	.12	.23	0	.004	.043	.14	2

Notes: This table reports summary statistics for the firm-year panel between 2006 and 2023 used in the empirical analysis. Predetermined variables are constructed using firms' pre-Alice patent portfolios and are summarized at firm level. Time-varying variables are reported separately for the pre-Alice period and the post-Alice period and summarized at firm-year level.

Table A6: Cited-Citing Patent Pairs

Panel A: Comparison of Cited and Citing Patents				
	Num. of Classes Increase	Num. of New Classes	I(Different Primary Classes)	Exposure Reduction
Class Exposure × Post	0.449***	0.316***	0.128***	0.110***
	(13.91)	(12.20)	(8.52)	(53.84)
Cited Patent FE	Yes	Yes	Yes	Yes
Citation Lag FE	Yes	Yes	Yes	Yes
Clustering	Cited Patent	Cited Patent	Cited Patent	Cited Patent
Pseudo/Adj. R^2	0.4514	0.1929	0.1415	0.5748
Num. of Observations	21710221	21295412	20791074	21710221
Model	OLS	PPML	PPML	OLS
Panel B: Exposure Distribution of Backward Citations				
	(1)	(2)	(3)	(4)
	Mean	Median	Mean of Top 25%	Mean of Bottom 25%
Class Exposure × Post	-0.0413***	-0.0490***	-0.0314***	-0.0395***
	(-31.10)	(-24.06)	(-20.36)	(-34.72)
Cited Patent FE	Yes	Yes	Yes	Yes
Citation Lag FE	Yes	Yes	Yes	Yes
Clustering	Cited Patent	Cited Patent	Cited Patent	Cited Patent
Pseudo/Adj. R^2	0.8380	0.7669	0.8071	0.7454
Num. of Observations	21710221	21710221	21710221	21710221
Model	OLS	OLS	OLS	OLS

Notes: This table examines whether inventions citing pre-Alice patents modified their technological composition after the Alice decision. The sample includes cited-citing patent pairs where the cited patent was filed before Alice (since 2006) and the citing patent was filed between 2006 and 2023. The treatment intensity is defined as the Alice exposure of the cited patent's primary CPC subclass. Panel A compares the technological composition of citing patents before and after Alice, including changes in the number of technology classes relative to the cited patent, newly added technology classes in the citing patent relative to the cited patent, changes in the primary technology class, and reductions in patent-level exposure. Panel B examines the exposure distribution of backward citations included in the citing patents. Exposure measures for cited patents are constructed using the Alice exposure of their technology classes.

Table A7: Continuation Children Generated by Knowledge Recombination

	Continuation (rewrite claims)		Continuation-in-Part (add new matters)	
Panel A: Number of Continuation Children				
	(1) in 3 years	(2) in 5 years	(3) in 3 years	(4) in 5 years
Post	0.0288	0.0445**	-0.000256	-0.00741
	(1.47)	(2.45)	(-0.01)	(-0.18)
Class Exposure×Post	0.345	-0.464*	0.733**	0.588**
	(1.25)	(-1.86)	(2.49)	(2.06)
Pending Duration	-0.730***	-0.257***	-0.104***	-0.0605***
	(-21.76)	(-20.05)	(-5.60)	(-3.85)
Primary Class FE	Yes	Yes	Yes	Yes
Filing Year FE	Yes	Yes	Yes	Yes
Number of Obs.	1593744	1594940	1593012	1593793
Panel B: Expand Number of Technology Classes by Continuity				
	Continuation (rewrite claims)		Continuation-in-Part (add new matters)	
	(1) in 3 years	(2) in 5 years	(3) in 3 years	(4) in 5 years
Post	-0.658***	-0.820***	-0.161***	-0.220***
	(-4.22)	(-6.03)	(-3.30)	(-4.68)
Post × Class Exposure	0.00965	-1.218	1.075***	0.898**
	(0.01)	(-1.30)	(2.92)	(2.42)
Pending Duration	-0.154**	-0.0553	-0.0429***	-0.000319
	(-2.50)	(-1.15)	(-2.59)	(-0.02)
Primary Class FE	Yes	Yes	Yes	Yes
Filing Year FE	Yes	Yes	Yes	Yes
Number of Obs.	1289778	1385673	1582891	1585638

Notes: This table examines whether applicants modified existing inventions after Alice through continuation applications. The sample includes parent applications filed before Alice. The treatment intensity is defined as the Alice exposure of the parent application's primary CPC subclass. We exploit whether parent applications were still pending at the time of the Alice decision, as pending applications retained the ability to pursue continuation applications under the post-Alice examination environment. Panel A reports the number of continuation children filed within three- and five-year windows after the parent application. Panel B reports the expansion of technological scope in continuation applications, measured by the number of newly added CPC subclasses relative to the parent application. Applications without continuation children are assigned a value of zero for newly added technology classes.

