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 prosecuted collusion cases in the United States from 1975 through 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 suppressed price competition, colluded firms increased patent filings by 20.5 percent and top-quality patents by 16 percent. A significant portion of these patents are attributable to fundamental innovation activities since innovation inputs—R&D investment and the number of unique patenting inventors—increased in tandem by 15.2 percent and 22.9 percent, respectively. Furthermore, firms broadened their scope of innovation by exploring new technological areas; the number of patented technology classes increased by 11.9 percent. 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 shed light on market profitability and firm financial constraints as key economic 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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> 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 of the utmost importance. Research and development (R&D) and the innovation processes, however, require risky and uncertain investment. The returns on R&D investment 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; 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 therefore 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 arguments important to determine which dominates and the mechanisms involved. 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 stemming 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; this is the key mission of the US Department of Justice's (DOJ's) antitrust enforcement (https://www.justice.gov/atr/mission). I have collected and digitized data on all known (nonfinancial) cartel cases in the United States from 1975 through 2016. The resulting sample consists of 461 cartel cases, along with 1,818 firms and 1,623 managers.

Further, existing studies tend to assume that innovative activities fall somewhere along an 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 colluded firms to carefully defined counterfactual firms, I find a negative causal relationship between price competition and innovation. When a cartel suppressed market competition, colluded firms increased patenting by 20.5 percent. A significant portion of the increase is attributable to fundamental 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 11.9–18.9 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 provides higher incentive to innovate. Further tests suggest that market profitability and firm financial constraints (i.e., the ability to innovate) are important economic mechanisms behind the trade-off between price competition and innovation growth. The 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 pursue innovation to survive, achieve a competitive advantage, and outperform their competitors. 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" (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). Although different from price competition in the product market, 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 nineteenth 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. Joshi and Nerkar (2011) find that patent pools in the global optical disc industry decreased 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." 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. Macher et al. (2021) studied how cement manufacturers adopt a new cost-saving technology at different levels of market competition. Even though all these manufacturers understood the effectiveness of new technology in reducing costs, their adoption pattern differed depending on the level of market competition. New technology adoption was 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 innovation activities by reducing its profits and resources.

Reduced competition could also provide *incentives* for innovation in three ways. First, reduced competition increases a firm's probability of survival. It also 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 innovate to sustain their market dominance and 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 because it becomes easier to monitor or communicate with other firms. This effect is magnified in the cartel setting because firms coordinate and monitor each other's production and pricing.[3]

Several empirical studies support the Schumpeterian view. Im et al. (2015) find in the US manufacturing sector that a firm's incentive to innovate increased in response to tariff cuts when market competition is mild; in contrast, the incentive decreased 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. (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 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 US manufacturing sector.

[3] See, for example, Igami and Sugaya (2021) on how colluded firms communicate with and monitor each other.

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 considered enough, 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 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. 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 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. This makes innovation activities in new areas more costly, risky, and 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).

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. When price competition in the market is suppressed, firms enjoy a higher profit and less uncertainty; they have slack time and financial and cognitive resources that can be devoted to longer-term and riskier projects. Thus, reduced competition can provide firms with incentives and the ability to broaden their technological horizon and conduct more aggressive and ambitious research.

Further, reduced competition can promote R&D coordination—either explicit or implicit—between firms. Collusion, for example, facilitates communication and increases visibility between competing firms. As colluded 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 firms' technological fields.

3 Data

Collusion Data. The Antitrust Division of the DOJ releases three types of documents in their Antitrust Case Filings repository: information (indictment), plea agreement, and final judgment. These documents contain detailed information about the identity of colluded 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 code (for older cases) or six-digit NAICS code (for recent cases). The documents arrive at the defendant firm or individual level, not at the collusion level. Using information on collusion period, market, and co-conspirators, I was able to group firms and individuals belonging to the same collusion. Another source of data for collusion is Wolters Kluwer's CCH (formerly Commerce Clearing House). Its Antitrust Cases (formerly Trade Regulation Reporter) provides summaries of the antitrust-related documents released by 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, I identified 461 collusion cases involving 1,818 firms in the United States from 1975 to 2016.[4] 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 US Patent & Trademark Office (USPTO), the PatentsView database has information on inventors, assignee firms, 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. 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 around 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, an important input when defining relevant markets and composing appropriate control groups. To navigate this problem, I converted the patent technology field, Cooperative Patent Classification (CPC), to the North American Industry Classification System (NAICS) and aggregated them at the firm level (see the Online Appendix A.2 for details).

I then matched firm names in the collusion data and the patent data using two different name-matching schemes. First, I created broad, case-insensitive regular expressions 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

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

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 filing. For any firm-year observation where I did not observe a patent, I assigned the value of zero if the year occurred between the firm's first and last year 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. The same name-matching process was used for firms in Compustat. 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. 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 "we have spent too much time calculating too many kinds of concentration ratios" (Joskow, 1975, p. 278), Concentration Ratio (CR_N) or 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 a "cartel," is an agreement between competitors to restrict competition. The utmost 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 simultaneously used. 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, 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 along with the number of indicted firms and individuals.

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, advance discussions, and 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.[5] This program grants immunity only to the first whistleblower that informs the DOJ of the existence of collusion and provides sufficient 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.[6] Online Appendix C.9, Figure C-12, shows the temporal heterogeneity of the effects.

4.2 Difference-in-Differences Estimation

In the difference-in-differences estimation, I compare colluded firms (the treatment group) to firms in the adjacent/similar market, but not in the same market. The control group is defined as firms that share the four-digit NAICS code, but not the six-digit NAICS code. For example, if a colluded 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 the difference-in-differences model in Equation (1) for four years before and after the year of event:

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

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 post-event periods at the firm

[5] 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).

[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.

and year 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 same sector, broadly defined. I exclude firms from 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 SIC codes as NAICS codes are available for recent years only (e.g., Kogan et al., 2017). 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):

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

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

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 event (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 post-event period.

The above approaches consider the formation and breakup of collusion as if they are 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 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:

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

where Pre_t^1 means four to six years prior to the formation of collusion. Pre_t^2 means one to three years prior

[7] The inverse hyperbolic sine transformation is defined as $y^{IHS} = \log(\, y + \sqrt{y^2+1}\,)$. It is defined at zero and approximately equal to $\log 2y = \log y + \log 2$ (except for very small values of y); 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).

[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.

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. $Post_t^1$ 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 potential threats to identification. First, the DOJ's enforcement may be negotiated ("prosecutorial discretion"). The start and end date reported by DOJ may not accurately present the actual duration of cartels. This, however, works against the findings, leading to an underestimation of the effects (see Online Appendix A.1). I also provide sensitivity tests in Section 5.4. Second, colluded 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, collusion tends to be formed by larger firms in the market, which are more likely to initiate scientific research (Arora et al., 2021). Still, because it is marginal firms that may be left out of collusion, I expect that their impact is small. More importantly, I excluded from the control group those non-colluded firms that are in the same six-digit NAICS industry. That stated, the results are more applicable to a moderately concentrated market than to a perfectly competitive market.

The cartel setting offers two important "treatment" events. The formation and breakup events 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 endogenous factors (other than the collusion) in market competition.

