How Does Price Competition Affect Innovation? Evidence from US Antitrust Cases*

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An online appendix is available at: https://hyokang.com/research

Abstract

This paper examines how price competition in the product market affects the intensity and breadth of innovation. I assemble a unique data set comprising all 461 collusion cases prosecuted in the United States from 1975 through 2016 and match 1,818 collusive firms to firm-level data on innovation. Empirical results from a difference-in-differences methodology show a negative relationship between price competition and innovation. When collusion suppressed price competition, colluding firms increased patent filings by 28 percent and top-quality patents by 20 percent. A significant portion of these patents are attributable to genuine innovation activities because innovation inputs—R&D investment and the number of unique patenting inventors—increased in tandem by 16 percent and 34 percent, respectively. Furthermore, the number of patented technology classes increased by 16 percent as firms broadened their scope of innovation by exploring new technological areas. When competition was restored by collusion breakup, the increased and broadened innovation activities reverted to their previous levels. The effects were greater for collusion that was stronger and in fast-growing industries. I further explore market profitability and financial constraints on firms as potential mechanisms driving the trade-off between price competition and innovation growth.

Key words: 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). Innovation benefits consumers, producers, and society at large by bringing new technologies and products to market. Promoting the innovative activities of firms is of the utmost importance. Research and development (R&D) and the innovation processes, however, require risky and uncertain investment. It takes a firm several years, if not decades, to reap the returns on R&D investment. Furthermore, the social return on investment in R&D and innovation is much higher than its private value (Griliches, 1992; Bloom et al., 2013; Arora et al., 2021) because firms may fail to internalize the broader impact of their innovation activities under the presence of technology spillovers (or positive externalities). These two features of innovation lead to underinvestment in R&D and underprovision of innovation. Understanding firms' incentives and ability to innovate is therefore necessary to promote firms' innovation activities.

Another source of social benefit is healthy competition, which keeps prices low and production efficient. However, a long-standing debate in the literature continues about the role of competition in innovation. One approach argues that competition promotes the innovation activities of firms (e.g., Arrow, 1962). On the other hand, drawing from the insights of Schumpeter (1942), a different body of work argues that a certain amount of market power can promote innovation—more than would be achieved in a competitive market—by giving firms access to financial resources and predictability required for innovative activities. The so-called "competition-innovation debate" confirms that competition and innovation are strongly related, yet no consensus exists about their direction. Given this theoretical ambiguity, an empirical study of the two opposing arguments is important to determine which dominates and the mechanisms involved. Any empirical findings would, in turn, contribute to the existing theoretical debates.

This paper examines how price competition in the market affects firms' innovation activities. It considers how firms change their intensity and breadth of innovation in response to market competitiveness. The critical obstacle to empirical studies in this field is that competition and innovation are endogenously determined; that is, changes in competition may be correlated with unobservable factors that also affect innovation. In addition, firms that are successful in innovation gain market power, implying a reserve causality. These conditions explain the limited number of systematic, large-sample empirical studies demonstrating a relationship between competition and innovation (Cohen and Levin, 1989; Sidak and Teece, 2009, p. 588).

I address some of these challenges by exploiting variations in price competition stemming from price-fixing cartels. The formation and breakup of price-fixing cartels provide a novel setting to proxy for competition, or the lack thereof. The *formation* of collusion suppresses market competition because the primary purpose of a cartel is to eliminate competition and to raise prices. The *breakup* of collusion, in turn, terminates the conspiracy to suppress competition and therefore increases market competitiveness; this is the key mission of antitrust enforcement by the US Department of Justice (DOJ). I have collected and digitized data on all known (nonfinancial) cartel cases from 1975 through 2016 in the United States. The resulting sample consists of 461 cartel cases, along with 1,818 firms and 1,623 managers.

Existing studies tend to assume that innovative activities fall along a unidimensional continuum. An important question receiving relatively little attention is how firms explore new technological areas as market competition changes. The nature of innovation is a recombination of existing technologies, so it is essential that firms explore new technologies and use diverse ingredients in their innovation processes. Taking a step beyond the intensity of innovation, therefore, I examine the *breadth* of innovation, or how firms explore new technological areas. Making this distinction between the intensity and breadth of innovation could lead to a better understanding of "creative destruction" processes (Schumpeter, 1942).

Using a difference-in-differences methodology and matching colluding firms to carefully defined counterfactual firms, I find a negative relationship between price competition and innovation. When a cartel suppressed market competition, colluding firms increased patenting by 28.3 percent. A significant portion of the increase is attributable to genuine innovation activities as innovation inputs—such as R&D expenditure and patenting inventors—were also increased. I also find evidence that the breadth of innovation changed in parallel. With decreased competition, firms broadened their areas of innovation by 15.8–26.1 percent. The increased and broadened innovation activities reverted to their previous levels as a cartel broke up and price competition was restored. The effects were greater for collusion that was stronger and in fast-growing industries that provide higher ability and incentive to innovate. Further analyses suggest that firms facing financial constraints and operating in profitable markets innovate more in response to softening price competition. These findings have important implications for managers who strive to create and sustain a competitive advantage through innovation and for policy and law makers who design incentive systems for promoting innovation and social welfare.

2 Market Competition and Innovation

2.1 Intensity of Innovation

A long-standing debate exists about which market structure incentivizes and enables businesses to innovate ("the competition-innovation debate"). Arrow (1962) argues that monopolistic firms do not have an incentive to invest in innovation activities. This is because these firms already enjoy excessive profits (markups), and the marginal benefit of engaging in risky and uncertain R&D projects is low. Firms in a highly competitive market, on the other hand, should innovate to outperform their competitors as the marginal return of innovation is higher (i.e., the escape-competition effect). The standpoint of the US DOJ and the European Commission is aligned with this view that "one of the best ways to support innovation is by promoting competition" (Vestager, 2016).

A model by Lefouili (2015) shows that the intensity of yardstick competition increases the incentives to invest in cost-reducing innovations. Several empirical studies support this view. Correa and Ornaghi (2014) find a positive relationship between innovation and foreign competition, 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, contributed to productivity growth in the manufacturing sector of Brazil (Schor, 2004) and benefitted trading firms in China (Yu, 2015).

Schumpeter (1942), on the other hand, argues that market power can promote innovation. R&D and innovation activities require a large amount of fixed investment and a long-term, risk-taking orientation, both of which can be achieved only when firms have the ability and incentives to innovate. Fierce competition in the market (and thus lower prices and profit) restricts a firm's *ability* to innovate, because firms have fewer financial resources that can be allocated to innovation processes. Loury's (1979, p. 408) model shows that "more competition reduces individual firm investment incentives in equilibrium." With reduced competition, on the other hand, firms set prices higher than the marginal cost and reap higher profits, which provide financial resources for innovation (Schumpeter, 1942; Cohen and Levin, 1989); several empirical studies support this view.

Reduced competition could also provide *incentives* for innovation in three ways. First, reduced competition enables firms to more confidently invest in long-term R&D projects. R&D projects and innovation processes 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 in the long term ("Schumpeterian rents"). Second, firms expect higher average returns from innovation (or appropriability) when fewer firms are competing against each other. This provides additional incentives for innovation (Cohen and Levin, 1989; Schumpeter, 1934). Put differently, no market power lasts forever. With this dynamic view of market competition, even monopolists have the incentive to innovate to sustain their market dominance and their stake in profits in the long term. Third, diminished competition could prevent duplicate R&D investment by reducing preemption risk and duplication of investments. A concern that competing firms will preemptively patent or commercialize new technology impedes firms' investment in new R&D projects. Reduced competition significantly decreases such concern. This effect is magnified in the cartel setting because firms coordinate and monitor each other's production and pricing.[1]

Several empirical studies support the Schumpeterian view. Macher et al. (2021) studied how cement plants invested in a new cost-saving technology that required a large amount of up-front design and installation costs (around $800 million). Cement producers were more likely to make such investments

[1] See, for example, Igami and Sugaya (2022) on how colluding firms communicate with and monitor each other.

when facing softer competition. The ability to recoup the fixed cost, thanks to lower market competition, is one key mechanism driving the results, which are consistent with the findings of this study. In a study on Chinese import competition with the US manufacturing sector, Gong and Xu (2017) find 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) finds a negative relationship between market competition and citation-weighted patenting of publicly traded manufacturing firms in the United States. Autor et al. (2020) also find that competitive pressure from Chinese imports decreased R&D expenditure and patenting by US manufacturing firms. The evaluation of R&D by financial markets 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 embrace these competing views and consider the nonmonotone relationship between market competition and innovation (e.g., Loury, 1979). Williamson (1965) finds 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) find an inverted U-shaped relationship between competition and the patenting behavior of UK firms in the United States. In line with this finding are a formal model developed by Boone (2001) and empirical studies on R&D intensity (Levin et al., 1985) and on the market value of innovation (Im et al., 2015) in the US manufacturing sector.

