Knowledge Recombination and Innovation Resilience: Evidence from Patent Eligibility Tightening

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Abstract

How can innovators remain resilient to adverse shocks? We argue that innovators' opportunity sets shape their ability to adapt when shocks reduce the returns to existing knowledge. We examine this mechanism using the U.S. Supreme Court's 2014 *Alice* decision, which unexpectedly tightened patent eligibility standards for several technology areas and reduced the expected returns of relevant innovations. We show that innovators adapt to the shock by recombining knowledge across technology classes, and that technologies with greater recombination opportunities, which capture a larger set of feasible alternatives, exhibit stronger adaptive responses. At the firm level, we show that firms with greater recombination capacity are better able to sustain innovation in highly exposed technologies after *Alice*. Moreover, this resilience extends beyond maintaining innovation activity: firms with greater recombination capacity preserve broader technological scope and better mitigate the adverse economic consequences of the shock. Our findings highlight that innovation resilience depends on the availability of alternative technological opportunities, while firm boundaries shape the extent to which firms can access and exploit these opportunities.

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1 Introduction

Innovation is inherently dynamic: technological opportunities emerge, evolve, and become more or less attractive as economic conditions change. Because innovation builds on accumulated knowledge, changes in the environment can alter the expected returns to existing technological capabilities and reshape the paths through which innovators pursue future discoveries (Arrow, 1962; Romer, 1990). Such changes can generate persistent and heterogeneous effects on innovation: some innovators continue to generate valuable innovations, whereas others experience substantial declines in their innovative activities. Understanding why innovators differ in their ability to remain resilient when facing changes in the returns to existing knowledge is an important question in the economics of innovation.

To understand heterogeneity in innovation resilience, it is useful to distinguish between the innovation candidates available to an innovator and the innovations that are ultimately realized. Innovators choose among many potential innovation candidates, but only those with the highest expected returns are realized. When adverse shocks reduce the expected returns to previously preferred innovation candidates, innovators re-optimize over their opportunity sets rather than stop innovating altogether. Their ability to remain resilient therefore depends on whether sufficiently attractive alternative innovation candidates remain available after the shock.

A particularly important class of adverse shocks reduces the private returns to existing knowledge while leaving its technological value largely intact, such as weakening of IP protection, patent invalidation, and trade secret leakage. In such settings, innovators need not abandon affected knowledge altogether. Instead, they can preserve the value of affected knowledge by recombining it with less affected knowledge to create new innovation candidates with higher expected returns. Knowledge recombination therefore becomes a natural margin of adjustment, allowing innovators to

retain valuable knowledge accumulated through prior research while adapting to a new incentive environment. Consequently, the relevant opportunity set is manifested through recombination opportunities, which capture the feasible scope for generating valuable alternatives through such recombination.

Implementing this framework empirically requires a tractable representation of the choice space over which innovators optimize. We use technology classifications to organize the otherwise latent knowledge space, allowing each innovation candidate to be represented as a combination of knowledge components. This representation makes innovators' opportunity sets empirically observable and allows us to examine how they adjust the composition of innovation activities after an adverse shock. Identifying such re-optimization, however, requires both an exogenous shock that changes the relative returns to innovation candidates and a measure of the recombination opportunities available within the knowledge space.

We satisfy the first requirement by exploiting the U.S. Supreme Court's *Alice Corp. v. CLS Bank International* decision in 2014 (*Alice*, henceforth). *Alice* restricted the patent eligibility of abstract ideas and has been widely interpreted as disproportionately affecting technology classes encompassing business-method and software innovations (Chien and Wu, 2018). By reducing the private returns to innovations in these technology classes, *Alice* reshuffled the expected value rankings of innovation candidates and induced innovators to re-optimize over their existing opportunity sets.

The remaining challenge is to characterize the alternative innovation candidates available during this re-optimization process, particularly the recombination opportunities surrounding affected technologies. To this end, we construct a technology network in which two technology classes are more closely connected when they have been more frequently combined in prior innovations. We interpret this historical network as a representation of technological compatibility, where past recombination

patterns reveal feasible pathways for future knowledge recombination. The network therefore provides a map of the opportunity set surrounding each technology class: technologies with more connected neighbors offer greater potential for adaptation through knowledge recombination.

Under this setting, we first examine whether innovators respond to the Alice shock through knowledge recombination across technology classes. Using changes in the technological composition of patent applications, we find that innovators in more exposed primary technology classes combine additional technological components after Alice and reduce the overall Alice exposure of their resulting inventions. This pattern suggests that innovators adapt by recombining affected knowledge with less affected technological components rather than abandoning innovation in affected areas.

We next examine whether the availability of recombination opportunities shapes heterogeneous responses to Alice. We find that highly exposed technologies exhibit stronger increases in technological breadth and larger reductions in patent-level exposure when they are surrounded by more compatible technologies. This evidence highlights the role of the innovation opportunity set in determining resilience: when adverse shocks reduce the returns to existing innovation paths, innovators are better able to adapt when alternative technological combinations remain available.

While the previous results show that technologies with greater recombination opportunities exhibit stronger adaptation after Alice, these opportunities are not equally accessible to all firms. We therefore construct firm-level recombination capacity based on the overlap between firms' existing knowledge portfolios and the broader technology network. We find substantial heterogeneity in innovation resilience: firms with greater recombination capacity are better able to sustain patenting in highly exposed technologies after Alice. These firms mitigate the decline in innovation activity associated with greater Alice exposure by redeploying existing knowledge toward alternative technological combinations, highlighting the role of internal knowledge resources in

converting potential recombination opportunities into realized innovation responses.

We further examine whether such innovation resilience translates into broader economic consequences. Firms with greater recombination capacity not only sustain innovation activity after Alice but also mitigate the adverse effects of the shock on firm performance. Specifically, these firms experience weaker declines in operating performance and market valuation when exposed to Alice-related patent eligibility risk. Their ability to redeploy internal knowledge resources allows them to preserve the economic value of affected technologies while continuing to expand their technological scope. These findings suggest that the value of a firm's knowledge portfolio lies not only in the technologies it currently contains, but also in the alternative innovation paths it enables when external conditions change.

Taken together, these findings reveal a broader mechanism through which innovators adapt to adverse shocks. When external changes reduce the returns to existing innovation paths, innovators do not necessarily abandon valuable knowledge. Instead, they can redeploy existing knowledge toward alternative opportunities within their accessible opportunity sets. Innovation resilience therefore depends not only on the magnitude of the shock, but also on the flexibility of the knowledge structures available to innovators.

