ELECTRONIC COMPANION

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

Hyo Kang

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A. Additional Description of Data and Sample

A.1 Collusion Data

Data sources and sample construction

Figure A-1 and Figure A-2, respectively, show the first page of information (indictment) and plea agreement documents released by the Antitrust Division of the US Department of Justice. The most important information on collusion is the names of (co-)conspirators and the years of collusion formation and breakup. The DOJ investigates collusion and estimates the dates of collusion formation and breakup. Their estimation is reasonably accurate because, in most cases, indictees and the DOJ agree on "plea bargaining," meaning that indictees pledge to fully cooperate with the investigation and to provide all the evidence in return for reduced punishment. Further, the DOJ should have robust and real evidence to claim the collusion period.

The Antitrust Division of DOJ also provides additional information on cartels such as the industry code (NAICS) of the affected market. For early documents that report relevant markets using SIC codes, I looked at the SIC-NAICS crosswalk and additionally consulted detailed descriptions of each industry classification to convert the SIC code to the NAICS code.

Figure A-1. A Sample Indictment Document (page 1 of 4)

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UNITED STATES DISTRICT COURT

FOR THE NORTHERN DISTRICT OF CALIFORNIA

SAN FRANCISCO DIVISION

UNITED STATES OF AMERICA	Case No. CR 11 0162 CRB
	INFORMATION
v.	VIOLATION: Title 15, United States Code, Section 1 (Conspiracy in Restraint of Trade)
SAMSUNG SDI COMPANY, LTD.,	
	San Francisco Venue
Defendant.	

The United States of America, acting through its attorneys, charges:

I.

DESCRIPTION OF THE OFFENSE

1. SAMSUNG SDI COMPANY, LTD. ("defendant") is made the defendant on the charge stated below.

2. From at least as early as January 1997, until at least as late as March 2006, the defendant and its coconspirators entered into and engaged in a combination and conspiracy in the United States and elsewhere to suppress and eliminate competition by fixing prices, reducing output, and allocating market shares of color display tubes ("CDTs"). The combination and conspiracy engaged in by the defendant and its coconspirators was in unreasonable restraint of

INFORMATION - SAMSUNG SDI - PAGE 1

Notes. This image shows the first page of an indictment document ("information") for collusion filed on March 18, 2011. Information on the defendant (the colluding firm), collusion period, and detailed conduct are described. *Data*: The US DOJ.

Figure A-2. A Sample Plea Agreement (page 1 of 16)

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UNITED STATES DISTRICT COURT

FOR THE NORTHERN DISTRICT OF CALIFORNIA

SAN FRANCISCO DIVISION

UNITED STATES OF AMERICA v. SAMSUNG SDI COMPANY, LTD., Defendant.	Case No. CR 11-0162 (WHA)

AMENDED PLEA AGREEMENT

The United States of America and Samsung SDI Company, Ltd. ("defendant"), a corporation organized and existing under the laws of the Republic of Korea, hereby enter into the following Amended Plea Agreement ("Plea Agreement") pursuant to Rule 11(c)(1)(C) of the Federal Rules of Criminal Procedure ("Fed. R. Crim. P."):

RIGHTS OF DEFENDANT

1. The defendant understands its rights:

(a) to be represented by an attorney;

(b) to be charged by Indictment;

(c) as a corporation organized and existing under the laws of the Republic of Korea, to decline to accept service of the Summons in this case, and to contest the jurisdiction of the United States to prosecute this case against it in the United States District Court for the Northern District of California;

Notes. This image shows the first page of a plea agreement for collusion between the United States of America and the defendant, filed on May 17, 2011, where the defendant voluntarily agrees to consent to the jurisdiction of the United States to prosecute the case and voluntarily waives the right to file any appeal. *Data*: The US DOJ.

The sample consists of *criminal* cases on *cartels*. The US Department of Justice lists "price fixing, bid rigging, or market division or allocation schemes" as forms of a cartel in its Antitrust Primer (https://www.justice.gov/atr/file/810261/download) and other documents. The cartel sample consists of 1,818 firms engaged in cartels that were detected by DOJ. These collusive conducts are felony punishable under Section 1 of the Sherman Antitrust Act. Cases concerning civil non-mergers, non-competes for employees, and failure to give timely HSR notice are *not* included in the sample.