2.2 Breadth of Innovation

Extant theories and empirical approaches tend to view innovative activities as falling along a one-dimensional continuum. An important aspect that has not been sufficiently considered, however, is the breadth or direction of innovation. Innovation is the recombination of existing technologies in a novel fashion (Grant, 1996; Henderson and Clark, 1990; Kogut and Zander, 1992; Nelson and Winter, 1982; Schumpeter, 1934). It is therefore crucial that firms engage in different types of activity and broaden the areas in which they innovate. A broader exploration of technologies could lead to unprecedented recombination of existing knowledge and breakthrough innovation. The broader scope of innovation also gives rise to a firm's absorptive capacity to identify, assimilate, and apply such knowledge ingredients (Cohen and Levinthal, 1990).

However, broadening the scope of technological innovation is even more difficult than increasing the intensity. Conducting R&D in a new technological field is more complicated and riskier than conducting R&D in an existing field. Firms do not possess as much absorptive capacity for new areas, and the project may develop slowly under a learning curve. This makes innovation activities in new areas costlier, riskier, and more time-consuming. All the difficulties in intensifying innovation apply more aggressively to broadening the scope of innovation. Consequently, firms that produce a new (substitute) technology are substantially more likely to fail (Lampe and Moser, 2013).

The impact of price competition on the breadth of innovation is ambiguous. On the one hand, it is possible that firms stop expanding their innovation scope and focus on a narrow technological area when competition softens. Firms may decide to focus on areas in which they face low levels of competition and enjoy high margins. On the other hand, when price competition in the market is suppressed, they have slack time and financial and cognitive resources that can be devoted to longer-term and riskier projects.[2] Thus, reduced competition can provide firms with incentives and the ability to broaden their technological horizon. Softening price competition can also promote R&D coordination—that is either explicit or implicit—between firms. Collusion, for example, facilitates communication and increases visibility between competing firms. As colluding firms discuss price levels and internalize each other's objectives, they learn about one another's R&D activities, which prevents multiple firms from duplicating efforts on the same technology. Since most firms tapped into rather small portions of entire technology fields (instead of fully saturating them), this suggests that reduced competition diversifies the R&D projects of individual firms, leading to an expansion of the firms' technological fields.

The relationship between price competition and the intensity and breadth of innovation thus boils down to an empirical question. Finding empirical patterns in the relationship should then, in turn, inform theory debates and arguments, enhancing our understanding of the relationship both theoretically and empirically. This paper aims to do so within the cartel context.

3 Data

Collusion Data. The Antitrust Division of the DOJ defines a cartel as price fixing, bid rigging, and market allocation in violation of Section 1 of the Sherman Antitrust Act. For cartel cases, the DOJ typically releases three types of documents in their Antitrust Case Filings repository: 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 operation was conducted. The documents also clearly define the relevant market by four-digit SIC code (for older cases) or six-digit NAICS code (for recent cases). The documents are prepared at the defendant firm or individual level, not at the collusion level. I grouped firms and individuals belonging to the same collusion using the information on the collusion period, market, and co-conspirators. Another source

[2] Consider the two types of investments: incremental (exploitative) investment and radical (explorative) investment. Up to a certain profit level, firms may keep investing in incremental innovation that cuts production costs or adds marginal features to their product; this is more relevant to a survival strategy to keep minimal competitiveness in the *current* market. Explorative investment, on the other hand, can be pursued only after securing a position in the market. When profit exceeds a certain threshold, the residual (extra profit) can be used for exploring new directions for innovation, the goal of which is to perform better in the *future* market.

of data on collusion is Wolters Kluwer's VitalLaw; its *Trade Regulation Reporter* provides summaries of the antitrust-related documents released by the DOJ and tracks recent developments of the cases. I digitized and analyzed all documents relevant to collusion (price fixing, bid rigging, and market allocation) and compared and verified the documents from the two sources line by line. As a result, I identified 461 collusion cases involving 1,818 firms in the United States from 1975 through 2016.[3] Table 1, Panel (a) presents descriptive statistics on these cartels. See the Electronic Companion ("EC") A.1 for details.

Patent Data. The primary source of patent data is the PatentsView platform. Supported by the Office of the Chief Economist in the US Patent & Trademark Office (USPTO), PatentsView contains information on inventors, assignee firms and their locations, and other details available in the original patent document. I used the 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. One concern is that information on location is sometimes inaccurate or inconsistent. To maneuver around this problem, I used Google Maps Geocoding API ("reverse geocoding") to convert geographic coordinates (GPS) consistently into names of corresponding countries, states/provinces, and cities. This process ensures that the geographic information for all assignee firms and inventors is accurate and consistent.

Another concern is that the patent data include no information on the industry at the patent or assignee firm levels, an important input when defining relevant markets and composing appropriate control groups. To navigate this problem, I converted the patent-technology fields, Cooperative Patent Classifications (CPC), to the North American Industry Classification System (NAICS) and aggregated them at the firm level. See EC A.2 for further information.

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 for the names of all firms that colluded. For example, "**^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 Electronics," "Sam-sung Elec," or "Sam sung Electronics, Ltd." Second, I applied string distance algorithms (q-gram and cosine distance) and listed the top-20 match candidates for each firm. I manually checked the quality of the match for both approaches. In the patent sample, 833 treated firms filed at least one patent. Table 1, Panel (b) presents firm-level descriptive statistics for patents.

Finally, I constructed a firm-year panel data set 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

[3] I exclude collusion cases in the financial sector (i.e., those in real estate, interest rate, or foreign currency exchange).

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 Collusion, Antitrust Enforcement, and Market Competition

A major difficulty in empirical studies on this topic is that competition is difficult to measure. Although, as Joskow (1975, p. 278) noted, "we have spent too much time calculating too many kinds of concentration ratios," the Concentration Ratio (CR_N) and the Herfindahl-Hirschman index (HHI) often fail to capture the level of market competition. Another challenge is that competition is endogenous; changes in competition may be correlated with observable and unobservable factors that also affect the outcome of interest. To mitigate concerns over endogeneity and capture the changes in price competition, this study exploits collusion cases.

Collusion, also referred to as the formation of a "cartel," is an agreement between competitors to restrict competition. The ultimate goal of collusion is to stifle price competition in the market. The Antitrust Division of the US DOJ categorizes collusion as (horizontal) price fixing, bid rigging, and 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 percent and that "American consumers and taxpayers pour billions of dollars each year into the pockets of cartel members" (Klein, 2006, p. 1). A survey of the literature concludes that price overages by collusion range from 18 percent to 37 percent (Connor and Lande, 2006). Government and competition authorities, therefore, have designed a strict set of rules that govern collusion. In the United States, since the enactment of the Sherman Antitrust Act (26 Stat. 209, 15 U.S.C. §1) in 1890, collusion has been *per se illegal* and punishable as a felony. Figure 1 shows the number of discovered collusion cases along with the number of indicted firms and individuals.

The formation and breakup of collusion change the level of price competition (in opposite directions) and provide unique opportunities to estimate how market competition affects key economic outcomes. The

[4] I used Compustat North America (as opposed to Global) to minimize the idiosyncratic variations in company size, scope, and regulations they face. Further analyses without non-US (particularly East Asian) firms can be found in EC C.7 and C.9.

formation, by definition, significantly suppresses market competition and inflates prices. The breakup of collusion in turn abruptly increases (recovers) the level of competition. Investigations of collusion are kept confidential to collect enough evidence before an indictment, 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, p. 466) estimate that "about 80 percent of the cartels in the sample ended with antitrust intervention" and that "the determinants of cartel breakup are legal, not economic, factors."[6]

4.2 Difference-in-Differences Estimation

In the difference-in-differences estimation, I compare firms that colluded (the treatment group) to firms in adjacent/similar markets that did not collude, but not to non-colluding firms in the same market. The control group is defined as firms that share a four-digit NAICS code, but not the 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 control group. The control group is chosen based on each firm's primary industry. In other words, a firm will be chosen as a control for NAICS **3254**11 if the firm has more patents or sales in this sector than in any other sector in which it operates; firms with marginal share in the market thus are not included in the control.

The primary research output comes from regression estimates that use linear regression techniques to explain how measures of innovation respond to collusion events that change competition. The two treatment events—the formation and breakup of collusion—provide unique opportunities when carefully considered in tandem. For example, the analysis of both events—and any opposite findings for the two—is doubly assuring and mitigates concerns that the effects may come from some idiosyncratic factors other than collusion. I estimate the difference-in-differences model in Equation (1) for four years before and after the year of the event (either cartel formation or breakup) with linear regressions:

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

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 for firm i) and $Post_{it}$ (an indicator variable meant to capture the post-event periods at the firm and year

[5] Another important detail about cartel enforcement is the leniency program. The DOJ has been implementing the leniency program since 1978; however, the program was not effective until major revisions were undertaken in 1993 (for corporate leniency) and 1994 (for individual leniency). This program grants immunity only to the first whistleblower that informs the DOJ of the existence of collusion and provides sufficient evidence to prosecute. EC C.12, Figure C-10, shows the temporal heterogeneity of the effects around the policy reform.

