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Price-Fixing Cartels and Firm Innovation*

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Abstract. This paper examines the relationship between price-fixing cartels and firm innovation using a dataset encompassing all 461 cartel cases and 1,818 firms identified in the United States in the years 1975–2016. A difference-in-differences estimation reveals a positive relationship between collusion and innovation. Colluding firms exhibited increases of 28% in patent filings, 20% in top-quality patents, and 16% in R&D investment. Innovation breadth also expanded by 16%, suggesting that firms explored new technological areas. Once cartels were dissolved, innovation activities reverted to pre-collusion levels. The effect varied across industries and was more pronounced in fast-growing and patent-intensive industries, underscoring the importance of technological opportunities. Further, the umbrella pricing effect that also benefits non-colluding competitors offers a unique opportunity to unpack mechanisms. Results reveal that the extra financial resources account for at least a quarter of the effect, with stronger cartels exhibiting more pronounced effects. Specifically, firms that relied more on internal financing before collusion and that generated higher revenues during collusion showed a greater effect; no evidence was found of capital reallocation within firms. As much as the remaining three-quarters of the effect can be attributed to managerial expectations of future profitability. These findings offer insights for managers and policymakers aiming to foster novel innovation, although careful interpretation is required given the heterogeneous effects.

Keywords. antitrust; collusion; competition; technological innovation; R&D investment

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1 Introduction

Innovation is considered an engine of economic growth and welfare (Schumpeter, 1934). Research and development (R&D) and innovation processes, however, require risky and uncertain investment. Reaping the returns on R&D investment can take a firm several years, if not decades. Further, the private return on firms' R&D investment is lower than its social return (Griliches, 1992; Bloom, Schankerman, and Van Reenen, 2013; Arora, Belenzon, and Sheer, 2021) because firms may not fully internalize the broader impact of their innovation under the presence of technology spillovers (or positive externalities). These two features of innovation result in underinvestment in R&D and in underprovision of novel innovation outputs. To promote firms' innovation activities, it is essential for managers and policymakers to understand firms' incentives and their ability to innovate.

An important and related research stream that has developed separately focuses on price-fixing cartels. In cartels, a group of competing firms in the same market colludes to suppress price competition and artificially inflate prices. Extensive studies (e.g., Connor and Lande, 2006) have explored the immediate price effects of cartels, but far fewer explore cartels' consequences for innovation activities. The influence of price-fixing cartels can extend far beyond inflating market prices to include altering firms' incentives and their ability to innovate. Therefore, investigating the relationship between cartels and firm innovation is crucial and provides valuable insights for managers and policymakers aiming to foster novel innovation.

More broadly, a study of cartels is closely related to the study of healthy market competition. The role of competition in fostering innovation has long been debated in the literature. One perspective argues that competition promotes firms' innovation activities (e.g., Arrow, 1962). Conversely, drawing from Schumpeter's (1942) insights, another body of work suggests that a certain degree of market power—more than would be achieved in a competitive market—can foster innovation by providing firms with the necessary financial resources and the predictability of gains from innovative activities. This "competition-innovation debate" acknowledges a strong relationship between competition and innovation, yet there is no consensus on whether the relationship is positive or negative or on what drives it. Given this theoretical ambiguity, it is important to study these arguments empirically to determine which dominates under specific conditions and which mechanisms are involved.

This paper examines how price-fixing cartels are associated with firms' innovation activities. A notable advantage of studying cartels is that they offer two valuable sources of variation in price competition. The *formation* of a cartel suppresses market competition and raises prices. Conversely, the *breakup* of a cartel terminates such collusion and thereby restores price competition in the market. Furthermore, the primary objective of cartels is to inflate market prices, which also benefits competitors not involved in the collusion. This so-called *umbrella pricing effect* of cartels offers a unique and valuable opportunity to unpack underlying mechanisms—those that work through market prices and those that do not.

I have collected and digitized data on all known nonfinancial cartel cases discovered in the United States from 1975 through 2016. The resulting data consists of 461 cases, along with 1,818 firms and 1,623 managers. These firms are then linked to firm-level data on innovation. Using a difference-in-differences methodology and comparing colluding firms with carefully defined non-colluding firms in an adjacent market, I find a positive relationship between price-fixing cartels and firm innovation. During collusion, firms increased their patent filings by 28.3% and increased top-quality patents by 20%. To fuel these innovation activities, public firms increased R&D investment by 16.4% in parallel. Furthermore, how firms explore new technological areas as market competition changes is an important question that has received relatively little attention. Innovation often involves recombining existing technologies, making it crucial for firms to explore and diversify their technological ingredients. I find that colluding firms expanded the number of unique technology classes in which they patented by 15.8%. When cartels broke up, the intensity and breadth of innovation reverted to their previous pre-collusion levels.

As the degree of heterogeneity is substantial, I further explore *where* and *why* the average effect arose. The effects are prominent when industries present technological opportunities, characterized by industry growth rate and patenting intensity. In industries that lack such opportunities, firms have little incentive or ability to innovate. Further, the primary driver of the effect seems to be the expectations of managers regarding the future appropriability of their innovations and the firms' profitability, which explains as much as three-quarters of the effect. The influx of financial capital via inflated prices also helps fuel innovation. Specifically, the role of financial resources was most significant among firms that relied less on external financing prior to collusion and achieved higher revenues during the collusion period. These financial resources work *within* the collusive market rather than being redirected from colluding businesses to other businesses within a firm. Although these explanations seem to best fit the patterns in the data, the findings require careful interpretations, as I have not been able to rule out all possibilities.

This study delivers novel insights into the relationship between price-fixing cartels that suppress price competition and the intensity and breadth of firm innovation. Further analyses of the heterogeneity and underlying mechanisms offer important perspectives as to the conditions under which the observed patterns are likely to arise and to their underlying mechanisms. The construction and examination of a unique dataset, derived from all collusion cases discovered in the United States, opens new avenues for future research. While price fixing via collusion is one particular way to suppress price competition, and while involvement in collusion is selective, the findings offer valuable implications regarding the incentives of private firms and their ability to innovate in response to market conditions and competitiveness.

2 Cartels, Competition, and Innovation

2.1 Price-fixing Cartels and the Intensity and the Breadth of Firm Innovation

Collusion, also referred to as a price-fixing cartel, involves agreement among competitors to suppress competition within the market. Colluding firms manipulate prices above the competitive level and often divide the market among themselves. Consequently, the formation of a cartel significantly stifles price competition, while its dissolution subsequently restores competitive dynamics to the market.

Since cartels have a profound impact on consumers, firms, and society as a whole, researchers and policymakers have conducted extensive research on their consequences. Studies have examined the factors influencing the formation and dissolution of cartels (e.g., Igami and Sugaya, 2021; Levenstein and Suslow, 2006; 2011; 2016), the extent of price overcharging (e.g., Connor and Lande, 2006), and the social welfare implications, particularly in terms of deadweight loss. Yet the impacts of cartels extend beyond merely inflating market prices, necessitating a deeper investigation into their indirect or longer-term consequences. The ability to offer innovative products and services is increasingly important, and the presence of cartels can, theoretically, alter firms' incentives and ability to innovate in either direction. This calls for a comprehensive understanding of cartels' broader implications for firm innovation activities.

Notably, cartels provide a unique opportunity to explore the mechanisms underlying their association with firm innovation. Theories suggest two primary channels through which cartels might influence innovation activities. The first channel is the extra *financial resources* that colluding firms gain as a result of inflated prices, which can provide them with the capital needed to invest in innovative activities. The second channel is the positive *managerial expectations* regarding the firm's future survivability and profitability and the appropriability of innovation outcomes that collusion enables. A crucial distinction between these channels is that the financial benefits from inflated prices extend to all firms in the market, including non-colluding competitors, whereas the managerial expectations regarding future prospects apply exclusively to the managers of colluding firms. By comparing the behaviors of colluding firms with those of their non-colluding competitors, one can infer whether and to what extent either channel works.

In addressing the research gap between cartels and firm innovation, this study also sheds light on the breadth of innovation, that is, on the extent to which firms explore new technological areas. Extant theories and empirical approaches offer valuable insights on the intensity of innovation, but they tend to view innovative activities along a one-dimensional continuum. However, because innovation essentially is the recombination of existing technologies in a novel fashion (Schumpeter, 1934; Nelson and Winter, 1982; Henderson and Clark, 1990; Kogut and Zander, 1992; Grant, 1996), firms must engage in a broad range of innovation activities to secure diverse input for future innovation. This broader exploration of technologies could foster unprecedented recombinations of existing knowledge, paving the way for breakthrough innovations. Yet, broadening the scope of innovation is even more difficult than increasing innovation's intensity, as every difficulty in intensifying innovation is applied more aggressively. Further, firms may not possess as much absorptive capacity to identify, assimilate, and apply knowledge ingredients in new areas (Cohen and Levinthal, 1990). Novel projects may also develop slowly under a learning curve. These make broadening the scope of innovation costlier, riskier, and more time-consuming, and firms developing a new technology are more likely to fail (Lampe and Moser, 2013). It is thus important to understand how cartels are related to the breadth of innovation.

2.2 The Competition-Innovation Debate

Price-fixing cartels are closely related to and have significant implications for market competition. Since the primary objective of cartels is to suppress competition and artificially inflate prices, the cartel context offers a valuable opportunity for researchers to grasp a broader relationship between competition and innovation.[1] Theoretical arguments regarding whether competition incentivizes and enables businesses to innovate are well-founded but have not yet reached a conclusive consensus. In a long-standing competition-innovation debate, Arrow (1962) argues that monopolistic firms do not have an incentive to invest in innovation activities because these firms already enjoy excessive profits; the marginal benefit of engaging in R&D projects, which are risky and uncertain, is low. Conversely, firms in a highly competitive market should innovate to outperform their competitors as their marginal return of innovation is higher (i.e., the escape-competition effect). The standpoint of the US DOJ and the European Commission, that "one of the best ways to support innovation is by promoting competition," is aligned with this view (Vestager, 2016).

A model by Lefouili (2015) shows that the intensity of yardstick competition increases the incentives to invest in cost-reducing innovations. Empirically, Correa and Ornaghi (2014) find a positive relationship between foreign competition and innovation, where innovation is measured by patents, labor productivity, and the total-factor productivity of publicly traded manufacturing firms in the United States. A reduction in tariffs, which promotes international competition, led to productivity growth for manufacturing firms in Brazil (Schor, 2004) and for trading firms in China (Yu, 2015).

Schumpeter (1942), on the other hand, argues that softening market competition could promote innovation. R&D and innovation activities require a large amount of fixed investment and a long-term, risk-taking orientation. Fierce competition in the market lowers the price to the marginal cost level and thereby restricts a firm's *ability* to innovate, because firms then have fewer financial resources that can be allocated to innovation processes. Loury's (1979:408) model shows that, in equilibrium, intense competition reduces firms' investment incentives. Conversely, with softened competition, firms charge prices higher than the

[1] Competition is generally very difficult to measure. Established measures such as the Concentration Ratio (CR_N) and the Herfindahl-Hirschman Index (HHI) often fail to capture the level of market competition or to track its changes over time.

marginal cost and reap extra profits, which provide financial resources for innovation (Schumpeter, 1942; Cohen and Levin, 1989).

Insulation from fierce competition could also provide *incentives* for innovation in several ways. First, softened competition enables firms to invest more confidently in long-term R&D, which are uncertain and take several years, if not decades. All other things equal, a softening competition increases a firm's probability of survival and thus its chances of reaping the gains of innovation ("Schumpeterian rents") in the long term. Second, when fewer firms are competing against each other, firms expect higher average returns from innovation; this provides additional incentives for innovation (Schumpeter, 1934; Cohen and Levin, 1989). Further, with a dynamic view that no market power lasts forever, even monopolists have the incentive to innovate to sustain their market dominance in the long term. Third, softened competition could prevent duplicate R&D investment and reduce preemption risk. What impedes firms' investment in new R&D projects is a concern that competing firms will preemptively patent or commercialize new technology. As softened competition (in particular, cartels) makes the behavior of competitors more visible and predictable, monitoring or communicating with competitors becomes easier.