5 Main Results

5.1 Intensity of Innovation

Patents. Table 2, columns 1–4, shows 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 colluded firms increased patenting by 20.5 percent after the formation of collusion. Colluded firms on average filed 40.4 patents per year immediately before the formation of collusion, so the 20.5 percent increase in patenting is equivalent, on average, to 8.3 more patents per year for each colluded firm. Table C-1 in Online Appendix C.1 shows a more flexible approach based on Equation (2). Colluded firms increased patenting by 15 percent in the short term ($Treat \times Post_A$) and by 23.5 percent in the longer term ($Treat \times Post_B$) after the formation of collusion. After the breakup, however, estimates in panel B show that colluded firms decreased patenting by 8.9 percent in the long term ($Treat \times Post_B$).

Next, I report estimates from the event study approach with distributed year leads and lags based on Equation (3). In Figure 2(a), each point and vertical bar represents 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. It shows that colluded firms gradually increased patent filings after they begin 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 formation of a vitamin cartel and reached a 100 percent increase in three years (Bernheim, 2008).

Panel B, on the other hand, indicates that colluded firms—though not precisely estimated—decreased patenting by 7.4 percent after the breakup of collusion. The imprecise point estimation and smaller effect size is an expected outcome 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 keep filing patents as the results of R&D activities undertaken during collusion. Figure C-2 in Online Appendix C.1 shows this trend: that colluded firms decrease patent filings after price competition is restored as collusion breaks 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 Online Appendix shows the regression results on innovation intensity. The results, illustrated in Figure 2(b) for patent counts, 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 ensures that the model indeed captured the effects of collusion-induced changes in competition and not those of some 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 their quality or impact. To better measure the fundamental innovation activities of firms, I also examine the 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 three-digit CPC × year. Table 2 (column 2) reports that firms indeed increased innovation activities and registered impactful and high-quality patents by 16 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 (19.8 percent), as shown in Table 2 (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 be due to the risky nature of exploration and the fact that it does not always turn out to be successful or to 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 shows that colluded firms increased their R&D expenditure by about 15.2 percent during collusion, compared to the pre-collusion period. This is equivalent to an additional $70 million being 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 the results for R&D investments to those for patents.

To further ensure the validity of the control group, I use Compustat Segment 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 3, 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 Online Appendix C.7, Table C-7). Third, I restrict the control group so that control firms operate in a similar set of markets except for the market where collusion occurs. Specifically, I additionally require that the treated and control firms have the same largest business segment. Another test restricts the control groups to firms that have at least 75 percent of revenue from a single segment. The results are robust to these additional restrictions on the control groups. Empirical analysis excluding colluded firms that participated in R&D collaboration also provides consistent results. These tests with business segment data consistently confirm that the results are not driven by a mismatch between treated and control firms (see Online Appendix C.7, Table C-7, for more details).

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] Table 2, panel A, column 6 indicates the number of patented technology fields increased

[9] In Online Appendix C.2, 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 average long-term influence of patents.

[10] I assigned zero to any firm-year observation without any filed patents. Excluding such cases does not qualitatively change the results.

by 11.9 percent when market competition was suppressed by collusion. This is equivalent to 0.77 additional fields as colluded firms patented in 6.5 technology fields before collusion. Figure 2(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 (Table 2, panel B, column 6) and up to 10.2 percent in the longer term (Online Appendix C.1, Table C-1). A single framework of the life cycle of collusion is shown in Figure 2(d) and Online Appendix 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. To further explore how firms allocate their innovation activities across existing (exploitative) versus new (explorative) fields of innovation, 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 its peripheral technological area, which is measured by patents not in each firm's three most frequently patented technology classes. The results in Table 2, columns 8–9, show that firms increased innovation in *both* primary (21.4 percent) and peripheral (20.1 percent) technology areas of the firm. In other words, reduced competition enabled firms to explore new technological areas as well as strengthen the innovation in existing areas. 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 explored 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. (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 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 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 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]

5.3 The Impact on Non-Colluded Firms

The analyses so far have focused on colluded firms. Yet the price-fixing behavior of colluded firms may not only change their own behavior but also affect the competitors in the same market. An important strategic question is how the competitor firms are affected by collusion, which 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 market).

Figure 3 graphically summarizes the results. Panels (a) and (b) shows the flexible difference-in-differences results for patent filings around cartel formation and breakup. In panel (c), the point estimates presented with light brown bars indicate that non-colluded firms decreased their intensity of innovation (patents) by 3.3 percent and the breadth of innovation by 0.4 percent, although statistically not distinguishable from zero. The effects on both colluded and non-colluded firms altogether, estimated at the firm-year level, likewise are close to zero. This suggests that colluded firms drove the innovation activities during collusion. Firms that were left out of the club consequently could not join the innovation race.

5.4 Robustness Checks

Model-free Evidence. Regression models may be sensitive to underlying assumptions and transformations. It is important to examine the data with minimal transformation. This task is challenging in the cartel setting because (1) collusion lasts several years and then breaks up (i.e., colluded firms are treated twice at different timing) and (2) the duration differs across cases. In consideration of these challenges, Figure 4 graphically presents the average patent filings around cartel formation by groups. To account for the different absolute level of patenting across firms, the only transformation made is normalization of the outcome variable based on their pre-collusion values. Without fixed effects and other adjustments, it is evident that colluded firms increased patenting activities after cartel formation.

Placebo Permutation Tests. To check 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 permutation tests, where the treatment indicator is randomly reassigned to five firms from the pool of both

[11] In Gross (2020), intensifying competition from *no* competition induced artists to produce original, untested ideas.

colluded and noncolluded firms that belong to the same four-digit NAICS industry. Figure 5 graphically summarizes the results for patents. Gray lines represent 1,000 placebo permutations and, on average, show no effect. The patenting activities by colluded firms are clearly distinct from placebo permutation results. I confirm that the effects do not come from spurious, arbitrary components of the data and models.

Robustness Test with Firms Excluded. To understand whether a small number of outlier firms are driving the entire results, I randomly excluded one to three treated firms from the sample and estimated the model. There are two randomization parts. First, the number of colluded firms (one to three) to be excluded are decided. Second, the chosen number of colluded firm(s) are randomly excluded from the sample. I repeat this process 1,000 times and plot the distribution of estimates in Figure 7. The estimates on the intensity and breadth of innovation are robust to the random exclusion of treated firms and are bunched closely together.

Sensitivity Test of Cartel Formation by Year. The DOJ process is likely negotiated for each firm ("prosecutorial discretion"), and the DOJ's ability to claim the collusion period is limited by the evidence they collect. To address this concern, I use the start date of collusion as the earliest start date among colluded firms. I also performed a sensitivity analysis around the start date of the collusion (T). I ran the test with an alternative collusion start date: $T-1$, $T-2$, and $T-3$. The results are robust to the alternative start dates. Figure C-10 in Online Appendix C.6 shows the sensitivity test for the intensity of innovation. The point estimate increases as the treatment year is adjusted by one to three years earlier. This is consistent with our prior that the effects are underestimated in the presence of term negotiation.

6 Further Analyses of the Mechanisms

6.1 Markets versus Firms

Some firms operate businesses in multiple areas. An interesting and crucial question is whether the increased innovation activities happened in the market where firms colluded (through market profitability) or in different markets in which the colluded firms operate (through firm-level financial constraint). I performed several tests to pinpoint the mechanism. First, with patent data, I measured the technological concentration of firms as the HHI of technology fields. If a firm patents exclusively on a few technology classes (i.e., high concentration), this firm is likely to have a single-unit business where the extra profit from collusion must be allocated to the same, colluded 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 business units outside the colluded one. I conducted a split-sample analysis comparing narrow versus broad firms. In Table 3, columns 1a–1b, the increase in patents comes primarily from narrow firms that focus on a small number of technology fields (32.7 percent), supporting the market profitability channel. Additional evidence is provided in Section 6.3 where I explain that the effects are greater for industries that grew fast pre-collusion. The profitability of the colluded market is highly associated with the pro-innovation effect.