[6] See Levenstein and Suslow (2006, 2011, 2016) and Igami and Sugaya (2021) for a more detailed discussion on the determinants of collusion duration and breakup.

levels).[7,8] The regression model also includes firm-fixed effects ρ_i (note that $Treat_i$ is absorbed by the firm-fixed effect) and industry group (four-digit NAICS)×year-fixed effects, γ_{jt}, to control for both time-invariant characteristics of a firm that may determine the outcome of interest as well as any industry- and time-varying components of economic activity that may influence innovation activities. Note that the four-digit NAICS code (j) is used in the industry group×year-fixed effects to compare treated and control firms in the adjacent sector. I exclude firms from the control group that share the same six-digit NAICS code with the colluding firms to avoid spillover effects of collusion in the same narrowly defined market. For firms in the Compustat data, I use SIC codes because NAICS codes are available for recent years only. The coefficient of interest is β_1, which captures the relationship between collusion-induced competition and innovation.

I also estimate several variants of this regression that include more flexible econometric specifications. Formal event-study regression techniques are expressed in Equations (2) and (3):

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

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

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 that takes the value of one for the first two years of collusion and zero otherwise, and $Post_t^B$ is an indicator for the following two years of collusion (i.e., from the third to the fourth year of collusion). X_{it} includes all lower-order terms. In Equation (3), τ is the year of the event (either cartel formation or cartel breakup). With this flexible event-study approach, I can explicitly check the parallel trend assumption for the pre-event period and how the effects vary over time for the post-event period.

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

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[7] The inverse hyperbolic sine transformation is defined as $y^{IHS} = \sinh^{-1} y = \log(\, y + \sqrt{y^2+1}\,)$. It has the same interpretation as a standard logarithmic dependent variable and is approximately equal to $\log 2y = \log y + \log 2$, except for very small values of y. One advantage of $\sinh^{-1}(.)$ transformation is that the function is defined for any real number including zero (Burbidge, Magee, and Robb, 2012; Bellemare and Wichman, 2019). Alternatively, I estimate the Poisson Pseudo-Maximum Likelihood Estimation with patent counts (results reported in EC C.2).

[8] 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.

the formation of collusion and serves as the baseline (an omitted category). $Collusion_t^1$ represents early 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. $Post_t^1$ means one to three years after the breakup of collusion. $Post_t^2$ means four to six years after the breakup of collusion. $Post_t^3$ means seven to nine years after the breakup of collusion. In all specifications, standard errors are clustered at the industry group level (four-digit NAICS).

There are three concerns about using cartel formation and breakup events. First, the DOJ's enforcement may be negotiated for each firm ("prosecutorial discretion"), and the DOJ's ability to claim the collusion period is limited by the evidence collected. The start and end dates reported by DOJ may not accurately represent the actual duration of cartels. 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 colluding firms. 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 et al., 2021). This selection needs to be carefully assessed in interpreting the results. The findings are more applicable to relatively large firms 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 a bad comparison where 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 et al., 2022; p. 374)," and a vast majority of firms in the sample (98 percent) are never-treated units. Further, with the industry (four-digit NAICS)×time fixed effects, the empirical estimation compares within the same four-digit NAICS sector. This approach avoids such problematic comparisons because there are few cases where multiple collusion happened in each four-digit NAICS sector, so "already treated" observations are not used as control in most cases.

5 Main Results

5.1 Intensity of Innovation

Patents. I start by examining the raw data as regression models may be sensitive to underlying assumptions and transformations. This task is challenging in the cartel setting because (1) there are two events to consider (i.e., each cartel forms and lasts several years and then breaks up) and (2) cartel duration differs across firms and/or cartels. In consideration of these challenges, Figure 2 graphically presents the average number of patent filings—standardized by their pre-collusion or pre-breakup levels, respectively—by colluding and comparison firms. The only transformation, normalization of the outcome variables based on pre-event values, is made to account for the different absolute levels of patenting across firms. Figure 2 shows the innovation activities of firms, measured by patent filings, for the colluding firms (the red line) and for comparison firms in the same four-digit NAICS sector (the blue line); the shaded region represents the standard errors from the mean. Without fixed effects and other adjustments, Panel (a) shows that, compared to the comparison firms, colluding firms significantly increased patent filings after forming cartels. In contrast, Panel (b) illustrates how such innovation activities of colluding firms declined gradually over time after the breakup of cartels.

To further check the raw data patterns for a case, I investigated the vitamin cartel that has been studied extensively in the industrial organization (IO) literature. The primary focus to date has been on the incentives that motivated the vitamin cartel to collude or to distort prices (e.g., Bernheim, 2008; Igami and Sugaya, 2022). The vitamin cartel has been found to have overcharged up to 100 percent of the but-for price, but their innovation activities have not been studied to date. Figure 3 shows the patent filings (standardized by Z-score) by colluding firms (the red line) and by non-colluding firms in the same industry (the blue line), and the linear benchmark based on their out-of-collusion patenting trend (the dashed line). The colluding firms significantly increased their innovation activities during collusion, compared to the benchmark. The non-colluding firms in the same market also tended to increase innovation, but the magnitude is much smaller than that of the colluding firms.

Having explored both the aggregated evidence and a case-specific model-free example, I turn to formal regression analysis of the data. Table 2(a), columns 1–4 show the effects of competition on three measures of innovation intensity—patent count, the count of top-10-percent-cited patents, and citation-weighted patents—based on Equation (1). Panel (a), column 1 indicates that firms that colluded increased patenting by 28.3 percent after the formation of collusion. Colluding firms on average filed 46.3 patents per year immediately before the formation of collusion, so the 28.3 percent increase in patenting is equivalent, on average, 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). After the formation of collusion, firms that colluded increased patenting by 19.4 percent in the short term ($Treat \times Post_A$) and by 33.2 percent in the longer term ($Treat \times Post_B$). Estimates shown in Panel (b), however, indicate that, after the breakup, firms that colluded decreased patenting by 10.4 percent in the long term ($Treat \times Post_B$). The estimates obtained with an alternative approach, Poisson Pseudo-Maximum Likelihood Estimation, are highly consistent (see EC C.2).

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 percent confidence intervals, with relative Year −1 as the baseline. Horizontal lines and the boxes around them represent the point estimates and 95 percent 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 increased patent filings after they began to suppress competition via a cartel. This gradual increase in innovation output is consistent with the patterns of price changes in cartels. For example, product prices began to increase right after the formation of the vitamin cartel and reached a 100 percent increase in three years (Bernheim, 2008).

Table 2(b), on the other hand, indicates that colluding firms decreased patenting after the breakup of collusion; in column 1, the pooled estimate is –7.3 percent 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 and patent filings 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 that firms that colluded decreased patent filings after price competition was restored as collusion broke down.

I then analyze the formation and breakup of collusion in a single framework and investigate how innovation changes over the life cycle of collusion. Table C-2, columns 1–3, in the EC C.1 shows the regression results on innovation intensity. The results for patent counts, illustrated in Figure 4(b), are consistent with the previous findings. The innovation intensity increased only during the collusion period and then gradually reverted to the pre-collusion level after collusion breakup. The opposite responses to the formation and breakup of collusion doubly ensure that the model indeed captured the effects of collusion-induced changes in competition and not those of factors unrelated to competition and unknown to researchers.

There is a significant amount of variation in the quality of patents. A count of patents may not capture the patents' quality or impact. To better measure the fundamental innovation activities of firms, I also examine quality-adjusted patents. First, I further examine the counts of high-quality patents: patents that belong to the 90th percentile or above in terms of citations received by later patents in the same three-digit CPC × year. Table 2(a), column 2, reports that firms indeed increased innovation activities and registered impactful and high-quality patents by 20.4 percent when collusion suppressed price competition. Second, studies find that citation-weighted patents are more highly correlated with patent quality or market value than with patent counts (Lampe and Moser, 2016; Hall et al., 2005; Trajtenberg, 1990). The results on citation-weighted patents are similar to those on patent counts and high-quality patents (27.1 percent), as shown in Table 2(a), column 3. This pattern reversed when collusion broke up, which is doubly assuring. It was not the case that firms engaged in marginal inventive activities that have little impact on future scientific progress.[9] This finding, taken together with the breadth of innovation results discussed in Section 5.2, may

[9] In EC C.3, I also tested the average long-term influence of patents (Corredoira and Banerjee 2015). This measure incorporates indirect forward citations and counts how many times the focal patent was cited, how many times the patents that cite the focal patent were cited, and so forth. I do not find evidence that price competition meaningfully changed the

be due to the risky nature of exploration and to the fact that exploration is not always successful or may not have long-lasting impacts across several generations of inventions.

R&D Investment. R&D investment is the most important input for innovation. Column 5 in Table 2(a) shows that colluding firms increased their R&D expenditure by about 16.4 percent during collusion, compared to the pre-collusion period. This is equivalent to an additional $76 million spent on R&D projects per firm per year. After the collusion breakup, the increased R&D expenditure gradually decreased. One important caveat is that the Compustat data consist of a selected sample of public firms that tend to be larger and higher in the organizational hierarchy. One should be careful when comparing R&D investment results to those for patents.