First, this paper contributes to the literature on knowledge recombination by showing that recombination is not only a source of technological novelty (Schumpeter, 1964; Henderson and Clark, 1990; Weitzman, 1998), but also a mechanism through which innovators adapt to adverse shocks. Prior research emphasizes how combining different or distant knowledge components can generate novel innovations (Fleming, 2001; Fleming and Sorenson, 2001; Uzzi et al., 2013). We extend this literature by showing that recombination also enables innovators to preserve and redeploy valuable knowledge when its original applications become less attractive. Specifically, we show that combining affected knowledge with less affected technological components

provides an adaptive response to changes in appropriability conditions.

Second, this paper contributes to the literature on firm-level determinants of innovation by identifying recombination capacity as an internal source of innovation resilience. Existing research has emphasized that firms differ in their ability to innovate because of differences in their capabilities to acquire and utilize external knowledge, such as absorptive capacity (Cohen et al., 1990; Woeppel and Yavuz, 2026), and in their ability to combine and organize knowledge within the firm (Kogut and Zander, 1992). We extend this literature by showing that firms also differ in their ability to redeploy accumulated knowledge when appropriation conditions change. Firm boundaries shape the set of recombination opportunities accessible within existing knowledge bases, generating heterogeneity in firms' ability to adapt to adverse shocks. Our findings identify the structure of accumulated knowledge as an innovation-specific source of resilience, complementing existing explanations based on innovation inputs and resources.

Third, this paper contributes to the literature on the implications of IP policy. Existing research has extensively studied how IP policies affect innovation incentives, investments, and firm outcomes (Galasso and Schankerman, 2018; Mezzanotti, 2021; Acikalin et al., 2026). We provide a complementary perspective by showing that changes in appropriability conditions can reshape the allocation of innovation efforts across technological opportunities. Rather than simply reducing innovation activity, an appropriation shock can induce innovators to reorganize existing knowledge through recombination. This perspective highlights that the consequences of IP policy depend not only on how policies affect the returns to innovation, but also on the alternative innovation paths available to innovators.

2 Institutional Background

On 19 June, 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 substantially narrowed the scope of patent protection available for computer-implemented inventions, particularly 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 firms' expected ability to appropriate returns through patent protection, the decision changed the incentives associated with developing and building upon this knowledge.

3 Conceptual Framework

3.1 Innovation Opportunity Set and Resilience

Innovation is a process of choosing among alternative opportunities. At any point in time, an innovator faces a set of potential innovation projects that differ in their expected returns, required investments, and technological feasibility. We refer to this collection of feasible alternatives as the innovation opportunity set, denoted by $\Omega = \{x_1, x_2, \ldots, x_n\}$. Each opportunity is associated with an expected private return $f(x)$, which reflects both the technological value of the innovation and the ability of

the innovator to appropriate the generated value.

An innovator selects opportunities based on their expected returns. An adverse shock affects innovation only when it reduces the return of the opportunities that the innovator would otherwise pursue. Importantly, the consequence of such a shock depends not only on the magnitude of the loss associated with the affected opportunity, but also on the availability of alternative opportunities within the opportunity set. When attractive alternatives remain available, innovators can redirect innovation efforts toward other projects rather than abandoning innovation activities altogether.

In this sense, innovation resilience depends on the ability to substitute across innovation opportunities after a shock. When an initially preferred project becomes less attractive, an innovator with sufficiently valuable alternatives can shift efforts toward these opportunities. In contrast, when attractive alternatives are limited, the same shock is more likely to cause a substantial decline in innovation activity.

3.2 Appropriation Shocks and Knowledge Redeployment through Recombination

While innovation opportunities can be disrupted by different types of shocks, appropriation shocks provide a particularly relevant setting to study how innovators adapt to adverse changes. Unlike shocks that directly eliminate the technological feasibility of an innovation, appropriation shocks reduce the expected return from an innovation while leaving the underlying knowledge intact. Therefore, affected knowledge may lose its value as an individual innovation project but can remain valuable as an input for subsequent innovation activities.

This distinction creates an opportunity for knowledge redeployment through recombination, as innovation often emerges through the recombination of existing knowledge components (Weitzman, 1998; Fleming, 2001). When the return from an existing

application declines, innovators do not necessarily abandon the associated knowledge. Instead, they can search for alternative ways to deploy it by combining the affected knowledge with other knowledge components. In this sense, an appropriation shock changes the relative attractiveness of innovation opportunities and induces a local reallocation of innovation efforts within the existing knowledge base. For example, an innovator with a knowledge component A may shift from its original application toward new combinations such as AB or AC when the return from the original application declines.

Such alternative combinations need not have been preferred before the shock. Although recombining knowledge across domains can generate valuable innovations (Uzzi et al., 2013), these combinations often require additional search and integration costs. Before the shock, these costs may make the original application of A the most attractive opportunity. An appropriation shock changes this trade-off by reducing the attractiveness of the original application and making previously less attractive combinations viable alternatives.

3.3 Accessibility of Innovation Opportunities

The availability of alternative applications of affected knowledge depends on the structure of the innovation opportunity set and the extent to which such opportunities are accessible to innovators. We distinguish between the economy-wide opportunity set shaped by technological compatibility and the firm-specific opportunity set constrained by organizational boundaries.

3.3.1 Technological Compatibility and the Structure of Opportunity Sets

At the economy-wide level, the opportunity set associated with a knowledge component is determined by the structure of the underlying knowledge space. Consider a

knowledge component A. Although knowledge can potentially be combined in many different ways, only a subset of these combinations are technologically feasible and economically meaningful. We denote this set of potential recombination opportunities as $\Omega(A)$.

The structure of $\Omega(A)$ is shaped by technological compatibility. Prior research shows that technological search is structured rather than random, as knowledge components differ in their positions within the technological landscape (Fleming and Sorenson, 2001). Therefore, different knowledge components provide different numbers of potential recombination opportunities after an adverse shock.

3.3.2 Firm Boundaries and Accessible Opportunity Sets

While technological compatibility determines the potential opportunity set in the broader knowledge space, firms can access only a subset of these opportunities. We denote firm i's knowledge base as K_i. The set of recombination opportunities accessible to firm i is therefore:

$$\Omega_i(A) = \Omega(A) \cap K_i$$

where opportunities must be both technologically compatible with A and accessible within the firm's existing knowledge base.

Firm boundaries restrict accessible opportunities through two main channels. First, Knowledge is not perfectly transferable across organizational boundaries because firms differ in their accumulated knowledge, routines, and capabilities for combining knowledge (Kogut and Zander, 1992). Although patents disclose codified information, firms possess substantial tacit knowledge, technical know-how, and organizational routines that are difficult to transmit. Moreover, knowledge recombination often relies on interactions among researchers, whose mobility and collaboration across

firms are naturally constrained.