Several empirical studies support the Schumpeterian view. Macher, Miller, and Osborne (2021) studied how cement plants invested in a new cost-saving technology with large up-front costs (around $800 million) for design and installation. Cement producers were more likely to make such investments when facing softer competition. The ability to recoup the fixed cost, thanks to lower market competition, is a key mechanism driving the results. In a study on Chinese import competition in the US manufacturing sector, Gong and Xu (2017) found that competition decreased the R&D expenditures of US public firms ($\epsilon = 0.64$) and that R&D investment was reallocated toward firms with higher profit margins or market power. Hashmi (2013) found a negative relationship between market competition and citation-weighted patenting of publicly traded manufacturing firms in the United States. According to Autor et al. (2020), competitive pressure from Chinese imports decreased R&D expenditure and patenting by US manufacturing firms. The financial market's evaluation of corporate R&D is also consistent with these findings; investors expect R&D to offer them higher returns when firms face lower competition (Greenhalgh and Rogers, 2006).

Some studies (e.g., Loury, 1979) have embraced these competing views and considered the nonmonotone relationship between competition and innovation. Williamson (1965) found an optimal concentration ratio of 30 from the linear model. Using the privatization of public firms and other industrywide changes in the regulatory regime, Aghion et al. (2005) found an inverted-U-shaped relationship between competition and the patenting behavior of UK firms. In line with this finding are a formal model developed by Boone (2001) and empirical studies on R&D intensity (Levin, Cohen, & Mowery, 1985) and on the market value of innovation in the US manufacturing sector (Im, Park, & Shon, 2015).

Extending the arguments to the exploration of new technological areas, the relationship between competition and the breadth of innovation is also found to be ambiguous. On one hand, firms facing softer competition may stop expanding their innovation scope. They can enjoy high profit margins by focusing on the current areas where they face low competition. On the other hand, when competition is reduced, firms have higher incentives and the ability to broaden their technological horizon. They have slack financial and cognitive resources that can be devoted to longer-term and riskier projects. Limited price competition can also promote R&D coordination—either explicitly or implicitly—between firms. Cartels, in particular, facilitate communication and increase visibility between competing firms. This implies a divergence of colluding firms' technological trajectories.

Given the intense debate and the inconclusive findings, a careful analysis of cartels can enhance our understanding of the association between competition and innovation. Collusion, while not representing all forms of competition, is not uncommon—evidenced by more than 2,000 indictments and $10 billion in criminal fines charged to colluding firms in the past five decades.

3 Data

Collusion Data. The DOJ's Antitrust Division defines a cartel as price fixing, bid rigging, and market allocation in violation of Section 1 of the Sherman Antitrust Act. In cartel cases, the DOJ typically publishes three types of documents in their Antitrust Case Filings: information (indictment), plea agreement (if applicable), and final judgment. These documents contain detailed information about the identity of firms that colluded, the start and end dates of the collusion, and the exact ways in which the collusion operated. Relevant markets are specified in the documents using the four-digit Standard Industrial Classification (SIC) code (for older cases) or the six-digit North American Industry Classification System (NAICS) code (for recent cases). The documents are based on the defendant firm or the individual level, not on the collusion level. To group firms and individuals participating in the same collusion, I used information on the collusion period, the relevant market, and the co-conspirators. Another source of data on collusion is Wolters Kluwer's VitalLaw; its *Trade Regulation Reporter* provides summaries of antitrust-related documents released by the DOJ and tracks recent developments of the cases. I digitized and analyzed all documents relevant to collusion and cross-verified the documents from the two sources. As a result, I identified 461 collusion cases involving 1,818 firms in the United States from 1975 through 2016.[2] Table 1, Panel (a) presents descriptive statistics. See the Electronic Companion (EC) A.1 for details.

Patent Data. The primary source of patent data is PatentsView, which is supported by the Office of the Chief Economist in the US Patent and Trademark Office. PatentsView contains information on inventors, assignee firms and their locations, and other details available in the original patent document. I used the

[2] I exclude collusion cases in the financial sector (i.e., those involving real estate, interest rates, or foreign currency exchanges).

August 11, 2021, release, which covers all patents granted from 1976 through 2020. The database provides a unique identifier for assignee firms and inventors based on a name disambiguation algorithm.

Another concern is that the patent data includes no information on the industry at the patent or assignee firm levels, an important input when defining relevant markets and composing appropriate comparison groups. To navigate this problem, I converted the patent technology fields from Cooperative Patent Classifications (CPC) to NAICS and aggregated them at the firm level (see EC A.2 for details).

I then matched firm names in the collusion data and the patent data using two different name-matching schemes. First, I created broad, case-insensitive regular expressions (e.g., `^sam.*sung.* elec`) for the names of all firms that colluded.[3] Second, I applied string distance algorithms (q-gram and cosine distance) and listed the top-twenty match candidates for each firm. I manually checked the quality of the match for both approaches. Table 1, Panel (b) presents firm-level descriptive statistics for patents. In the patent sample, 833 firms involved in collusion filed at least one patent.

Finally, I constructed firm-year panel data using the universe of patents granted from 1976 through 2020. For each assignee firm, I identified the year of its first and last patent filings. For any firm-year observation where I did not observe a patent, I assigned the value of zero if the year occurred between the firm's first and last years of patenting. This led to a balanced panel within the lifetime of firms.

R&D Data of Public Firms. Standard & Poor's Compustat North America provides accounting, financial, and market information on firms in North America.[4] The same name-matching process was used for firms in Compustat. Compustat consists only of publicly traded companies, and the resultant sample is different from the patent sample. Table 1, Panel (c) presents descriptive statistics for the Compustat data. For a more detailed analysis, I also use Compustat Segment data, which provides granular accounting and financial information by business and geographic segments within firms.

4 Research Design and Empirical Strategy

4.1 Price-Fixing Cartels and Antitrust Enforcement

The DOJ's Antitrust Division categorizes collusion as (horizontal) price fixing, bid rigging, or market allocation. In many cases, multiple schemes are used simultaneously. Standard economic theory predicts that, by suppressing competition, collusion increases prices, transfers consumer surplus to producers, and reduces social welfare via a deadweight loss to society. The DOJ estimates that collusion can raise prices by more than 10% and that Americans "pour billions of dollars each year into the pockets of cartel members"

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[3] `^sam.*sung.* elec` captures all firm names that (1) start with `sam`, (2) are followed by `sung`, no matter what characters are between, and (3) are followed by a space and `elec`, no matter what characters are between; this approach captures several variants that may be due to typos, including "Samsung Electroniks," "Sam-sung Elec," or "Sam sung elec. Co., Ltd."

[4] I used Compustat North America (as opposed to Global) to minimize the idiosyncratic variations in company size and scope, and in the regulations they face. Analyses without non-US (particularly East Asian) firms can be found in EC C.6 and C.8.

(Klein, 2006:1). A survey of the literature suggests that price overcharges due to collusion range from 18% to 37% (Connor and Lande, 2006). Government and competition authorities, therefore, have designed a strict set of rules that govern cartels. In the United States, collusion has been *per se illegal* and punishable as a felony since the enactment of the Sherman Antitrust Act (26 Stat. 209, 15 U.S.C. §1) in 1890. Figure 1 shows the number of discovered collusion cases along with the number of indicted firms and individuals.

Collusion offers a rich research setting with two different groups of firms—colluding firms and their competitors not in collusion. It also comes with two events that change the level of price competition in opposite directions. The formation, by definition, significantly suppresses market competition and inflates prices, although which industries are cartelized and which firms participate in collusion are not random. The breakup of collusion, in turn, recovers and increases the level of competition. Investigations of collusion are kept confidential to collect enough evidence, and the "DOJ may investigate cartel conduct without notice by issuing search warrants to search companies or conducting dawn raids" (DOJ).[5] Levenstein and Suslow (2011:466) argue that "the determinants of cartel breakup are legal, not economic, factors" and that "about 80 percent of the cartels in the sample ended with antitrust intervention."

4.2 Difference-in-Differences Estimation

In the difference-in-differences estimation, I compare colluding firms (the treatment group) to non-colluding firms that are in adjacent but different markets (the comparison group). That is, firms in the comparison group must share a four-digit NAICS code but need not share a six-digit NAICS code. For example, if a colluding firm belongs to NAICS **3254**11, firms that belong to NAICS **3254**12, **3254**13, and **3254**14 constitute the comparison group. This process considers each firm's primary industry; a firm will be chosen as a comparison for NAICS **3254**11 if it has more patents or sales in this sector than in any other sector in which it operates; firms with marginal share in the market of question are thus excluded.

The primary research output comes from linear regression estimates to explain how measures of innovation change around cartel events. In Equation (1), I estimate the difference-in-differences model for four years before and after the year of the event (either cartel formation or breakup) with linear regressions:

$$y_{it} = \beta_1 \cdot [Treat_i \cdot Post_{it}] + \beta_2 \cdot Post_{it} + \rho_i + \gamma_{jt} + \epsilon_{it}, \tag{1}$$

where the outcome of interest y_{it} for firm i in year t with the inverse hyperbolic sine transformation (IHS), $\sinh^{-1}(\cdot)$, is regressed on an interaction term between $Treat_i$ (an indicator variable for collusion participation

[5] The leniency program established in 1978 is another important detail in cartel enforcement; however, this program was not effective until major revisions were undertaken in 1993 (for corporate leniency) and 1994 (for individual leniency). This program grants immunity to the first whistleblower who informs the DOJ of the existence of collusion and provides evidence to prosecute. The temporal heterogeneity of the effects around the policy reform are shown in EC C.11, Figure C-10.

for firm i) and $Post_{it}$ (an indicator variable meant to capture the post-event periods at the firm×year levels).[6,7] The regression model also includes firm-fixed effects ρ_i and industry-group (four-digit NAICS)×year-fixed effects, γ_{jt}, to control both for a firm's time-invariant characteristics that may determine the outcome of interest as well as for any industry- and time-varying components of economic activity that may influence innovation activities. The four-digit NAICS code (j) is used in the industry-group×year-fixed effects to compare treated firms and comparison firms in the adjacent sector. To avoid spillover effects of collusion in the same narrowly defined market, I exclude from the comparison group those firms sharing the same six-digit NAICS code with the colluding firms. For firms in the Compustat data, I use SIC codes because NAICS codes are available only for recent years. The coefficient of interest is β_1. The analysis of both formation and breakup events—and any opposite findings for the two—mitigates concerns that the effects may come from idiosyncratic factors other than collusion.

I also estimate several variants of this regression with more flexible econometric specifications:

$$y_{it} = \beta_1 \cdot [Treat_i \cdot Pre_t] + \beta_2 \cdot \left[Treat_i \cdot Post_t^A\right] + \beta_3 \cdot \left[Treat_i \cdot Post_t^B\right] + X_{it} + \rho_i + \gamma_{jt} + \epsilon_{it}, \tag{2}$$

$$y_{it} = \beta_1 \cdot [Treat_i \cdot \textstyle\sum(t-\tau)] + \beta_2 \cdot \textstyle\sum(t-\tau) + X_{it} + \rho_i + \gamma_{jt} + \epsilon_{it}, \tag{3}$$

where Pre_t is an indicator variable that takes the value of one for two to four years before the event of interest. $Pre_{t=-1}$ is an indicator for the year before the event and serves as the baseline (an omitted category). $Post_t^A$ is an indicator variable for the first two years of collusion, and $Post_t^B$ is an indicator for the third and the fourth years of collusion. X_{it} includes all lower-order terms. In Equation (3), τ is the year of the event.