To further ensure the validity of the control group, I use Compustat Segments Data, which provides granular information by business and geographic segments of firms. First, I compare firms that have one or two business segments to those with three or more segments. In Table 5, columns 3a and 3b, the effects are driven primarily by firms that operated in no more than two business segments. Second, I restrict the sample to those with at least 75 percent of sales from a single sector (four-digit SIC). I find a greater effect with this restriction (see EC C.8, Table C-11). Third, I restrict the control group so that control firms operate in a similar set of markets in addition to the market where collusion occurs. Specifically, I additionally require treated and control firms to have their largest amount of business in the same segment. The results are robust to these additional restrictions on the control groups. Empirical analysis excluding colluding firms that participated in R&D collaboration also provides consistent results (see EC C.4, Table C-8, for more details). These analyses with business segment data consistently indicate that the results are not driven by a mismatch between treated and control firms.

5.2 Breadth of Innovation

Firms may also broaden their scope of innovation as they increase their innovation intensity. I measure the breadth of innovation by counting (1) the number of unique technology fields, defined by the four-digit CPC, at the firm-year level, and (2) technology-class-weighted patents, measured in the same way as citation-weighted patents.[10] Table 2(a), column 6 indicates that the number of patented technology fields increased by 15.8 percent when market competition was suppressed by collusion. This is equivalent to one additional field as colluding firms patented in 6.5 technology fields before collusion (out of 674 fields). Figure 4(c) illustrates the results from flexible event-time estimations. After the breakup of collusion, on the other hand, the breadth of patenting dropped by 6.5 percent as shown in Table 2(b), column 6, and up to 12 percent in the longer term (EC C.1, Table C-1).

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average long-term influence of patents.

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

A single framework of the life cycle of collusion is shown in Figure 4(d) and EC C.1, Table C-2. The results show solid evidence that firms explored new fields and broadened their scope of innovation during collusion. An alternative measure, the technology-class-weighted patents, also confirms these findings.

The results, however, offer no indication of how patenting activities are distributed across different technology fields. Firms may allocate their innovation activities across either existing fields of innovation (exploiting) or new fields of innovation (exploring). To further examine this, I test patenting activities in a firm's primary technological area, which is defined by each firm's three most frequently patented technology classes (according to CPC), 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 percent) and peripheral (26.9 percent) technology areas. In other words, reduced competition enabled firms to explore new technological areas as well as strengthen their innovation in existing areas. Firms managed a well-balanced portfolio of exploitive and explorative innovations. The estimates from an alternative approach, Poisson Pseudo-Maximum Likelihood Estimation, are highly consistent (see EC C.2).

These results are, to some extent, consistent with recent empirical findings in different contexts. Krieger, Li, and Papanikolaou (2022) study the pharmaceutical industry and find that R&D on "novel" drugs (as opposed to "me-too" drugs) is riskier and that more profits promote R&D on novel drug candidates. The key mechanism here is that financial frictions hinder the ability to invest in novel, riskier drugs and the incentives for doing so. Turner et al. (2010) find that, in a less competitive market, US software firms became more responsive to generational product innovations (GPIs) by external actors and less responsive to their own historical patterns of innovation. In other words, as the level of competition decreased, firms explored unprecedented innovations that were new to the firm. As discussed in Section 2, the focus of Macher et al. (2021) is on the adoption of a cost-saving technology for a manufacturer's current line of products. This "inability to invest in new technology" must be exacerbated for new areas of innovation that are not directly linked to a firm's current products or technologies.

While firm-level evidence is rather scarce, individual- or team-level studies support this view. 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 ("labor effort") in a head-to-head tournament competition, whereas they were more likely to choose more complicated tasks ("cognitive effort") in a pay-for-performance setting without competition. Gross (2020) finds from a logo competition platform that intense competition decreased the originality and unprecedentedness of artists' ideas.

5.3 The Impact on Non-Colluding Firms

The analyses so far have focused on firms that colluded. Yet the price-fixing behavior of colluding firms may not only change their own behavior but may also affect competitors in the same market. An important strategic question is how competitor firms are affected by collusion; this is a critical issue in the competition-innovation debate. I run a set of analyses where the new treatment group is (1) firms in the focal industry that were *not* part of the collusion and (2) all firms in the focal industry regardless of their participation in collusion. The control group remains the same (i.e., firms in the adjacent/similar markets).

Figure 5 graphically summarizes the results. Panels (a) and (b) show the flexible difference-in-differences results for patent filings around cartel formation and breakup. In Panel (c), the point estimates presented with blue bars indicate that non-colluding firms did not meaningfully change their intensity and breadth of innovation (–1.3 percent for both, statistically not distinguishable from zero).[11] The effects on both colluding and non-colluding firms altogether, estimated at the firm-year level, likewise are close to zero. This suggests that colluding firms drove the innovation activities, and firms that were left out of the club could not join the innovation race.

5.4 Heterogeneity and Robustness Checks

Which Firms and Cartels Drive the Result? Leave-one-out iterations. The results in Sections 5.1 and 5.2 are average effects. It is important to understand the heterogeneity, in particular for the firms or cartels for which we see the largest (or smallest) effects. To understand whether a small number of outlier firms is driving the entire results, I randomly excluded one to three treated firms from the sample and estimated the model. There are two randomization parts: (1) the number of colluding firms (one to three) to be excluded are decided and (2) the chosen number of colluding firm(s) are randomly excluded from the sample.

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 4, Panel (a) shows the summary statistics from all iterations, Panel (b) shows the top five firms that magnified the size of the effect (i.e., the estimate decreases without this firm), and Panel (c) shows the top five firms that shrank the size of the effect (i.e., the estimate increases without this firm). Those contributing most to upward estimates were pharmaceutical and semiconductor firms, and three Japanese firms were among top contributors in either direction. Further, I performed the same exercise at the cartel level. The results in EC C.6 are consistent with the firm-level findings.

Second, the distribution of estimates from 1,000 iterations is illustrated in Figure 6. The estimates on the intensity and breadth of innovation are robust to the random exclusion of treated firms and are bunched closely together, suggesting that the effects are not driven by a small number of outlier firms.

Placebo Permutation Tests. To check the possibility that the findings resulted from a mechanical, spurious

[11] Although I used most granular, six-digit NAICS sectors to define non-colluding firms in the same market, the list may also include firms that don't directly compete in the collusive market. As such, the findings provide the lower bound of the effects.

pattern generated in the data construction and empirical analysis stages, 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 non-colluding firms that belong to the same four-digit NAICS industry. Figure 7 graphically summarizes the results for patents. Gray lines represent 1,000 placebo permutations and, on average, show no effect. The patenting activities by colluding firms are clearly distinct from placebo permutation results, suggesting that the effects do not come from spurious, arbitrary components of the data and models.

6 Further Analyses of Potential Mechanisms

6.1 Financial Constraints

One main argument in the Schumpeterian view is that softening price competition affords firms more financial resources, which then can be allocated to innovation activities. Two predictions arise. First, firms that had limited access to external finance *before* collusion are predicted to benefit more from the extra profit earned during collusion. Second, firms that enjoyed high revenue growth *during* collusion are predicted to benefit more and to invest in R&D activities compared to firms that experienced low revenue growth. The estimation results are provided in Table 3. First, in columns 1 and 2, firms that had limited access to external finance prior to collusion responded more aggressively by increasing R&D expenditures by 27.5 percent (column 2). In addition, analyses on revenue growth are provided in columns 3 and 4. The increase in R&D expenditure was driven primarily by firms that reaped higher revenue during collusion (35.4 percent; column 3), while the estimate for firms with low revenue growth during collusion (2 percent) is economically small and statistically indistinguishable from zero.

One potential concern is that East Asian firms often have better access to financial resources. For example, these large conglomerates may own financial institutions within the corporation and may more easily fund their innovation projects; but that does not seem to be the case. Additional analyses without East Asian firms did not qualitatively change the results (see EC C.9 for details). In fact, East Asian countries in the sample (e.g., South Korea and Japan) have certain regulations in place to ensure the separation of industrial and financial capital.

Note that the reliance on external finance before collusion is correlated with the expected profitability of the market. Similarly, revenue growth during collusion also signals the expected profitability in future periods. Due to the inherently intermingled nature of financial constraints and future profitability, this investigation does not rule out the future profitability channel. Carefully designed follow-on studies—perhaps lab or field experiments—may tease out the current revenue streams from the expectations on future profitability.

6.2 Corporate Scope: Market Profitability and Corporate Financial Reallocation

Some firms have broader business scope and operate in multiple business segments. It is therefore important to understand whether innovation occurs in exactly the same market where firms colluded (through market profitability) or in different markets in which the colluding firms operate (through corporate-level financial reallocation). In this section, we further explore the financial channels in relation to firm scope. The question is whether the expected profitability of a particular, collusive market is the main driver for innovation or whether the extra profit from the collusive market is reallocated across units within a corporation and boosts their innovation rather than that of the colluding unit. I take three approaches to answer this inquiry.

First, with patent data, I measured the technological concentration of firms using the HHI of patent-technology fields. If a firm patents exclusively on a few technology classes (i.e., high concentration), this firm likely has narrow scope (e.g., a single-unit business), and the extra profit from collusion must be allocated to the same, collusive market. On the other hand, if a firm's patenting activity spans many different technology fields (i.e., low concentration), the extra profit from collusion may be allocated across broad business units outside the collusive business segment or unit. I conducted a split-sample analysis comparing narrow versus broad firms. In Table 5, column 1a, reports the increase in patents during collusion came primarily from narrow, focused firms (39 percent), consistent with the market profitability channel. Interestingly, after the breakup of collusion, firms with broader scope were more responsive and decreased patenting (–32.8 percent), as reported in Table 5, column 7b, possibly due to criminal fines and treble damage compensation that could affect the entire corporation.