Second, firms are not solely organizations for producing innovations; they pursue profits through existing business activities. Even when a firm can technically identify a valuable knowledge combination, exploiting it may require substantial changes in production processes, commercialization capabilities, and market relationships. As a result, firms do not pursue every technologically feasible recombination opportunity, but rather a subset consistent with their existing knowledge base and business activities.

Therefore, the ability of firms to respond to appropriation shocks through recombination depends not only on the opportunities embedded in the broader knowledge space, but also on the extent to which these opportunities are accessible within the firm's organizational boundaries.

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 opportunities, 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 frame-

work. 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

The ability of innovators to respond to an appropriation shock depends on whether affected knowledge can be recombined with other compatible technologies. To measure such recombination opportunities, we rely on the idea that past technological combinations reveal the feasibility of future combinations. Specifically, technologies that

have been successfully combined in previous inventions are more likely to provide viable recombination opportunities when innovators search for alternative technological paths.

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 is connected to a broader set of feasible technological combinations. 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). However, our interpretation differs from the traditional network interpretation of centrality. Rather than measuring technological importance, influence, or prominence within the network, we interpret weighted degree as an economic measure of the size of a technology's accessible recombination opportunity set.

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.

The ability of firms to respond to an appropriation shock depends on whether they have access to alternative technologies within their own knowledge base. We therefore construct firm-level recombination capacity by restricting the potential recombination partners to the firm's existing portfolio rather than the entire technology space.

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 technol-

ogy classes. This measure captures the extent to which a firm's existing knowledge base provides alternative technological pathways for recombination when facing an innovation constraint.

We thus summarize 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 an alternative definition to assess the robustness of our findings.

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 innovators adapted to the stricter patent eligibility environment. 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 potential mechanism 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 patenting strategies 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 associated with greater resilience to Alice-related eligibility challenges even before innovators fully adapted to the post-Alice environment, motivating our analysis of knowledge recombination as an adaptive 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 definition allows us to distinguish knowledge recombination from a simple shift toward less exposed technological areas. When facing an appropriation shock, innovators may either redirect innovation toward less affected technologies or preserve their existing technological domain while combining it with additional technological components. The latter strategy allows innovators to largely retain the value embedded in existing knowledge while reducing vulnerability to the stricter eligibility standard with potentially lower adjustment costs. Our empirical design captures this recombination margin by examining whether patents associated with more exposed primary classes combine more technology classes and achieve greater reductions in patent-level exposure after Alice.

Table 4 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 expanded the technological breadth of patents

after Alice, particularly 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 technological breadth is accompanied by a reduction in patent-level exposure, consistent with innovators combining exposed technologies with less exposed components to reduce the overall Alice exposure of resulting inventions.

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 technological breadth 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 indicate that innovators responded to the Alice decision by recombining existing technological domains with less exposed knowledge components, providing evidence that knowledge recombination served as an important adaptation mechanism following the tightening of patent eligibility standards.

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 how likely a focal technology is to be combined with other technologies. 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 highly exposed technologies exhibit stronger increases in technological breadth when more compatible technologies are available. A similar pattern appears for exposure reduction in Columns (3) and (4), suggesting that recombination opportunities also facilitate the reduction of patent-level Alice exposure.

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 highlight the role of recombination opportunities in shaping innovation resilience. Although Alice increased incentives to modify technological

compositions in highly exposed areas, innovators were better able to adapt when compatible technological alternatives were available.

5.4 Changes of Inputs in Innovation Production

Technological classes capture only the final output of the innovation process. To provide complementary evidence that the adjustment occurred during the innovation process itself, we examine whether innovators changed two key inputs of innovation production: human capital, represented by inventor teams, and knowledge input, 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. Together, these patterns suggest that the response to Alice was not limited to changes in the final technological composition of inventions, but also involved adjustments in the human and knowledge inputs underlying innovation production.

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 ap-

plicant strategies in addition to technological knowledge flows (Kuhn et al., 2020). Therefore, these outcomes complement the technology-class evidence by showing that changes consistent with knowledge recombination also occurred 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, it has two limitations. First, applicants may anticipate classification rules and strategically shape patent descriptions in ways that affect observed technology assignments. Second, this definition captures changes in the technological composition of inventions but does not directly establish whether post-Alice inventions redeploy and recombine knowledge from pre-Alice inventions.

To address these limitations, we consider an alternative definition in which each invention represents a knowledge component. Under this definition, innovation proceeds through the recombination of previously developed inventions, and an appropriation shock may affect the composition of inventions selected for recombination. We examine this mechanism using citation and continuation relationships, which allow us to trace connections between inventions over time.

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 innovators adjusted both the focal knowledge component and the broader set of knowledge inputs used in subsequent inventions.

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 provide a closer measure of whether innovators redeploy and modify existing knowledge rather than simply develop unrelated inventions. 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.

Together, these results complement the technology-class evidence by showing that post-Alice adaptation was not merely a change in observable technological classifications. Instead, innovators modified the selection and recombination of previously developed knowledge after the appropriation shock, consistent with knowledge recombination as a mechanism through which innovators adapt to changes in appropriability.

6 Firms' Innovation Resilience

In this section, we move from the technology-level perspective to the firm-level perspective and examine how firms' ability to access recombination opportunities shapes innovation resilience. While the previous analysis shows that technological compatibility determines the availability of potential recombination opportunities, firms can access only a subset of these opportunities based on their existing knowledge bases and organizational boundaries. We thus examine how heterogeneity in recombination capacity shapes firms' innovation responses and how recombination capacity 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 firms' ability to access combinative technological components within their existing knowledge bases.

Table 5 examines firms' patenting responses by firm exposure and recombination capacity. The heterogeneous effect of recombination capacity is strongest for patenting in high-exposure technologies and is not significant for low-exposure technologies. 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.

Firm boundaries are essential for identifying heterogeneous adaptation because an alternative measure of recombination potential that ignores firm boundaries fails to distinguish differences in firms' innovation responses. We construct recombination potential by assuming that firms can access all technologically compatible knowledge components in the broader technology space and repeat the regressions in Table A8. This unconstrained measure does not significantly predict heterogeneous innovation responses after Alice, highlighting that the relevant source of innovation resilience is not simply the existence of technological opportunities, but firms' ability to access and integrate these opportunities within their own knowledge bases.