The above approaches consider the formation and breakup of collusion as if they were separate events. As these events go hand in hand, it is useful to analyze them in a single framework to paint a complete picture. A difficulty arises because each instance of collusion has a different duration, and the relative time from cartel formation to breakup varies across cases. To address this problem, I merge the relative years into seven time groups and let one of these time groups represent all the later periods of collusion:

$$\begin{aligned} y_{it} = {} & \beta_1 \cdot \left[Treat_i \cdot Pre_t^1\right] + \beta_2 \cdot \left[Treat_i \cdot Collusion_t^1\right] + \beta_3 \cdot \left[Treat_i \cdot Collusion_t^2\right] + \\ & \beta_4 \cdot \left[Treat_i \cdot Post_t^1\right] + \beta_5 \cdot \left[Treat_i \cdot Post_t^2\right] + \beta_6 \cdot \left[Treat_i \cdot Post_t^3\right] + X_{it} + \rho_i + \gamma_{jt} + \epsilon_{it}, \end{aligned} \tag{4}$$

where Pre_t^1 means four to six years prior to the formation of collusion. Pre_t^2 means one to three years prior to the formation of collusion and serves as the baseline (an omitted category). $Collusion_t^1$ represents early

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[6] The IHS transformation is defined as $y^{IHS} = \sinh^{-1} y = \log(y + \sqrt{y^2+1})$. It is approximately equal to $\log 2y = \log y + \log 2$, except for very small values of y, and has a similar interpretation as a standard logarithmic dependent variable. One advantage of $\sinh^{-1}(.)$ transformation is that the function is defined for any real number including zero (Burbidge, Magee, and Robb, 1988; Bellemare and Wichman, 2020). Chen and Roth (2024) raised concerns about estimating log models with zero values, highlighting that such estimates can be sensitive to scale. To address this in a way that best suits our context, I adopt one of their suggested approaches that explicitly calibrates the weighting of the intensive and extensive margins for our primary outcome of interest, patent filings. The results are detailed in Section 5.1.1.

[7] For all estimations based on Equation (1), the year of formation or breakup is omitted because it is unclear where this year should belong. The results remain robust to the inclusion of these years.

collusion periods: one to three years after the formation of collusion. To account for varied collusion periods, $Collusion_t^2$ represents the fourth year of collusion and thereafter up to the year before the collusion breakup. $Post_t^1$, $Post_t^2$, and $Post_t^3$ refer to 1–3, 4–6, and 7–9 years after the breakup of collusion, respectively. In all specifications, standard errors are clustered at the industry-group level (four-digit NAICS).

4.3 Addressing Potential Concerns

There are several concerns about using cartel formation and breakup events that merit further discussion. First, the start and end dates reported by DOJ may not accurately represent the actual duration of cartels. The DOJ's enforcement may be negotiated ("prosecutorial discretion") for each firm, and the DOJ's ability to claim the collusion period is limited by the evidence collected. This generally works against the findings, leading to an underestimation of the effects (see EC A.1). To further address this concern, I use the start date of collusion as the earliest start date among all firms in each collusion. Second, colluding firms face a trade-off between their coverage in the market (i.e., the price-setting power) and the risk of discovery by the DOJ. As a result, cartels tend to be formed by larger firms in the market, which are more likely to initiate scientific research (Arora, Belenzon, Kosenko, Suh, & Yafeh, 2022). This selection must be carefully considered in interpreting the results. The findings are more applicable to relatively large firms—those with certain market power—than to small firms. Third, the treatment timing varies across cartels, and the effect is likely heterogeneous over time and across groups. In such a case, standard two-way fixed effect models may make "bad comparisons" when earlier-treated units act as controls for later-treated units. This is less of an issue in this study for two reasons. The bad comparison problem is "mitigated to the extent that units that never receive treatment account for a more significant portion of the sample" (Baker, Larcker, & Wang, 2022:374), and a vast majority of firms in the sample (98%) are never treated. Further, with the industry×time fixed effects, the empirical estimation compares within the same four-digit NAICS sector. This approach avoids "bad comparisons" because there are few cases where multiple collusion happened in a given sector. Hence, already treated observations are not used as controls in most cases.

5 Estimation Results

5.1 Main Findings

5.1.1 Intensity of Innovation. I start by examining the raw data as regression models may be sensitive to underlying assumptions and transformations. Figure 2 graphically presents the average number of patent filings by colluding firms (red line) and comparison firms (blue line) separately around the formation events (Panel a) and breakup events (Panel b). The only transformation, Z-scores of the outcome variable based on pre-event values, is made to account for the different absolute levels of the two groups. The shaded region represents one standard error from the mean. Without fixed effects and other adjustments for covariates, Panel (a) shows that, after forming cartels, colluding firms increased patent filings significantly more than the comparison firms did. In contrast, Panel (b) illustrates how such innovation activities of colluding firms declined gradually over time (with some lags) after the breakup of cartels.

To further check the raw data patterns for a cartel case, I investigate the vitamin cartel, which has been studied extensively in the industrial organization literature. Although the vitamin cartel has been found to have overcharged up to 100% of the but-for price (Bernheim, 2008), the innovation activities of colluding firms in the vitamin cartel have not been studied to date. Figure 3 shows the vitamin-related patent filings by colluding firms, standardized by Z-score (red line). The blue line represents patent filings by non-colluding firms in technology fields (4-digit CPC) that overlap with the top ten fields of colluding firms; simply put, these are vitamin patents filed by competitors not in collusion. The brown line, which shows patent filings in the remaining technology fields where colluding firms patented, serves as a benchmark; this line largely coincides with the linear projection based on their out-of-collusion patenting trend. The colluding firms significantly increased their vitamin-related patent filings once collusion began, but the filings reverted to the benchmark level after the collusion ended (see EC C.12 for a list of vitamin-related patents). This trend is consistent with the average non-parametric pattern from all cases shown in Figure 2.

Having explored both the aggregated model-free evidence and a case-specific example, I turn to formal regression analysis. Table 2(a), columns 1–4 show how three measures of innovation intensity—patent count, the count of top-10%-cited patents, and citation-weighted patents—changed around collusion formation, based on Equation (1). Panel (a), column 1 indicates that patent filings increased by an average of 28.3% (or 24.9 log points). Colluding firms on average filed 46.3 patents per year immediately before the cartel formed, so the 28.3% increase in patenting is equivalent to 13.1 more patents per year for each colluding firm. Table C–1 in EC C.1 shows a more flexible approach based on Equation (2). The results indicate that colluding firms increased patent filings by 19.4% in the short term and by 33.2% in the longer term. However, after the breakup, patent filings by colluding firms decreased by 10.4% in the long term.

Chen and Roth (2024) highlight that estimates using log-like transformations, including the IHS, are influenced by the units of the outcome variable, which can complicate interpreting these estimates as percentage effects. This issue arises because units of the outcome affect the weight placed on the extensive margin (i.e., for cases where the outcome shifts from zero to a nonzero value post-treatment). To address this, I follow their recommendations by examining the role of the extensive margin (e.g., a change in patent count from zero to positive) versus the intensive margin (i.e., changes within positive patent counts). A parameter x is used to assign different weights, with a change from 0 to 1 valued at $100x$ log points. For values $x \in \{0, 0.1, 0.5, 1, 3\}$, the estimates are 0.252 ($p{\approx}0.001$), 0.252 ($p{\approx}0.001$), 0.255 ($p{\approx}0.001$), 0.257 ($p{\approx}0.002$), and 0.268 ($p{\approx}0.02$), all closely aligned with our baseline estimate of 0.249. These results, along with those from the Poisson models, suggest our estimates are unlikely to be affected by such concerns.

Next, I report estimates from the event-study approach with distributed year leads and lags, based on Equation (3). In Figure 4, each point and the vertical bar represent yearly event-time estimates and 95% confidence intervals, with relative Year −1 as the baseline. Horizontal lines and the boxes around these represent the point estimates and 95% confidence intervals, where relative years are grouped by two or three years around the event of interest. Figure 4(a) shows that colluding firms gradually yet substantially increased patent filings after forming cartels. This gradual increase in innovation output is consistent with the patterns of price changes in cartels. In the vitamin cartel, for example, product prices began to increase immediately after the cartel formed and reached a 100% increase within three years (Bernheim, 2008).

Table 2(b), on the other hand, indicates that colluding firms decreased patent filings after the breakup of collusion; in column 1, the pooled estimate is −7.3%, though not precisely estimated. The imprecise point estimation and smaller effect size are expected outcomes because firms would not suddenly and instantaneously cease all ongoing R&D projects after the breakup of collusion. Furthermore, even after the breakup, firms would continue to file patents as a result of R&D activities undertaken during collusion. The event-study approach illustrated in Figure C-1(b) in EC C.1 shows the dynamic trend: colluding firms decreased patent filings after collusion breakup, with several years of lag.

The results from a single-framework analysis over the life cycle of collusion are illustrated in Figure 4(b). Colluding firms increased patent filings during the collusion period and then, after collusion breakup, gradually decreased filings back to the pre-collusion level (see EC C.1, Table C-2 for regression results). Overall, the opposite responses to the formation and breakup of collusion reassures that the effects are driven by collusion events rather than by factors unrelated to cartels and unknown to researchers.

Note that there is a significant variation in the quality of patents and that a count of patents may not fully capture their quality or impact. To account for the quality of inventions, I first examine the counts of high-quality patents, defined as those that belong to the 90^{th} percentile or above in terms of citations by later patents within the same three-digit CPC×year. Table 2(a), column 2, reports that firms indeed increased patent filings of high-quality inventions by 20.4% during collusion. Second, studies have found that citation-weighted patents are more highly correlated with patent quality or market value than with patent counts (Trajtenberg, 1990; Hall, Jaffe, and Trajtenberg, 2005; Lampe and Moser, 2016). The results for citation-weighted patents, a 27.1% increase, are consistent with those for patent counts and high-quality patents (column 3). This pattern reversed when collusion broke up. While colluding, firms engaged in developing high-quality inventions, but not necessarily in low-quality or marginal ones.

5.1.2 Breadth of Innovation. To examine how firms explore new technological areas and expand their innovation activities, I measure the breadth of innovation by counting (1) the number of unique technology fields (four-digit CPC) where firms patented at the firm-year level, and (2) technology class-weighted patents, measured in the same way as citation-weighted patents.[8] In Table 2(a), column 5, the average number of unique technology fields shows a 15.8% increase during collusion. Figure 4(c) presents the results from flexible event-time estimations. This 15.8% increase is equivalent to tapping into one additional technology field, as colluding firms patented in 6.5 of 674 technology fields before collusion. In contrast, after the breakup of collusion, the breadth of patenting dropped by 6.5% as shown in Table 2(b), column 13, and up to 12% in the longer term (EC C.1, Table C–1). A single framework of the life cycle of collusion is shown in Figure 4(d) and EC C.1, Table C–2. The results from an alternative measure, the technology class-weighted patents, are reported in columns 6 and 14 and are consistent.

The results, however, offer no indication of the types of technology fields in which the colluding firms engaged. Firms may allocate their innovation efforts across either existing fields of innovation (exploitation) or new fields of innovation (exploration). To further examine this, I measure patenting activities in a firm's primary technological area, which is defined by each firm's three most frequently patented technology classes, and in the firm's peripheral technological area, which is measured by its patents that are not in the three patent technology classes where it files most frequently. The results in Table 2(a), columns 7–8, show that firms increased innovation in *both* their primary (28.5%) and peripheral (26.9%) technology areas. In other words, cartels and the inflated prices they enforced enabled firms to explore new technological areas while also strengthening their innovation in existing primary areas. Firms appear to maintain a balance between exploitive and explorative innovations while colluding.

The results on the breadth of innovation align with recent empirical findings in different contexts. Turner, Mitchell, and Bettis (2010) find that, in a less competitive market, US software firms became more responsive to generational product innovations by external actors and less responsive to their own historical patterns of innovation. That is, firms explored unprecedented innovations that were new to the firm as market competition softened. From the pharmaceutical industry, Krieger, Li, and Papanikolaou (2022) find that greater profits promote R&D on novel drug candidates (rather than on me-too drugs). Several individual- or team-level studies offer consistent findings. From a lab experiment, Bracha and Fershtman (2013) find that competition induces agents to work harder, but not necessarily smarter. Subjects were more likely to choose simple tasks requiring labor effort in a head-to-head tournament competition, while they favored more complicated tasks requiring cognitive effort in a pay-for-performance setting without competition. Similarly, intense competition decreased the originality and unprecedentedness of artists' ideas in a logo competition (Gross, 2020).

