How Does Competition Affect Innovation? Evidence from U.S. Antitrust Cases*

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Abstract

This paper examines how market competition affects the intensity and breadth of innovation. I assemble a unique data set comprising all 461 prosecuted collusion cases in the United States from 1975 to 2016, where I match 1,818 collusive firms to firm-level data on innovation. Empirical results from a difference-in-differences methodology show a negative causal relationship between price competition and innovation. When collusion suppresses price competition, colluding firms increase patent filings by 48% and top-quality patents by 33%. A significant portion of these patents are attributable to fundamental innovation activities as innovation inputs, which are measured by R&D investment and patenting inventors, increased in tandem by 18% and 57%, respectively. Furthermore, firms broadened their scope of innovation by exploring new technological areas; the number of patented technology classes increased by 30%. When competition was restored by collusion breakup, the increased and broadened innovation activities reverted to their previous levels. I shed light on financial constraints and industry growth rate as key economic mechanisms driving the trade-off between price competition and innovation growth.

Key words: antitrust; collusion; competition; technological innovation; R&D investment
JEL classifications: D40; D43; L41; O31; O32

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The incentive to invent is less under monopolistic than under competitive conditions.
—Kenneth Arrow (1962, p. 619)

A monopoly position is in general no cushion to sleep on. As it can be gained, so it can be retained only by alertness and energy. —Joseph A. Schumpeter (1942, p. 102)

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 therefore important. Research and development (R&D) and the innovation processes, however, require risky and uncertain investment, the returns on which take several years, if not decades, for a firm to reap. Furthermore, the social return on investment in R&D and innovation is much higher than its private value (Griliches, 1992; Bloom et al., 2013) 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 necessary in order 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, motivated by 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 its direction. Given this theoretical ambiguity, an empirical study of the two opposing effects, to determine which dominates and the mechanisms involved, is important. Any empirical findings would also contribute to the existing theoretical debates.

This paper examines how price competition in the market affects the innovation activities of firms. Put differently, how do 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 reasons explain the limited number of systematic, large-sample studies demonstrating a causal relationship between competition and innovation (Cohen and Levin, 1989; Sidak and Teece, 2009, p. 588).

I address these challenges by exploiting variations in price competition coming from price-fixing cartels. The formation and breakup of price-fixing cartels provide an ideal, novel setting to proxy for competition, or 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, which is the key mission of the U.S. Department of Justice's (DOJ's) antitrust enforcement (https://www.justice.gov/atr/mission). I have collected and digitized data on all known cartel cases in the United States from 1975 to 2016 rather than focusing on a single collusion case. As a result of this effort, I have identified a total of 461 (nonfinancial) cartel cases, along with 1,818 firms and 1,623 managers.

In addition, existing studies tend to assume that innovative activities fall somewhere along a unidirectional continuum. An important question receiving relatively little attention is how firms explore new technological areas as market competition changes. Taking a step beyond the intensity of innovation, I explore the *breadth* of innovation, or how firms change their scope of innovation. The nature of innovation is a mixture or a recombination of existing technologies, so it is essential that firms explore new technologies and use several ingredients in their innovation processes. The broader scope of innovation also relies on a firm's absorptive capacity to identify, assimilate, and apply such knowledge ingredients (Cohen and Levinthal, 1990). Making this distinction between the intensity and breadth of innovation therefore 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 causal relationship between price competition and innovation. When a cartel suppressed market competition, colluding firms increased patenting by 48%. A significant portion of the increase is attributable to fundamental innovation activities as they also increased innovation inputs, such as R&D expenditure and patenting inventors. I also find evidence that the breadth of innovation changes in parallel. With decreased competition, firms broadened their areas of innovation by 30%. The increased and broadened innovation activities revert to their previous levels as a cartel breaks up and price competition is restored. Further tests suggest that financial constraints (the "ability to innovate") and the industry's growth rate (the "incentive to innovate") are important economic mechanisms behind the trade-off between price competition and innovation growth.

These findings have important implications for managers who strive to create and sustain a competitive advantage for their firm through innovation and for policy 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 because these firms already enjoy excessive profits (markups), so 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 pursue innovation to survive, achieve a competitive advantage, and, outperform their competitors. The standpoint of the U.S. DOJ and the European Commission is aligned with this view that "one of the best ways to support innovation is by promoting competition" (European Commission, 2016).

A model by Lefouili (2015) shows that the intensity of (regulator-induced) 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 for trading firms in China (Yu, 2015). Another interesting setting for studying the effects of competition on innovation is a patent pool, where two or more patent owners agree to pool a set of their patents and license them as a package (Lerner and Tirole, 2004). A patent pool can reduce technological competition among pool members. Lampe and Moser (2010) find that patent pools in the 19th century sewing machine industry decreased the patenting intensity of pool members. Interestingly, another measure of productivity—sewing machine speeds—barely changed during the pool period and then increased after the pool was dissolved. Lampe and Moser (2016) again find that patent pools decreased patenting intensity and citations across 20 industries. An important mechanism behind this relationship is that patent pools weaken competition in R&D, which in turn decreases innovation output. In the context of the global optical disc industry, Joshi and Nerkar (2011) find that patent pools—interpreted as a unique form of R&D consortia—decrease both the quantity and the quality of patents of the pool member firms.

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 restricts a firm's *ability* to innovate, because lower prices and profit suggest 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." Reduced competition, on the other hand, suggests that firms set prices higher than the marginal cost and enjoy higher profits, providing financial resources for innovation (Schumpeter, 1942; Cohen and Levin, 1989). Several empirical studies support this view. Macher et al. (2015) study how cement manufacturers adopt a new cost-saving technology at different levels of market competition. Although these manufacturers understand the effectiveness of new technology in reducing costs, their adoption pattern differed depending on the level of competitiveness in the market. Adoption was indeed higher under low levels of market competition. Gong and Xu (2017) study how Chinese import competition changed the R&D reallocation of publicly traded manufacturing firms in the United States and find that (1) competition decreased R&D expenditures and (2) R&D investment was reallocated toward more profitable firms within each sector. This suggests that competition hampers a firm's ability to engage in R&D and innovation activities by reducing its profits (or slack resources).

Reduced competition could also provide *incentives* for innovation in three ways. First, reduced competition increases a firm's probability of survival and makes the behavior of competitors more visible and predictable, which enables firms to more confidently invest in long-term R&D projects. R&D projects and innovation processes take several years, if not decades, so it is important that firms anticipate their own survival and that they can reap the gains of innovation ("Schumpeterian rents"). Second, firms expect higher 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 an incentive to invest in R&D in the current period to sustain their competitive advantage and their stake in profits in future periods.

Several empirical studies support this view. Im et al. (2015) find in the U.S. manufacturing sector that a firm's incentive to innovate increases in response to tariff cuts when market competition is mild (and the incentive decreases when firms face fierce market competition). 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. (2017) also find that competitive pressure from Chinese imports decreased R&D expenditure and patenting among U.S. 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). Third, diminished competition could prevent duplicate R&D investment by reducing preemption risk and wasted resources when firms develop the same technology. 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 or risk because monitoring or communicating with other firms in the market is easier. This effect is magnified for cartels, because competing firms coordinate and monitor each other's production levels and pricing.[3]

Studies that embrace these competing views consider the nonmonotone relationship between

[3] See, for example, Igami and Sugaya (2017) on how colluding firms communicate with and monitor each other.

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 U.K. 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 U.S. manufacturing sector.

2.2 Breadth of Innovation

Many theories and empirical approaches tend to view innovative activities as falling along a one-dimensional continuum. An important aspect that has not been considered enough, however, is the breadth 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), so it is crucial that firms engage in different types of innovation and broaden their area of innovation as an input for further innovation. A broader exploration of technologies could lead to an unprecedented recombination of existing knowledge and breakthrough innovation.

However, broadening the scope of technological innovation is even more difficult to do than increasing the intensity. Conducting R&D on a new technological field is more complicated and riskier than conducting R&D on an existing field. Firms do not possess as much absorptive capacity for new areas, and the project may develop slowly under a learning curve (Cohen and Levinthal, 1990). This makes innovation activities in new areas more costly, risky, and time consuming. In this sense, all the requirements for and difficulties in innovating discussed earlier in this section apply more aggressively to broadening the scope of innovation.

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 technology or 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 searching for new innovation that had not yet been pursued, the goal of which is to perform better in the *future* market. When firms enjoy a higher profit and face less uncertainty, thanks to reduced market competition, they have "slack" time, financial resources, and cognitive resources that can be devoted to longer-term and riskier projects. In this sense, reduced competition provides firms with incentives and the ability to broaden their technological area and conduct more aggressive and ambitious research.

In addition, reduced competition can promote R&D coordination between firms, either explicit or implicit. Collusion, for example, facilitates communication and increases visibility between competing firms. As colluding firms discuss price level and internalize each other's objectives, they learn about one another's R&D activities, which prevents multiple firms from investing in or duplicating efforts on the same technology. In other words, reduced competition dehomogenizes and diversifies the R&D projects of firms, leading to an expansion of technological fields.