Second, exploiting the nature of collusion—that colluding firms fix the price on the *same* products or services—I identified patent filings in the overlapping and non-overlapping technology fields among colluding firms. The overlapping fields are defined as the five most frequent intersections of patented technology fields (i.e., primary and secondary four-digit CPC) among all colluding firms. I checked whether colluding firms increased their patent filings in the overlapping technology fields to a greater extent than did those in the non-overlapping (or distinct) technology fields. Table 5, column 2a, shows that the magnitude of the effects is greater for overlapping technology fields (25.1 percent), providing another support for the market profitability channel. Column 2b indicates that patenting in non-overlapping fields also increased by 19.5 percent (the difference between the two is not statistically significant); this estimate likely captures the increased breadth of innovation activities during collusion, as discussed in Section 5.2.

Third, granular business segment data offered by Compustat Segment provides an opportunity to measure firm scope. I ran a split-sample analysis comparing firms with 1–2 business segments and those with three or more segments before collusion. Table 5, columns 3a–3b, show that the R&D expenditure disproportionately increased for narrow firms, consistent with the market profitability channel. Additional analyses on single-segment firms or firms with most sales (75% or higher) from a single segment are provided in Table C-11, EC C.8. In sum, a series of analyses herein is consistent with market-level profitability being the driver of pro-innovation effects during collusion.

6.3 Industry Growth: Growing versus Mature Sectors

The industry life cycle could change the dynamics of price competition and innovation. On the one hand, a fast-growing market can promote innovation for reasons discussed in Sections 6.1 and 6.2. If the market is mature and does not grow, a softening price competition may not spur innovation effectively because financial resources for innovation or the expected return on innovation are lower in stagnant markets. On the other hand, a mature market can promote innovation—in particular, explorative innovation. Collusion may form in mature markets as incumbent firms face limited profitability and seek to avoid price competition; this also implies that firms may search for opportunities in other markets and broaden their innovation activities. The two arguments provide opposing predictions on how industry cycles are associated with the intensity and breadth of innovation during collusion. To find an empirical pattern, I examine the average rate of industry growth five years prior to cartel formation as measured by patents filed in four-digit NAICS sectors×year. The top fast-growing sectors include nanobiotechnology, computer storage devices, engine manufacturing, display manufacturing, and wireless communications (see EC C.10, Table C-13). I ran regressions as in Equation (1) on key measures of innovation.

Figure C-8 in the EC C.10 illustrates the results. The estimates from firms in the fast-growing sectors are greater in magnitude and more precisely estimated than those in the mature sectors along all three aspects of innovation—all patents, top 10 percent of patents, and patent-technology classes. Firms in the mature markets, however, did not increase their innovation intensity or breadth as much.

One may argue that this empirical pattern is observed because firms might seek to escape the mature, colluding market and reallocate resources toward different markets. In such a case, however, we expect to observe greater effects on the breadth of innovation for firms in mature sectors as they rebalance their innovation portfolio. The results in EC C.10 are not consistent with this view as the technology-class estimate for firms in mature industries is smaller in magnitude than in fast-growing industries. In addition, after collusion breakup, the breadth of innovation reverted to the original level as shown in Figure 4(d); this is not consistent with the "escaping the sinking ship" effect. Taken together, the results are more consistent with the argument that firms shift toward innovation competition when price competition is suppressed.

6.4 Innovation versus Intellectual Property Strategy

The effects of collusion on R&D expenditure are smaller than those on patenting activities. One reason may be that the Compustat database consists of corporations that are already large and active in research and that are likely to be in at a later point in their business life cycle. Another explanation is that price competition changes firms' strategy toward intellectual property. Cartels, or market competition in general, change a firm's incentives and propensity to patent, and not all patents are born of genuine innovation activities. The observed change in patenting, for example, may be due to changes in the need for strategic patenting (e.g., Hall and Ziedonis, 2001; Lerner, 1995; Kang and Lee, 2022), to patent (cross) licensing (Priest, 1977; Eswaran, 1993; Arora, 1997; Arora and Castagnoli, 2006), or to incentives to show off their innovation.

To determine whether firms indeed innovate, it is important to examine how they changed their innovation *input*. One could infer that a significant portion of patenting comes as a result of more input (R&D) into innovation activities. Assuming a directly proportional relationship between patents and R&D investments, roughly 61 percent of the increase in patenting shown in Table 2, column 1, can be explained by a firm's genuine R&D efforts (a caveat is that the effects on patents and R&D expenditure are estimated from a different sample).

Another more direct measure of innovation input concerning patenting is the number of inventors that engaged in inventive activities. If the patenting results come entirely from an intellectual property strategy, one should expect the same pool of inventors to have registered more patents (including those previously kept secret), and the number of inventors to not have changed meaningfully. In contrast, if firms increased their innovation activities, these activities should accompany patent filings by inventors new to the firm. I thus examine how the number of unique inventors who patented in a given year change over time (three-year moving average), around the collusion formation and breakup.

Table 5, column 4 shows that the unique number of inventors increased by 22.9 percent during collusion. Moreover, the yearly estimate of unique inventor counts closely follows the changes in patents (see EC C.1, Figure C-5). This suggests that increased patenting was accompanied by an increased number of new inventors, more consistent with the innovation argument (than with the propensity to patent or IP strategy argument). Furthermore, as a new set of inventors is expected to bring knowledge that is distinct from that of existing inventors, this finding provides further support that firms indeed broadened their innovation scope by bringing new inventors and consequently new knowledge.

6.5 The Strength of Collusion

Cartels differ in several aspects. To achieve the common goal of fixing or raising prices, one of a cartel's most important characteristics is the strength of its collusion or its ability to set the price. If market competition suppressed by price fixing indeed drove the results, greater effects should be observed for firms in strong collusion. In contrast, firms in weak collusion may fail to promote intensity and breadth of innovation.

I measure the strength of collusion by the patent share (for patent analysis) and sales share (for R&D analysis) of colluding firms. I run a split-sample analysis for strong collusion (those with above-median share) and weak collusion (those with below-median share). Table 5 shows the patent results in columns 5a and 5b and R&D results in columns 6a and 6b around the cartel formation (Figure C-9 in the EC C.11 illustrates the results). Firms in strong collusion on average increased their patenting activities by 33.8 percent and R&D expenditure by 22.3 percent, whereas those in weak collusion exhibited economically small and statistically insignificant effects. The results provide support for the theory that the ability of collusion to suppress price competition indeed drove the empirical pattern between competition and innovation.

7 Discussion

Consistent with Schumpeter (1942; p. 102), a softened competition may not be "a cushion to sleep on". In this study's setting, in which firms in technology-intensive industries colluded to fix prices, firms shifted toward innovation competition and broadened their technological exploration after forming a cartel. Managers must understand this fundamental shift (i.e., from price to innovation) in the arena of competition and set appropriate innovation strategies. Firms that rely on the high price-cost margin may fall behind in competition for innovation. Channels through which this shift occurred—namely, corporate scope, access to external finance pre-collusion, extra revenue earned during collusion, the industry business cycle, and the strength of collusion—provide additional insights on the primary empirical patterns found. In particular, an investigation of heterogeneity suggests that high-tech sectors such as biopharmaceuticals, semiconductors, disk storage, and liquid crystal display exhibit greater pro-innovation effects.

Implications for public policy and law enforcement also merit further discussion. The goal of the DOJ has been, understandably, to promote price competition. Since "cartels inflate prices, restrict supply, inhibit efficiency, and reduce innovation" (Pate, 2003), collusion is considered a *supreme evil* of antitrust. The European Commission (EC) maintains a similar view that cartels "reduce their [firms'] incentives to provide new or better products and services at competitive price" and that the competition is the mother of invention. This view, however, may not fully consider that price in turn affects firms' incentives and their ability to innovate in the long run. Innovation activities of firms could promote consumer welfare with new products or services that had not been available before; in price terms, new inventions reduce the price of previously unavailable products (e.g., a vaccine for the Zika virus or the coronavirus) from infinity to a finite level. With the empirical patterns discovered in this study, therefore, the prevailing view that price competition always promotes innovation and social welfare becomes less clear.

In addition, considering the social return of innovation to be higher than the private return magnifies the importance of innovation. Social return is estimated to be at least twice as high as private return (Bloom et al., 2013). To the extent that the social benefit of innovation outweighs the social loss of price distortion, therefore, it is important to promote market structures that provide firms with incentives and the ability to innovate (Gilbert, 2006a, 2006b). Further, the heterogeneity by sectors discussed in Sections 5.4 and 6.3 also has important policy implications for how the competition authority allocates its limited resources and attention over different markets based on the industry characteristics.