6.2 Technological Scope Adjustment: Exploitative and Exploratory Search

If recombination enables firms to redeploy affected knowledge toward alternative applications, firms with greater recombination capacity should be able to sustain innovation across a broader set of technological areas after the shock. Moreover, if recombination relies on firms' existing knowledge bases, the adjustment should be concentrated among technology classes that firms have previously developed rather than requiring 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 are more likely to reuse previously developed technological domains. In contrast, firms with limited

recombination capacity experience a larger contraction in technological scope, consistent with their reduced ability to redeploy affected knowledge toward alternative technological applications.

Interestingly, greater recombination capacity is also associated with more frequent entry into new technological domains, although the effect is weaker than that for existing technology reuse. This pattern suggests that exploration is not the primary mechanism through which firms overcome the Alice shock. Rather, firms with stronger recombination capabilities are better positioned to maintain innovation resilience and subsequently expand into new technological areas. One possible explanation is that firms with richer and more compatible knowledge bases possess broader capabilities for knowledge integration and learning, allowing them not only to recombine existing knowledge but also to absorb and incorporate new technological components.

This distinction is related to the broader literature on exploration and exploitation, which emphasizes that innovation requires firms to balance the refinement of existing knowledge with the search for new technological opportunities (March, 1991). In the context of technological search, recombinant capabilities shape firms' ability to explore and combine knowledge components with different degrees of familiarity (Fleming, 2001). Our results suggest that recombination capacity supports both the reuse of existing technological domains and the expansion into new technological areas.

6.3 Economic Consequences of Innovation Resilience

If recombination capacity enables firms to preserve innovation activities after an appropriation shock, such innovation resilience may also generate economic value. We therefore examine whether firms with greater recombination capacity experience better economic outcomes following the Alice decision.

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 treatment 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 are better able to preserve economic performance after the appropriation shock.

These results suggest that innovation resilience can generate competitive advantages in product markets. By sustaining patenting activities and continuing to develop affected technologies, firms with greater recombination capacity are better able to maintain their technological positions when firms operating in exposed technologies face greater challenges in obtaining patent protection. These advantages are reflected in stronger operating performance and higher market valuations. Therefore, recombination capacity allows firms not only to adapt their innovation strategies after an appropriation shock but also to preserve the economic value associated with their innovation activities.

7 Discussion and Further Study

7.1 One Perspective on a New Innovation Landscape

The Alice decision represents more than a change in the patent eligibility standard for a specific set of inventions. By altering which types of inventions could obtain

effective patent protection, the appropriation shock changed the expected returns associated with developing and commercializing knowledge in affected technology areas, generating broad consequences for innovation activities, firm performance, and market structures.

Existing studies have examined multiple margins of the implications generated by appropriation shocks. One strand of literature focuses on how weaker intellectual property protection affects market competition and entry (Feng and Williams, 2026; Guler et al., 2026). In our setting, such outcomes may arise when affected knowledge cannot be effectively redeployed through recombination, leaving opportunities for other firms to enter and build upon previously protected knowledge. Our analysis is closely related to studies examining heterogeneity in firms' responses to such shocks. While existing literature mainly emphasizes heterogeneity associated with firm size (Galasso and Schankerman, 2018; Acikalin et al., 2026), we further uncover a specific innovation-related mechanism underlying resilience: firms' recombination capacity. By enabling firms to combine affected knowledge with alternative technological components, recombination capacity helps sustain innovation pipelines after an appropriation shock. Other internal capabilities and resources, such as business diversification, cash holdings, and financing capacity, may also contribute to firms' performance resilience, although they may not directly explain firms' ability to sustain innovation in affected technologies.

More broadly, innovation resilience represents only one margin through which knowledge recombination may shape the innovation landscape under adverse shocks. A weaker intellectual property protection regime may reduce the effective scope of existing IP rights: while IP owners may attempt to preserve the value of their released knowledge through follow-on innovation, the same change may create new opportunities for other innovators to build upon previously protected knowledge (Galasso and Schankerman, 2015; Sampat and Williams, 2019). Our study focuses on the former

mechanism by examining how existing innovators remain active in affected technologies. An important complementary question is which firms are better positioned to enter and exploit newly available technological opportunities, which may depend on their ability to absorb and integrate external knowledge in affected areas (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 trading. 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 Beyond Innovation Resilience

More broadly, our conceptual framework of innovation choice over an opportunity set is not limited to understanding how innovators adapt to appropriation shocks. Instead, it provides a general framework for analyzing how firms respond to exogenous changes in the expected returns of alternative innovation opportunities. When the relative returns of innovation opportunities change, firms may reallocate innovation efforts toward alternative opportunities within their accessible opportunity sets, with the extent of adjustment depending on the availability and accessibility of such alternatives.

One example is the emergence of artificial intelligence, which may fundamentally

alter the structure of innovation opportunities by reducing search and integration costs across technological domains (Cockburn et al., 2019). Unlike appropriation shocks that reduce the returns of existing opportunities, AI may expand firms' effective opportunity sets by lowering the costs of identifying and combining previously distant knowledge components. An important question is therefore whether AI disproportionately benefits firms with greater recombination capacity or instead reduces the importance of existing technological boundaries.

8 Conclusion

This paper studies how innovators respond to shocks that reduce the private returns to existing knowledge. We develop a framework in which innovation resilience depends on the availability of alternative opportunities within an innovator's opportunity set. When an appropriation shock reduces the value of existing innovation paths, innovators can adapt by recombining affected knowledge with less affected technologies rather than abandoning innovation activities.

We examine this mechanism using the 2014 Alice decision, which tightened patent eligibility standards for a broad range of technologies. Exploiting variation in Alice exposure across technology classes and measuring recombination opportunities from historical technological combinations, we show that innovators responded to the shock by increasing knowledge recombination. Applications in more exposed technologies combined broader technological components and reduced their exposure to Alice-related eligibility risks, suggesting adaptation through changes in the structure of innovation rather than withdrawal from affected areas.

We further show that firms' ability to adapt depends on their internal knowledge resources. Firms with greater access to recombination opportunities were better able to sustain innovation in highly exposed technologies after Alice. Their subsequent

innovations expanded into new technological areas, highlighting that the value of a firm's knowledge portfolio lies not only in the knowledge it contains, but also in the alternative innovation paths it enables.

These findings contribute to the literature on innovation and technological change by showing that internal resources shape firms' resilience to external shocks. Firms differ in their ability to adapt because their accumulated knowledge determines the set of feasible innovation paths available when existing opportunities become less attractive. More broadly, innovation resilience depends not only on creating new knowledge, but also on firms' capacity to redeploy internal resources and reorganize existing knowledge in response to changing environments.