3 Data

Collusion Data. The Antitrust Division of the DOJ typically releases three types of documents for each collusion case in their Antitrust Case Filings repository: information (indictment), plea agreement, and final judgment. These documents contain detailed information about the identity of colluding firms, when the collusion started and ended, and how exactly the collusion was operated. The documents also clearly define the relevant market by four-digit SIC (for older cases) or six-digit NAICS (for recent cases) code.[4] Another source of data for collusion is the Commercial Clearing House (CCH). Its Antitrust Cases section (formerly the Trade Regulation Reporter) provides summaries of the aforementioned original documents of 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 in violation of Section 1 of the Sherman Antitrust Act. As a result of this effort, I identified 461 collusion cases of 1,818 firms in the United States from 1975 to 2016.[5] Table 1, panel A, presents descriptive statistics on cartels.

Patent Data. The primary source of patent data is PatentsView. Supported by the Office of Chief Economist in the U.S. Patent & Trademark Office (USPTO), the PatentsView database has information on inventors, assignee firms, their locations, and other details available in the original patent document and covers all patents granted from 1976 to 2017. It 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 with this problem, I use Google Maps Geocoding API ("reverse geocoding") to convert geographic coordinates into country, state/province, and city names. This process ensures that the geographic information for all assignee firms and inventors is accurate and consistent. Another concern is that the patent data have no information on the industry at the patent or assignee firm level, and such information is important when defining relevant markets and assigning appropriate control groups. To navigate this problem, I convert the patent-level technology field (Cooperative Patent Classification [CPC]) to the North

[4] The documents arrive at the defendant firm and/or individual level (not necessarily at the collusion level), so I group indicted individuals and firms at the collusion level. This process is straightforward for most cases because co-conspirators in the same collusion case are usually mentioned in the indictments. Information on the collusion period and relevant market are used to further check the quality of a collusion grouping.

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

American Industry Classification System (NAICS) and then aggregated it at the firm level (see the Online Appendix Section A.2 for details).

I then match firm names in the collusion data and the patent data, using two different name matching schemes. First, I introduce case-insensitive regular expressions for the names of all colluded firms. For example, ^sam.*sung.* elec captures all firm names that (1) start with sam, (2) followed by sung, no matter what characters are in-between, and (3) followed by space and elec, no matter what characters are in-between (e.g., Samsung Electronics, Sam-sung Elec, or Sam sung Electronics, Ltd.). Second, I apply string distance algorithms (q-gram and cosine distance) and list the top-20 match candidates for each firm. I then manually check the quality of the match for both approaches, based on firm names and addresses. Of 1,668 colluded firms, 554 firms (33%) filed at least one patent. Table 1, panel B, presents firm-level descriptive statistics for patents.

As a result of the above processes, I construct a firm-year panel data set, using the universe of patents granted from 1976 to 2017. For each assignee firm, I identify the year of their first and last patent filing. For any firm-year observation where I do not observe a patent, I assign the value of zero if the year occurred between the firm's first and last year of patenting. This leads 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. The same name matching processes used for firms in the patent data are used for firms in Compustat. An important note is that Compustat consists only of publicly traded companies in North America, and the resultant sample is different from the patent sample. Table 1, panel C, presents descriptive statistics for the Compustat data.

4 Research Design and Empirical Strategy

4.1 Collusion, Antitrust Enforcement, and Market Competition

A major difficulty in empirical studies on competition is that competition is difficult to measure. Although "we have spent too much time calculating too many kinds of concentration ratios" (Joskow, 1975, p. 278), C3 (the sum of the market share of the three largest firms), C5 (the sum of the market share of the five largest firms), or the Herfindahl-Hirschman index (HHI) often fail to capture the level of market competition. Another challenge is that competition is endogenous; in many cases, changes in competition may be correlated with observable and unobservable factors that also affect the outcome of interest.

I exploit collusion cases to capture the changes in competition and to mitigate concerns over endogeneity. Collusion or a cartel is an agreement between competitors to restrict competition, deter the entry of new firms, and inflate prices. The Antitrust Division of the U.S. DOJ categorizes collusion as (horizontal) price fixing, bid rigging, and market allocation. In many cases, multiple schemes are simultaneously used, and the utmost goal of collusion is to stifle competition in the market.

Standard economic theory predicts that, by suppressing competition, collusion increases prices, transfers consumer surplus to producers, and reduces social welfare (via a deadweight loss to society). The DOJ estimates that collusion can raise prices by more than 10% and that "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% to 37% (Connor and Lande, 2006). Government and competition authorities, therefore, 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 felony punishable. Figure 1 shows the number of discovered collusion cases (brown bars) along with the number of indicted firms and individuals (solid blue and dashed lines, respectively).

The formation and breakup of collusion change the level of price competition in the market (in opposite directions) and provide unique opportunities to estimate how market competition affects key economic outcomes. 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). This confidentiality ensures an exogeneity of collusion breakup, compared to the privatization of public firms, tariff changes, or other regulatory reform, which require public announcements and advance discussions (e.g., a public hearing). 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."

Another important reason to treat the breakup of collusion as an exogenous shock is the leniency program in the United States.[6] This program grants immunity only to the first whistleblower that informs the DOJ of the existence of collusion and provides enough evidence to prosecute. If any collusion participants (either a firm or an individual in the firm) expect a breakup of collusion, it is their dominant strategy to report it to the DOJ before any of their co-conspirators do and thus be exempt from criminal punishments.[7] The formation events also provide an opportunity to study my question when carefully considered in conjunction with the breakup event. As long as the sources of endogeneity are different, my analysis of both events—and any opposite findings for the two—is doubly assuring and mitigates concerns that the findings may come from some endogenous factors other than the collusion-induced change in

[6] 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).

[7] See Levenstein and Suslow (2006, 2011, 2016) and Igami and Sugaya (2017) for a more detailed discussion on the determinants of collusion duration and breakup.

market competition.

4.2 Difference-in-Differences Estimation

In the difference-in-differences estimation, I compare colluding firms (the treatment group) to firms in the adjacent/similar market, but not in the same market, as a counterfactual (the control group). The control group is defined as firms that share the same four-digit NAICS code, but not the same 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 primary research output comes from regression estimates that explain how measures of innovation respond to collusion events that change competition, using linear regression techniques. I estimate various forms of the difference-in-differences model in Equation (1):

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

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 postevent, either collusion formation or collusion breakup, periods at the firm and year levels).[8,9] 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 entrepreneurial and 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 within the same broadly defined sector. I exclude firms in the control group that share the same six-digit NAICS code with the colluded firms to avoid spillover effects of collusion in the same narrowly defined market. For firms in the Compustat data, I use three- and four-digit SIC codes because NAICS codes are available for recent years only (e.g., Kogan et al., 2017; see the Online Appendix Section A.3 for more details). The coefficient of interest in this model is β_1, which tells me the relationship between collusion-induced competition and innovation.

I also estimate a number of variants of this regression that include more flexible econometric

[8] A great advantage of the inverse hyperbolic sine transformation is that it is defined at zero. The transformation is defined as $y^{IHS} = \log\left(y + \sqrt{y^2 + 1}\right)$. The inverse sine is approximately equal to $\log 2y = \log y + \log 2$ (except for very small values of y), so it has the same interpretation as a standard logarithmic dependent variable. If any, the transformed variables "place less weight on impacts in the upper quantiles of the conditional distribution of outcomes" (Kline et al., 2017, pp. 20, 65). For all specifications, I perform robustness checks with the natural logarithm (by adding an arbitrarily small number ϵ to address zero values) and find very similar results.

[9] For all analysis on collusion breakup, the year of breakup is omitted because it is unclear where this year should belong to. For an analysis on collusion formation, the year before formation is omitted to further account for the misestimation of the true year of collusion formation. The results remain robust to the inclusion of these years.

specifications. Formal event study regression techniques are expressed in Equations (2) and (3):

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

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

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 event (i.e., either cartel formation or cartel breakup). With this flexible event study approach, I can explicitly test the parallel trend assumption for the pre-event period and how the effects vary over time for the postevent period.

The above approaches consider the formation and breakup of collusion as if they are separate events. As these events go hand in hand, analyzing them in a single framework to paint a complete picture is useful to do. A difficulty arises because each instance of collusion has a different duration, and the relative time to cartel formation and 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:

$$y_{it} = \beta_1 \cdot \left[Treat_i \cdot Pre\text{-}collusion_t^1\right] + \beta_2 \cdot \left[Treat_i \cdot Collusion_t^1\right] + \beta_3 \cdot \left[Treat_i \cdot Collusion_t^2\right] + \\ \beta_4 \cdot \left[Treat_i \cdot Postcollusion_t^1\right] + \beta_5 \cdot \left[Treat_i \cdot Postcollusion_t^2\right] + \\ \beta_6 \cdot \left[Treat_i \cdot Postcollusion_t^3\right] + X_{it} + \rho_i + \gamma_{jt} + \epsilon_{it}, \quad (4)$$

where $Precollusion_t^1$ means four to six years prior to the formation of collusion. $Precollusion_t^2$ means one to three years prior to the formation of collusion and serves as the baseline (an omitted category). $Collusion_t^1$ represents early 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. $Postcollusion_t^1$ means one to three years after the breakup of collusion. $Postcollusion_t^2$ means four to six years after the breakup of collusion. $Postcollusion_t^3$ 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).