Note that many DOJ case filings charge more than one defendant individual and/or business per case. Table A-1 shows a few examples of such cases:

Table A-1. Selected Examples of DOJ Antitrust Case Filings Charging Multiple Defendants

Case open date	Case name	Case type	Case violation	Defendants	DOJ case filing link
6/15/2016	United States v. Maruyasu Industries Co., Ltd., Curtis-Maruyasu America, Inc., Tadao Hirade, Kazunori Kobayashi, Satoru Murai, and Yoshihiro Shigematsu	Criminal	• Price Fixing - Horizontal • Bid Rigging • Customer, Territorial or Market Allocation – Horizontal	• Maruyasu Industries Co., Ltd. • Curtis-Maruyasu America, Inc. • Tadao Hirade • Kazunori Kobayashi • Satoru Murai • Yoshihiro Shigematsu	https://www.justice.gov/atr/case/us-v-maruyasu-industries-co-ltd-et-al
11/12/2008	United States v. LG Display Co., Ltd. and LG Display America, Inc.	Criminal	• Price Fixing – Horizontal	• LG Display Co., Ltd. • LG Display America, Inc.	https://www.justice.gov/atr/case/us-v-lg-display-co-ltd-and-lg-display-america-inc
9/6/2006	United States v. Stolt-Nielsen S.A., Stolt-Nielsen Transportation Group Ltd. (Liberia), Stolt-Nielsen Transportation Group Ltd. (Bermuda), Samuel A. Cooperman, and Richard B. Wingfield	Criminal	• Price Fixing - Horizontal • Bid Rigging • Customer, Territorial or Market Allocation - Horizontal	• Stolt-Nielsen S.A. • Stolt-Nielsen Transportation Group Ltd. (Liberia) • Stolt-Nielsen Transportation Group Ltd. (Bermuda) • Samuel A. Cooperman • Richard B. Wingfield	https://www.justice.gov/atr/case/us-v-stolt-nielsen-sa-et-al
8/27/2003	United States v. Windshield Sales & Service, Inc., Windshield Sales & Service of Dallas, Inc., and Mesquite Auto Glass, Inc.	Criminal	• Price Fixing - Horizontal	• Windshield Sales & Service, Inc. • Windshield Sales & Service of Dallas, Inc. • Mesquite Auto Glass, Inc.	https://www.justice.gov/atr/case/us-v-windshield-sales-service-inc-et-al
4/10/1978	United States v. Black Millwork Co., Inc., Hussey-Williams Millwork Co., Inc., Sturtevant-Millwork Corp., and Whittier-Ruhle Millwork Co.	Criminal	• Price Fixing - Horizontal	• Black Millwork Co., Inc. • Hussey-Williams Millwork Co., Inc. • Sturtevant-Millwork Corp. • Whittier-Ruhle Millwork Co.	https://www.justice.gov/atr/case/us-v-black-millwork-co-inc-et-al

Further, some cases are added or removed from the DOJ antitrust case filings website over time (although such cases are rather rare). I have done several web-scrapings of their website and found out that (1) even old cases (e.g., in the 1980s) had been added in the last few years and (2) some cases are removed from the website. For this reason, I collected antitrust enforcement data from another, more comprehensive source: Wolters Kluwer's VitalLaw (legal research database for attorneys). Its *Trade Regulation Reporter* keeps close track of any cases released by the US DOJ and provides detailed reports on them (https://www.wolterskluwer.com/en/solutions/vitallaw-law-firms/antitrust-competition-law). The reports can be found under "Antitrust & Competition" → "Reporters" → "Trade Regulation Reporter" → "Federal Enforcement Actions" → "U.S. Antitrust Cases." Since this report is created as soon as DOJ releases any document, VitalLaw is a more complete repository of DOJ Antitrust Filings—i.e., it is not subject to later additions and removals from the DOJ website. Another great advantage is that the *Trade Regulation Reporter* is constantly updated with the latest developments in the case. For example, it is updated as soon as the court rules on the case. I accessed this database through an institutional subscription.

I read and compared all case fillings on the DOJ webpage and the *Trade Regulation Reporter* in VitalLaw (there are more than 2,000 documents from each source). I checked the accuracy and consistency of information from the two sources and created a master database on criminal cartel cases (i.e., price fixing, bid-rigging, and market allocation schemes in violation of Section 1 of the Sherman Antitrust Act). This data contains links to the relevant DOJ antitrust case filings and/or *VitalLaw*'s *Trade Regulation Reporter*.