5.1.3 Innovation Inputs. It is possible that collusion merely alters firms' strategies regarding intellectual property management. For instance, the observed increase in patenting may be due to changes in the need

[8] I assign zero to any firm-year observation where no patent was filed. Excluding such cases does not qualitatively change the results.

for strategic patenting (e.g., Lerner, 1995; Hall and Ziedonis, 2001; Kang and Lee, 2022), to patent (cross) licensing (Priest, 1977; Eswaran, 1993; Arora, 1997; Arora and Castagnoli, 2006), or to incentives to signal their innovation. To assess this, I examine whether the increased innovation outputs are indeed accompanied by greater R&D expenditure. Table 2, column 4 indicates that colluding firms increased their R&D expenditure by an average of 16.4% during collusion. This is equivalent to an additional $76 million spent on R&D projects per firm per year. Assuming a directly proportional relationship between patents and R&D investments, at least 61% of the increase in patent filings can be explained by a firm's genuine R&D efforts. Note that the effects on patents and R&D expenditure are estimated from different samples since R&D data is only available for publicly listed firms. These firms are typically larger with a diverse business portfolio, so their involvement in a collusive market may represent a smaller portion of their overall operations. This broader scope could dilute the impact of collusion on their R&D investment, explaining why the estimated increase in R&D is smaller compared to the increase in patent filings.[9]

5.2 Which Firms and Cartels Drove the Results?

The analysis presented in Section 5.1 provides valuable insights into *average* effects, but these effects may not apply to every firm. It is crucial to investigate the heterogeneity across firms and cartels. To find out which firms experienced the most significant impacts and whether a small number of firms drove the overall results, I randomly exclude one to three treated firms from the sample and estimate the model. The randomization process consists of two parts: (1) determining the number (ranging from one to three) of colluding firms to be excluded, and (2) selecting the specific colluding firm(s) to exclude.

The 1,000 iterations of this exercise provide two important details: the top contributors to the effect size and the distribution of estimates. First, by averaging the estimates at the firm level, I identify the top contributors to the effect size. Table 3, Panel (a) shows the summary statistics from all iterations; Panel (b) shows the top five firms that magnified the effect size (i.e., the estimate decreases without this firm); and Panel (c) shows the top five firms that shrank the effect size (i.e., the estimate increases without this firm). Those contributing most to upward estimates were firms engaging in electronics (digital storage, optoelectronics, and semiconductors) and pharmaceuticals, both of which are highly technologically intensive. In contrast, those contributing most to downward estimates were in chemical and manufacturing businesses. Second, the distribution of estimates from 1,000 iterations is illustrated in EC C.4. The

[9] Another indicator of innovation input is the size of the inventor pool. When firms ramp up their innovation efforts, they need to recruit new inventors; conversely, when firms reduce R&D, they generally cut employment of skilled researchers (Mezzanotti and Simcoe, 2023). In contrast, if firms merely alter their propensity to patent—e.g., choosing to patent inventions they previously kept secret—the size of the inventor pool may not change. Empirical analysis reveals that, during collusion, the inventor pool size increased by 34.2% (p=0.002), a figure that aligns closely with the growth in patent filings (28.3%). After the breakup of collusion, the inventor pool size decreased by 14.4% (p=0.063) (see also EC C.1, Figure C-5). Hence, patents increased in tandem with the expansion of inventor pools and reflect genuine innovation effort.

estimates regarding the intensity and breadth of innovation remain robust even when colluding firms are randomly excluded from the analysis. Excluding five, seven, or ten firms, and extending the analysis to the cartel level (see EC C.5), show consistent and robust results. Overall, the clustering of estimates suggests that despite the heterogeneity, the effects are not driven entirely by a very small number of outlier firms.

5.3 Did Stronger Cartels Exhibit Greater Effects?

Cartels vary across multiple dimensions. One critical attribute for achieving the common objective of fixing prices is the strength of the cartels. I measure the strength of a cartel using the patent share (for patent analysis) and the sales share (for R&D analysis) of participating colluding firms relative to all firms in the industry (6-digit NAICS). If the cartel and its suppression of price competition is indeed accountable for the observed outcomes, I expect to see more pronounced effects among firms engaged in strong collusion.

I conduct a split-sample analysis, comparing firms with above-median shares (indicative of strong collusion) against those with below-median shares (indicative of weak collusion). Table 4 presents the findings around the cartel formation, with patent results in columns 1a and 1b, and R&D results in columns 2a and 2b (see Figure C-9 in the EC C.10 for details). The results reveal that firms engaging in strong collusion, on average, increased their patenting activities by 33.8% and their R&D expenditure by 22.5%. In contrast, those in weak collusion showed economically small and statistically insignificant estimates. These outcomes indicate that not all cartels are the same in facilitating firm innovation and also lend support to the argument that each cartel's ability to inflate the price is a driving force behind the main empirical patterns.

5.4 Variation by Industry (Technological Opportunities)

Industry dynamics can alter the association between cartels and innovation. First, I examine how industry growth affected the relationship. Cartels in rapidly growing markets can fuel innovation as demand from both existing and potential customers expands and appropriability increases. In contrast, in slow-growing or stagnant markets, cartels may not stimulate innovation effectively. This is because anticipated returns on R&D investments are lower, and managers face lower incentives or have fewer financial resources to allocate for innovation. To investigate this relationship empirically, I analyze the average industry growth rate for five years prior to the formation of a cartel using the number of patents filed in four-digit NAICS sectors×year. The sectors identified as experiencing the fastest growth include nanobiotechnology, computer storage devices, engine manufacturing, display manufacturing, and wireless communications (see EC C.9, Table C–11). Figure 6, Panel (a) illustrates the results of regressions similar to those outlined in Equation (1). The estimates from firms in fast-growing industries are larger in magnitude and more precisely estimated compared to those in slow-growing industries across all three dimensions of innovation.[10]

[10] An alternative interpretation of this pattern might be that firms attempt to escape a slow-growing market by forming a cartel and by exerting innovation efforts in different markets. However, under such a scenario, one would expect a more

Second, I explore the heterogeneous effects by industry-patenting intensity, which is defined as the average number of patents filed at the four-digit NAICS level within the five years preceding the formation of collusion. The findings, presented in Figure 6, Panel (b), indicate that the positive association between cartels and innovation arises mostly in patent-intensive industries. Conversely, for industries characterized by low patent intensity, the effects are significantly smaller and statistically not distinguishable from zero. One could argue that patent-intensive sectors might coincidentally encompass fast-growing industries. Given that the two metrics exhibit a very small correlation (0.12 for raw values and 0.09 for indicator variables), however, it is unlikely that the analyses capture effects from a similar set of firms or industries.

These results collectively underscore technological opportunity as an important boundary condition. Put differently, the positive association between cartels and innovation is more likely to be observed in industries with abundant technological opportunities, where firms actively file patents and the rate of patenting increases rapidly. Conversely, in industries with limited technological opportunities, firms may lack the incentive or ability to innovate.

5.5 Robustness Checks

To check the possibility that the findings capture a spurious pattern in the data or arise from model misspecifications, I run a set of placebo permutation tests, where the treatment indicator is randomly reassigned to five firms from the pool of both colluding and comparison firms. Figure 5 graphically summarizes the results around the formation of cartels (see EC C.4 for additional figures). Gray lines represent 1,000 placebo permutations and, on average, show no effect. Colluding firms' patent filings in Panel (a) and their breadth in Panel (b) are clearly distinct from the results of placebo permutation, suggesting that the effects do not stem from arbitrary or spurious components of the data or the models.

To further check the validity of the comparison group for the analysis of R&D investment in public firms, I restrict the comparison group to firms that operate in a similar set of non-collusive markets in addition to the market where collusion occurs. Specifically, using Compustat Segment data, I require treated and comparison firms to have their largest business segment in the same industry. The results are robust under these additional restrictions on the comparison group. Additionally, empirical analysis excluding colluding firms that participated in R&D collaborations provides consistent results (see EC C.3, Table C-6, for more details). The results are unlikely to be driven by a mismatch between treated and comparison firms.

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significant increase in the breadth of innovation among firms in slow-growing sectors as they diversify their innovation activities. The findings do not align with this hypothesis (see EC C.9), as the estimates for the breadth of innovation among firms in slow-growing industries are smaller in magnitude compared to those in fast-growing industries. Further, after collusion breakup, the breadth of innovation returned to its pre-collusion level, as depicted in Figure 4(d), contradicting the idea of an "escaping the sinking ship" effect. No evidence supports the reallocation of resources across different business units (Section 6.2.2). These results support the idea that firms engaged more actively with innovations when collusion was formed in fast-growing industries and do not support the idea of firms diverting their efforts out of stagnant industries.

For some regression analyses, the outcomes of interest are count variables. The preferred specification used is IHS ($\sinh^{-1}$) or log transformation. The estimates obtained with an alternative approach, Poisson Pseudo-Maximum Likelihood Estimation, are consistent with main findings (see EC C.2).

6 Exploration of Potential Mechanisms

Having established average patterns and heterogeneous effects, I explore the potential mechanisms. In Section 6.1, I analyze the presence and relative impact of two major channels: financial resources and managerial expectations. To further explore how financial resources influence innovation, in Section 6.2 I examine firms' tendency to finance externally and their business scope. While it is not feasible to exhaustively explore or conclusively validate all potential mechanisms, this section aims to provide the best possible explanations for what drives the observed patterns between cartels and firm innovation and how it does so.

6.1 Did Financial Resources and Managerial Expectations Matter and How Much?

Price-fixing cartels may foster innovation in firms through two primary channels: (1) the generation of extra financial resources due to inflated market prices ("financial resources") and (2) the optimistic expectations managers hold regarding the firms' future survivability and profitability ("managerial expectations"). First, higher market prices provide firms with additional financial means, which can then be allocated to new R&D projects. This influx of extra resources can act as a direct input for innovation. Second, managers in colluding firms likely have more foresight and a more positive outlook on the future, believing that collusion will enhance their firm's survivability, profits, and the appropriability of R&D outputs. This expectation encourages managers to adopt a long-term perspective and to embrace the risks associated with innovation.

The key questions are: how do financial resources and managerial expectation drive pro-innovation effects, and to what extent does each influence this dynamic? Collusion offers a unique empirical opportunity to distinguish between the two. The fundamental difference is that financial resources are influenced by actual market prices faced by *both* colluding and non-colluding firms, whereas managerial expectations are based only on the foresight of collusive managers. Colluding firms that inflate the market price create a "price umbrella" effect that benefits non-colluding firms within the cartelized market by enabling them to gain additional financial resources. If financial resources are the primary channel, we would expect non-colluding firms to exhibit pro-innovation effects similar to those of their colluding counterparts. Conversely, if managerial expectations are the main driver, the pro-innovation effect should not extend to non-colluding firms because the strategies and behaviors associated with price fixing are limited to the colluding firms; non-colluding firms remain unaware of the details of collusion and cannot benefit from it.

To identify direct competitors that could benefit from the collusion's price umbrella, I categorize non-colluding firms that share a 6-digit NAICS sector with colluding firms as *Competitors not in collusion* and

Other firms not in collusion, based on their history of patent filings in collusion-related technology spaces before the collusion. I then run separate regressions for three groups: (1) Colluding firms, (2) Competitors not in collusion, and (3) Other firms not in collusion, while maintaining the same comparison group—that is, firms in adjacent markets.