An important assumption underlying the difference-in-differences approach is the Stable Unit Treatment Value Assumption (SUTVA). I make efforts to ensure that the SUTVA is met and, even if it is not, many potential violations (e.g., noncolluding firms follow the suit of colluders) work against my estimation, leading to an underestimation of the effects. See the Online Appendix Section B.2 for further details.

5 Results

5.1 Intensity of Innovation

Patents. Table 2, columns (1)–(3), shows the effects of competition on three measures of innovation intensity—patent count, citation-weighted patents, and the count of top 10% cited patents—based on Equation (1). In panel A, colluding firms increase patenting by 47.7% after the formation of collusion. Colluding firms on average filed 33 patents per year immediately before the formation of collusion, so the 47.7% increase in patenting is equivalent, on average, to 15.7 more patents per year for each colluding firm. In panel B, on the other hand, colluding firms decrease patenting by 2.9% after the breakup of collusion, though this result is not precisely estimated. The imprecise point estimation and smaller effect size is a reasonable and expected outcome because firms would not suddenly and instanteously cease all ongoing R&D projects and patent filings after the breakup. Furthermore, even after a collusion breakup, firms keep filing patents based on R&D undertaken before the breakup. The longer-term effects (discussed later in this section and shown in Figure 4(a)) confirm that patent filings gradually revert to the precollusion level.

Table 3 shows a more flexible approach based on Equation (2). In panel A, column (1), colluding firms increase patenting by 41.3% in the short term ($Treat \times Post_A$) and by 62.1% in the longer term ($Treat \times Post_B$) after the formation of collusion. After the breakup, however, estimates in panel B show that colluding firms decrease patenting by 16.4% in the long term ($Treat \times Post_B$). Figure 2 illustrates these estimates. Horizontal lines and the boxes around them represent the point estimates and 95% confidence intervals based on pooled difference-in-differences estimations, where relative years are grouped by two or three years around the event of interest.

Next, I report estimates from the event study approach with distributed leads and lags based on Equation (3). In Figure 2, each point and vertical bar represents yearly event-time estimates and 95% confidence intervals, with relative year −1 as the baseline. Panel (a) shows that colluding firms gradually increase patent filings after they begin to suppress competition via a cartel. This immediate jump in patenting and gradual increase thereafter is consistent with the patterns of price changes in cartels. A vitamin cartel, for example, began to increase prices right after cartel formation, which reached a 100% increase (twice the precollusion price) in three years (Bernheim, 2002). Panel (b) then shows the opposite: that colluding firms decrease patent filings after price competition is restored as collusion breaks down.

There is a significant amount of variation in the quality of patents, and a count of patents may not capture their quality or impact. To better measure the fundamental innovation activities of firms, I look at quality-adjusted patents. First, 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, as shown in Table 2 and Table 3 (column 2). Second, I further examine the counts of high-quality patents: patents that belong to the 90th percentile or above in terms of citations received by future patents. As shown in column 3 in Table 2 and Table 3, the results are consistent with what I find from patent counts and citation-weighted patents, though smaller in magnitude. It is not the case that firms engaged in marginal inventive activities that have little impact on future scientific progress. Firms indeed increased innovation activities and registered impactful and high-quality patents when collusion suppressed price competition. This pattern reverses when collusion breaks up, which is doubly assuring.

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 4, columns 1–3, shows the regression results on innovation intensity. The results, which are illustrated in Figure 4(a) for citation-weighted patents, are mostly consistent with the previous findings. Furthermore, the opposite responses to the formation and breakup of collusion (and the finding that innovation intensity increases only during the collusion period and then gradually reverts to the precollusion level after collusion breakup) doubly ensures that I have indeed captured the effects of collusion-induced changes in competition and not those of some unobservable factors unrelated to competition and unknown to researchers.

R&D Investment. I then examine the R&D investment of publicly traded firms using Compustat North America. Column 4 in Table 2, Table 3, and Table 4 shows that colluding firms increased their R&D expenditure by about 18% (simple DiD) to 28% (flexible DiD) during collusion, compared to the precollusion period. This is equivalent to an additional \$104 million to \$162 million being spent on R&D projects. After the collusion breakup, the increased R&D expenditure gradually decreases. 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 in comparing and interpreting the results for patenting and R&D investments.

Fundamental Innovation versus Intellectual Property Strategy. The effects on R&D expenditure is smaller than those on patenting activities. One reason may be that Compustat consists of already large and research-active corporations that are in the later period of the business life cycle. Another account is that price competition changes firms' intellectual property strategy. Cartels, or market competition in general, change a firm's incentives and propensity to patent, and not all patents are born of fundamental 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, 2020), patent (cross)licensing (Priest, 1977; Eswaran, 1993; Arora, 1997; Arorar and Ceccagnoli, 2006), or incentives to show off their innovation.

To determine whether firms innovate (rather than simply increasing their propensity to patent), it is important to examine how firms change their *input* when innovating. While it is not possible to survey the intrinsic motivation for each patent, one could infer that a significant portion of patenting comes as a result of more input (R&D) in the innovation activities. Assuming a direct proportional relationship between patents and R&D investments, one sees in in Table 2, column 1, that at least 36.7% of the increase in patenting comes from a firm's genuine R&D efforts.

Another more direct measure of innovation input concerning patenting is the number of scientists that engage in inventive activities. If the patenting results come entirely from an intellectual property strategy, one should expect that the same pool of scientists are registering more patents (that were previously kept a secret), and the number of inventors does not change much. If, on the other hand, firms indeed increased their fundamental R&D, these activities should accompany the recruitment of and patenting by *new* scientists to the firm. I thus test how the number of unique inventors patented in a given year change over time (three-year moving average), around the collusion formation and breakup. Table 5, column 1, shows that the number of inventors increased by 56.6% during collusion, compared to precollusion periods. This suggests that increased patenting is accompanied by an increased number of "new" scientists and provides additional strong evidence of the fundamental innovation activities of firms. In addition, the yearly estimates of unique inventor counts closely follow the changes in patenting activities. That is, the 47.7% increase in patenting is accompanied by the expansion of at least the same number of scientists, supporting the hypothesis that fundamental innovation activities are undertaken during collusion.

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 the same way as citation-weighted patents.[10] In Table 2, panel A, column 5, the breadth of technological innovation increased by 30.3% when market competition was suppressed by collusion. This is equivalent to 2.7 additional fields as colluding firms patented in 8.9 technology fields before collusion. After the breakup of collusion, on the other hand, the breadth of patenting dropped by 2% (Table 2) and up to 15.3% in the longer term (Table 3). A single framework of the life cycle of collusion is shown in Table 4, columns 5 and 6, and Figure 4(b). The results show strong evidence that firms engaged in explorative research and broadened their scope of innovation during collusion. An alternative measure, the technology class-weighted patents, also confirms these findings (column 6 in Table 2, Table 3, and Table 4).

The results, however, offer no indication of how patenting activities are distributed across different

[10] I assigned zero to any firm-year observation without any filed patents. Excluding such cases does not qualitatively change the results. In addition, the results remain unchanged when I divide the number of unique technology fields by the maximum possible number of CPC to take it into account that (1) a firm can explore at most *n* CPC subsections if it filed only *n* patents and (2) a firm can explore at most the total number of CPC subsections, which is 626.

technology fields. To further explore how firms allocate their innovation activities across existing (exploitative) versus new (explorative) fields of innovation, I test how patenting changes for a firm's primary technological area, which is defined by each firm's three most frequently patented technology classes (CPC), and for its peripheral technological area, which is measured by patents not in each firm's three most frequently patented technology classes. The results in Table 5, columns 2 and 3, show that firms increase innovation in *both* primary (38.9%) and peripheral (32.8%) technology areas of the firm. In other words, reduced competition enabled firms to explore new technological areas, and, in so doing, firms managed a well-balanced portfolio of exploitive and explorative innovations.

These results are, to some extent, consistent with recent empirical findings in different contexts. Krieger et al. (2018) 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 and incentives to invest in novel, riskier drugs. Turner et al. (2010) find that, in a less competitive market, software firms in the United States became more responsive to generational product innovations (GPIs) by external actors (and less responsive to their own historical patterns of innovation). In other words, firms explore unprecedented innovations that are new to an organization as the competition level decreases. Findings on patent pools also are in line with these results in that firms in the pool (i.e., reduced technological competition) increase innovation in an alternative technology (Lampe and Moser, 2013) despite the decrease in innovation in the focal technology (Lampe and Moser, 2010). As discussed in Section 2, the focus of Macher et al. (2015) is on the adoption of a cost-saving technology for a manufacturer's current line of products. This "inability to invest in new technology" should be much higher for new areas of innovation that are not directly linked to a firm's current products or technologies. This is especially the case when I consider the finding that firms that produce a substitute technology are substantially more likely to fail (Lampe and Moser, 2013).

While firm-level evidence is scarce, individual- or team-level studies support this view. Bracha and Fershtman (2013) find from a lab experiment that competition induces agents to work harder, but not necessarily smarter. Subjects are likely to choose simple tasks ("labor effort") in a head-to-head tournament competition, whereas they are more likely to choose more complicated tasks ("cognitive effort") in a pay-for-performance setting without competition. Gross (2018) finds from a logo competition platform that heavy competition decreases the originality and unprecedentedness of ideas; too much competition stifles individual artists' exploration of a wide range of possibilities and ideas.[11]

[11] Note that intensifying competition from *no* competition induces artists to produce original, untested ideas. These findings, altogether, are in line with an inverted U-shaped relationship between competition and creativity.