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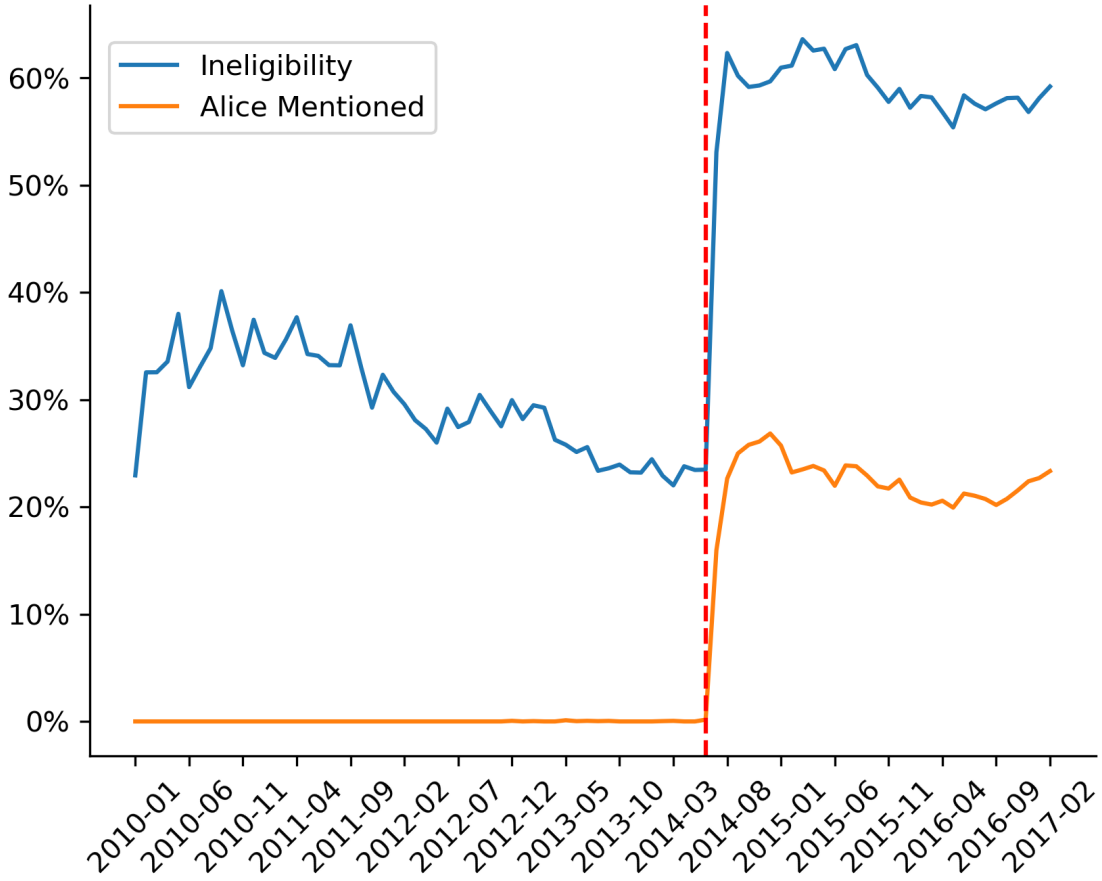
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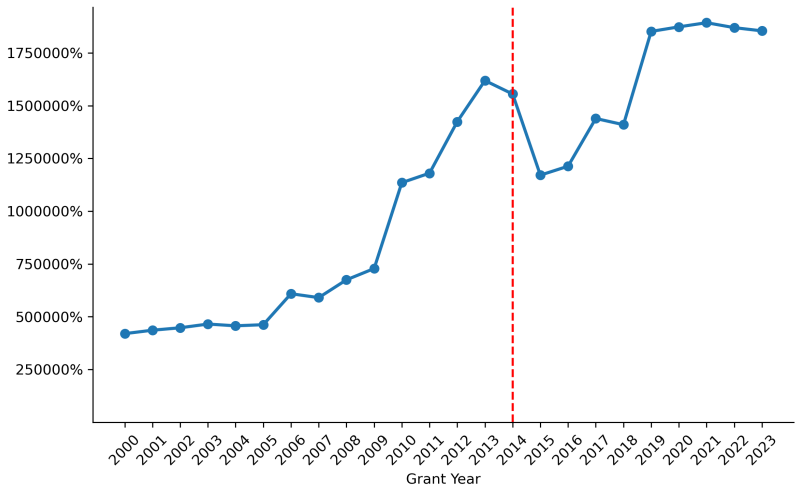
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Figure 1: The Immediate Increase in Patent Examination Rejections (High-Exposure Technologies)

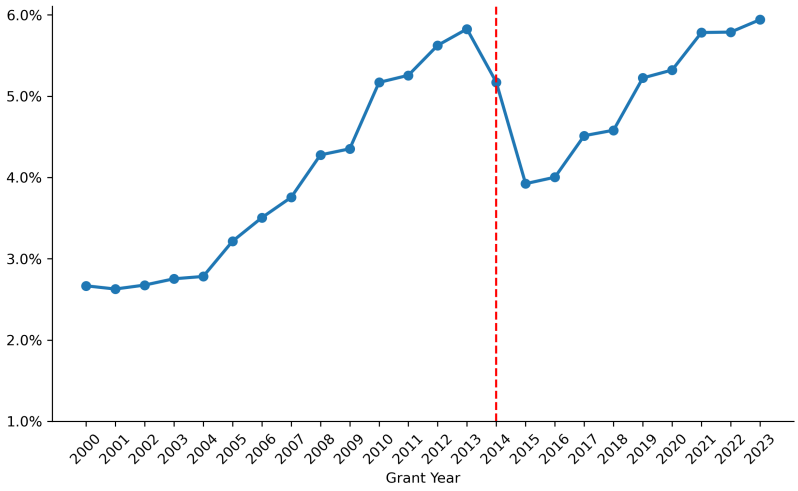


Notes: This figure reports the monthly share of recorded patent examination rejections within high-exposure technologies that fall into two categories. High-exposure technologies are defined as CPC technology subclasses with Alice exposure of at least 5%. The blue line represents the fraction of all 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