Figure 7 visually summarizes the findings. Panels (a) and (b) depict the flexible difference-in-differences analysis for patent filings around the formation and breakup of cartels. Panel (c) illustrates the average effects on the intensity and breadth of innovation by group. In Panel (c), blue bars show that *Competitors not in collusion* experienced changes in innovation intensity and breadth, albeit to a lesser degree than colluding firms (6.3% and 4.8%, respectively, with a p-value of 0.05 for both). The effects on *Other firms not in collusion* were minimal and statistically indistinguishable from zero. Given that both colluding firms and their competitors are exposed to cartelized market prices, a back-of-the-envelope calculation suggests that financial resources contribute to 25.3% of the total effect (0.063/0.249).

Note that this percentage represents a lower bound, as the definition of the *Competitors not in collusion* group might still include firms not competing directly in the same market (false positives), leading to an underestimation. Additionally, the increased innovation of colluding firms (which is the main finding of this study) suggests that colluders differentiate their products and improve their quality. Consequently, *Competitors not in collusion* may not be able to charge the same inflated price as colluding firms, resulting in a *partial* umbrella effect. With that caveat, the remaining variation is attributed to factors that are associated with collusion membership but that do not directly involve market prices. Hence, managerial expectations (broadly defined) could account for up to 74.7% of the observed effect. While all potential channels cannot be exhaustively excluded, evidence does not support alternatives like R&D collaboration among colluding firms as significant factors (see EC C.3). These results indicate that both financial resources and managerial expectations serve as key mechanisms driving the positive association between cartels and firm innovation and that the expectations of colluding managers appear to play a more substantial role than do the immediate gains from inflated market prices and extra revenues.

The vitamin cartel case provides another opportunity to examine this point. In Figure 3, vitamin-related patent filings by competitors (blue line) increased, but only to 33% of the extent observed for colluding firms. That is, the extra financial resources generated from inflated market prices account for a third of the observed innovation outcomes. The remaining two-thirds is likely attributable to managerial expectations. These numbers from the vitamin cartel case align closely with the regression results from the full sample.

6.2 How Did Financial Resources Influence Innovation?

How are financial gains from collusion specifically channeled toward innovation? I investigate whether the innovation effect is more pronounced for firms that relied more on internal financing but less on external financing prior to the collusion. In addition, I explore whether innovation occurs within the cartelized business or market, or whether financial resources are reallocated to other business units.

6.2.1 Did Financial Resources Benefit Firms in Need?

If additional financial resources made available through cartels played a role, we expect a greater effect in firms that (1) relied on internal financing before collusion or that (2) accrued higher capital during collusion (Krieger et al., 2022; Mezzanotti and Simcoe, 2023). The first argument is based on the idea that firms relying on internal funds *before* collusion would benefit more from inflated prices because they may have limited access to or are reluctant use external financing. The second argument posits that firms experiencing high revenue growth *during* collusion would have more capital to invest in R&D projects.

Table 5 provides the results for public firms. Firms that relied more on internal financing prior to collusion exhibited a significant increase of 27.5% in their R&D expenditures. Further, the increase in R&D expenditure was driven primarily by firms that experienced higher revenue growth during collusion (35.4% increase), while the effect on firms with low revenue growth during collusion was economically small and statistically indistinguishable from zero. These results suggest that the extra financial resources benefited firms in need of them—particularly those relying more on internally-sourced capital.

6.2.2 Were Financial Resources Reallocated within a Firm? (Markets versus Firms)

The allocation of financial resources within a firm prompts an investigation into whether innovations are driven by the profitability of a collusive market ("market channel") or whether the extra profits from collusion are redistributed within the corporation to enhance innovation in units other than the colluding one ("firm channel"). I employ three approaches to tackle these questions. First, I measure the technological concentration of firms using the Herfindahl-Hirschman Index (HHI) of patents' technology fields. If a firm patents exclusively in a few technology classes (i.e., high concentration), this firm's scope is likely narrow, and the extra profit from collusion must be reinvested into the same market. If a firm's patenting activity spans many different technology fields (i.e., low concentration), the extra profit from collusion may be allocated across several businesses and technology spaces outside the collusive segment. In Table 6, column 1a, narrowly focused firms increased their patenting activities by 39% during collusion (an amount higher than that of firms with broader scope), supporting the market channel. Interestingly, after the breakup of collusion, the firms with broader scope showed a steeper decrease in patenting (column 4b), potentially due to the financial strain from criminal fines and damages affecting the entire corporation.

Second, leveraging the inherent characteristic of collusion, I analyzed patent filings within overlapping and non-overlapping technology fields among colluding firms. Overlapping fields are defined as the five most frequent intersections of patented technology fields (primary and secondary four-digit CPC codes) across all colluding firms. The results, presented in Table 6, column 2a, reveal that patent filings in overlapping technology fields saw a more substantial increase (25.1%). That is, colluding firms tended to focus their innovation efforts on areas directly related to the collusion, lending further support to the market channel. Although patenting in non-overlapping fields also rose, the magnitude was smaller (19.5%), and this may also indicate a broadened scope of innovation during collusion, as studied in Section 5.1.2.

Third, using granular business segment data from Compustat Segment to assess firm scope, I compare the changes in R&D expenditure between firms with narrow scope (one or two business segments) versus broad scope (three or more segments) before collusion. The increase in R&D spending was notably higher in narrower firms, aligning with the market channel. This trend holds, even when focusing on single-segment firms or on those with a significant portion of sales from one segment (75% or higher; see EC C.7).

Internal access to financial institutions represents another potential channel for innovation. East Asian firms, for instance, are known for their broad scope and sometimes own their own banks, which could support innovation across their business units. However, analyses excluding East Asian firms reveal that the innovation effects remain unchanged, as detailed in EC C.8. That is, the observed innovation dynamics were not significantly affected by regional differences in financial access. In fact, regulations in countries like South Korea and Japan enforce a separation between industrial and financial capital, emphasizing that market-level profitability, rather than internal financing mechanisms within broad corporations, is the main driver of innovation. Collectively, these findings highlight the role of the market channel, where extra profits from collusion stimulate innovation in that collusive market.

7 Discussion

When firms colluded and suppressed price competition, they shifted toward competing for innovation—especially in industries where technological opportunities are high and such collusion is strong. This suggests that softened competition may not always be a cushion to sleep on (Schumpeter, 1942: 102). To devise appropriate innovation strategies, it is therefore crucial for managers to recognize this shift in the competition arena, as well as when and why this happens.

The implications for public policy also deserve further discussion. The US DOJ aims to promote price competition, viewing collusion as a significant antitrust violation because "cartels inflate prices, restrict supply, inhibit efficiency, and reduce innovation" (Pate, 2003). The European Commission shares a similar stance, considering price competition to be the mother of invention and arguing that cartels diminish firms' incentives to introduce new products and services. However, this perspective may overlook how price competition influences firms' incentives (e.g., managerial expectations) and ability (e.g., financial resources) to innovate and how such innovation could enhance consumer welfare. In addition, the social return on innovation is at least twice as great as the private return (Bloom et al., 2013). Hence, with the empirical findings in this study, the prevailing view—that price competition always promotes innovation and social welfare—becomes less clear. The heterogeneity and underlying mechanisms examined here could inform policymakers as to where competition authorities might prioritize their resources across various markets and as to how they might promote private innovation by, for instance, influencing managerial expectations and firms' access to internal or external financial resources.

This argument does not imply that price competition is always detrimental to innovation or that collusion inherently fosters innovation, nor does it suggest halting the promotion of market competition. There is a significant amount of heterogeneity, and policymakers need to weigh the potential advantages and disadvantages of price competition depending on the specific context (*rule-of-reason*) rather than deeming a conduct of reducing competition *per se illegal*.[11] In line with this view, the DOJ increasingly recognizes the significance of fostering innovation in antitrust enforcement (Alford, 2018), and discussions with DOJ and Federal Trade Commission officials confirm a growing emphasis on the benefits of innovation.

8 Concluding Remarks

Innovation is the key driver of a firm's competitive advantage and economic growth. An analysis of price-fixing cartels reveals, on average, a positive association between cartels (which limit price competition) and firm innovation; this is seen in both intensity and breadth of innovation. But under what conditions is this likely to hold? Technological opportunities in industries, as indicated by growth rates and patent intensity, appear to be crucial factors. Specifically, high-tech sectors such as biopharmaceuticals, semiconductors, and electronics (including digital storage and liquid crystal display) exhibit greater innovation effects. The strength of collusion, which determines the ability to inflate prices, is also associated with increased innovation activities. The effects seem to arise primarily by altering managers' expectations of future profitability and by securing additional financial resources through inflated market prices. No empirical evidence was found for resource reallocation across units within firms.

The findings of this study require careful interpretation and application. Although causal story is one plausible interpretation of the relationship between cartels and innovation, the empirical findings do not necessarily establish a causal relationship and may be subject to confounding factors. Collusion did not arise randomly across industries, and firms were self-selected into the collusion (e.g., cartels tend to be formed by larger firms; see EC A.2). Breakups are subject to unobservable factors such as whistleblowers taking advantage of the leniency policy (see EC C.11). In addition, the findings come from innovating firms that invest in R&D and file patents and may not readily apply to other types of firms.

With regard to external validity, the focus of this study is on collusion, which is a particular form of suppressing price competition that tends to arise in a concentrated market. However, the consequences of competition may differ across contexts such as competition induced by foreign trade (import penetration),

[11] A similar change was made in 2007 concerning the minimum resale price maintenance. This is no longer *per se illegal* and is judged under the rule of reason. See *Leegin Creative Leather Products, Inc. v. PSKS, Inc.*, 551 U.S. 877 (2007).

government subsidies, mergers, patent pools, or privatization of public firms. For example, Autor et al. (2020) find similar results in that US manufacturers decreased their patenting activities when facing higher competition from Chinese import penetration. Yet, the competitive pressure from low-cost products of foreign countries may have consequences and implications differing from those of the price competition manipulated by collusion among leading companies in technology-intensive industries.

This study contributes to the literature in several ways. First, the results broaden our understanding of the effects of collusion beyond the price level. I consider another important economic outcome—innovation—and shed light on the important trade-off between price competition and innovation growth. Second, taking a step beyond the intensity of innovation, I also consider its breadth. Exploring new technological areas is crucial as it enhances long-term innovativeness and competitiveness of firms. Third, by leveraging the umbrella pricing effect that also benefits non-colluding competitors—which is unique in a cartel setting—I offer a rough estimate of the relative influence of managerial expectations and financial resources underlying the main relationship. Last, collusion—a highly strategic (yet illegal) conduct between competitors—represents an important research agenda. I have collected data on all discovered collusion cases and estimated the average effect on colluding firms, along with the heterogeneous effects and the potential mechanisms. I hope that comprehensive collusion data and their linkage to various databases provide new avenues for future research.