5.3 Robustness Checks

Placebo Tests. To control for the possibility that the findings resulted from a mechanical, spurious pattern generated in the data construction and empirical analysis stages, I run a set of placebo tests by reshuffling the treatment indicator to create the placebo treatment group for each collusion. In other words, I *randomly* reassign the treatment status within the same four-digit NAICS sector for each collusion case and run regression models in Equations (1) through (4). This random assignment experiment was repeated 1,000 times. Figure 8 graphically summarizes the results for citation-weighted patents. Gray lines represent 1,000 placebo simulations. I confirm from this experimentation that the findings for colluded firms are clearly distinct and do not come from spurious, arbitrary components of the models.

Pairwise Synthetic Control Method. In the main regression models, I include sector × year fixed effects to compare firms in the same four-digit NAICS sector and in the same year. An alternative way of balancing the treatment and control groups and testing the parallel trend assumption is the synthetic control method (Abadie et al., 2010). This method provides a powerful tool for a single treatment unit and many control units. In this study, I apply this method to each colluding firm to synthesize its counterfactual. Each control unit is synthesized to mimic the trend of an outcome variable of firms in the treatment group for the pre-event period only. I repeat this work for all colluded firms, and, doing so, results in many pairs of colluding firms and their synthetic controls. With a sample of colluding firms and their synthetic controls, I estimate a difference-in-differences model. The results are qualitatively and quantitatively very similar to those of the main analysis.

6 Further Analyses of the Mechanisms

6.1 Financial Constraints

One of the main arguments in line with Schumpeter's view is that reduced competition affords firms with more financial resources, which then can be allocated to innovation activities. A testable implication of this argument is that firms experiencing high revenue growth *during* collusion should invest more in R&D activities compared to those experiencing low revenue growth. I test this hypothesis by calculating each firm's revenue growth during collusion compared to precollusion periods and dividing them into quartile groups based on it. I then run separate regressions by group. Figure 5 graphically shows four regressions on R&D expenditure by group, based on Equation (1). The increase in R&D expenditure during collusion is positively correlated with revenue growth during collusion; the estimates are larger and precisely estimated for firms that reaped above-median revenue during collusion. In other words, the increased innovation activities indeed come from firms that successfully secure more financial resources via collusion. The result confirms that growth in revenue (or ease of financial constraints) is one important economic mechanism behind the negative causal relationship between competition and innovation intensity identified in Section 5.1.

6.2 Industry Growth Rate

Industries differ along many characteristics, and a response to market competition should therefore differ across industries. One important characteristic that distinguishes industries in terms of innovation is their growth rate (or maturity in the industry life cycle). If an industry is growing rapidly, the expected return to innovation and its appropriability are higher, thanks to the growing pie. The effects on innovation therefore should be higher in fast-growing industries. On the other hand, if an industry is mature or stagnant, a reduction in competition may not effectively spur innovation. I test the heterogeneity within the industry growth rate as follows. First, I calculate the average growth rate of innovation activities (measured by successful patents) in each industry for five years *prior to* the formation of collusion. Second, I divide firms into quartile groups based on this measure and run regressions as in Equation (1) on three measures of innovation activities.[12] Figure 6 shows the results for all patents (red bars), the top 10% of high-quality patents (brown bars), and the number of unique technology fields (blue bars). The measures of innovation intensity and breadth are higher for industries that grow faster, especially for those with above-median growth rates. This finding also has an important policy implication for how the competition authority with limited resources allocates its attention over different markets based on the industry's growth rate.

6.3 Antitrust Policy Changes (Temporal Heterogeneity)

An important source of heterogeneity is a temporal change in competition, collusion, and innovation. During the sample period, the U.S. antitrust policy experienced two major changes: the revision of the leniency program in 1993–1994 and the enactment of Antitrust Criminal Penalty Enhancement and Reform Act in 2004 (Ghosal and Sokol, 2020). Advances in communication technologies and transportation may also have affected how colluding firms discuss price levels and share information. Furthermore, patterns of technological innovation have also changed. For example, we have witnessed rapid growth in the artificial intelligence and machine learning fields, and the role of competition in these fields may be different from the role of competition in the emerging fields in the 1970s and 1980s.

It is therefore vital to check whether my main results change over time. I ran regressions based on Equation (1) separately for periods before and after the two significant policy changes, based on the breakup year of collusion. This roughly divides my sample period into three large bins: 1976–1993, 1994–2003, and 2004–2016. Figure 7 graphically presents the results. I did not find a noticeable, systematic difference in innovation activities between the three time periods. This suggests that, despite new competition policies

[12] Importantly, the innovation growth rates are measured at the industry group (four-digit NAICS) level, whereas my regression approach compares firms in treatment and control groups within such industry groups. Doing so mitigates any concern that my estimates are solely driven by the preexisting growth pattern of each industry group.

and advancements in technologies, the main findings remain robust and are not driven by specific time-varying factors.

7 Discussion

Firms shift toward innovation competition and broaden their search for new technological opportunities when price competition weakens. In this setting in which firms operate in technology-intensive industries and collude to fix prices, reduced competition is not a cushion to sleep on (Schumpeter, 1942) but implies that firms now compete for innovation. Managers must understand this fundamental change in the rules of the game and set the appropriate innovation strategies. Conditions under which this major shift in the types of competition happens, namely, extra revenue earned and the growth rate of industries, provide additional insights. Firms that sleep on the cushion of the high price-cost margin will fall behind in the competition for innovation happening under the surface.

Implications for public policy and law enforcement also merit further discussion. The ultimate goal of the DOJ has been to promote the competition of *prices*. While the DOJ acknowledges the importance of promoting innovation (Alford, 2018), and my conversations with DOJ and FTC officials consistently reveal that they do discuss innovation in great detail, the DOJ in principle maintains the position that "cartels inflate prices, restrict supply, inhibit efficiency, and reduce innovation" (Pate, 2003) and concludes that collusion is a *supreme evil* of antitrust. The European Commission (EC) has a similar attitude. In their innovation theory of harm (ITOH), the EC views competition as the mother of invention, and mergers and collusion reduce innovation (European Commission, 2016). This view makes sense in a narrowly defined market in terms of product scope and time horizon; the price of the focal product is distorted due to the reduced competition.

This view, however, does not consider the possibility that price in turn affects the innovation activities of firms and future new products. [13] While the aim of the antitrust authority has been (understandably) to promote price competition, the other important economic outcomes, such as the intensity and/or breadth of innovation, are numerous. With the findings of this study, the prevailing view that competition always promotes innovation (and social welfare) becomes less clear. It is possible that the proinnovation effect of market power is greater than its antiprice effect (or price distortion), providing net positive social value. Firms that overcharge on cold medicine, for instance, could broaden their innovation scope and put more effort into developing new medicine for the Zika virus or the coronavirus, for example. It is therefore important to have a comprehensive and balanced view that competition in the product market not only affects the price of products but also changes a firm's incentives and ability to innovate and the quality of new products and services a firm offers.

[13] In price terms, new inventions reduce the price of previously unavailable products from infinity to a finite level.

Furthermore, the importance of innovation magnifies when considering that the social return to innovation is higher than the private return: "the gross social returns to R&D are at least twice as high as the private returns" (Bloom et al., 2013). Thus, it is important to promote market structures that provide firms with incentives and the ability to innovate (Gilbert, 2006a, 2006b), to the extent that the social benefit of innovation outweighs the social loss of price distortion.

This line of argument is by no means to say that competition harms innovation and therefore promotions of market competition should be stopped. The results suggest, however, that a certain level of insulation from fierce price competition *may* facilitate the innovation activities of firms, especially in fast-growing, technology-intensive industries. One implication may be that policy makers may need to consider the potential benefits and costs of reduced competition under the *rule of reason*, rather than making it always unlawful under any circumstances (*per se illegal*).[14] We will need to keep discussing how to achieve the social optimum by balancing the price and innovation consequences of market competition.

8 Concluding Remarks

Innovation is the primary source of a firm's competitive advantage and economic growth. I find that firms shift toward innovation competition and broaden their search for new technological opportunities when price competition weakens. In this setting in which firms operate in technology-intensive industries and collude to fix prices, reduced competition is not a cushion to sleep on (Schumpeter, 1942) but invokes an important change to the rules of the game; namely, firms now compete for innovation. The fact that firms explore new technological areas has further implications for the novelty and quality of innovation via the recombination of such inputs. Furthermore, financial constraints and industry growth rate are important drivers for the trade-off between price competition and innovation growth; the magnitude of a transition to an innovation race is greater for firms that reap more profits and in industries that grow fast.