Second, I use the nature of collusion that the participating companies, by construction, fix the price on the same products or services. I test whether colluded firms increase their patent filings in the overlapping technology fields to a greater extent than those in the distinct technology fields. I defined the overlapping fields as the five most frequent intersection of patented technology fields (using primary and secondary four-digit CPC) across all colluded firms in collusion. I then estimated the patents in overlapping fields and the remaining distinct (or firm-specific) fields. Table 3, columns 2a–2b, shows that the magnitude of the effects is greater for overlapping technology fields (18.6 percent), supporting the market mechanism. The company-wide financial constraint channel also seems to work, although at a smaller magnitude, because firms increased their patenting activities in distinct fields by 14.3 percent.

Third, granular business segment data offered by Compustat Segment provides an opportunity to compare firms operated in one or two business segments to those that operated in three or more segments before collusion. A split-sample analysis in Table 3, columns 3a and 3b, show that the increase in R&D expenditure disproportionately came from narrow firms, again supporting the market profitability mechanism (see Online Appendix C.7, Table C-7, for additional tests). In sum, the findings consistently suggest that market-level profitability is the primary driver of innovation during collusion.

6.2 Financial Constraints

One of the main arguments in line with Schumpeter's view is that suppressed price competition affords firms with more financial resources, which then can be allocated to innovation activities. Two testable implications arise. First, firms that had limited access to external finance before cartel should benefit more from collusion and the extra profit. Second, firms that enjoyed high revenue growth during collusion should invest more in R&D activities compared to those that experienced low revenue growth. I first test the two hypotheses separately by quartile group. Figure 6(a) shows that firms that had restricted access to external finance (in the bottom quartile) responded in a more aggressive way in terms of R&D investment. Likewise, the increase in revenue growth during collusion is positively associated with R&D expenditure; the estimates are larger and precisely estimated for firms that enjoyed higher revenue growth during collusion.

I then jointly test the hypothesis using a two-by-two matrix. Figure 6 (b) summarizes the results in a heatmap. The results support the view that firms that (1) had limited access to external finance before collusion but (2) could reap higher revenues during collusion exhibited the highest increase in R&D expenditure ($\beta = 0.549, p = 0.001$). In contrast, I find no R&D effect for firms that already relied on external finance before collusion and that did not experience revenue growth during collusion ($\beta = 0.021, p = 0.788$). The increased innovation activities indeed came from firms that faced difficulty in finding outside financial resources (before collusion) and successfully secured more financial resources during collusion. The results confirm that the firms' financial constraint is one important economic mechanism behind the negative causal relationship between competition and innovation intensity.

6.3 Growing versus Mature Markets

The industry life cycle could change the price competition and innovation dynamics. On the one hand, if the market is mature, a suppressed price competition may not effectively spur innovation because the expected return on innovation is lower in the stagnant market (i.e., growing market promotes innovation). On the other hand, collusion may form in mature markets as existing 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 (i.e., mature market promotes explorative innovation). The two arguments provide opposing predictions on how industry life cycles are associated with the intensity and breadth of innovation during collusion. To empirically test, I measure the industry growth rate as the compound annual growth rate (CAGR) of patents in four-digit NAICS industries for the five years prior to cartel formation and ran regressions as in Equation (1) on key measures of innovation activities.

Figure 8 illustrates the results by quartile group. The effects are greater for markets that exhibited moderate to high growth rate before cartel formation. They increased patenting activities by 21–30 percent (red bars), the top 10 percent of high-quality patents by 12–27 percent (brown bars), and the number of unique technology classes 9–22 percent (blue bars). However, firms in the mature markets (in the bottom quartile) did not increase their innovation activities as much.[12]

The results suggest that the increase in the breadth of innovation was not driven by firms in mature markets that try to escape the colluded market; the estimates are greater for firms in the rapidly growing markets. Furthermore, if firms sought to escape the mature colluded market, it is expected that firms further increase the breadth of innovation after the cartel breakup; in other words, firms' efforts to escape the market should be accelerated if they must compete head-to-head in the mature market. In Figure 2(d), the breadth of innovation instead reverted to the original level. Taken together, the results are more consistent with the argument that firms shift toward innovation competition when price competition is suppressed.

6.4 Fundamental Innovation versus Intellectual Property Strategy

The effects on R&D expenditure are 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

[12] This finding has an important policy implication for how the competition authority with limited resources allocates its attention over different markets based on the industry life cycle.

be due to changes in the need for strategic patenting (e.g., Hall and Ziedonis, 2001; Lerner, 1995; Kang and Lee, 2021), to patent (cross)licensing (Priest, 1977; Eswaran, 1993; Arora, 1997; Arora and Ceccagnoli, 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) in the innovation activities. Assuming a direct proportional relationship between patents and R&D investments, one sees in Table 2, columns 1 and 5, that roughly 74.1 percent of the increase in patenting can be explained by a firm's genuine R&D efforts. One notable caveat, however, 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 scientists that engaged in inventive activities. If the patenting results come entirely from an intellectual property strategy, one should expect that the same pool of scientists registered more patents (including those previously kept a secret), and the number of inventors does not change meaningfully. If firms increased their fundamental innovation activities, in contrast, these activities should accompany the patent filings by scientists new 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 3, column 4, shows that the unique number of inventors increased by 22.9 percent during collusion. Moreover, the yearly estimates of unique inventor counts closely follow the changes in patents (see Online Appendix C.1, Figure C-6). This suggests that increased patenting was accompanied by an increased number of new scientists, providing strong support for the fundamental innovation activities of firms. Furthermore, as a new set of inventors are expected to bring distinct knowledge compared to existing inventors, this finding also supports the conclusion that firms indeed broadened their innovation scope through 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 the suppressed market competition via price fixing indeed drove the results, greater effects should be observed for firms in strong collusion. In contrast, weak collusion may fail to promote the intensity and the breadth of innovation.

I measure the strength of collusion by the patent share (for patent analysis) and sales share (for R&D analysis) of colluded firms. I run split-sample analysis for strong collusion (those with above-median share) and weak collusion (those with below-median share). Table 3 shows the patent results (columns 5a and 5b) and R&D results (columns 6a and 6b) around the cartel formation (Figure C-11 in the Online Appendix C.8 illustrates the results). Firms in strong collusion on average increased their patenting activities by 24.6 percent and R&D expenditure by 20.3 percent, whereas those in weak collusion exhibit economically small and statistically insignificant effects. The results confirm that the collusion's ability to suppress price competition indeed drove the causal relationship between competition and innovation.

7 Discussion

In this setting, in which firms in technology-intensive industries colluded to fix prices, reduced competition was not a cushion to sleep on (Schumpeter, 1942). Firms shifted toward innovation competition and broadened their technological exploration when price competition weakened. Managers must understand this fundamental change in the arena of competition and set the appropriate innovation strategies. Conditions under which this major shift in the types of competition happened—namely, access to external finance, extra revenue earned, and the life cycle 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.

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 and put more weight on it, 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 view. In their innovation theory of harm (ITOH), the EC views competition as the mother of invention, and views mergers and collusion as reducing innovation (European Commission, 2016). This argument touches the point that the price of the focal product is distorted in a given market in the short run.