Figure A-3 presents the screenshot of the *Hynix Semiconductor, Inc.* case as an example (highlights added by the author). Panel (a) shows a screenshot of the first part of the indictment found in DOJ antitrust case filings (highlights added by the author). The defendant is *Hynix Semiconductor, Inc.* (highlighted yellow). The charge makes it clear that the defendant violated Section 1 of the Sherman Antitrust Act by fixing the prices (green highlights) in the DRAM products from April 1999 through June 2002 (blue highlights). The screenshot of the equivalent report by VitalLaw's *Trade Regulation Reporter* is presented in Panel (b). The headnote indicates that this is a price-fixing case violating Section 1 of the Sherman Antitrust Act (highlighted green).

Figure A-3. Hynix case in DOJ's Antitrust Case Filings and VitalLaw's Trade Regulation Reporter

(a). DOJ Antitrust Division's Antitrust Case Filings

UNITED STATES DISTRICT COURT NORTHERN DISTRICT OF CALIFORNIA
SAN FRANCISCO DIVISION

UNITED STATES OF AMERICA v. HYNIX SEMICONDUCTOR INC., Defendant.	Case No. CR 05 00249 SI **INFORMATION** VIOLATION: Title 15, United States Code, Section 1 (Price Fixing) San Francisco Venue

The United States of America, acting through its attorneys, charges:

I. DESCRIPTION OF THE OFFENSE
1. HYNIX SEMICONDUCTOR INC. ("HYNIX") is made a defendant on the charge stated below.

2. From on or about April 1, 1999, until on or about June 15, 2002, defendant HYNIX and its coconspirators, entered into and engaged in a combination and conspiracy in the United States and elsewhere to suppress and eliminate competition by fixing the prices of Dynamic Random Access Memory ("DRAM") to be sold to certain original equipment manufacturers of personal computers and servers ("OEMs"). The combination and conspiracy engaged in by the defendant and its coconspirators was in unreasonable restraint of interstate and foreign trade and commerce in violation of Section 1 of the Sherman Act (15 U.S.C. § 1).

Source. https://www.justice.gov/atr/case/us-v-hynix-semiconductor-inc.

(b). Trade Regulation Reporter by Wolters Kluwer's VitalLaw

Trade Regulation Reporter, 4779. United States of America v. Hynix Semiconductor, Inc., U.S. District Court, N.D. California, ¶45,105, (Apr. 21, 2005)

4779. United States of America v. Hynix Semiconductor, Inc.

¶45,105. U.S. District Court, N.D. California, Criminal No. 05 00249

– Headnote

(Sec. 1, Sherman Act, DYNAMIC RANDOM ACCESS MEMORY, price fixing).

On April 21, 2005, Hynix Semiconductor Inc., a Korean manufacturer of DYNAMIC RANDOM ACCESS MEMORY (DRAM), agreed to plead guilty and to pay a $185 million fine for participating in an international conspiracy to fix prices in the multi-billion dollar DRAM market, the Department of Justice announced. Hynix's fine is the third-largest criminal antitrust fine in U.S. history and the largest in five years.

Including the suit against Hynix, two companies and five individuals have been charged and fines totaling more than $346 million have resulted from the Department's ongoing antitrust investigation into price fixing in the DRAM industry.

DRAM is the most commonly used semiconductor memory product, providing high-speed storage and retrieval of electronic information for a wide variety of computer, telecommunication, and consumer electronic products. DRAM is used in personal computers, laptops, workstations, servers, printers, hard disk drives, personal digital assistants, modems, mobile phones, telecommunication hubs and routers, digital cameras, video recorders, televisions, game consoles, and digital music players. There were approximately $7.7 billion in DRAM sales in the United States in 2004.

"Price fixing imperils free markets, impairs innovation, and harms American consumers," said Attorney General Alberto R. Gonzales. "Today's charge and its resulting guilty plea are another significant step forward in the Department's ongoing fight to break up and prosecute international cartels that harm American consumers. This case shows that high-tech price-fixing cartels will not be tolerated."

According to the one-count felony charge filed in the federal district court in San Francisco, from April 1, 1999 to June 15, 2002, Hynix conspired to fix the prices of DRAM sold to certain computer and server manufacturers. The customers directly affected by the price-fixing conspiracy were: Dell Inc., Compaq Computer Corporation, Hewlett-Packard Company, Apple Computer Inc., International Business Machines Corporation, and Gateway Inc.