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&As) and how each affects firm innovation (e.g., Autor et al., 2013, 2017; Miller and Weinberg, 2017). It should be noted, however, that the focus of this study is on collusion, and the findings herein may not be generalizable to other contexts. Implications for the competition that are induced by foreign trade (import penetration), subsidies, mergers, patent pools, or privatization of public firms may differ across contexts. For example, Autor et al. (2017) find a similar outcome, specifically that U.S. manufacturers decrease their patenting activities when facing higher competition from Chinese import

[14] A similar change was made in 2007 for the minimum resale price maintenance (i.e., the price floor). The minimum resale price maintenance has been 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).

penetration. However, the competitive pressure from low-end, cheaper products is not readily comparable to the formation and breakup of collusion among incumbent leaders in technology-intensive industries. The generalizability of these findings requires further study and careful interpretation.

This study contributes to the literature in the following ways. First, the results broaden our understanding of the effects of competition beyond the price level. I consider another important outcome, innovation, and thereby move beyond the assumption that competition changes only the prices of focal products. The market competition also changes the intensity and breadth of innovation of firms for future products and services. This sheds light on the important trade-off between price competition and innovation growth, and the latter is becoming increasingly important in the knowledge-based economy. Second, taking a step beyond the intensity of innovation, I shed light on the breadth of innovation. This distinction enables me to investigate the relationship between competition and innovation at a deeper level. Firms not only change the intensity of innovation but also alter the breadth of their technological search and innovation, both of which consequently affect the novelty of future innovations. Third, I collect data on all known collusion cases and use the formation and breakup of collusion as plausibly exogenous sources of variation in the competition level. This novel approach enables researchers to measure competition and test its effects on important economic outcomes. Perhaps more importantly, a cartel is a highly strategic (yet illegal) agreement not to compete on prices between firms in the same market. Collusion itself is a very interesting and 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 implications for firm performance and the society.

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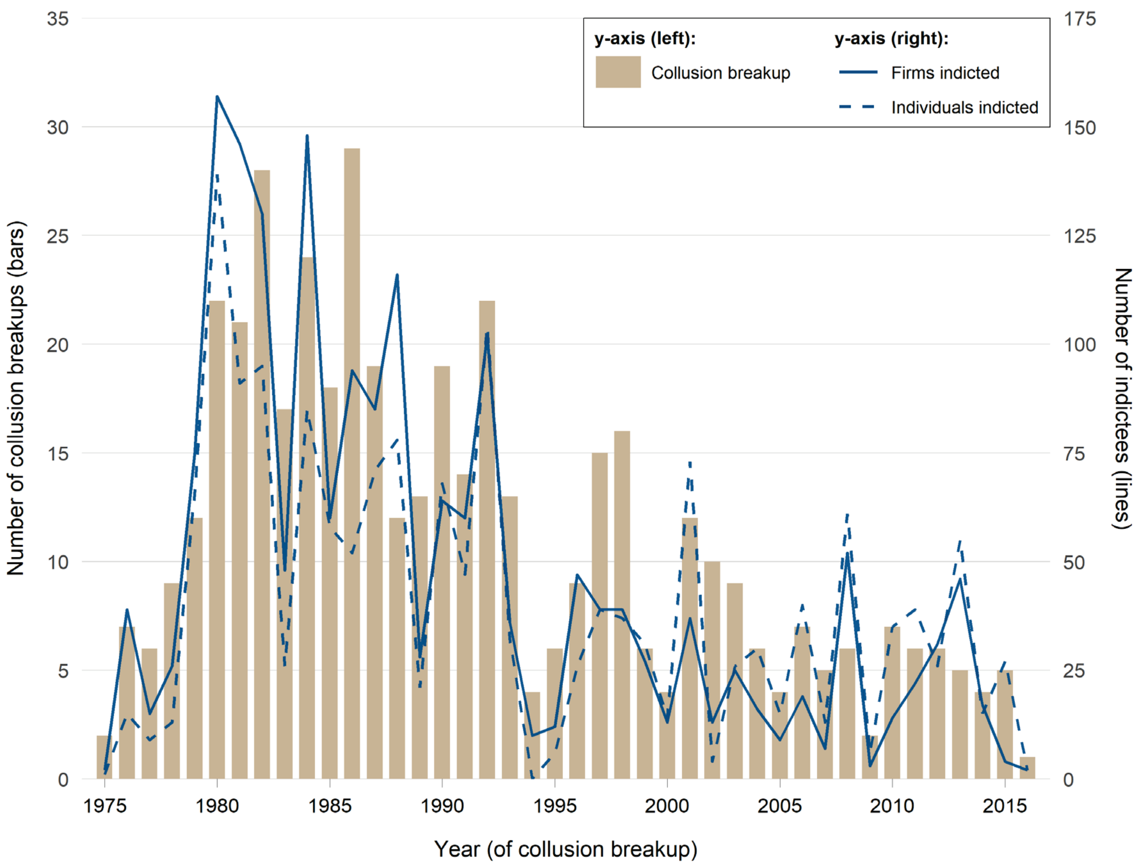
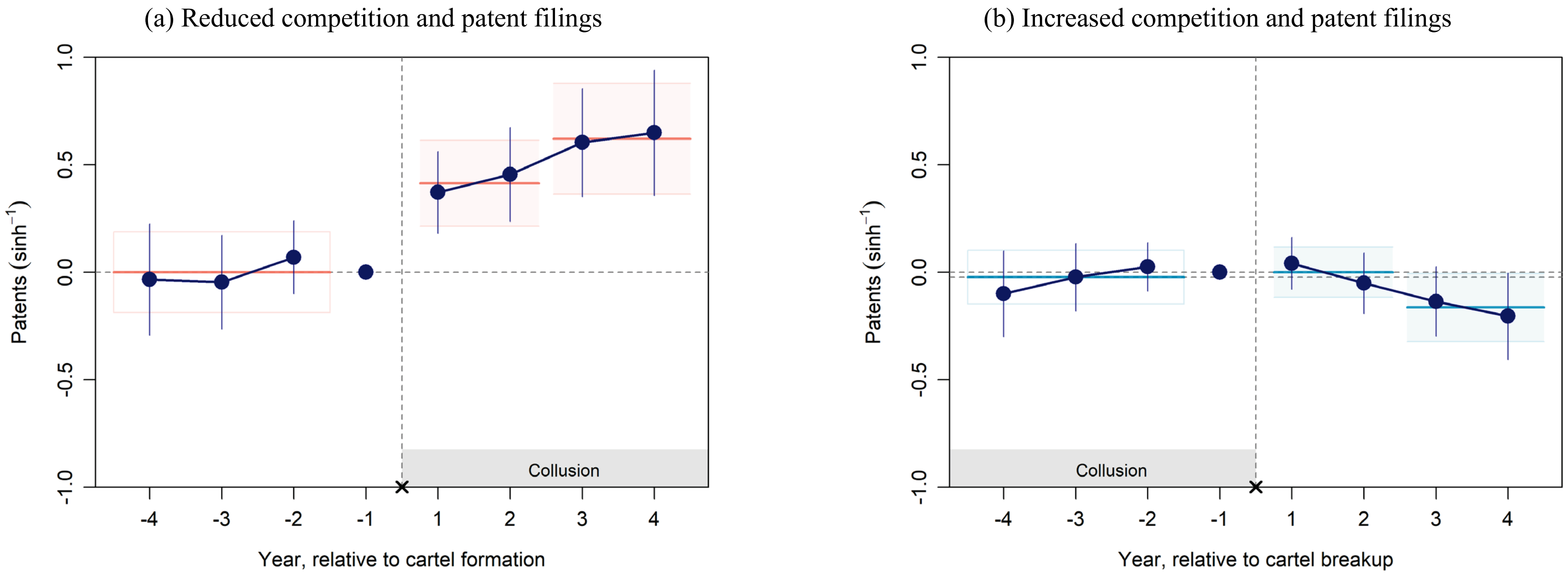
Figure 1. Cartels in the United States, 1975–2016