This line of argument by no means suggests that price competition harms innovation and therefore that promotions of market competition should be stopped. The empirical findings show, however, that a certain level of insulation from fierce price competition *may* facilitate the innovation activities of firms, especially for firms facing (or expected to face) financial constraints and for those in fast-growing, technology-intensive industries. Thus, antitrust authorities and policy makers may need to consider the potential benefits and costs of reduced competition under the *rule of reason*, rather than making it unlawful under any circumstances (*per se illegal*).[12] DOJ indeed increasingly acknowledges the importance of promoting innovation (Alford, 2018). My conversations with DOJ and FTC officials and economists also reveal that they consider the benefits of innovation and put more weight on it. More research in different industrial and competitive contexts is required to enhance our understanding of how to achieve the social optimum by balancing the price and innovation consequences of product market competition.

8 Concluding Remarks

Innovation is the primary source of a firm's competitive advantage and economic growth. The key empirical relationships found in this study are that firms shifted toward innovation competition and broadened their innovation scope when price competition weakened due to collusion. That is, the reduced competition was not a cushion to sleep on (Schumpeter, 1942) but induced an important change to the rules of the game: from price competition to innovation competition. Further analyses reveal that firms with narrow business scope, firms with limited access to external finance before colluding, and firms in fast-growing sectors reaped higher revenues during collusion exhibited greater effects in terms of innovation intensity and breadth. The strength or effectiveness of the cartel also helped firms engage in innovation during collusion. The relationship between collusion-driven competition and innovation is highly relevant to the growing literature on how market competition is associated with international trade and with mergers and acquisitions (M&A) and on how each affects firm innovation (e.g., Autor et al., 2013, 2020; Miller and Weinberg, 2017).

The empirical patterns found in this study require careful interpretation and application. First, the findings do not necessarily establish a causal relationship and may be subject to confounding factors. Firms were not assigned to collusion in a random manner, and there is a certain selection into the treatment (e.g., larger firms tend to form a cartel; see EC A.2). Breakups are also subject to unobservable factors such as whistleblowers taking advantage of the leniency policy. Whether the cartel is prosecuted with the cooperation of a whistleblower and the identity of the firm is kept strictly confidential even within the DOJ. Second, I estimated the effects for the colluding firms caught by DOJ, which may not be generalizable to undiscovered cartelists and non-colluding firms left out of the cartel. In this sense, the estimate is at best the average effect *on the treated* (those who colluded and were caught). Relatedly, the estimates are from innovating firms that invest in R&D and file patents; the findings may not readily apply to other types of

[12] A similar change was made in 2007 for the minimum resale price maintenance (i.e., the price floor). It 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).

firms. Third, the focus of this study is on collusion, which tends to arise in a moderately concentrated market, so the findings herein may not be readily generalizable to highly competitive markets. Further, collusion is one particular form of competition or the suppression thereof. The implications of competition induced by foreign trade (import penetration), government subsidies, mergers, patent pools, or privatization of public firms may differ across contexts. 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. However, the competitive pressure from low-cost products by foreign countries should have consequences and implications different from the price competition manipulated by collusion among leading companies in technology-intensive industries.

With these cautionary remarks, this study contributes to the literature in several ways. First, the results broaden our understanding of the effects of competition beyond the price level. I consider another important economic outcome—innovation—and find that price competition could change firms' incentives and ability to innovate. This sheds light on the important trade-off between price competition and innovation growth; the latter is becoming increasingly important in the knowledge-based economy. Second, taking a step beyond the intensity of innovation, I study the breadth of innovation. This distinction enables a deeper understanding of the relationship between competition and innovation and has important implications for the quality and novelty of innovation and the value of future technologies and products. Third, I collected data on all discovered collusion cases and estimated the average effect on firms that colluded. This novel approach enables researchers to measure competition and examine its association with important economic outcomes. More broadly, collusion is a highly strategic (yet illegal) agreement between firms in the same market to not compete on prices and thus presents an important research agenda in the fields of business, economics, strategic management, and public policy. I hope that new, comprehensive collusion data and their linkage to various databases provide new avenues for studying important questions about competition, strategic interactions between firms, and firm performance and their relationship to society.

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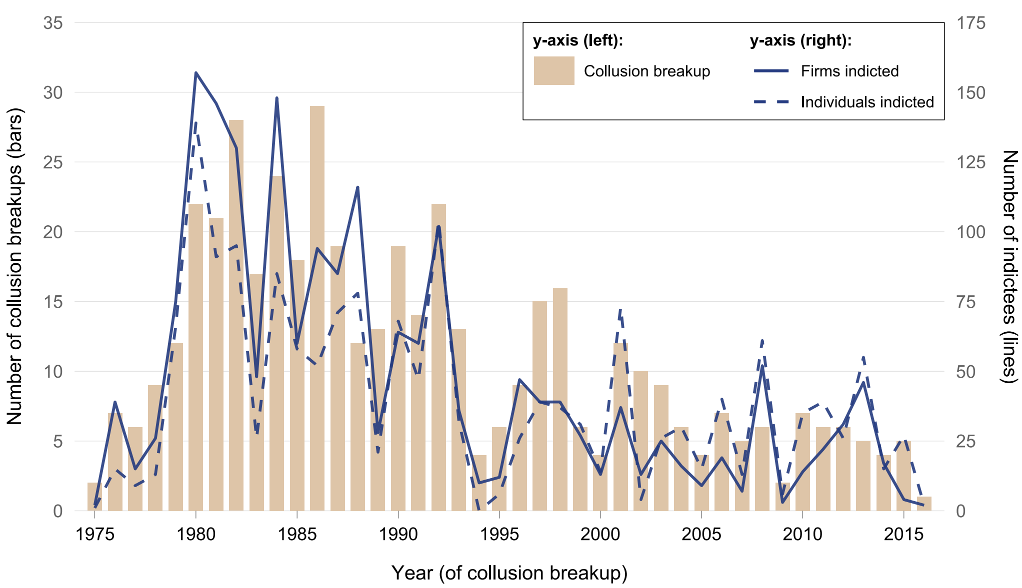
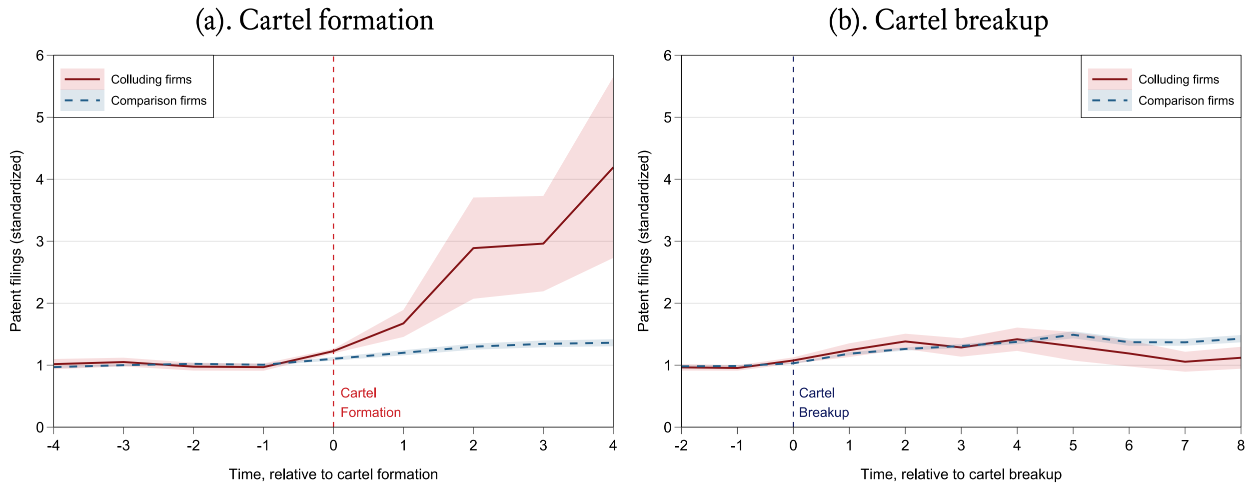
Figure 1. Cartels in the United States, 1975–2016



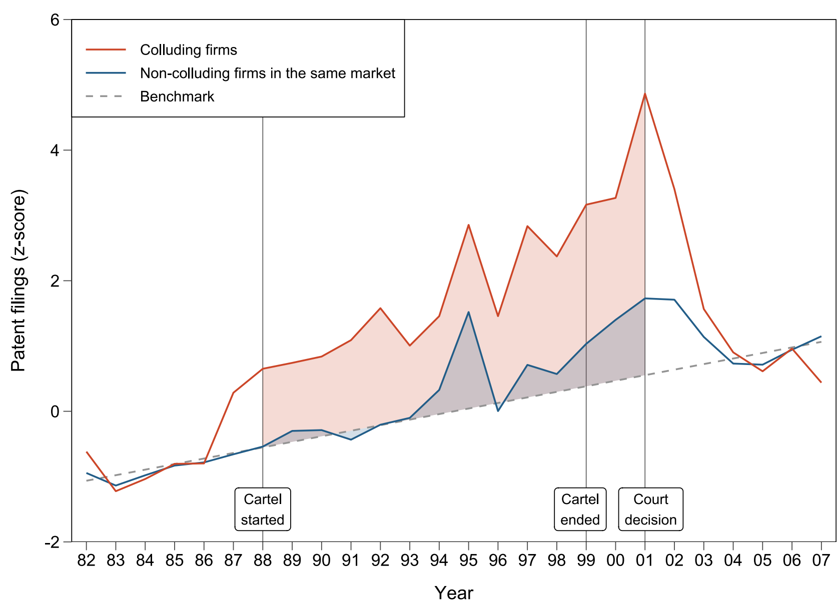
Notes. This figure tracks the trend in antitrust enforcement and collusion breakup in the US from 1975 through 2016. Brown bars represent the number of collusion breakup cases by year. The solid blue line represents the number of firms indicted for collusion each year, whereas the dashed blue line represents the number of managers accused of participating in collusion. Collusion cases in the finance sectors (e.g., real estate brokerage, mortgage rate, interest rate) 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 (DOJ) and the *Trade Regulation Reporter* of Wolters Kluwer's VitalLaw.