Source. Wolters Kluwer's VitalLaw (*Trade Regulation Reporter* #4779). Accessed via institutional subscription.

The accuracy of collusion period

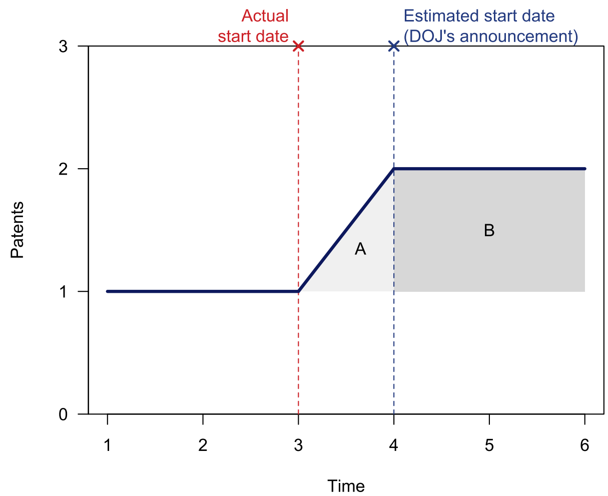
Colluding firms have a strong incentive to understate the correct collusion period (unless the DOJ has strong evidence). This suggests that the DOJ's estimation of the duration of collusion is rather a lower bound for the actual duration; the true collusion start date, in particular, may be earlier than the estimated date appearing in the indictment. The accuracy of the breakup date is less of a concern because many collusion cases are broken down by the investigation and intervention of the DOJ (Levenstein and Suslow, 2011), and therefore the DOJ has more information about and more accurate data on the true breakup date.

Another complication is that the DOJ process is likely negotiated. They confirmed that a firm or an individual may receive a reduced criminal punishment as a result of "prosecutorial discretion." I addressed the concern in three ways. First, I use the start date of collusion as the *earliest start date* among colluding firms. The negotiation is firm-specific; some firms successfully negotiate, while others do not. I indeed see a different collusion start date for firms in the same collusion, even if it is evident that they started the collusion at the same time (it takes two to tango). Thus, I infer and use as the collusion-level start date the earliest collusion start date among the participant firms in each collusion. Likewise, I use the end date of collusion as the latest end date among colluding firms.

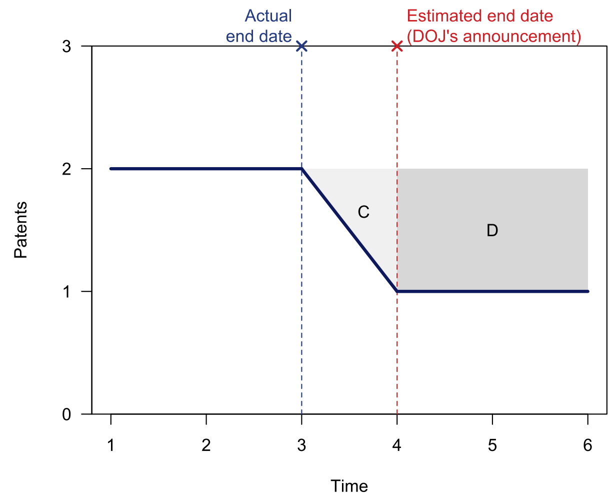
Second, the measurement error is likely biased towards shorter periods of collusion compared to the true period. For the formation of collusion, if negotiation occurs, a firm's start date must be changed to a later (not earlier) date. This will introduce a downward bias (bias toward zero) because the pre-treatment period may include several years where firms actually colluded. In Figure A-4(a), if the start date is negotiated (or underestimated), the specification underestimates the effect size equal to the A area. For the breakup of collusion, a firm's end date must be changed to an earlier (not later) date if negotiation occurs. Again, this introduces a downward bias (bias toward zero) because the post-treatment period may include the years when firms actually colluded. In Figure A-4(b), if the end date is negotiated (or underestimated), the specification underestimates the effect size equal to the C area.