This view, however, does not consider the possibility that price in turn affects the innovation activities of firms and the new product and services offered in the long run.[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 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 pro-innovation effect of restrained price competition is greater than price distortion and provides net positive social value. Firms that overcharge on influenza vaccine, for instance, could intensify their innovation effort for new medicine such as a vaccine for the Zika virus or the coronavirus, thanks to the extra profit earned from flu vaccine. It is therefore important to have a comprehensive and balanced view that competition in the product market not only affects the price of (existing) products but also changes a firm's incentives and ability to innovate and the quality of new products and services a firm might offer.

Furthermore, the importance of innovation is magnified when considering that the social return to

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

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). It thus 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 by no means suggests that competition harms innovation and therefore promotions of market competition should be stopped. The results show, however, that a certain level of insulation from fierce price competition *may* facilitate the innovation activities of firms, especially for firms facing financial constraints and in fast-growing, technology-intensive industries. 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 always unlawful under any circumstances (*per se illegal*).[14] 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 market competition.

8 Concluding Remarks

Innovation is the primary source of a firm's competitive advantage and economic growth. I find that firms shifted toward innovation competition and broadened their innovation scope when price competition weakened. That is, reduced competition is not a cushion to sleep on (Schumpeter, 1942) but invokes an important change to the rules of the game. The fact that firms explored 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 were 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 had limited access to external finance, that reaped more profits, and that were in fast-growing industries.

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, 2020; 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 readily generalizable to other contexts. Implications on innovation by competition that is 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 that US manufacturers decreased their patenting activities when facing higher competition from Chinese import penetration. However, the competitive pressure from low-end products by foreign countries should

[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).

have different consequences and implications than the price competition manipulated by collusion among leading companies in technology-intensive industries. The generalizability of the findings in this study 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 changed 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 and direction of innovation. This distinction enables a deeper understanding of the relationship between competition and innovation. Firms not only changed the intensity of innovation but also altered the breadth of innovation, both of which affect the novelty and value of future technologies and products. Third, I collected data on all known collusion cases and used 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 is a highly 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, firm performance, and society.

References

Aghion, P., Bloom, N., Blundell, R., Griffith, R. and Howitt, P. 2005. Competition and Innovation: an Inverted-U Relationship. *The Quarterly Journal of Economics*, 120, 701–728.

Alford, R. 2018. *The Role of Antitrust in Promoting Innovation*. U.S. Department of Justice. https://www.justice.gov/opa/speech/file/1038596/download.

Arora, A. 1997. Patents, Licensing, and Market Structure in the Chemical Industry. *Research Policy*, 26(4–5), 391–403.

Arora, A. and Ceccagnoli, M. 2006. Patent protection, complementary assets, and firms' incentives for technology licensing, *Management Science*, 52(2), 293–308.

Arora, A., Belenzon, S., Kosenko, K., Suh, J. and Yafeh, Y. 2021. The Rise of Scientific Research in Corporate America. *NBER Working Paper #29260*.

Arora, A., Belenzon, S. and Sheer, L. 2021. Knowledge Spillovers and Corporate Investment in Scientific Research. *American Economic Review*, 111(3): 871–98.

Arrow, K. J. 1962. Economic Welfare and the Allocation of Resources for Invention. In *The rate and direction of inventive activity* (Ed.) R. R. Nelson. Princeton University Press. Princeton, NJ, 609–626.

Autor, D. H., Dorn, D. and Hanson, G. H. 2013. The China Syndrome: Local Labor Market Impacts of Import Competition in the United States, *American Economic Review*, 103, 2121–2168.

Autor, D. H., Dorn, D., Hanson, G. H., Pisano, G. and Shu, P. 2020. Foreign Competition and Domestic Innovation: Evidence from US Patents. *American Economic Review: Insights*, 2(3): 357–374.

Bernheim, B. D. 2008. Expert Report of B. Douglas Bernheim, In *Re: Vitamin C Antitrust Litigation*, MDL No. 1738.

Bloom, N., Schankerman, M. and Van Reenen, J. 2013. Identifying Technology Spillovers and Product Market Rivalry. *Econometrica*, 81, 1347–1393.

Boone, J. 2001. Intensity of Competition and the Incentive to Innovate. *International Journal of Industrial Organization*, 19(5), 705–726.

Bracha, A. and Fershtman, C. 2013. Competitive Incentives: Working Harder or Working Smarter? *Management Science*, 59, 771–781.

Cohen, W. M. and Levin, R. C. 1989. Empirical studies of innovation and market structure. *Handbook of Industrial Organization*, 2, 1059–1107.

Cohen, W. M. and Levinthal, D. A. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, 35, 128–152.

Connor, J. M. and Lande, R. H. 2006. The Size of Cartel Overcharges: Implications for U.S. and EU Fining Policies. *The Antitrust Bulletin*, 51, 983–1022.

Correa, J. A. and Ornaghi, C. 2014. Competition & Innovation: Evidence from U.S. Patent and Productivity Data. *The Journal of Industrial Economics*, 62, 258–285.

Corredoira, R. A. and Preeta, M. B. 2015. Measuring Patent's Influence on Technological Evolution: A Study of Knowledge Spanning and Subsequent Inventive Activity. *Research Policy*, 44(2): 508–521.

Eswaran, M. 1993. Cross-Licensing of Competing Patents as a Facilitating Device. *Canadian Journal of Economics*, 27(3), 689-708.

Gilbert, R. 2006a. Competition and Innovation, *Journal of Industrial Organization Education*, 1, 1–23.

Gilbert, R. 2006b. Looking for Mr. Schumpeter: Where are We in the Competition-Innovation Debate? *Innovation Policy and the Economy*, 6, 159–215.

Gong, K. and Xu, R. 2017. Does Import Competition Induce R&D Reallocation? Evidence from the U.S. *SSRN Working Paper #3013441*.

Grant, R. M. 1996. Towards a Knowledge-based Theory of the Firm. *Strategic Management Journal*, 17, 109–122.

Greenhalgh, C. and Rogers, M. 2006. The Value of Innovation: The Interaction of Competition, R&D and IP. *Research Policy*, 35(4), 562–80.

Griliches, Z. 1992. The Search for R&D Spillovers. *Scand. Journal of Economics*, 94, 29–47.

Gross, D. P. 2020. Creativity Under Fire: The Effects of Competition on Creative Production. *The Review of Economics and Statistics*, 102(3): 583–599.

Hall, B. H. and Ziedonis, R. H. 2001. The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995. *The RAND Journal of Economics*, 101–128.

Hall, B. H., Jaffe, A. and Trajtenberg, M. 2005. Market Value and Patent Citations. *The RAND Journal of Economics*, 36, 16–38.

Hashmi, A. R. 2013. Competition and Innovation: The Inverted-U Relationship Revisited. *The Review of Economics and Statistics*, 95, 1653–1668.

Henderson, R. M. and Clark, K. B. 1990. Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. *Administrative Science Quarterly*, 35, 9–30.

Igami, M. and Sugaya, T. 2021. Measuring the Incentive to Collude: The Vitamin Cartels, 1990-1999. *The Review of Economic Studies*, forthcoming.

Im, H. J., Park, Y. J., and Shon, J. 2015. Product Market Competition and the Value of Innovation: Evidence from US Patent Data. *Economics Letters*, 137, 78–82.

Joshi, A. M. and Nerkar, A. 2011. When Do Strategic Alliances Inhibit Innovation by Firms? Evidence from Patent Pools in the Global Optical Disc Industry, *Strategic Management Journal*, 32, 1139–1160.

Joskow, P. L. 1975. Firm Decision-making Processes and Oligopoly Theory. *American Economic Review*, 65, 270–279.