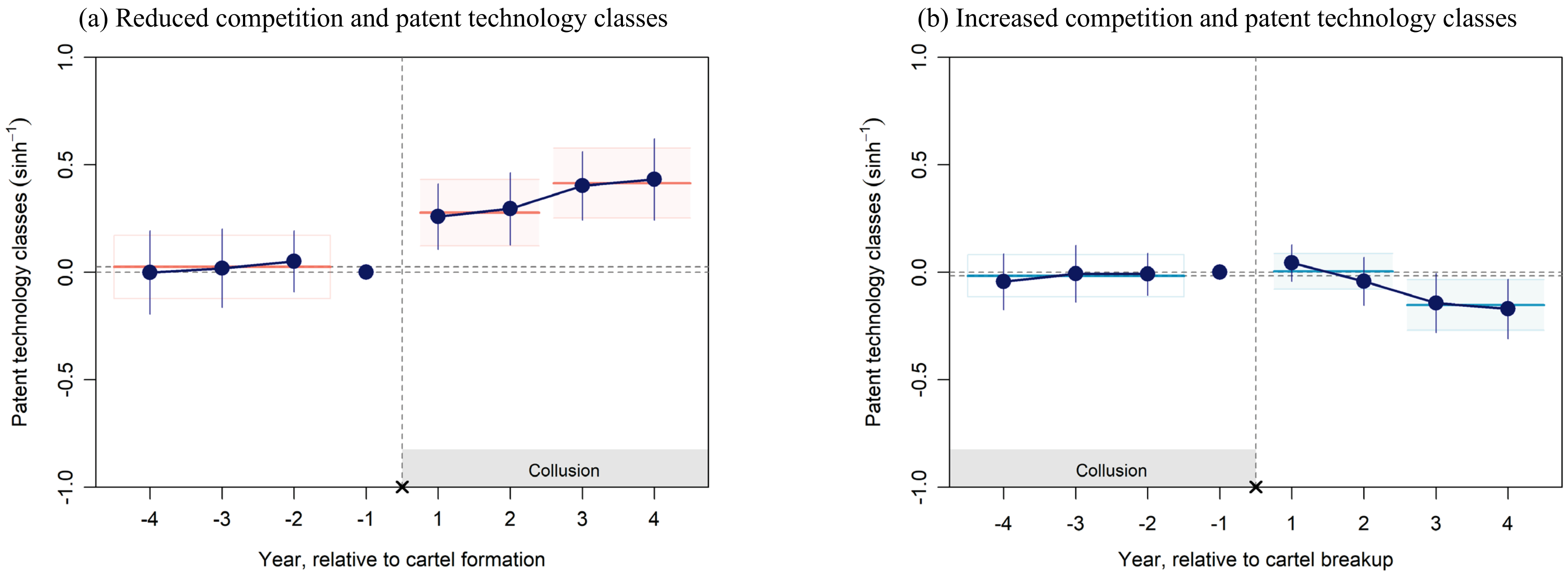
Notes. This figure tracks the trend in antitrust enforcement and collusion breakup in the United States from 1975 to 2016. Brown bars represent the number of collusion breakup cases by year. The solid blue line represents the number of firms indicted for collusion each year, whereas the blue dashed line 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. Note that the number of collusion breakup cases is right-censored; more cases of collusion breakup may have occurred in 2016 but have not yet been indicted due to ongoing closed investigations. *Sources*: The author's data collection from the Antitrust Case Filings of the U.S. Department of Justice (DOJ) and the Antitrust Cases of the Commercial Clearing House (CCH).

Figure 2. Effects of Collusion and Price Competition on the Intensity of Innovation



Notes. Plotted are the event-time coefficient estimates (dots) from a version of Equations (2) and (3), where the dependent variable consists of the number of patent filings (that are eventually granted) with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence intervals. 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 regression model controls for assignee firm fixed effects and sector × year fixed effects. A sector is defined by the four-digit North American Industry Classification System. The year of collusion breakup (in panel (b)) corresponds to year zero in the graphs and is omitted. For collusion formation (in panel (a)), the year before the formation is omitted to further account for the misestimation of the true year of collusion formation. Year –1 is used as the baseline. Standard errors are clustered at the sector level. *Source*: PatentsView.

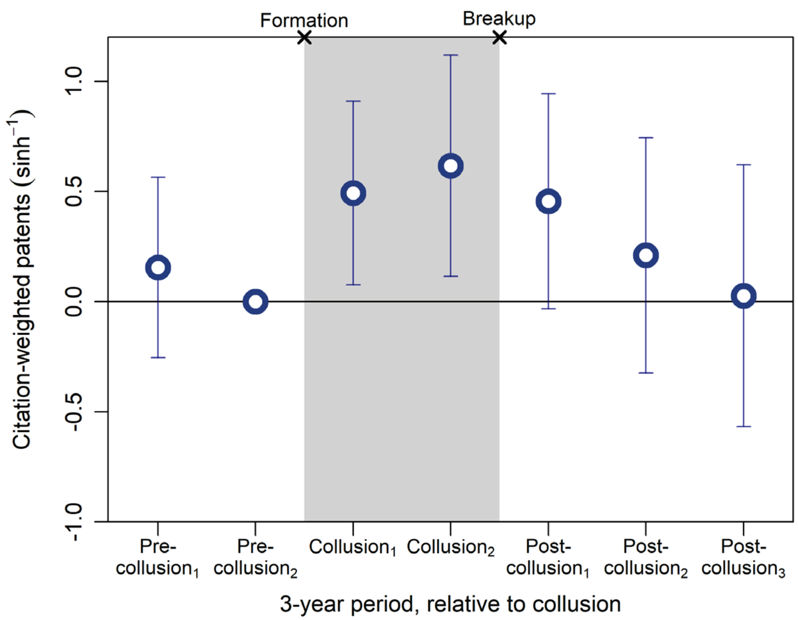
Figure 3. Effects of Collusion and Price Competition on the Breadth of Innovation



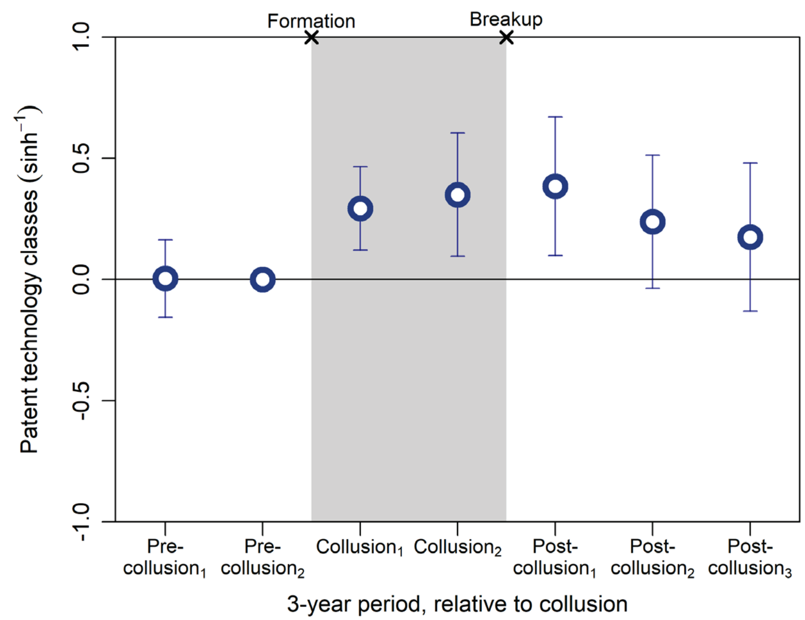
Notes. Plotted are the event-time coefficient estimates (dots) from a version of Equations (2) and (3), where the dependent variable consists of the number of unique technology classes of patents (three-digit CPC) with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence intervals. 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 regression model controls for assignee firm fixed effects and sector × year fixed effects. A sector is defined by the four-digit North American Industry Classification System. The year of collusion breakup (in panel (b)) corresponds to year zero in the graphs and is omitted. For collusion formation (in panel (a)), the year before the formation is omitted to further account for the misestimation of the true year of collusion formation. Year –1 is used as the baseline. Standard errors are clustered at the sector level. *Source*: PatentsView.

Figure 4. Life Cycle of Collusion and the Intensity and Breadth of Innovation

(a) Intensity of innovation: Citation-weighted patents

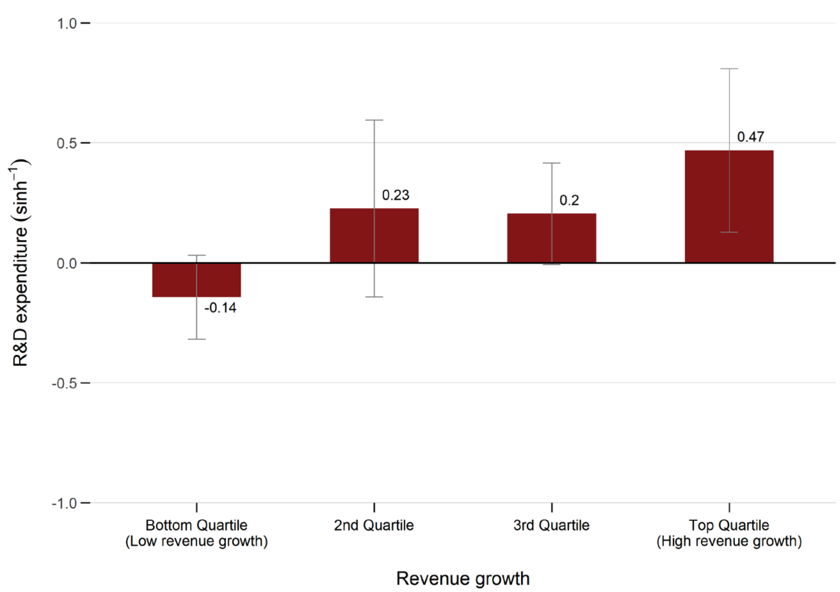


(b) Breadth of innovation: Patent technology classes



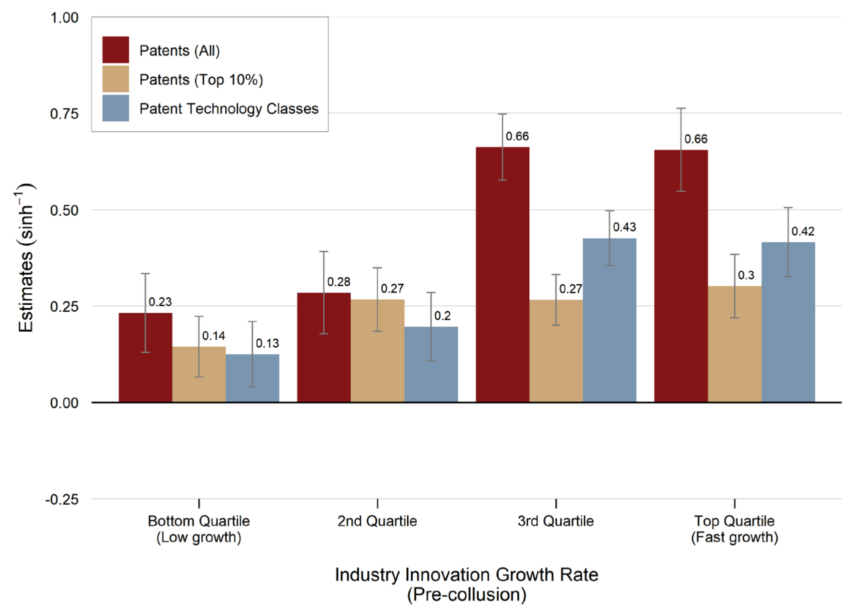
Notes. Plotted are the event-time coefficient estimates from a version of Equation (4), where the dependent variable consists of (a) citation-weighted patents and (b) the number of unique technology classes of patents (three-digit CPC) with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence intervals. 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. A sector is defined by the four-digit North American Industry Classification System (NAICS). Standard errors are clustered at the sector level. *Source*: PatentsView.