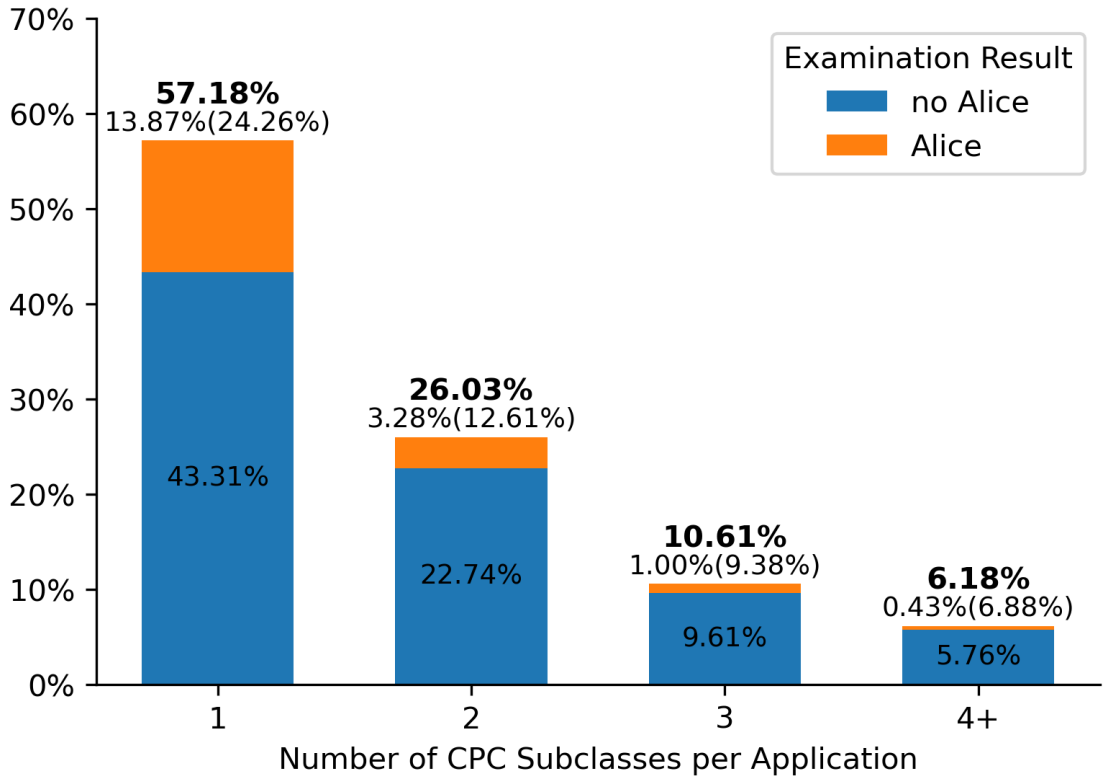
(a) Number of Patent Grants in High-Exposure Technologies



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

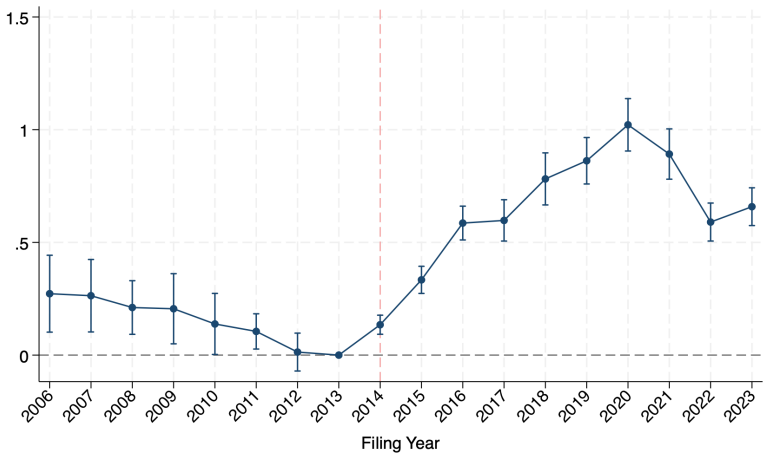
Notes: This figure illustrates patent grants in high-exposure technologies over time. High-exposure technologies are defined as CPC subclasses whose estimated class exposure to Alice-related rejection risk is greater than or equal to 0.05. Class exposure is constructed using the GLMM-based exposure measure 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-Class Recombination and Patent Exposure

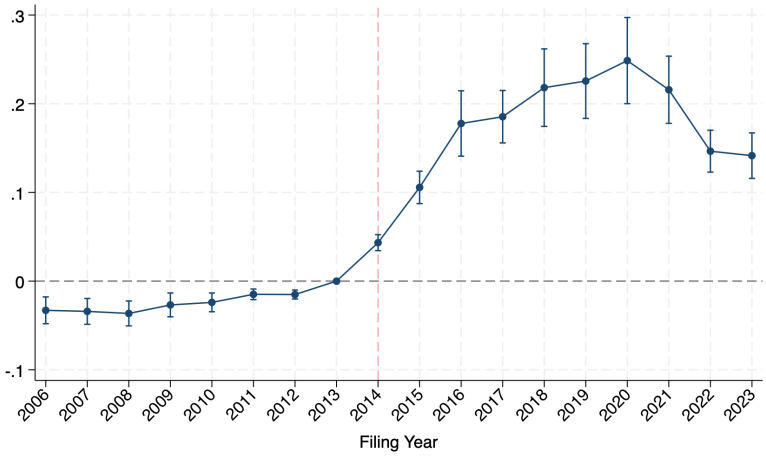


Notes: This figure shows the relationship between technological combinations and Alice-related rejection risk. The sample consists of patent applications whose primary CPC subclass belongs to the high-exposure category. Applications are grouped according to the number of CPC subclasses assigned to the 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



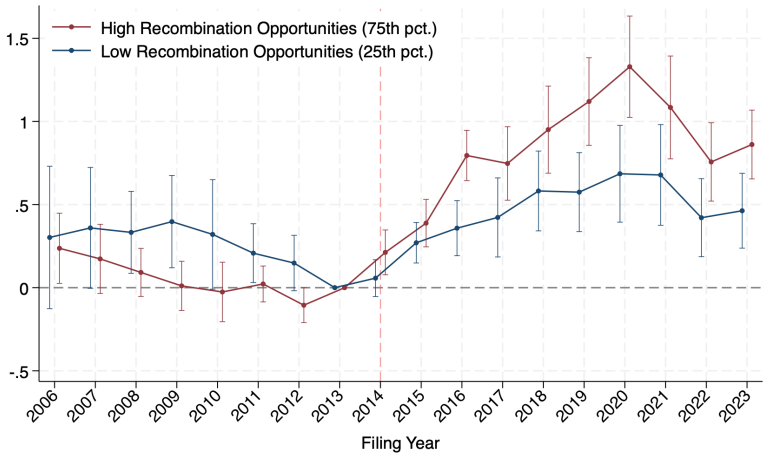
(a) Treatment Effect on Knowledge Recombination