Kang, H. and Lee, W. 2021. How Innovating Firms Manage Knowledge Leakage: A Natural Experiment on the Threat of Worker Departure, *SSRN Working Paper #3171829*.

Klein, J. I. 2006. *Antitrust Enforcement and the Consumer*. U.S. Department of Justice. https://www.justice.gov/atr/file/800691/download.

Kline, P., Petkova, N., Williams, H. L. and Zidar, O. 2017. Who Profits from Patents? Rent-Sharing at Innovative Firms, *The Quarterly Journal of Economics*, 134(3): 1343–1404.

Kogan, L., Papanikolaou, D., Seru, A. and Stoffman, N. 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2): 665–712.

Kogut, B. and Zander, U. 1992. Knowledge of the Firm, Combinative Capabilities, and the Replication of Technology. *Organization Science*, 3(3), 383–397.

Krieger, J. L., Li, D., and Papanikolaou, D. 2018. Developing Novel Drugs, *NBER Working Paper #24595*.

Lampe, R. and Moser, P. 2010. Do Patent Pools Encourage Innovation? Evidence from the Nineteenth-Century Sewing Machine Industry. *The Journal of Economic History*, 70(4), 898–920.

Lampe, R. and Moser, P. 2013. Patent Pools and Innovation in Substitute Technologies - Evidence from the 19th-century Sewing Machine Industry. *The RAND Journal of Economics*, 44, 757–778.

Lampe, R. and Moser, P. 2016. Patent Pools, Competition, and Innovation - Evidence from 20 US Industries under the New Deal. *Journal of Law, Economics, and Organization*, 32, 1–36.

Lefouili, Y. 2015. Does Competition Spur Innovation? The Case of Yardstick Competition. *Economics Letters*, 137, 135–139.

Lerner, J. 1995. Patenting in the Shadow of Competitors. *The Journal of Law & Economics*, 38, 463–495.

Lerner, J. and Tirole, J. 2004. Efficient Patent Pools. *American Economic Review*, 94, 691–711.

Levenstein, M. C. and Suslow, V. Y. 2006. What Determines Cartel Success? *Journal of Economic Literature*, 44, 43–95.

Levenstein, M. C. and Suslow, V. Y. 2011. Breaking Up Is Hard to Do: Determinants of Cartel Duration. *Journal of Law and Economics*, 54, 455–492.

Levenstein, M. C. and Suslow, V. Y. 2016. Price Fixing Hits Home: An Empirical Study of US Price-Fixing Conspiracies. *Review of Industrial Organization*, 48, 361–379.

Levin, R. C., Cohen, W. M., and Mowery, D. 1985. R&D Appropriability, Opportunity, and Market Structure: New Evidence on some Schumpeterian Hypotheses. *American Economic Review*, 75, 20–24.

Loury, G. C. 1979. Market Structure and Innovation. *The Quarterly Journal of Economics*, 93, 395.

Macher, J., Miller, N. H., and Osborne, M. 2021. Finding Mr. Schumpeter: Concrete Evidence on Competition and Technology Adoption. *The RAND Journal of Economics*, 52(1): 78–99.

Miller, N. H. and Weinberg, M. C. 2017. Understanding the Price Effects of the MillerCoors Joint Venture. *Econometrica*, 85, 1763–1791.

Nelson, R. R. and Winter, S. G. 1982. *An Evolutionary Theory of Economic Change*. Harvard Business School Press, Cambridge.

Pate, R. H. 2003. *Anti-cartel Enforcement: The Core Antitrust Mission*. U.S. Department of Justice. https://www.justice.gov/atr/file/518801/download.

Priest, G. 1977. Cartels and Patent License Arrangements. *Journal of Law and Economics*, 20(2), 309-377.

Schor, A. 2004. Heterogeneous Productivity Response to Tariff Reduction. Evidence from Brazilian Manufacturing Firms. *Journal of Development Economics*, 75, 373–396.

Schumpeter, J. A. 1934. *The theory of economic development*. Transaction Publishers.

Schumpeter, J. A. 1942. *Capitalism, Socialism and Democracy.* Routledge.

Sidak, J. G. and Teece, D. J. 2009. Dynamic Competition in Antitrust Law. *Journal of Competition Law and Economics*, 5, 581–631.

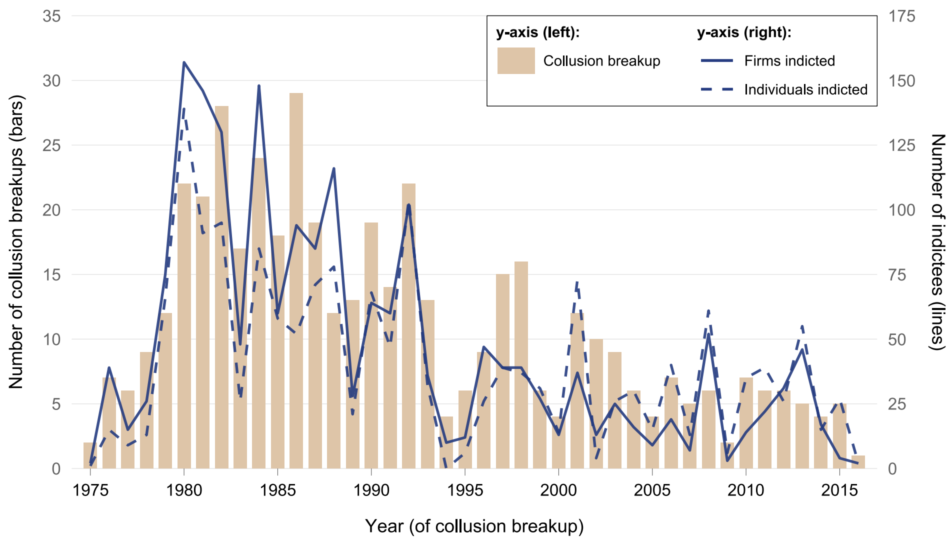
Trajtenberg, M. 1990. A Penny for Your Quotes: Patent Citations and the Value of Innovations. *The RAND Journal of Economics*, 172–187.

Turner, S. F., Mitchell, W., and Bettis, R. A. 2010. Responding to Rivals and Complements: How Market Concentration Shapes Generational Product Innovation Strategy. *Organization Science*, 21, 854–872.

Williamson, O. E. 1965. Innovation and Market Structure. *Journal of Political Economy*, 73, 67–73.

Yu, M. 2015. Processing Trade, Tariff Reductions and Firm Productivity: Evidence from Chinese Firms. *The Economic Journal*, 125, 943–988.