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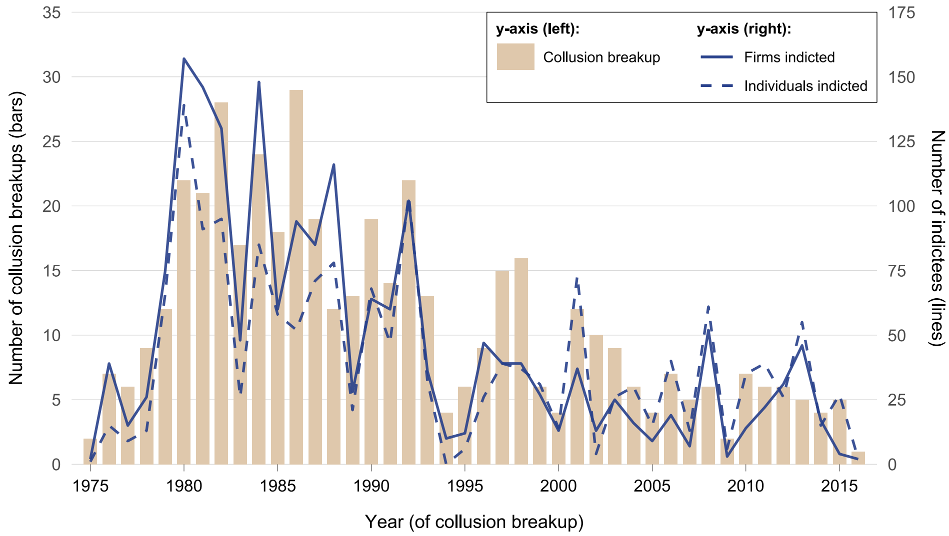
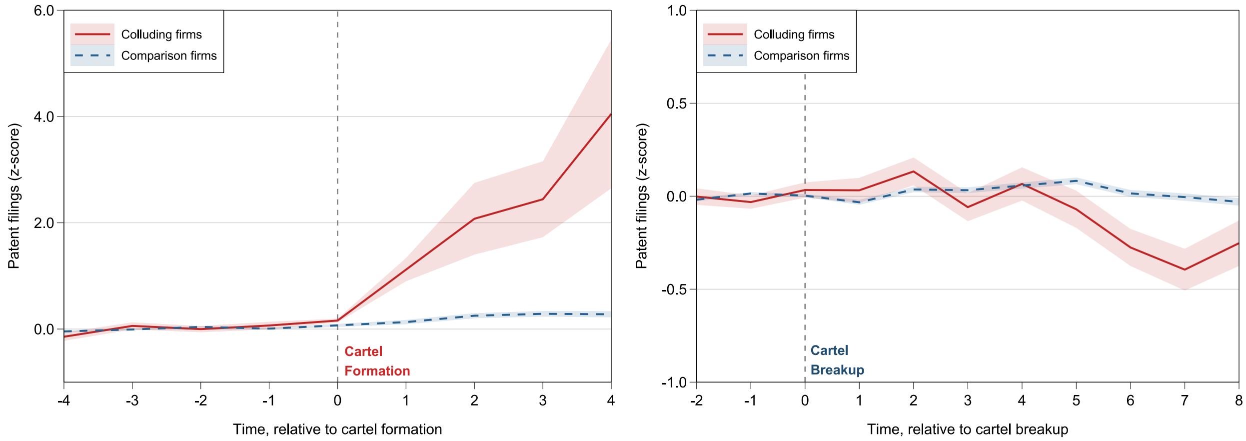
Figure 1. Number of Cartel Breakups and Indictments in the United States, 1975–2016



Notes. This figure tracks the trend in antitrust enforcement and collusion breakup in the United States from 1975 through 2016. Brown bars represent the number of collusion breakup cases by year. The solid blue line represents the number of firms indicted for collusion each year, whereas the dashed blue line represents the number of individuals indicted of participating in collusion. Collusion cases in the finance sectors (e.g., real estate brokerages, foreign currency, mortgage rates, interest rates) are excluded. The number of collusion breakup cases is right-censored; more cases of collusion breakup may have occurred in 2016 but may have not yet been indicted due to ongoing closed investigations. *Data*: The author's data collection from the *Antitrust Case Filings* of the US Department of Justice and the *Trade Regulation Reporter* of Wolters Kluwer's VitalLaw.

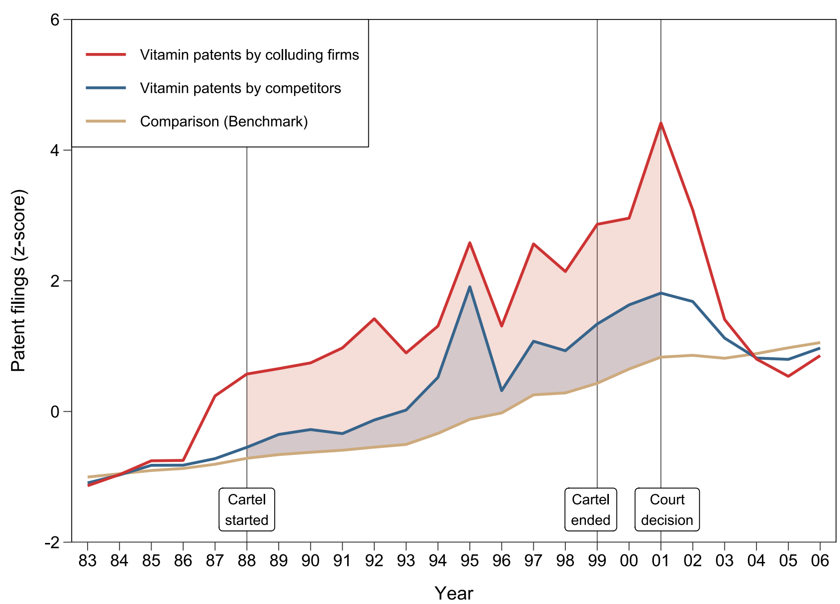
Figure 2. Price-Fixing Cartels and Innovation: Model-Free Evidence

(a). Cartel formation and patent filings (b). Cartel breakup and patent filings



Notes. Plotted are the Z-scores of average patent filings around cartel formation by the treatment group (colluding firms) as the red solid line and the comparison group (non-colluding firms in the adjacent industries) as the blue dashed line. The shaded area represents one standard deviation from the estimate. The mean and the standard deviation from the pre-collusion years (e.g., four years prior to cartel formation) were used in Z-score transformation. *Data*: PatentsView.

Figure 3. Vitamin Patents by Colluding and Non-Colluding Firms in the Vitamin Cartel: Model-Free Evidence

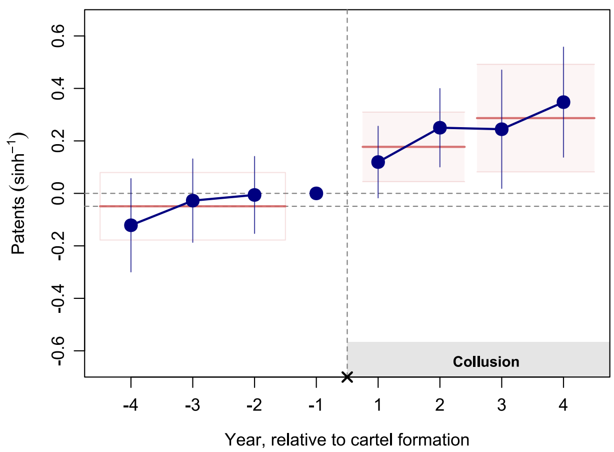


Notes. Plotted are the Z-scores of vitamin-related patent filings by *Colluding firms* in the vitamin cartel (red solid line). *Competitors not in collusion* (those in the same 6-digit NAICS as colluding firms and that patented in one of the top ten technology fields of colluding firms) are represented by the blue solid line. To compare the trends for the three groups, the mean and the standard deviation from the non-colluding years—that is, for 1982 through 1986 and for 2003 through 2007—are used in Z-score transformation. The vitamin cartel formed in 1988 and lasted until 1999. The final court decision was issued in 2001. The vitamin cartel overcharged up to 100% of the benchmark price during collusion (Bernheim, 2008; Igami and Sugaya, 2022). The brown line (on the bottom) shows the patent filings of *Other firms not in collusion* (those that were in the same 6-digit NAICS as colluding firms but did not patent in the top ten technology fields of colluding firms), which serve as the benchmark. The shaded area represents the deviation from this benchmark during the collusion period. During collusion, the average increase in patenting by *Competitors not in collusion* was 35% that of *Colluding firms*.

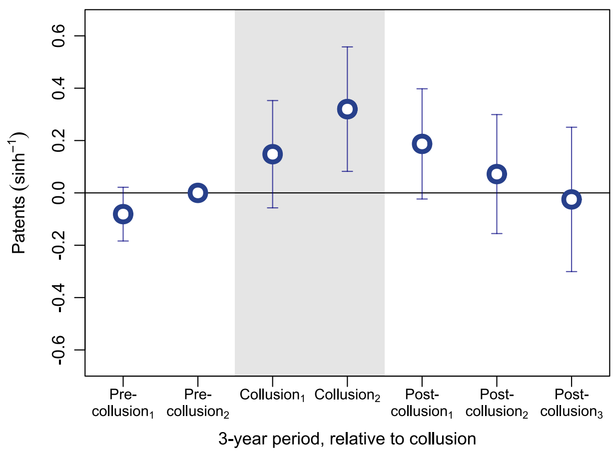
Figure 4. Price-Fixing Cartels and the Intensity and the Breadth of Innovation