Table A8: Firm-Level Patenting Responses by Combination Opportunities

	Number of Patent Applications		
	Total	High-Exposure Tech	Low-Exposure Tech
	(1)	(2)	(3)
Firm Exposure × Post	-0.0184**	-0.0239**	0.000414
	(-2.41)	(-2.24)	(0.05)
Recombination Potential × Post	0.0850	-0.00951	0.0431
	(0.83)	(-0.07)	(0.41)
Firm Exposure × Recombination Potential × Post	-0.0239	-0.0386	0.0166
	(-0.80)	(-0.97)	(0.41)
Firm Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
Clustering	Firm	Firm	Firm
Pseudo R^2	0.9636	0.8854	0.9569
Num. of Observations	29998	16234	26365

Notes: This table examines whether unconstrained recombination potential predicts heterogeneous firm-level patenting responses following the Alice decision. Columns (1), (2), and (3) examine the total number of patent applications, patent applications in high-exposure technologies, and patent applications in low-exposure technologies, respectively. Firm Exposure captures the extent to which a firm's pre-Alice patent portfolio was exposed to Alice-related eligibility risk. Recombination Potential measures the availability of technologically compatible knowledge components in the broader technology space, assuming that firms can access all potential recombination partners. The measure is constructed based on the knowledge network described in the paper. The sample consists of publicly listed U.S. firms observed annually from 2006 to 2023. All specifications include lagged firm-level controls (Firm Size, Tobin's Q, Leverage, Cash, and R&D Expenses), firm fixed effects, and industry-by-year fixed effects. All regressions are estimated by PPML. Standard errors are clustered at the firm level. t statistics are reported in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

B Construction of the Alice Exposure Measure

B.1 Simplifying the Patent Examination Process

Patent examination is a sequential interaction between an examiner and an applicant. After each round of examination, the examiner may either allow the application, which terminates the process, or issue rejections. The applicant may then respond to the rejection and continue prosecution, or abandon the application by failing to respond within the statutory period.

Figure B1a summarizes the duration and outcomes of the examination process. Most applications experience two rounds of examination, and a substantial share of allowances occurs in the second and third rounds.

In the main analysis, I simplify this sequential process to a one-shot screening based on the first office action. I use only first-round examination outcomes, rather than later rounds or combinations across rounds, for three reasons.

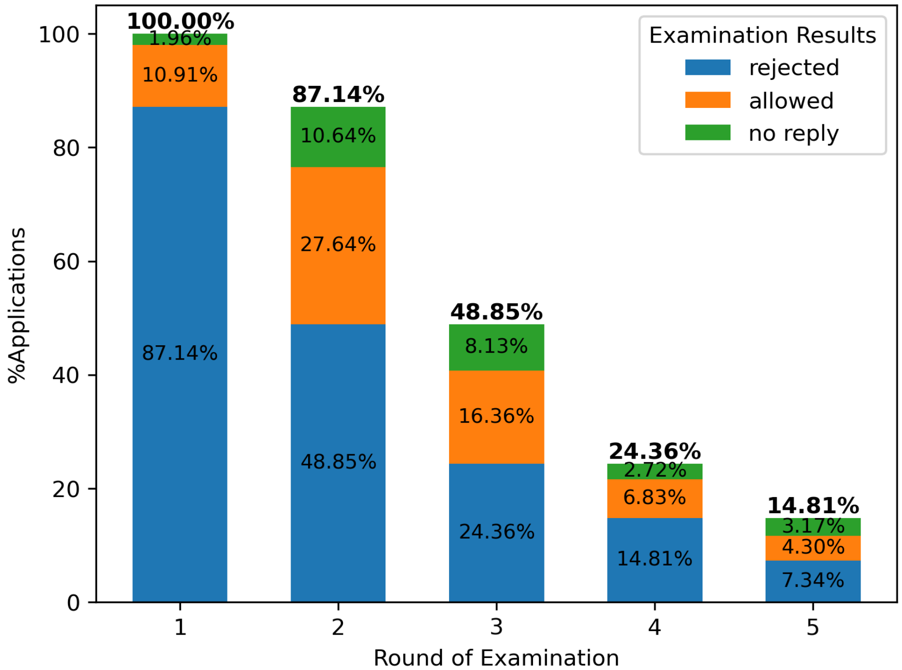
First, Figure B1b shows that examiners rarely introduce entirely new rejection grounds in later rounds. Second, rejection grounds appearing in later rounds are often responses to issues raised in earlier examinations. Third, incorporating later-round rejections would introduce selection bias, because subsequent examination rounds occur only for applications whose applicants choose to continue prosecution.