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

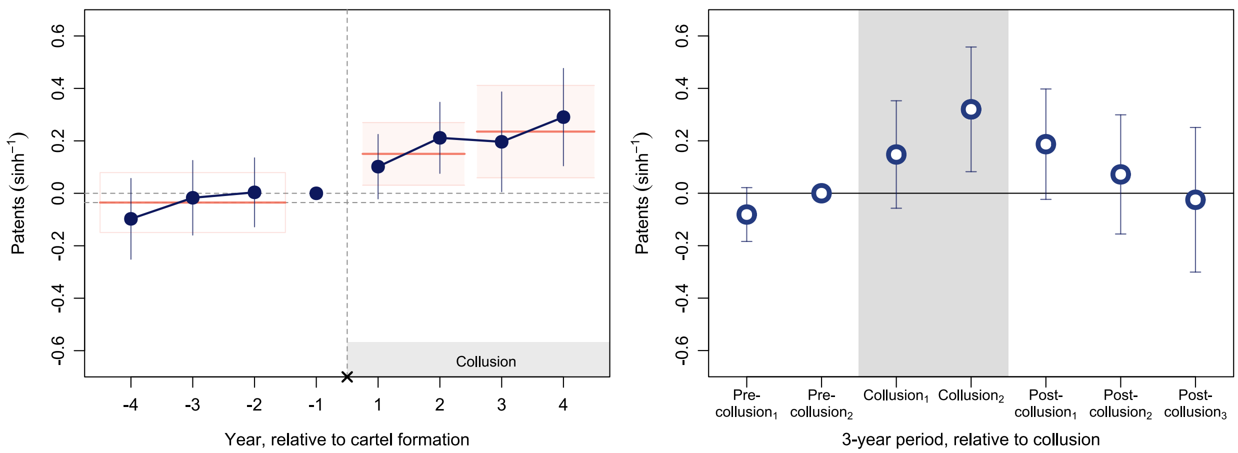


Notes. This figure tracks the trend in antitrust enforcement and collusion breakup in the US from 1975 through 2016. Brown bars represent the number of collusion breakup cases by year. The solid blue line represents the number of firms indicted for collusion each year, whereas the blue dashed line represents 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. 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. *Data*: The author's data collection from the Antitrust Case Filings of the US Department of Justice (DOJ) and the Antitrust Cases of the CCH.

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

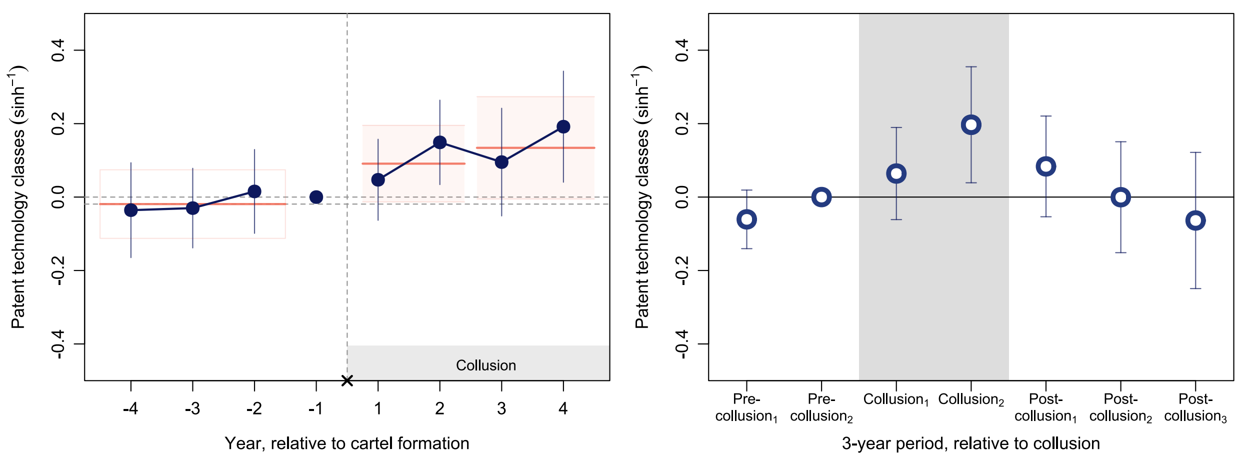
A. Intensity of innovation: Patent filings

(a) Reduced competition and patents (b) Life cycle of collusion and patents



B. Breadth of innovation: Number of unique technology classes

(c) Reduced competition and unique patent classes (d) Life cycle of collusion and unique patent classes



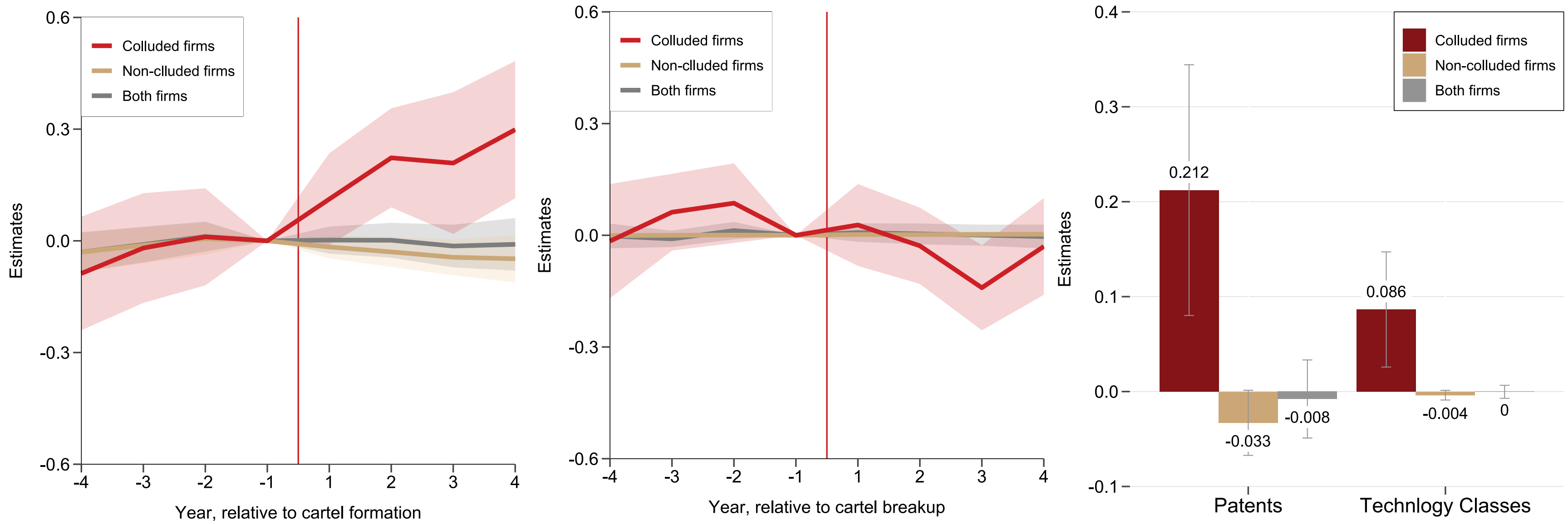
Notes. The dependent variable consists of (1) the number of patent filings (that are eventually granted) and (2) the number of unique technology classes of patents (three-digit CPC) with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence 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 3. The Effects on Colluded and Non-Colluded Firms