Figure A-4. Potential Measurement Error on Cartel Duration and Its Implications

(a). Measurement error in cartel formation



(b). Measurement error in cartel breakup



A.2 Patent Data

A recent project of the USPTO and the Commerce Data Service uses Natural Language Processing (NLP) to create the Cosine Similarity table (many-to-many crosswalk) between all six-digit NAICS codes and the four-character CPC subclasses. A detailed explanation and the crosswalk files are available online at https://github.com/CommerceDataService/cpc-naics. Using this bridge, I first construct a one-to-one bridge between NAICS and CPC at the patent level using the highest cosine similarity.

For the firm-level match, I use a granular many-to-many bridge. For each patent and its CPC subclass, I construct a vector of the CPC's Cosine Similarity score for each NAICS code. I then sum this vector of similarity scores for all patents at the assignee-firm-NAICS level. The resultant similarity score represents each assignee firm's engagement in each six-digit NAICS industry. I assign the top-scored NAICS industry to each firm as the main industry. I also vary this approach, either by normalizing its similarity score at the patent level (i.e., percentage score) or by calculating the score for each year (rather than pooling the years).

Figure A-5 illustrates the total patenting activities by six-digit NAICS sectors. I marked the sectors where collusion occurred as red (and light brown otherwise). Note that collusion happened at different points in time during the sample period, 1976–2016, and I do not have the event years for non-collusive sectors. As such, I compare general patenting activities across industries during the full sample year and illustrate their total patent counts over the sample period, 1976–2016.

Figure A-5 shows that sectors where collusion happened tend to have higher patents than the rest. I performed the t-test and report the results in Table A-2; the average patenting in collusive sectors is greater than and statistically different from that in non-collusive sectors.

Figure A-5. Total Number of Patents by Collusive and Non-collusive Industries (Six-digit NAICS)