A. Intensity of innovation: Patent filings

(a). Cartel formation and patent filings

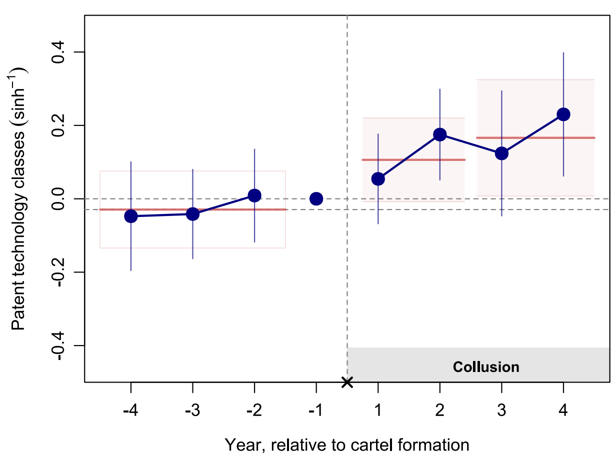


(b). Life cycle of cartel and patent filings

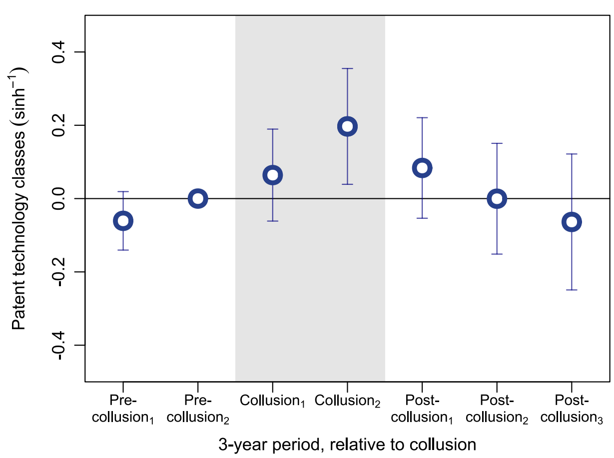


B. Breadth of innovation: Number of unique technology classes

(c). Cartel formation and patent technology classes

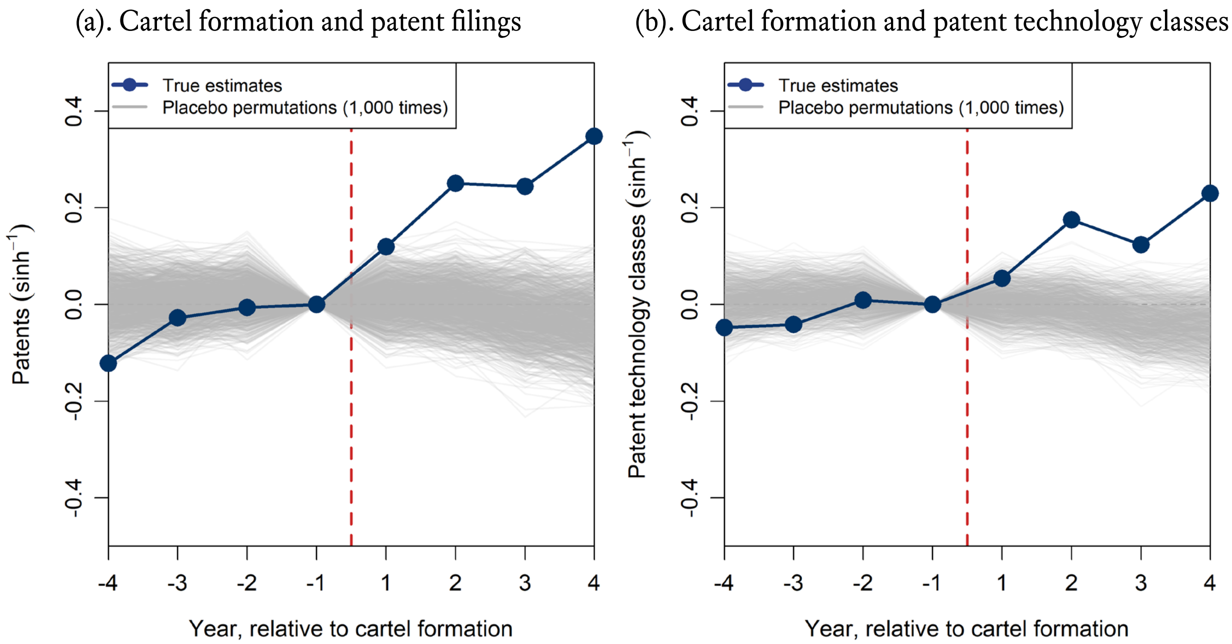


(d). Life cycle of cartel and patent technology classes



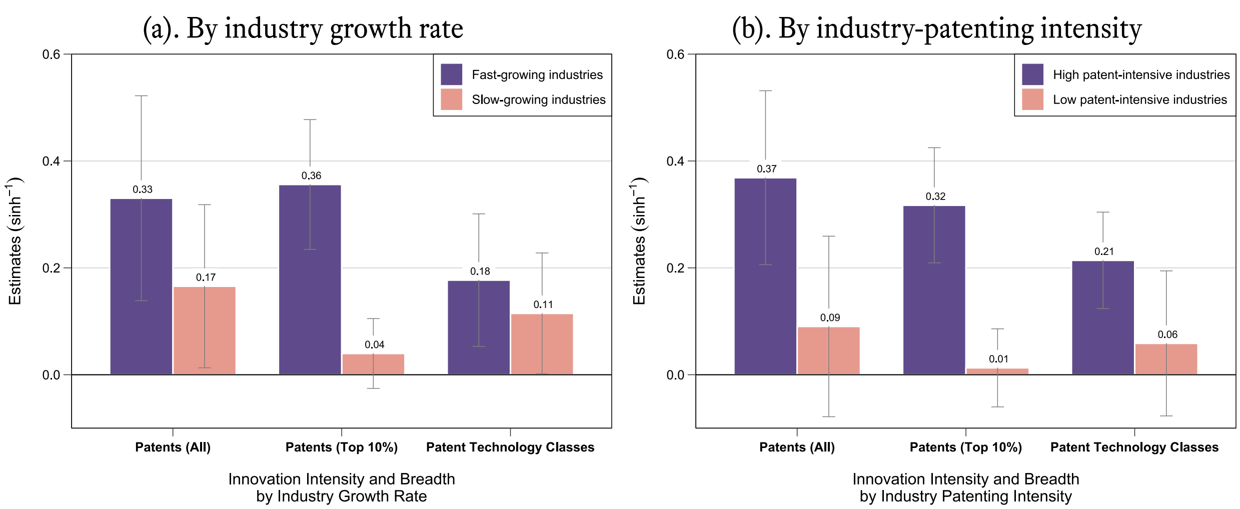
Notes. The dependent variable consists of (1) the number of patent filings (that were eventually granted) and (2) the number of unique technology classes of patents (three-digit CPC) with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence intervals. Standard errors are clustered at the sector level. *Panels (a) and (c)*: Plotted are the event-time coefficient estimates (dots) from a version of Equations (2) and (3). Colored horizontal lines and the boxes around them represent the pooled difference-in-differences estimates and 95% confidence intervals from a version of Equation (2), grouped by two or three years around the event of interest. The year of collusion formation corresponds to year zero in the graphs and is omitted. Year –1 is used as the baseline. *Panels (b) and (d)*: Plotted are the event-time coefficient estimates from a version of Equation (4). This figure incorporates both the formation and the breakup of collusion to paint a complete picture and compares the size of effects in a single framework. Years are grouped into seven time periods, each representing the three-year period around the events of interest. *Precollusion*$_1$ means four to six years prior to the formation of collusion. *Precollusion*$_2$ means one to three years prior to the formation of collusion and serves as the baseline. *Collusion*$_1$ represents early collusion periods, one to three years after the formation of collusion. To account for varied collusion periods, *Collusion*$_2$ represents the fourth year of collusion and thereafter up to the year before the collusion breakup. *Post-collusion*$_1$ means one to three years after the breakup of collusion. *Postcollusion*$_2$ means four to six years after the breakup of collusion. *Post-collusion*$_3$ means seven to nine years after the breakup of collusion. The regression model controls for assignee firm-fixed effects and sector × year-fixed effects. *Data*: PatentsView.

Figure 5. Placebo Permutation Tests: Random Reassignment of Cartel Participation (1,000 Times)



Notes. Plotted are the event-time coefficient estimates from a version of Equation (4). The dependent variable consists of the number of patents with the inverse hyperbolic sine transformation in an assignee firm × year. Blue dots and lines represent the treatment group (colluding firms), whereas 1,000 gray lines represent the results of the placebo permutation tests. In the placebo tests, the treatment indicator is randomly reassigned to five firms from the pool of both colluding and non-colluding firms that belong to the same four-digit NAICS industry. This random assignment simulation is repeated 1,000 times. *Data*: PatentsView.

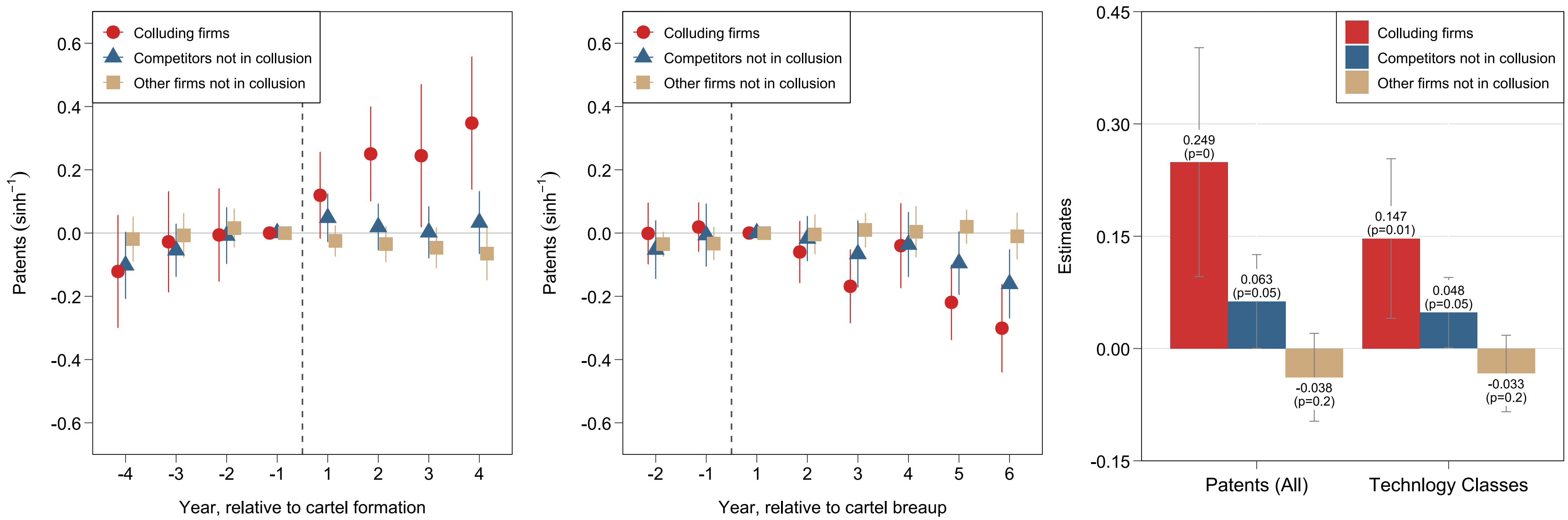
Figure 6. Price-Fixing Cartels and Innovation: Heterogeneous Effects by Industry



Notes. Plotted are the difference-in-differences coefficient estimates from separate regressions based on Equation (1), with the formation of collusion as an event of interest. In Panel (a), the industry-patenting intensity is calculated as the number of patent filings five years prior to cartel formation at the industry group level (four-digit NAICS). In Panel (b), the innovation growth rate is calculated for five years prior to cartel formation at the industry group level (four-digit NAICS). Each colluding firm is divided into two groups based on the median. The dependent variable consists of the number of patent filings, the top 10% most-cited patents compared to peers in the same three-digit CPC×year, and the unique technology classes of patents, all of which are transformed by the inverse hyperbolic sine function in an assignee firm × year. Numbers above the bar show regression estimates, whereas vertical bars represent 90% confidence intervals. The regression model controls for assignee firm-fixed effects and industry group (four-digit NAICS) × year-fixed effects. *Data*: PatentsView.

Figure 7. Price-Fixing Cartels and Innovation by Colluding Firms and Their Direct Competitors

(a). Cartel formation and patent filings (b). Cartel breakup and patent filings (c). Key outcomes compared by group



Notes. Panels (a) and (b): Plotted are the event-time coefficient estimates (dots) of three separate regressions based on Equation (3): firms that colluded (red dots); firms in the focal industry (six-digit NAICS) that were not part of the collusion (blue dots); and all firms in the focal industry regardless of their participation in collusion (light brown dots). The dependent variable is the number of patent filings with the inverse hyperbolic sine transformation in an assignee firm × year. The year of collusion formation (Panel a) or breakup (Panel b) corresponds to year zero and is omitted. Year -1 is used as the baseline. The vertical lines represent 95% confidence intervals. Standard errors are clustered at the sector level. Panel (c): Plotted are the difference-in-differences coefficient estimates from six separate regressions based on Equation (1), with the formation of collusion as an event of interest. The treatment group consists of (1) firms that colluded (red bars) (2) firms in the focal industry (six-digit NAICS) that were not part of the collusion (blue bars), and (3) all firms in the focal industry regardless of their participation in collusion (light brown bars), respectively. The dependent variable consists of (1) the number of patent filings (that are eventually granted) and (2) the number of unique technology classes of patents (three-digit CPC) with the inverse hyperbolic sine transformation in a firm × year. Numbers above or below the bar show regression estimates, whereas vertical bars represent 95% confidence intervals. The regression model controls for firm-fixed effects and major group (four-digit NAICS or two-digit SIC) × year-fixed effects. *Data*: PatentsView and Compustat.