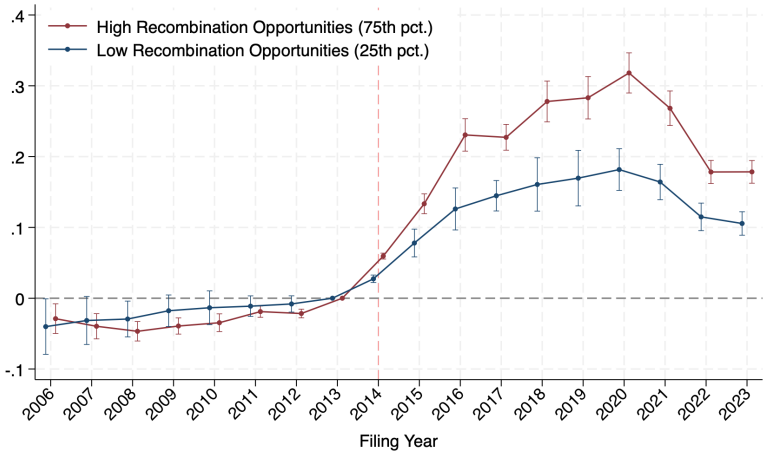
(b) Treatment Effect on Exposure Reduction

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



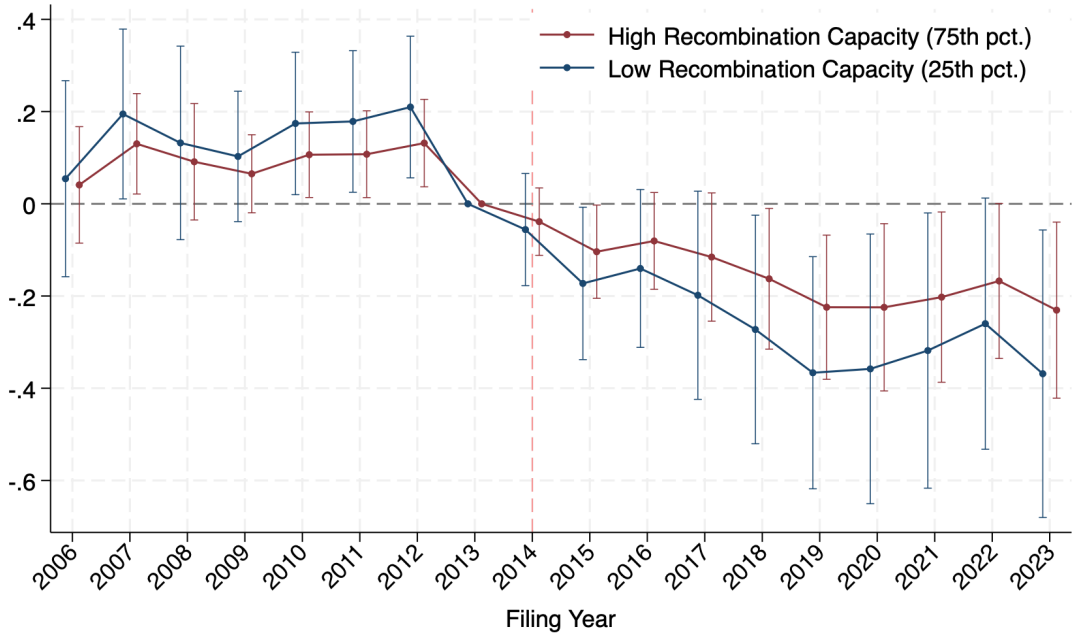
(a) Treatment Effect on Knowledge Recombination



(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 Capacity × Post		-0.000840		-0.00602***		0.000327
		(-0.07)		(-2.90)		(0.26)
Class Exposure × Recombination Capacity × 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. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

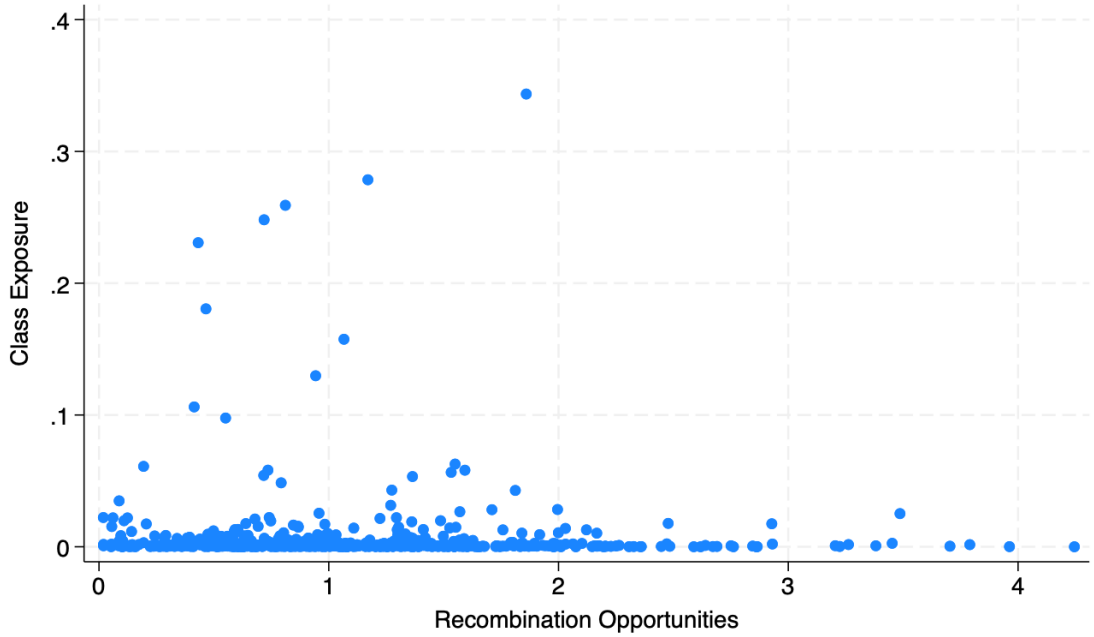
Table 7: Firm-Level Consequences of Innovation Resilience

	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 the firm-level consequences of innovation resilience following the Alice decision. 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. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