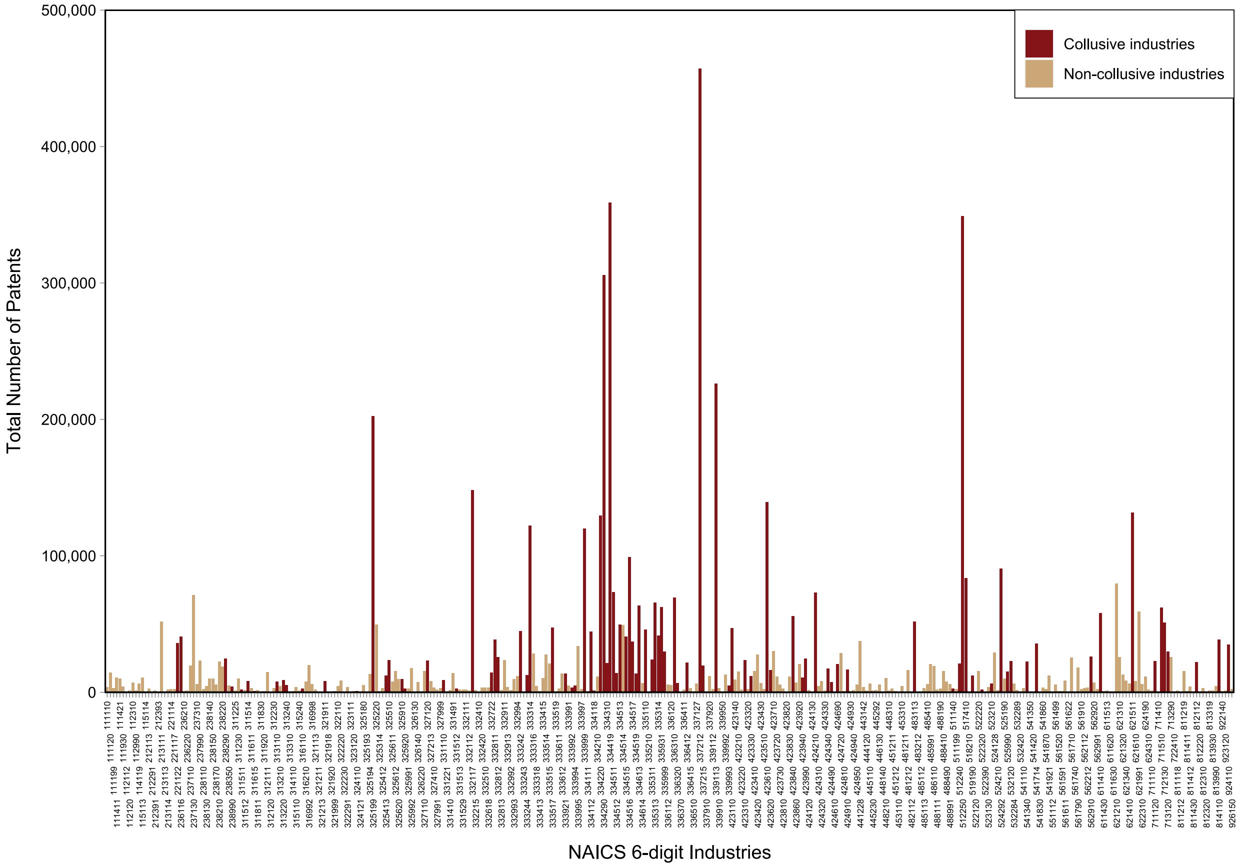


Table A-2. Comparison of Patents in Collusive and Non-collusive Industries (Six-digit NAICS)

Average patents		Difference (t-test)	
Collusive industries	Non-collusive industries	*t*-statistic	*p*-value
49,739.19	10,702.12	4.592	0.000

A.3 R&D Data

Unlike in the patent data, there are missing observations for R&D expenditure (XRD) in the Compustat data. Prior studies have regarded missing observations as no R&D expenditure (i.e., by assigning zero to missing values). However, I identified missing values even if a firm (1) reports positive employment and revenue in the focal year and/or (2) reports positive R&D expenditure in the years before and after the focal year. In this case, the validity of assigning zero R&D expenditure to the missing observation is questionable. I include firm fixed effects in every specification, so my primary approach is to exclude missing observations from the analysis.

The treatment group comprises colluding firms, and the control group comprises a set of firms that share three-digit SIC codes, but not four-digit SIC codes. Some SIC codes, however, have unique three-digit codes, which makes it not possible to construct the control group based on three-digit SIC codes. In this case, I use the neighboring industry based on three-digit SIC codes as a control group. For example, SIC code 2810 has no subclassification within the 281- family, so I use firms in the 280- and 282- families as the control group.

B. Additional Notes on Empirical Strategy

B.1 Collusion, Antitrust Enforcement, and Competition

The latest revision of Section 1 of the Sherman Antitrust Act (as amended on June 22, 2004) states the following:

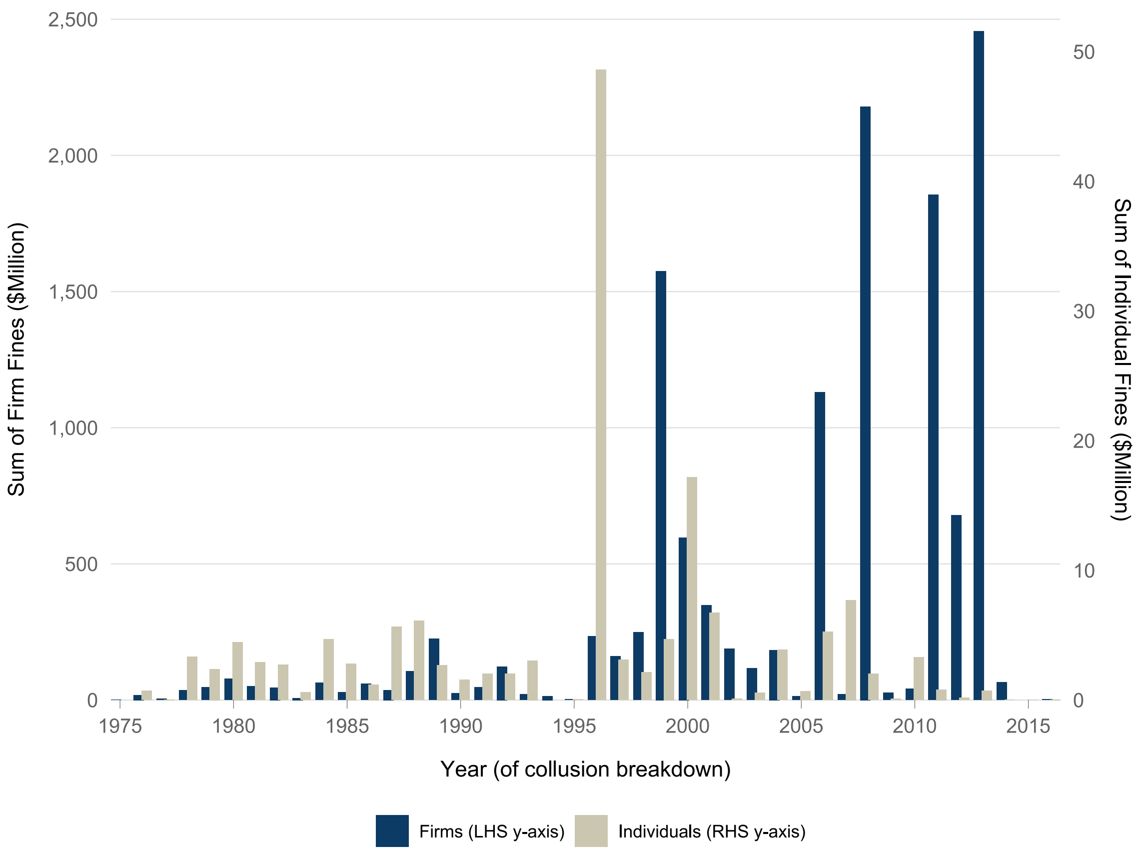
> ***15 U.S. Code § 1 - Trusts, etc., in restraint of trade illegal; penalty***
> Every contract, combination in the form of trust or otherwise, or conspiracy, in restraint of trade or commerce among the several States, or with foreign nations, is declared to be illegal. Every person who shall make any contract or engage in any combination or conspiracy hereby declared to be illegal shall be deemed guilty of a felony, and, on conviction thereof, shall be punished by fine not exceeding \$100,000,000 if a corporation, or, if any other person, \$1,000,000, or by imprisonment not exceeding 10 years, or by both said punishments, in the discretion of the court.