(a). Cartel formation and patents

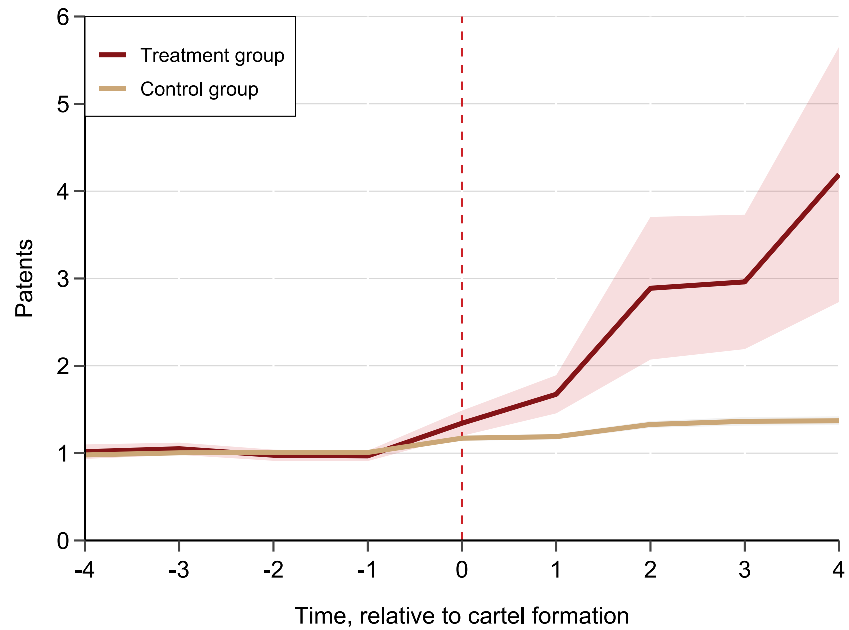
(b). Cartel breakup and patents

(c). Comparing key outcomes by group



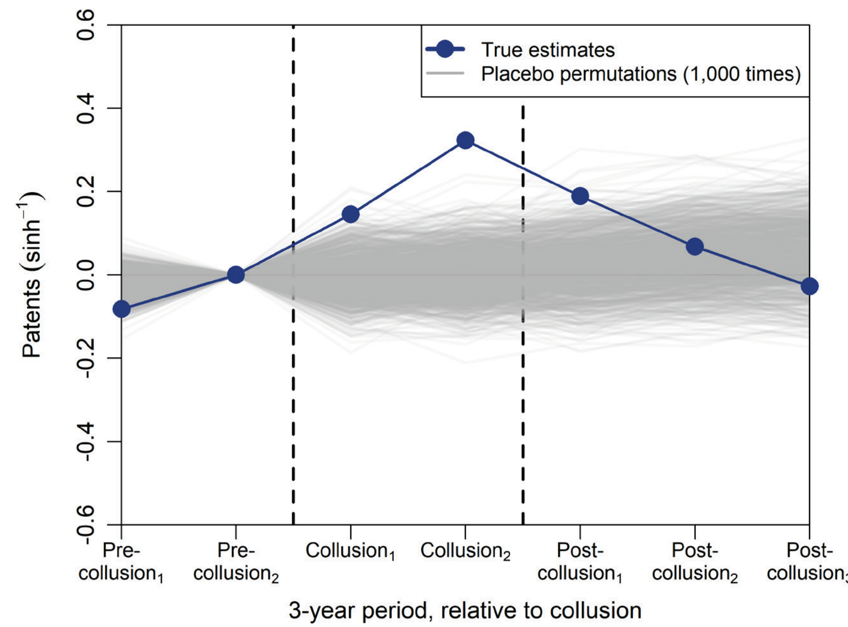
Notes. Panel (c): Plotted are the difference-in-differences coefficient estimates from six separate regressions based on Equation (1), with the formation of collusion as an event of interest. The treatment group consists of (1) colluded firms (2) firms in the focal industry that were not part of the collusion, and (3) all firms in the focal industry regardless of their participation in collusion, 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 4. Collusion Formation and Patents: Model-Free Evidence



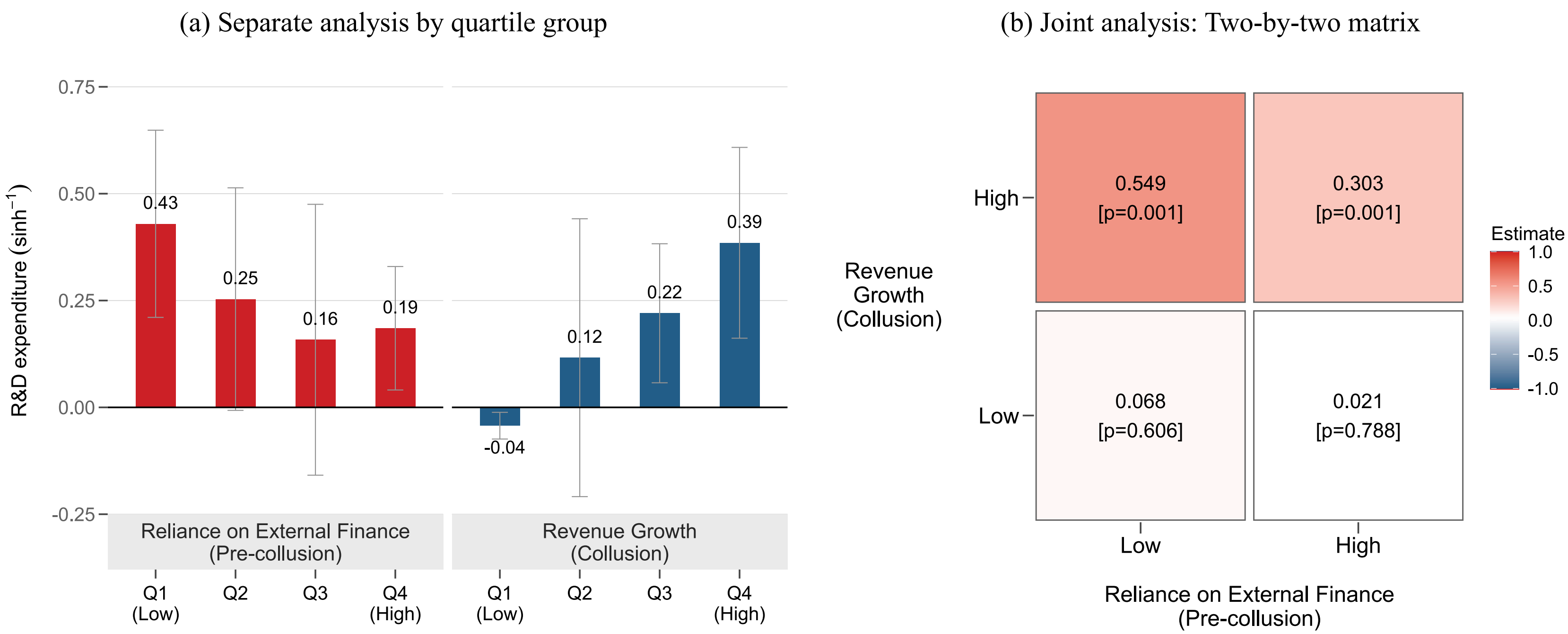
Notes. Plotted are the average patent filings around cartel formation by the treatment group (colluded firms) in red solid line and the control group (non-colluded firms in the adjacent industries) in brown solid line. The shaded area represents the one standard deviation from the estimate. The dependent 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 5. Placebo Permutation Tests:
Random Reassignment of Treatment Status (1,000 times)



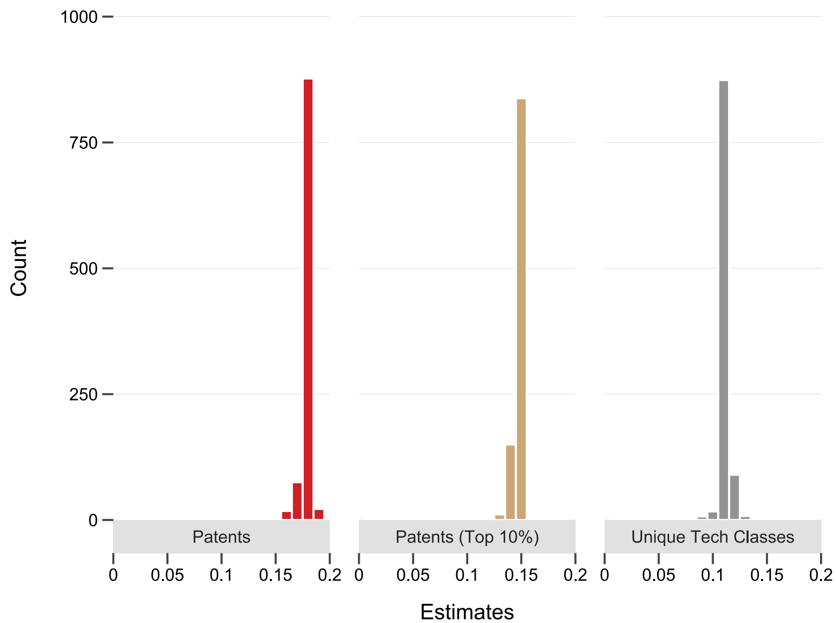
Notes. Plotted are the event-time coefficient estimates from a version of Equation (4). The dependent variable consists of the number of patents with the inverse hyperbolic sine transformation in an assignee firm × year. Blue dots and lines represent the treatment group (colluded firms), whereas 1,000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