Figure 2. Collusion Formation and Patents: Model-Free Evidence



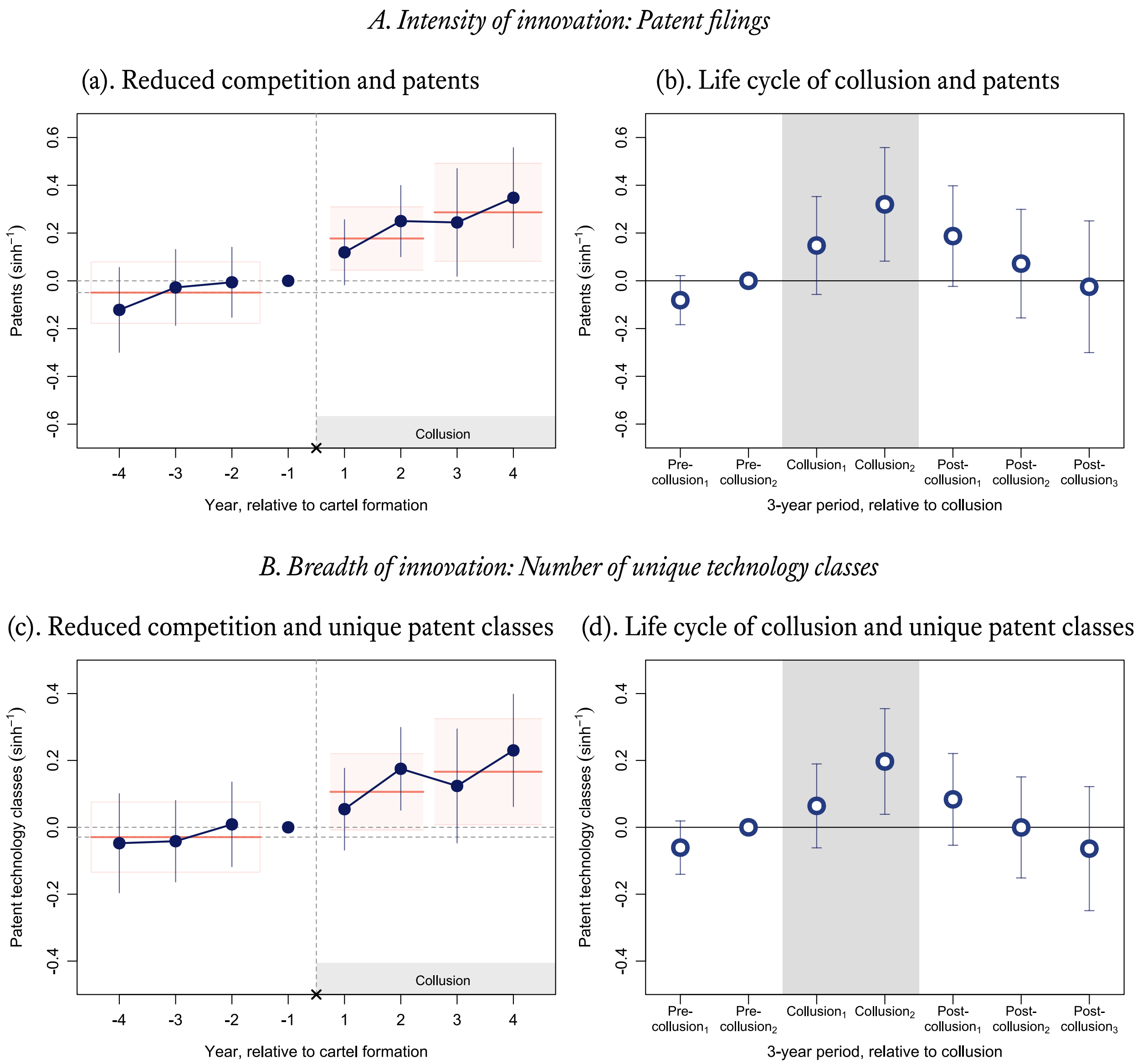
Notes. Plotted are the average patent filings around cartel formation by the treatment group (colluding firms) in red solid lines and the comparison group (non-colluding firms in the adjacent industries) in blue dashed line. The shaded area represents the one standard deviation from the estimate. The dependent variable is the number of patent filings, normalized based on its pre-collusion values—i.e., four years prior to cartel formation. *Data*: PatentsView.

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



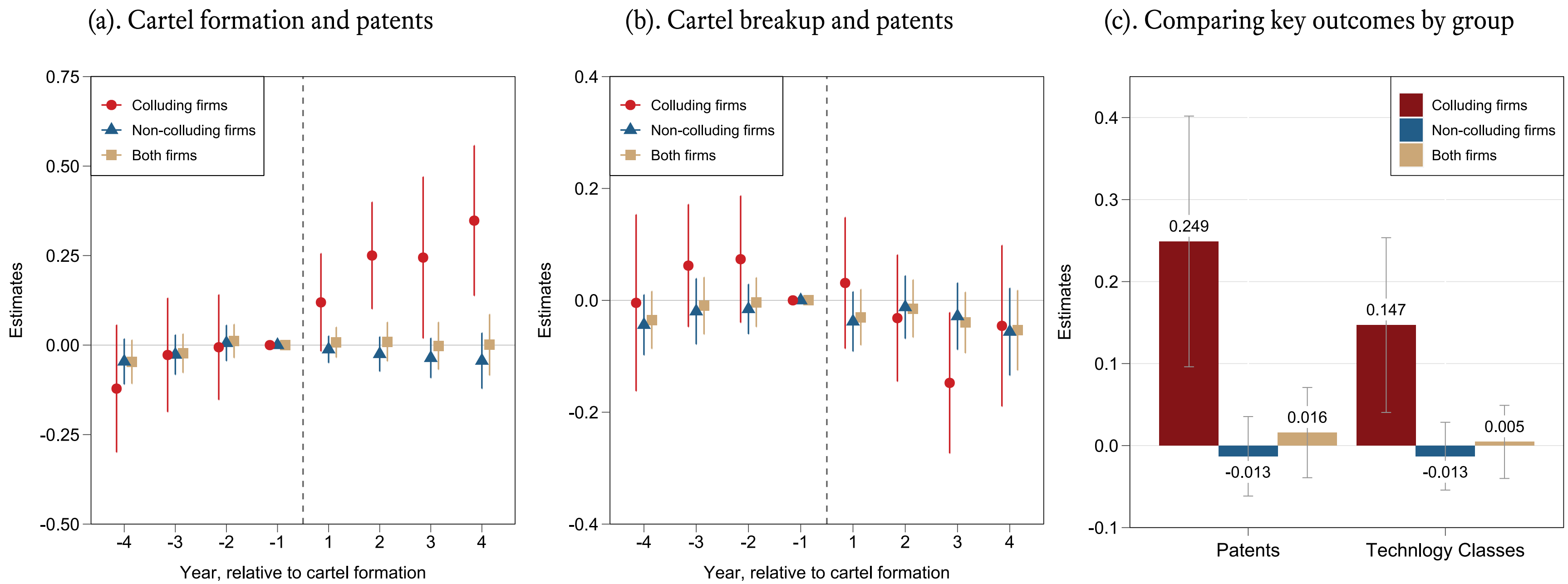
Notes. Plotted are the Z-scores of patent filings by colluding firms in the vitamin cartel (red solid line) and non-colluding firms in the same market—i.e., non-colluding firms filed patents in the top three 4-digit CPCs of colluding firms (blue solid line). In Z-score transformation, the mean and the standard deviation from the non-colluding years—i.e., 1982 through 1986 and 2003 through 2007—are used to compare the trends for the colluding and non-colluding firms. 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 gray dashed line shows the benchmark, calculated as the linear prediction of Z-scores based on those of both groups in non-colluding years. The shaded area represents the deviation from predicted patent filings during the collusion period. The colluding firms on average filed 31.5% more patents than the benchmark; the non-colluding firms in the same market on average filed 11% more patents than the benchmark.