I therefore define an application as exposed to Alice if it receives a Section 101 rejection citing Alice in the first office action. Applications that first receive Alice-related rejections only in later rounds are classified as unexposed.

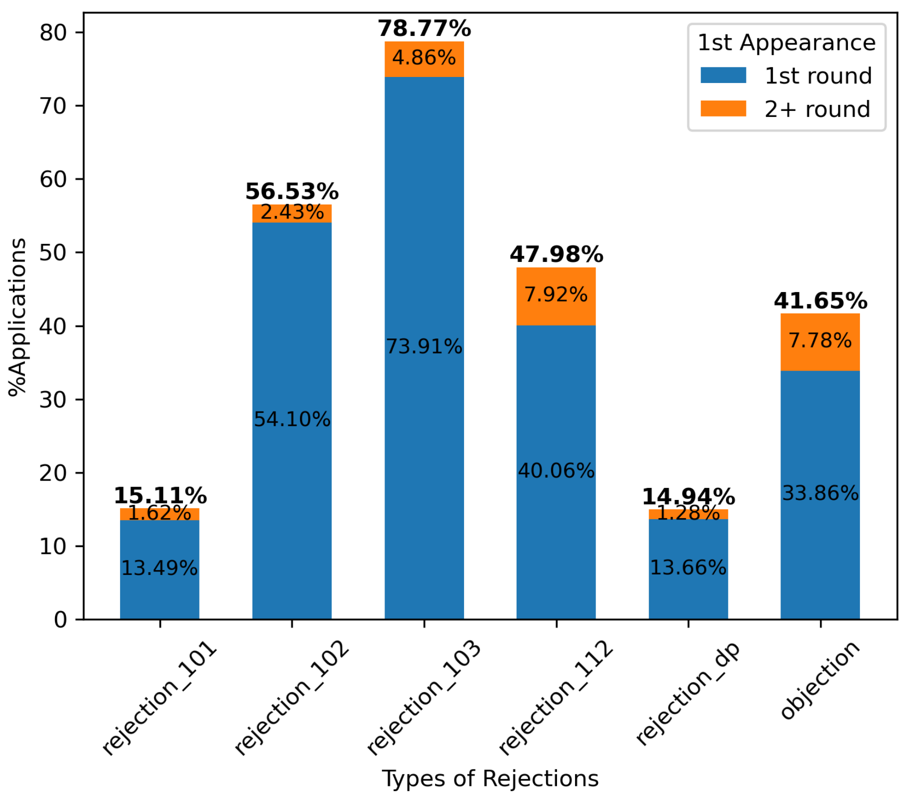
B.2 Measuring Exposure by OLS

We first construct a transparent benchmark measure using OLS. In the first step, we regress the Alice-rejection indicator on CPC subclass effects using the application's

Figure B1: Facts in Patent Examination



(a) Sequential Patent Examination and Examination Results



(b) Rejection Types and the Round of First Appearance primary subclass. The estimated subclass effects provide a benchmark measure of relative exposure across technology subclasses. The results shows that Alice-related rejection risk is highly concentrated in a small set of technology areas.

A complication arises because many applications are assigned more than one CPC subclass. In such cases, rejection risk may depend not only on the primary subclass but also on technological components captured by secondary subclasses. We therefore estimate the relative importance of primary and secondary subclasses when predicting Alice-related rejection. Specifically, for applications with multiple subclasses, we regress the rejection indicator on the exposure of the primary subclass and the average exposure of the secondary subclasses, separately by the number of assigned subclasses. The contribution of secondary subclasses increases with the number of subclasses assigned to the application, indicating that secondary technological components become increasingly informative when inventions combine technologies from multiple domains.

B.3 Measuring Exposure by GLMM

We then estimate a generalized linear mixed model (GLMM) that addresses several limitations of the benchmark approach. The model jointly estimates the probability that technologies are associated with Alice-related Section 101 rejections while accounting for the hierarchical structure of the CPC classification system and the heterogeneous contributions of primary and secondary technological components.