Figure 5. Financial Constraints:
R&D Expenditure by Collusion Revenue



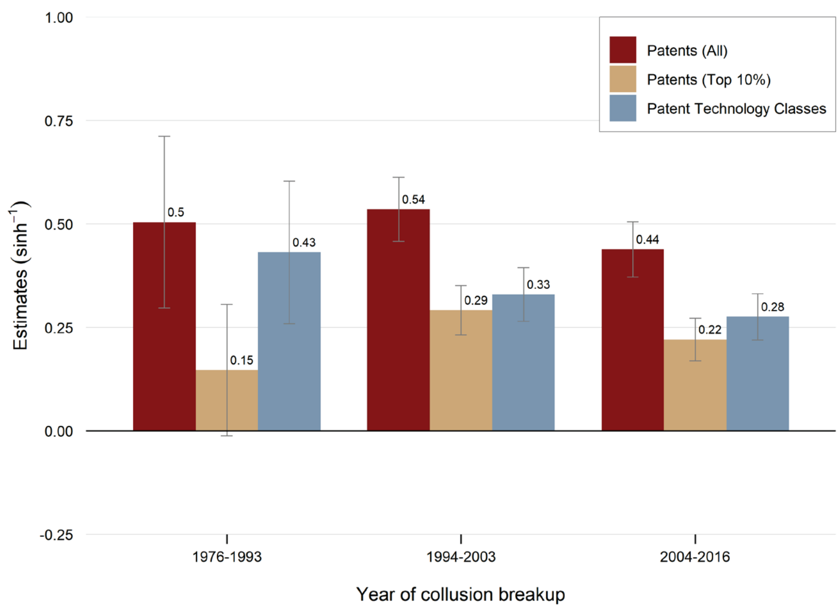
Notes. Plotted are the difference-in-differences coefficient estimates from four separate regressions based on Equation (1), with the formation of collusion as an event of interest. Firms in the treatment group are subgrouped by their revenue growth from precollusion ($t \in [-5,-1]$) to collusion periods ($t \in [1,5]$). Cutoffs for quartiles are 22.9% (lower quartile), 54.4% (median), and 92.4% (upper quartile). The dependent variable consists of R&D expenditure 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 (two-digit SIC) × year fixed effects. *Source*: Compustat.

Figure 6. Intensity and Breadth of Innovation
by Precollusion Industry Growth Rate



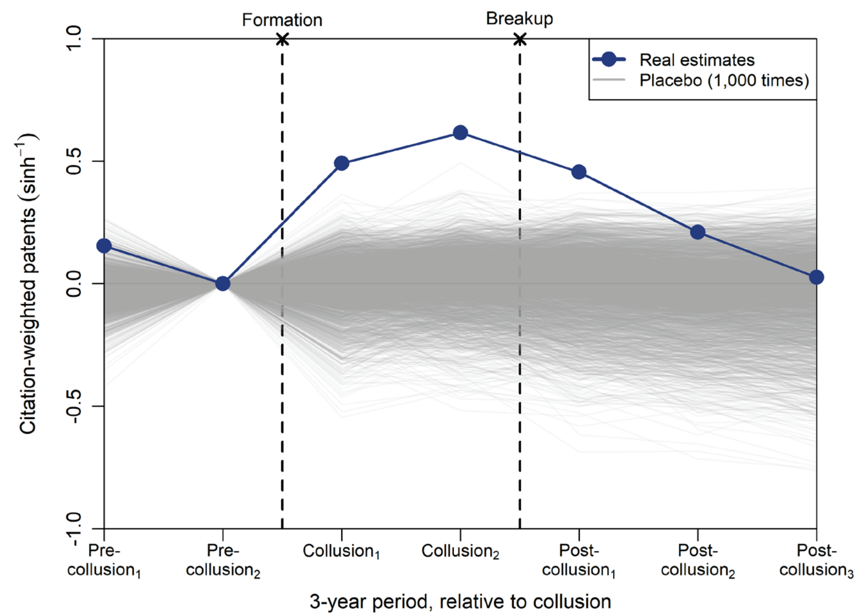
Notes. Plotted are the difference-in-differences coefficient estimates from 12 separate regressions (three outcomes of interest for four quartile groups) based on Equation (1), with the formation of collusion as an event of interest. Average annual innovation growth rates are measured at the industry group level (4-digit NAICS), and each colluding firm (along with their counterfactual firms) is divided into four quartile groups based on this rate. Cutoffs for quartiles are 4.3% (lower quartile), 7.9% (median), and 13% (upper quartile). The dependent variable consists of the number of patent filings (red-colored bars), the top 10% most cited patents compared to peers in the same three-digit CPC × year (brown bars), and the unique technology classes of patents (blue bars), all of which are transformed by the inverse hyperbolic sine function in an assignee firm × year. Numbers above the bar show regression estimates, whereas vertical bars represent 95% confidence intervals. The regression model controls for assignee firm fixed effects and industry group (four-digit NAICS) × year fixed effects. *Source*: PatentsView.

Figure 7. Temporal Heterogeneity:
The Intensity and Breadth of Innovation over Time



Notes. Plotted are the difference-in-differences coefficient estimates from nine separate regressions (three outcomes for three time periods) based on Equation (1), with the formation of collusion as an event of interest. The dependent variable consists of the number of patent filings (red colored bars), the top 10% most cited patents compared to peers in the same three-digit CPC × year (brown bars), and the unique technology classes of patents (blue bars), all of which are transformed by the inverse hyperbolic sine function in an assignee firm × year. Numbers above the bar show regression estimates, whereas vertical bars represent 95% confidence intervals. The regression model controls for assignee firm fixed effects and industry group (four-digit NAICS) × year fixed effects. *Source*: PatentsView.

Figure 8. Life Cycle of Collusion and Citation-Weighted Patents:
A Placebo Test



Notes. Plotted are the event-time coefficient estimates from a version of Equation (4). The dependent variable consists of citation-weighted patents with the inverse hyperbolic sine transformation in an assignee firm × year. Blue dots and lines represent the real treatment group (colluded firms), whereas 1,000 gray lines represent the results for the placebo tests. In the placebo tests, the treatment indicator is randomly reassigned to five firms from the pool of both colluded and noncolluded firms that belong to the same six-digit NAICS industry. This random assignment simulation is repeated 1,000 times. *Source*: 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, 1976–2016)

	Obs.	Mean	Std. Dev.	Min.	Median	Max.
Patents	1,844,146	3.09	37.59	0.00	1.00	8,935.00
Citation-weighted patents	1,844,146	38.64	517.55	0.00	1.00	158,906.00
Patents in main areas	1,844,146	1.38	12.09	0.00	1.00	4,289.00
Patents in peripheral areas	1,844,146	1.66	19.31	0.00	1.00	3,753.00
Patent technology classes	1,844,146	1.19	3.99	0.00	1.00	223.00
Tech class-weighted patents	1,844,146	4.29	40.43	0.00	2.00	9,107.00
Backward citations	1,844,146	8.11	24.87	0.00	2.00	5,834.50
Forward citations	1,844,146	7.36	26.77	0.00	0.00	2,804.00
Inventors (3-year moving avg.)	1,844,146	10.61	110.86	0.00	1.00	17,917.00

C. Compustat data (company level, 1976–2016)

	Obs.	Mean	Std. Dev.	Min.	Median	Max.
Employment (in thousands)	286,154	7.28	32.93	0.00	0.56	2,545.21
Capital expenditure ($mil)	300,204	137.01	928.45	0.00	2.95	65,028.00
R&D expenditure ($mil)	150,101	65.96	436.25	0.00	1.57	16,085.00

Notes. Panel A shows the descriptive statistics for all nonfinancial collusion cases in the United States for 1975–2016 at the collusion, firm, and individual manager levels, respectively. Panel B shows the pooled (cross-sectional) descriptive statistics for the patent data (1976–2016) at the assignee firm level. Assignee firms are identified by name disambiguated *assignee_id*, which is provided by PatentsView. Panel C shows the pooled (cross-sectional) descriptive statistics for the Compustat data (1976–2016) 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 (1976–2016).
Sources: The author's own data collection from the Antitrust Case Filings of the U.S. Department of Justice (DOJ) and the Antitrust Cases of the Commercial Clearing House (CCH) (panel A); PatentsView (May 28, 2018, version) (panel B); and Compustat (June 2018 version) (panel C).