Figure 4. Effects of Collusion and Price Competition on the Intensity and the Breadth of Innovation



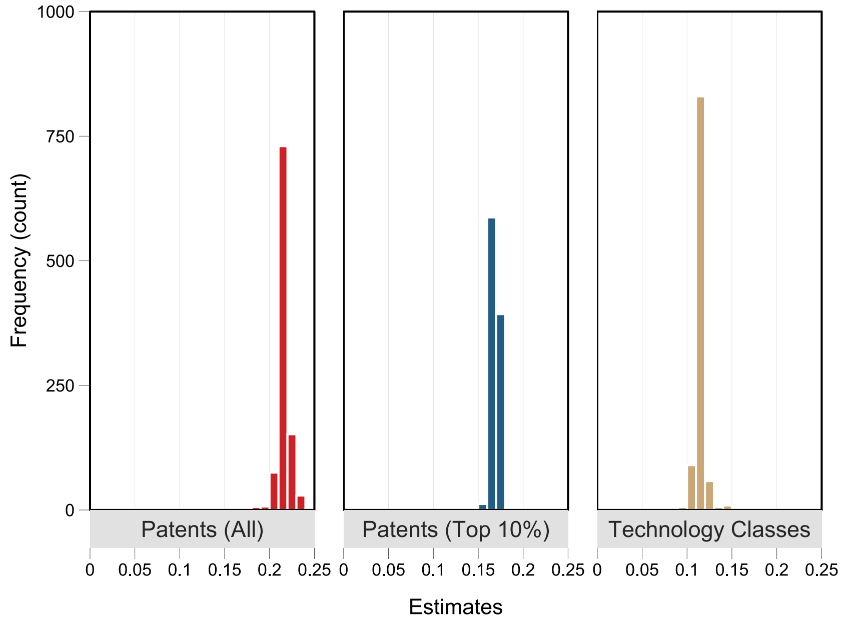
Notes. The dependent variable consists of (1) the number of patent filings (that were eventually granted) and (2) the number of unique technology classes of patents (three-digit CPC) with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence 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. $Post\text{-}collusion_1$ means one to three years after the breakup of collusion. $Postcollusion_2$ means four to six years after the breakup of collusion. $Post\text{-}collusion_3$ 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. The Effects on Colluding and Non-Colluding Firms



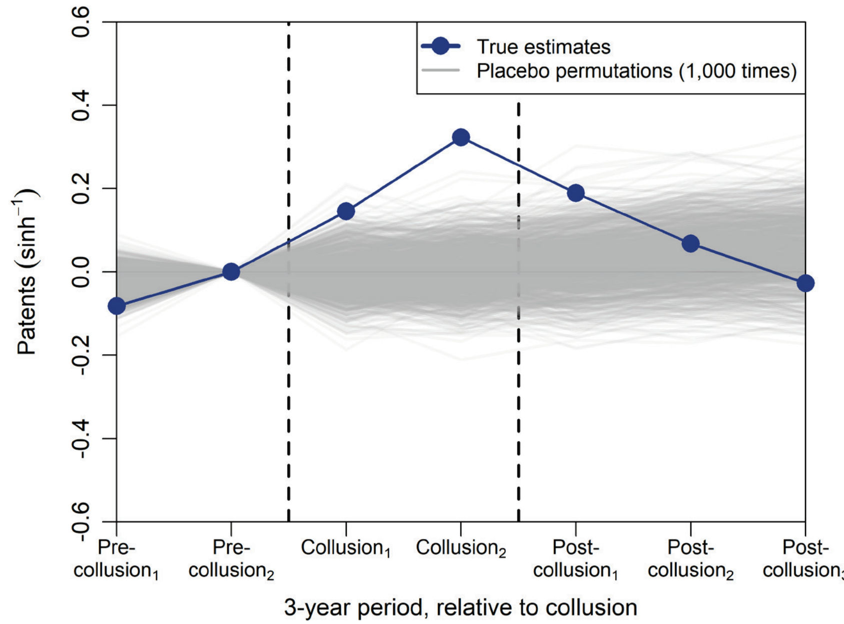
Notes. Panels (a) and (b): Plotted are the event-time coefficient estimates (dots) of three separate regressions based on Equation (3) for firms that colluded (red dots), firms in the focal industry (six-digit NAICS) that were not part of the collusion (blue dots), and all firms in the focal industry 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 in the graphs and is omitted, respectively. 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.

Figure 6. Leave-One-Out Iterations:
Estimation with Randomly Excluding 1–3 Firms (1,000 times)



Notes. Plotted are the three histograms of difference-in-differences coefficient estimates from Equation (1) after excluding one to three firms from the sample. First, the number of colluding firms (one to three) to be excluded was decided. Second, the chosen number of colluding firm(s) was randomly excluded from the sample. The estimation with the resulting sample was repeated 1,000 times. The dependent variable consists of (1) the number of patent filings (that were eventually granted) (2) the top 10% of patents in terms of forward citations, and (3) the number of unique technology classes of patents (three-digit CPC), all with the inverse hyperbolic sine transformation in an assignee firm × year. *Data*: PatentsView.

Figure 7. Placebo Permutation Tests:
Random Reassignment of Treatment Status (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.

Table 1. Descriptive Statistics

(a). Collusion data (1975–2016)

	Mean	Std. Dev.	Min.	Median	Max.
A. Collusion 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 fine ($mil)	8.361	38.77	0.00	0.20	500.00
Sum of all criminal fine ($mil)	10,676.57	–	–	–	–
C. Individual level (N=1,623)					
Criminal fine ($mil)	0.133	1.17	0.00	0.03	29.60
Sum of all criminal fine ($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.)	2,209,709	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 (DOJ) 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. Effects of Collusion and Competition on Innovation

(a). Collusion formation: Reduced competition 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). Collusion breakup: Increased competition 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 percent 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 (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 and Compustat. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 3. Financial Constraints and R&D: Reliance on External Finance and Revenue Growth

	Dependent variables ($\sinh^{-1}$): R&D expenditure			
	Reliance on External Finance 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. Column (3) shows the estimates from ten treated firms that had above-median revenue growth during collusion; Column (4) shows nine treated firms below-median. *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. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 4. 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 Company, 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 estimation sample. Panel (b) lists the top five firms that boosted the magnitude of the estimate; in other words, leaving this firm out shrank the estimate most. Panel (c) then lists top five firms that shrank the magnitude of the estimate; i.e., leaving this firm out magnified the estimate most.

Table 5. Effects of Collusion and Competition on Innovation: Analyses of Potential Mechanisms

(a). Collusion formation: Reduced competition and innovation

	Dependent variables ($\sinh^{-1}$):											
	Scope of Firms						*IP Strategy*	*Strength of Collusion*				
	Split-sample		Patents in overlapping fields	Patents in distinct fields	Split-sample		Unique patent inventors	Split-sample				
	Patents by narrow firms	Patents by broad firms			R&D by narrow firms	R&D by broad firms		Patents by strong cartel	Patents by weak cartel	R&D by strong cartel	R&D by weak cartel
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4)	(5a)	(5b)	(6a)	(6b)
Treat × Post	0.330***	0.073	0.224**	0.178**	0.347***	−0.017	0.293***	0.291***	−0.052	0.203**	0.054
	(0.149)	(0.138)	(0.076)	(0.082)	(0.124)	(0.100)	(0.096)	(0.083)	(0.191)	(0.098)	(0.048)
			$\chi^2(1)$=0.17, p=0.68								
Observations	431,613	431,359	432,448	432,448	149,833	149,815	432,448	432,275	431,000	149,874	149,825
R^2	0.541	0.553	0.451	0.439	0.920	0.921	0.591	0.554	0.540	0.921	0.920
Adjusted R^2	0.426	0.440	0.312	0.298	0.909	0.910	0.488	0.442	0.424	0.910	0.909

(b). Collusion breakup: Increased competition and innovation

	Dependent variables ($\sinh^{-1}$):										
	Scope of Firms						*IP Strategy*	*Strength of Collusion*			
	Split-sample		Patents in overlapping fields	Patents in distinct fields	Split-sample		Unique patent inventors	Split-sample			
	Patents by narrow firms	Patents by broad firms			R&D by narrow firms	R&D by broad firms		Patents by strong cartel	Patents by weak cartel	R&D by strong cartel	R&D by weak cartel
	(7a)	(7b)	(8a)	(8b)	(9a)	(9b)	(10)	(11a)	(11b)	(12a)	(12b)
Treat × Post	0.085	−0.398***	−0.076	0.0002	−0.082	−0.004	−0.136*	−0.023	0.124	−0.045	−0.133*
	(0.115)	(0.146)	(0.054)	(0.058)	(0.163)	(0.125)	(0.076)	(0.066)	(0.120)	(0.090)	(0.075)
			$\chi^2(1)$=0.37, p=0.54								
Observations	431,421	431,327	432,993	432,993	149,820	149,813	432,993	432,659	431,043	149,941	149,847
R^2	0.543	0.554	0.557	0.454	0.920	0.921	0.594	0.452	0.406	0.921	0.920
Adjusted R^2	0.428	0.442	0.445	0.316	0.909	0.910	0.492	0.313	0.257	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, 5a, 5b, 7a, 7b, 11a, 11b), the number of patents in overlapping fields among colluding firms (columns 2a and 8a), the number of patents in distinct fields among colluding firms (columns 2b and 8b), R&D expenditure (columns 3a, 3b, 6a, 6b, 9a, 9b, 12a, and 12b), and the unique number of inventors (columns 4 and 10), 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.