Table 1. Descriptive Statistics

(a). Cartel data (1975–2016)

	Mean	Std. Dev.	Min.	Median	Max.
A. Cartel level (N=461)					
Duration (year)	6.28	5.27	1.00	5.00	36.00
Number of firms indicted	4.34	5.71	1.00	3.00	47.00
Number of managers indicted	5.29	6.50	1.00	3.00	44.00
Total criminal fine for firms ($mil)	25.20	156.52	0.00	0.30	1,902.63
Total criminal fine for managers ($mil)	0.22	12.77	0.00	0.00	31.32
B. Firm level (N=1,818)					
Criminal fines ($mil)	8.361	38.77	0.00	0.20	500.00
Sum of all criminal fines ($mil)	10,676.57	–	–	–	–
C. Individual level (N=1,623)					
Criminal fines ($mil)	0.133	1.17	0.00	0.03	29.60
Sum of all criminal fines ($mil)	98.881	–	–	–	–
Prison sentence (days)	360.8	441.13	1.00	182.00	5,110.00
Sum of all prison sentence (days)	203,878	–	–	–	–

(b). Patent data (Assignee firm level, 1976–2020)

	Obs.	Mean	Std. Dev.	Min.	Median	Max.
Patents	2,209,709	3.11	39.77	0.00	1.00	9,207.00
Citation-weighted patents	2,209,709	43.80	597.46	0.00	1.00	177,156.00
Patents in main areas	2,209,709	1.11	12.85	0.00	0.00	4,215.00
Patents in peripheral areas	2,209,709	1.15	19.83	0.00	0.00	3,861.00
Patent technology classes	2,209,709	1.17	3.93	0.00	1.00	208.00
Tech class-weighted patents	2,209,709	4.28	42.54	0.00	2.00	9,395.00
Backward citations	2,209,709	8.12	26.92	0.00	1.00	5,834.50
Forward citations	2,209,709	8.10	31.42	0.00	0.00	3,468.00
Inventors (3-year moving avg.)	1,185,883	19.90	160.30	0.00	3.00	21,121.00

(c). Compustat data (company level, 1976–2020)

	Obs.	Mean	Std. Dev.	Min.	Median	Max.
Employment (in thousands)	359,728	7.35	34.27	0.00	0.55	4,776.00
Capital expenditure ($mil)	368,608	141.18	937.63	0.00	3.05	65,028.00
R&D expenditure ($mil)	172,453	73.90	525.75	0.00	1.77	42,740.00

Notes. Panel (a) shows the descriptive statistics for all nonfinancial collusion cases in the United States for 1975–2020 at the collusion, firm, and individual manager levels, respectively. Panel (b) shows the pooled (cross-sectional) descriptive statistics for the patent data (1976–2020) at the assignee firm level. Assignee firms are identified by name disambiguated *assignee_id* provided by PatentsView. Panel (c) shows the pooled (cross-sectional) descriptive statistics for the Compustat North America data (1976–2020) at the firm level. Firms are identified by Compustat ID (*GVKEY*). Descriptive statistics are calculated for all firms that operated at least two years in the sample period (1976–2020). *Data*: The author's own data collection: Panel (a) is from the *Antitrust Case Filings* of the US Department of Justice and the *Antitrust Cases* published by CCH; Panel (b) is from PatentsView (August 11, 2021 version); and Panel (c) is from Compustat (May 2021 version).

Table 2. Price-Fixing Cartels and the Intensity and Breadth of Innovation

(a). Cartel formation and innovation

	Dependent variables ($\sinh^{-1}$):							
	Intensity of innovation				*Breadth of innovation*			
	Patents	Patents (Top 10%)	Citation-weight patents	R&D expenditure	Unique tech classes	Tech-weighted patents	Patents in primary fields	Patents peripheral fields
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × *Post*	0.249***	0.186***	0.240**	0.152**	0.147**	0.232***	0.251***	0.238***
	(0.078)	(0.056)	(0.113)	(0.069)	(0.054)	(0.079)	(0.079)	(0.069)
Observations	432,448	432,448	432,448	149,190	432,448	432,448	432,448	432,448
R^2	0.555	0.560	0.483	0.921	0.522	0.508	0.493	0.642
Adjusted R^2	0.442	0.449	0.353	0.910	0.401	0.384	0.365	0.552

(b). Cartel breakup and innovation

	Dependent variables ($\sinh^{-1}$):							
	Intensity of innovation				*Breadth of innovation*			
	Patents	Patents (Top 10%)	Citation-weight patents	R&D expenditure	Unique tech classes	Tech-weighted patents	Patents in primary fields	Patents peripheral fields
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treat × *Post*	−0.076	0.061	−0.318***	−0.073	−0.067	−0.103	−0.042	−0.005
	(0.056)	(0.046)	(0.114)	(0.063)	(0.043)	(0.064)	(0.052)	(0.049)
Observations	432,993	432,993	432,993	149,289	432,993	432,993	432,993	432,993
R^2	0.561	0.569	0.483	0.921	0.526	0.512	0.500	0.652
Adjusted R^2	0.450	0.460	0.353	0.910	0.406	0.389	0.373	0.564

Notes. These tables report regression coefficients from eighteen separate regressions based on Equation (1). Panel (a) uses cartel formation as an event, and Panel (b) uses cartel breakup as an event. The dependent variable consists of the number of patent filings (column 1), the top 10% of patents in terms of forward citations (column 2), citation-weighted patents (column 3), R&D expenditure (column 4), the unique number of technology classes (column 5), technology-class-weighted patents (column 6), patents in a firm's primary technology fields (column 7), and patents in a firm's peripheral technology fields (column 8), all of which are transformed by the inverse hyperbolic sine function in a firm × year. *Treat* is an indicator variable that takes the value of one for colluding firms and zero otherwise. *Post* is an indicator variable that takes the value of one for the post-event period (either collusion formation or collusion breakup) and zero otherwise. A sector is defined by the four-digit North American Industry Classification System. All of the regressions control for firm-fixed effects and sector × year-fixed effects. Standard errors are in parentheses and are clustered by sector. *Data*: PatentsView and Compustat. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 3. Top Firms that Magnify or Shrink the Estimates from Leave-One-Out Iterations

(a). Summary statistics across all 1,000 iterations

	Mean	Std. Dev.	Min	Median	Max
Patent filings	0.217	0.005	0.189	0.217	0.239

(b). Top five firms that magnified the estimate

Order	Firm	Country	Patent estimate *without* this firm
1	Denso Corporation	Japan	0.189
2	Hitachi-LG Data Storage, Inc.	Japan	0.197
3	Infineon Technologies AG	Germany	0.199
4	Daiichi Pharmaceutical Co., Ltd.	Japan	0.202
5	Optoelectronics Technology Co., Ltd.	China	0.202

(c). Top five firms that shrank the estimate

Order	Firm	Country	Patent estimate *without* this firm
1	Atochem	France	0.239
2	Tokai Carbon Co., Ltd.	Japan	0.235
3	Rhone-Poulenc Sante	France	0.235
4	Taiyo Ink Manufacturing Co., Ltd. (Fuji Manufacturing)	Japan	0.231
5	Nippon Carbon Co., Ltd.	Japan	0.230

Notes. Panel (a) shows summary statistics from 1,000 iterations that randomly left out one to three firms from the estimation sample. Panel (b) lists the top five firms that boosted the magnitude of the estimate; in other words, leaving out this firm shrank the estimate most. Panel (c) then lists top five firms that shrank the magnitude of the estimate; i.e., leaving out this firm magnified the estimate most.

Table 4. Price-Fixing Cartels and Innovation: Heterogeneous Effects by the Strength of Collusion

(a). Cartel formation and innovation

	Dependent variables ($\sinh^{-1}$): *Strength of Collusion (Split-sample)*			
	Patents by strong cartel (1a)	Patents by weak cartel (1b)	R&D by strong cartel (2a)	R&D by weak cartel (2b)
Treat × *Post*	0.291***	−0.052	0.203**	0.054
	(0.083)	(0.191)	(0.098)	(0.048)
Observations	432,275	431,000	149,874	149,825
R^2	0.554	0.540	0.921	0.920
Adjusted R^2	0.442	0.424	0.910	0.909

(b). Cartel breakup and innovation

	Dependent variables ($\sinh^{-1}$): *Strength of Collusion (Split-sample)*			
	Patents by strong cartel (3a)	Patents by weak cartel (3b)	R&D by strong cartel (4a)	R&D by weak cartel (4b)
Treat × *Post*	−0.119**	0.195	−0.045	−0.133*
	(0.056)	(0.166)	(0.090)	(0.075)
Observations	432,659	431,043	149,941	149,847
R^2	0.559	0.541	0.921	0.920
Adjusted R^2	0.448	0.425	0.910	0.909

Notes. These tables report regression coefficients from separate regressions based on Equation (1). Panel (a) uses cartel formation as an event, and Panel (b) uses cartel breakup as an event. The dependent variable consists of the number of patent filings (columns 1a, 1b, 3a, 3b) and R&D expenditure (columns 2a, 2b, 4a, 4b), all of which are transformed by the inverse hyperbolic sine function in a firm × year. *Treat* is an indicator variable that takes the value of one for colluding firms and zero otherwise. *Post* is an indicator variable that takes the value of one for the post-event (either collusion formation or collusion breakup) period and zero otherwise. A sector is defined by the four-digit North American Industry Classification System. All of the regressions control for firm-fixed effects and sector × year-fixed effects. Standard errors are in parentheses and are clustered by sector. *Data*: PatentsView. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 5. Financial Resources and R&D Investment: Reliance on External Finance and Revenue Growth

	Dependent variables ($\sinh^{-1}$): *R&D expenditure*			
	External financing before collusion		Revenue growth during collusion	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Treat × *Post*	0.083	0.243**	0.303***	0.021
	(0.057)	(0.116)	(0.087)	(0.077)
Observations	149,085	149,085	149,086	149,084
R^2	0.920	0.920	0.921	0.921
Adjusted R^2	0.910	0.910	0.909	0.910

Notes. This table reports regression coefficients from two sets of split-sample regressions based on Equation (1), around the formation of cartels. The dependent variable is R&D expenditure transformed by the inverse hyperbolic sine function in a firm × year. Column (1) shows the estimates from ten treated firms in sectors with above-median reliance on external finance, pre-collusion; Column (2) shows nine treated firms in sectors with below-median revenue growth. Column (3) shows the estimates from ten treated firms in sectors with above-median revenue growth; Column (4) shows nine treated firms with below-median revenue growth. *Treat* is an indicator variable that takes the value of one for colluding firms and zero otherwise. *Post* is an indicator variable that takes the value of one for colluding periods and zero for pre-collusion periods. A sector is defined by the four-digit North American Industry Classification System. All of the regressions control for firm-fixed effects and sector × year-fixed effects. Standard errors are in parentheses and are clustered by sector. *Data*: Compustat. **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

→ *Notes for Table 6*. These tables report regression coefficients from separate regressions based on Equation (1). Panel (a) uses cartel formation as an event, and Panel (b) uses cartel breakup as an event. The dependent variable consists of the number of patent filings (columns 1a, 1b, 4a, 4b), the number of patents in overlapping fields among colluding firms (columns 2a and 5a), the number of patents in distinct fields among colluding firms (columns 2b and 5b), and R&D expenditure (columns 3a, 3b, 6a, 6b), all of which are transformed by the inverse hyperbolic sine function in a firm × year. *Treat* is an indicator variable that takes the value of one for colluding firms and zero otherwise. *Post* is an indicator variable that takes the value of one for the post-event period (either collusion formation or collusion breakup) and zero otherwise. A sector is defined by the four-digit North American Industry Classification System. All of the regressions control for firm-fixed effects and sector × year-fixed effects. Standard errors are in parentheses and are clustered by sector. *Data*: PatentsView. **p* < 0.1; ***p* < 0.05; ****p* < 0.01.

Table 6. Price-Fixing Cartels and Innovation: Further Analyses on Firm Scope

(a). Cartel formation and innovation

	Dependent variables ($\sinh^{-1}$): *Scope of Firms*					
	Split-sample		Full sample		Split-sample	
	Patents by narrow firms	Patents by broad firms	Patents in overlapping fields	Patents in distinct fields	R&D by narrow firms	R&D by broad firms
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Treat × *Post*	0.330***	0.073	0.224**	0.178**	0.347***	−0.017
	(0.149)	(0.138)	(0.076)	(0.082)	(0.124)	(0.100)
			$\chi^2(1)$=0.17, p=0.68			
Observations	431,613	431,359	432,448	432,448	149,833	149,815
R^2	0.541	0.553	0.451	0.439	0.920	0.921
Adjusted R^2	0.426	0.440	0.312	0.298	0.909	0.910

(b). Cartel breakup and innovation

	Dependent variables ($\sinh^{-1}$): *Scope of Firms*					
	Split-sample		Full sample		Split-sample	
	Patents by narrow firms	Patents by broad firms	Patents in overlapping fields	Patents in distinct fields	R&D by narrow firms	R&D by broad firms
	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Treat × *Post*	0.085	−0.398***	−0.048	0.0002	−0.082	−0.004
	(0.115)	(0.146)	(0.052)	(0.058)	(0.163)	(0.125)
			$\chi^2(1)$=0.37, p=0.54			
Observations	431,421	431,327	432,993	432,993	149,820	149,813
R^2	0.543	0.554	0.468	0.454	0.920	0.921
Adjusted R^2	0.428	0.442	0.334	0.316	0.909	0.910