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*	
	Patent filings	Citation-weighted Patents	Patents (top 10%)	R&D expenditure	Technology classes	Technology class-weighted patents
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × *Post*	0.477***	0.573***	0.334***	0.175*	0.303***	0.485***
	(0.099)	(0.146)	(0.071)	(0.096)	(0.065)	(0.096)
Observations	443,898	443,898	443,898	136,626	443,898	443,898
R^2	0.565	0.489	0.534	0.922	0.527	0.519
Adjusted R^2	0.450	0.354	0.412	0.911	0.402	0.392

B. Collusion breakup: Increased competition and innovation

	Dependent variables ($\sinh^{-1}$):					
	Intensity of innovation				*Breadth of innovation*	
	Patents	Citation-weighted patents	Patents (top 10%)	R&D expenditure	Patent technology classes	Technology class-weighted patents
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × *Post*	−0.029	−0.120	0.117**	−0.168**	−0.020	−0.021
	(0.053)	(0.094)	(0.052)	(0.084)	(0.041)	(0.059)
Observations	444,003	444,003	444,003	137,129	444,003	444,003
R^2	0.568	0.489	0.539	0.922	0.529	0.521
Adjusted R^2	0.454	0.354	0.417	0.911	0.404	0.395

Notes. These tables report regression coefficients from 12 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), citation-weighted patents (column 2), the top 10% of patents in terms of forward citations (column 3), R&D expenditure (column 4), the unique technology classes of patents (column 5), and technology class-weighted patents (column 6), 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 postevent (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. *Sources*: PatentsView and Compustat. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 3. Effects of Collusion and Competition on Innovation: Flexible Approach

A. Collusion formation: Reduced competition and innovation

	Dependent variables ($\sinh^{-1}$):					
	Intensity of innovation				*Breadth of innovation*	
	Patents	Citation-weighted patents	Patents (top 10%)	R&D expenditure	Patent technology classes	Technology class-weighted patents
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × *Pre*	0.0002	0.159	0.018	0.001	0.025	0.064
	(0.096)	(0.191)	(0.061)	(0.042)	(0.075)	(0.110)
Treat × $Post_A$	0.413***	0.563***	0.318***	0.143	0.277***	0.460***
	(0.102)	(0.194)	(0.076)	(0.099)	(0.079)	(0.115)
Treat × $Post_B$	0.621***	0.772***	0.434***	0.194**	0.414***	0.654***
	(0.132)	(0.206)	(0.098)	(0.093)	(0.083)	(0.133)
Observations	444,172	444,172	444,172	137,089	444,172	444,172
R^2	0.566	0.490	0.535	0.922	0.528	0.520
Adjusted R^2	0.452	0.355	0.413	0.911	0.403	0.394

B. Collusion breakup: Increased competition and innovation

	Dependent variables ($\sinh^{-1}$):					
	Intensity of Innovation				*Breadth of innovation*	
	Patents	Citation-weighted patents	Patents (top 10%)	R&D expenditure	Patent technology classes	Technology class-weighted patents
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × *Pre*	–0.023	–0.014	–0.063	0.058	–0.017	0.005
	(0.064)	(0.109)	(0.077)	(0.075)	(0.050)	(0.073)
Treat × $Post_A$	–0.001	–0.069	0.111**	–0.055	0.004	0.025
	(0.060)	(0.112)	(0.056)	(0.068)	(0.042)	(0.068)
Treat × $Post_B$	–0.164**	–0.384**	0.005	–0.122**	–0.153**	–0.159*
	(0.081)	(0.150)	(0.070)	(0.060)	(0.060)	(0.093)
Observations	444,283	444,283	444,283	137,174	444,283	444,283
R^2	0.570	0.490	0.540	0.922	0.530	0.523
Adjusted R^2	0.457	0.355	0.419	0.911	0.406	0.397

Notes. This table reports regression coefficients from 12 separate regressions based on Equation (2). 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), citation-weighted patents (column 2), the top 10% of patents in terms of forward citations (column 3), R&D expenditure (column 4), the number of unique technology classes of patents (column 5), and technology class-weighted patents (column 6), 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. *Pre* is an indicator variable that takes the value of one for –4 to –2 years prior to collusion formation or breakup and zero otherwise. $Post_A$ is an indicator variable that takes the value of one for the first two years of collusion or its breakup and zero otherwise. $Post_B$ is an indicator variable that takes the value of one for the third and fourth years of collusion formation and/or breakup and zero otherwise. $Pre_{t=-1}$ is omitted and serves as the baseline. A sector is defined by the four-digit North American Industry Classification System. All of the regressions implicitly or explicitly control for firm fixed effects and sector × year fixed effects. Standard errors are in parentheses and are clustered by industry group (four-digit NAICS). *Sources*: PatentsView and Compustat. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 4. Life Cycle of Collusion and the Intensity and Breadth of Innovation

	Dependent variables ($\sinh^{-1}$):					
	Intensity of innovation				*Breadth of innovation*	
	Patents	Citation-weighted patents	Patents (top 10%)	R&D expenditure	Patent technology classes	Technology class-weighted patents
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × *Pre-collusion*$_1$	–0.010	0.149	–0.015	–0.060	0.004	0.005
	(0.121)	(0.210)	(0.103)	(0.086)	(0.082)	(0.126)
Treat × *Collusion*$_1$	0.513***	0.505**	0.330***	0.246*	0.293***	0.499***
	(0.139)	(0.215)	(0.093)	(0.144)	(0.088)	(0.137)
Treat × *Collusion*$_2$	0.641***	0.631**	0.434***	0.356**	0.350***	0.610***
	(0.204)	(0.258)	(0.138)	(0.173)	(0.130)	(0.205)
Treat × *Post-collusion*$_1$	0.699***	0.469*	0.626***	0.153	0.385***	0.661***
	(0.220)	(0.251)	(0.227)	(0.174)	(0.146)	(0.216)
Treat × *Post-collusion*$_2$	0.538**	0.228	0.558***	0.275***	0.238*	0.491**
	(0.220)	(0.275)	(0.194)	(0.087)	(0.140)	(0.216)
Treat × *Post-collusion*$_3$	0.429*	0.045	0.545**	0.175*	0.176	0.390
	(0.240)	(0.304)	(0.219)	(0.091)	(0.156)	(0.242)
Observations	474,899	474,899	474,899	136,986	474,899	474,899
R^2	0.575	0.499	0.512	0.923	0.536	0.529
Adjusted R^2	0.455	0.358	0.374	0.912	0.405	0.382

Notes. This table reports regression coefficients from six separate regressions based on Equation (4), where the dependent variable consists of the number of patent filings (column 1), citation-weighted patents (column 2), the top 10% of patents in terms of forward citations (column 3), R&D expenditure (column 4), the unique technology classes of patents (column 5), and technology class-weighted patents (column 6), 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. Years are grouped into seven time periods, each representing the three-year period around the events of interest into one time group. *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 (an omitted category). *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. *Postcollusion*$_1$ means one to three years after the breakup of collusion. *Postcollusion*$_2$ means four to six years after the breakup of collusion. *Postcollusion*$_3$ means seven to nine years after the breakup of collusion. *Precollusion*$_2$ serves as the baseline. The regression model controls for the assignee firm fixed effects and sector × year fixed effects. A sector is defined by the four-digit North American Industry Classification System (NAICS). Standard errors are in parentheses and are clustered by sector. *Sources*: PatentsView and Compustat. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 5. Effects of Collusion and Competition on Innovation: Additional Tests

A. Collusion formation: Reduced competition and innovation

	Dependent variables ($\sinh^{-1}$):		
	Innovation input	*Innovation by a firm's technological areas*	
	Inventors	Patents in a firm's main area	Patents in a firm's peripheral area
	(1)	(2)	(3)
Treat × *Post*	0.566***	0.389***	0.328***
	(0.111)	(0.082)	(0.085)
Observations	443,898	443,898	443,898
R^2	0.603	0.508	0.538
Adjusted R^2	0.498	0.378	0.416

B. Collusion breakup: Increased competition and innovation

	Dependent variables ($\sinh^{-1}$):		
	Innovation input	*Innovation by a firm's technological areas*	
	Inventors	Patents in a firm's main area	Patents in a firm's peripheral area
	(1)	(2)	(3)
Treat × *Post*	−0.017	0.048	−0.029
	(0.082)	(0.050)	(0.042)
Observations	444,003	444,003	444,003
R^2	0.605	0.511	0.542
Adjusted R^2	0.500	0.382	0.421

Notes. These tables report regression coefficients from six 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 unique inventors, the three-year moving average (column 1), the number of patent filings in a firm's main technological fields (column 2), and the number of patent filings in a firm's peripheral technological fields (columns 3), 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 postevent (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. *Source*: PatentsView. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.