Data Structure. The estimation uses a sample consisting of patent applications filed before the Alice decision but first examined afterward. For each application i, we observe whether the first office action includes an Alice-related rejection under Section 101. Let $y_i \in \{0, 1\}$ denote an indicator equal to one if the application receives an Alice-related rejection.

Patent applications may contain multiple CPC subclasses. For each application i, I identify the primary subclass $s_p(i)$ and the set of secondary subclasses $S_s(i)$. Let $m_i = |S_s(i)|$ denote the number of secondary subclasses. Each subclass s belongs to a CPC class $c(s)$.

Model Specification. I estimate a Bernoulli GLMM with a logit link. The probability that application i receives an Alice-related rejection is given by

$$y_i \sim \text{Bernoulli}(p_i), \tag{1}$$

$$\text{logit}(p_i) = \beta_0 + w_p(m_i)\eta_p(i) + w_s(m_i)\eta_s(i), \tag{2}$$

where β_0 is a constant, and $\eta_p(i)$ and $\eta_s(i)$ represent the technological contributions of the primary and secondary subclasses, respectively.

The contribution of the primary subclass is

$$\eta_p(i) = r_{c(s_p(i))} + v_{s_p(i)}, \tag{3}$$

while the contribution of the secondary subclasses is defined as the average of their random effects,

$$\eta_s(i) = \frac{1}{m_i} \sum_{s \in S_s(i)} \left(r_{c(s)} + v_s \right), \tag{4}$$

which is set to zero when the application contains no secondary subclasses.

Primary and Secondary Weights. The relative importance of primary and secondary technological components depends on the number of secondary subclasses assigned to the application. Specifically, let

$$m_i^{cap} = \min(m_i, 6), \tag{5}$$

and define

$$k(m_i) = \gamma m_i^{cap}, \qquad \gamma = \exp(\kappa), \tag{6}$$

where κ is estimated from the data. The weights applied to primary and secondary components are

$$w_p(m_i) = \frac{1}{1 + k(m_i)}, \qquad w_s(m_i) = \frac{k(m_i)}{1 + k(m_i)}. \tag{7}$$

This structure guarantees that applications with a single subclass rely entirely on the primary technology ($w_p = 1$, $w_s = 0$), while the aggregate contribution of secondary technologies increases with the number of assigned subclasses.

Hierarchical Random Effects. The model accounts for the hierarchical structure of the CPC system by allowing random effects at both the CPC class and subclass levels:

$$r_c \sim \mathcal{N}(0, \tau^2_{\text{class}}), \tag{8}$$

$$v_s \sim \mathcal{N}(0, \tau^2_{\text{subclass}}). \tag{9}$$

The class-level random effects r_c capture broad technological differences across CPC classes, while the subclass effects v_s capture finer variation across subclasses within each class. This hierarchical specification allows for partial pooling across related technologies and stabilizes exposure estimates for sparsely observed subclasses.

Estimation Procedure. Conditional on the variance parameters $(\tau_{\text{class}}, \tau_{\text{subclass}})$, the fixed effects and random effects $(\beta_0, \kappa, r_c, v_s)$ are estimated using maximum likelihood with a Laplace approximation to integrate out the random effects. The variance parameters are selected by maximizing the profile likelihood over a grid of candidate values.

Construction of Exposure Measures. After estimation, technology exposure is defined as the model-implied probability that an application in a given technology receives an Alice-related rejection. For a CPC subclass s, class-level exposure is computed as

$$\text{Exposure}_s = \text{logit}^{-1}\left(\beta_0 + r_{c(s)} + v_s\right). \tag{10}$$

These subclass-level estimates capture the extent to which technologies are associated with Alice-related patent eligibility scrutiny during examination.

B.4 Economic Relevance of the Exposure Measure

To examine the economic relevance of the exposure measure, I construct patent-level exposure for each application by aggregating the exposure of its CPC subclasses using the weights described in Appendix B.3. I then exploit variation in examination timing around the Alice decision.

Specifically, I focus on applications filed before Alice, some of which were examined before the decision while others were examined afterward due to examination delays. Using examination year as the timing dimension, I compare the abandonment probability of these applications before and after the decision.

If the exposure measure captures technologies that were more closely associated with Alice-related eligibility scrutiny, applications with higher exposure should exhibit a larger increase in abandonment probability (1−grant rate) when they are examined after Alice. Figure B2 shows that applications with higher predicted exposure are more likely to be abandoned when examination occurs after the Alice decision.

Figure B2: Abandonment of Patent Applications by Examination Year