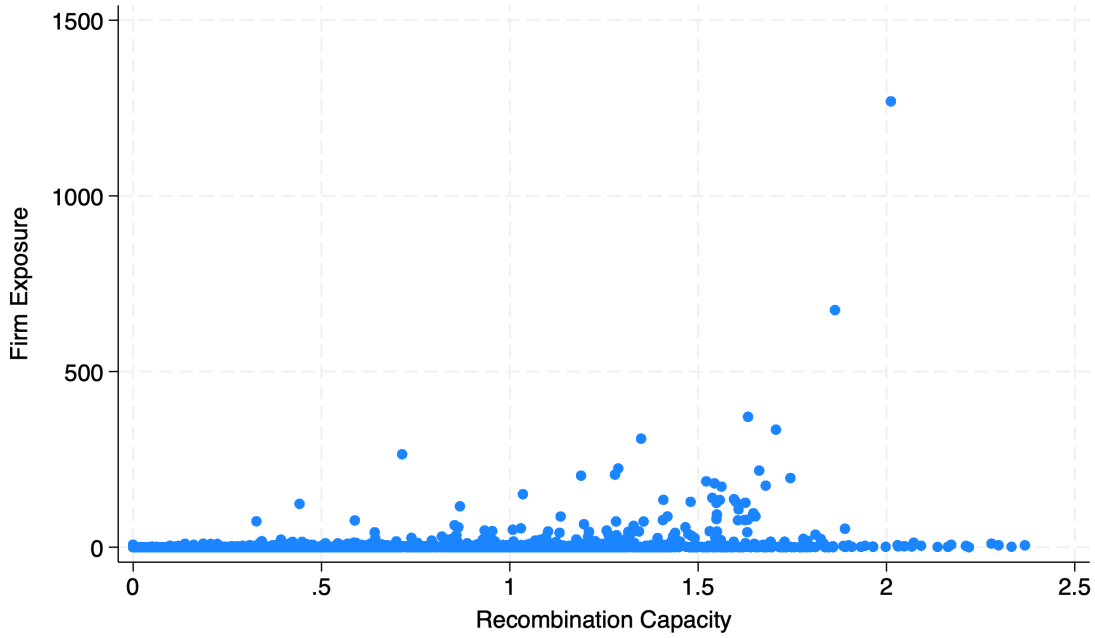
A Additional Figures and Tables

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

Panel A: Published Applications								
	N	Mean	S.D.	Min	P.25	Median	P.75	Max
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

Panel A: Number of Continuation Children				
	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	0.0288	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) 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 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.

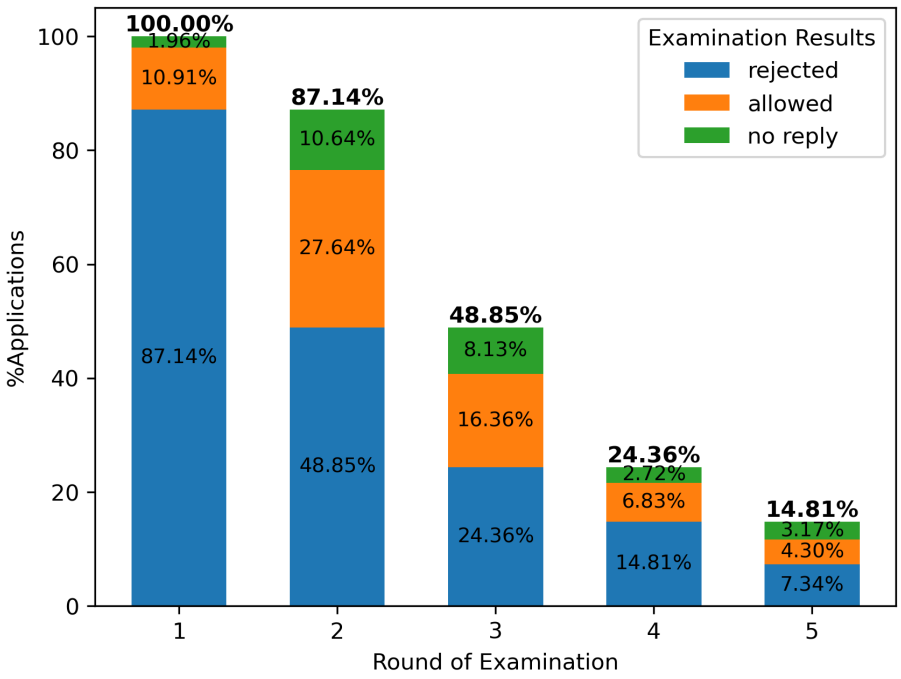
First, Figure B1b shows that examiners rarely introduce entirely new rejection grounds in later rounds. Second, rejection grounds appearing in later rounds are often responses to issues raised in earlier examinations. Third, incorporating later-round rejections would introduce selection bias, because 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.

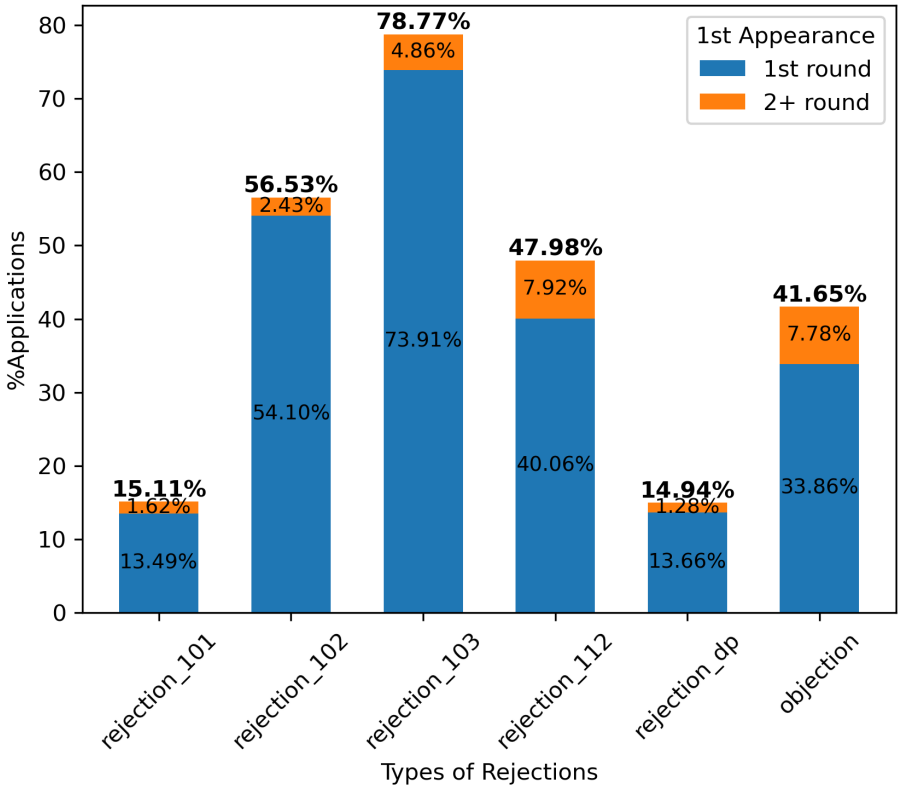
B.2 Measuring Exposure by OLS

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