Figure 6. Financial Constraints and R&D: Reliance on External Finance and Revenue Growth



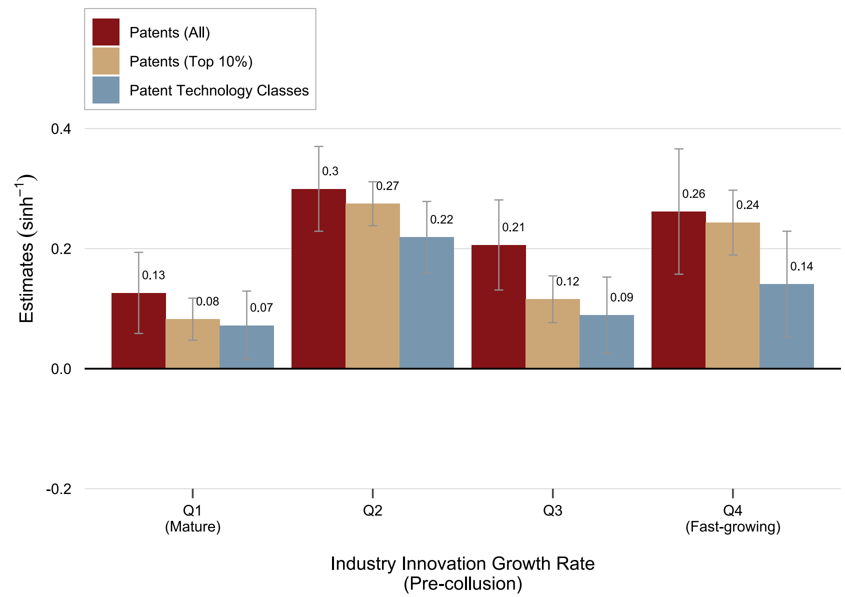
Notes. Panel (a): Plotted are the difference-in-differences coefficient estimates from eight separate regressions based on Equation (1), with the formation of collusion as an event of interest. Firms in the treatment group are subgrouped by their reliance on external finance before collusion ($t \in [-5, -1]$, red bars) and the revenue growth during collusion ($t \in [1,5]$, blue bars). 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. Panel (b): 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 two-by-two matrix based on firms' reliance on external finance before collusion and revenue growth during collusion. Low represents the bottom two quartiles (below median) and High represents the top two quartiles (above median). The colors in the heatmap represent the size of the estimates. P-values are provided in square brackets. *Data*: Compustat.

Figure 7. Robustness Test with Excluding 1–3 Firms (1,000 times)



Notes. Plotted are the three histograms of difference-in-differences coefficient estimates from Equation (1) after excluding 1–3 firms from the sample. First, the number of colluded firms (one to three) to be excluded was decided. Second, the chosen number of colluded 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 are 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 8. Intensity and Breadth of Innovation by Pre-Collusion Industry Growth Rate



Notes. Plotted are the difference-in-differences coefficient estimates from twelve separate regressions 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 (four-digit NAICS), and each colluded firm (along with their counterfactual firms) is divided into four quartile groups based on this rate. Cutoffs for quartiles are 4.80% (lower quartile), 9.18% (median), and 15.11% (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. *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 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 from the Antitrust Case Filings of the US Department of Justice (DOJ) and the Antitrust Cases of CCH (panel A); PatentsView (August 11, 2021, version) (panel B); and Compustat (May 2021 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*			
	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*	0.205***	0.160***	0.198*	0.152**	0.119**	0.189***	0.214***	0.201***
	(0.068)	(0.052)	(0.102)	(0.069)	(0.049)	(0.071)	(0.068)	(0.061)
Observations	433,279	433,279	433,279	149,932	433,279	433,279	433,279	433,279
R^2	0.555	0.560	0.484	0.921	0.522	0.509	0.493	0.642
Adjusted R^2	0.443	0.449	0.354	0.910	0.402	0.385	0.366	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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × *Post*	–0.074	0.057	–0.289***	–0.073	–0.065	–0.100*	–0.039	–0.004
	(0.052)	(0.043)	(0.111)	(0.063)	(0.041)	(0.060)	(0.048)	(0.046)
Observations	433,778	433,778	433,778	150,025	433,778	433,778	433,778	433,778
R^2	0.561	0.569	0.484	0.921	0.526	0.513	0.500	0.652
Adjusted R^2	0.451	0.460	0.354	0.910	0.407	0.390	0.374	0.564

Notes. These tables report regression coefficients from eighteen separate regressions based on Equation (1). Panel A uses cartel formation as an event, and panel B uses cartel breakup as an event. The dependent variable consists of the number of patent filings (column 1), the top 10% of patents in terms of forward citations (column 2), citation-weighted patents (column 3), R&D expenditure (column 4), the unique number of technology classes (column 5), technology class-weighted patents (column 6), patents in a firm's primary technology fields (column 7), and patents in a firm's peripheral technology fields (column 8), all of which are transformed by the inverse hyperbolic sine function in a firm × year. *Treat* is an indicator variable that takes the value of one for colluded 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. Effects of Collusion and Competition on Innovation: Tests of the Mechanisms

A. Collusion formation: Reduced competition and innovation

	Dependent variables ($\sinh^{-1}$):										
	Scope of Firms						*IP Strategy*	*Power 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*	0.327**	0.031	0.186***	0.143**	0.347***	–0.017	0.229**	0.246***	–0.057	0.203**	0.054
	(0.130)	(0.117)	(0.067)	(0.072)	(0.124)	(0.100)	(0.089)	(0.073)	(0.145)	(0.098)	(0.048)
Observations	432,267	431,968	433,279	433,279	149,833	149,815	433,279	433,059	431,645	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	0.441	0.313	0.298	0.909	0.910	0.488	0.4442	0.425	0.910	0.909

B. Collusion breakup: Increased competition and innovation

	Dependent variables ($\sinh^{-1}$):										
	Scope of Firms						*IP Strategy*	*Power 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*	0.072	–0.397***	–0.046	0.0001	–0.082	–0.004	–0.129*	–0.117**	0.177	–0.045	–0.133*
	(0.098)	(0.125)	(0.049)	(0.055)	(0.163)	(0.125)	(0.073)	(0.053)	(0.153)	(0.090)	(0.075)
Observations	432,156	431,935	433,778	433,778	149,820	149,813	433,778	433,406	431,665	149,941	149,847
R^2	0.544	0.554	0.469	0.454	0.920	0.921	0.595	0.560	0.541	0.921	0.920
Adjusted R^2	0.429	0.442	0.335	0.317	0.909	0.910	0.493	0.449	0.426	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 colluded firms (columns 2a and 8a), the number of patents in distinct fields among colluded 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 colluded 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. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.