Figure B-1 shows criminal fines for firms and individuals indicted for collusion from 1975 through 2016. Note that the antitrust punishment for collusion is right-censored. In other words, more cases of collusion breakup and subsequent punishment may have occurred in 2016 but have not yet been indicted due to ongoing closed investigations. See Ghosal and Sokol (2020) for changes in US cartel enforcement and how the formation and discovery of cartels may have changed.

To date, only a few studies have used collusion to measure market competition. Symeonidis (2008) uses the introduction of cartel law (i.e., antitrust law) in the UK in the late 1950s and finds a positive impact on labor productivity but no effect on wages. Symeonidis (2008) compares *previously* cartelized industries to non-cartelized industries, abstracting away from each cartel case and the actual existence of a cartel. Levenstein et al. (2015) use the collapse of seven international cartels and find no significant effect of competition (due to cartel breakup) on spatial patterns of trade.

I study how collusion-induced competition affected innovation. This study is distinct from existing ones in the following ways. First, I collect *all* known collusion cases and colluding firms in the US and study their average effects, while carefully considering heterogeneous effects and the underlying mechanisms. Second, I exploit both formation and breakup events to doubly ensure that the findings indeed come from competition effects. Third, the focus of this study is not limited to prices (which have been the main focus of the cartel study). I highlight a wide range of innovation outcomes.

Figure B-1. Collusion Criminal Fines for Firms and Individuals, 1975–2016



Notes. This figure tracks the trend in antitrust punishment for collusion in the United States from 1975 through 2016. Blue and brown bars represent the total amount of criminal fines (in million dollars) for firms and their managers, respectively, in each year of collusion breakup. Price levels are adjusted using the CPI-U index, which is provided by the Bureau of Labor and Statistics (BLS), 1982-1984=100, and seasonally adjusted. Collusion cases in the finance sectors (e.g., real estate brokerage, mortgage rate, interest rate) are excluded. Note that the antitrust punishment for collusion is right-censored. In other words, more cases of collusion breakup and subsequent punishment may have occurred in 2016 but have not yet been indicted due to ongoing closed investigations. *Sources*: The author's own data collection from the antitrust case filings of the Antitrust Division of the US Department of Justice (DOJ) and the Trade Regulation Reporter by Wolters Kluwer's VitalLaw.

References.

Ghosal, V. and Sokol, D. 2020. The Rise and (Potential) Fall of U.S. Cartel Enforcement. *University of Illinois Law Review*, 2: 471– 507.

Levenstein, M. C., Sivadasan, J. and Suslow, V. Y. 2015. The Effect of Competition on Trade: Evidence from the Collapse of International Cartels. *International Journal of Industrial Organization*, 39, 56–70.

Symeonidis, G. 2008. The Effect of Competition on Wages and Productivity: Evidence from the United Kingdom. *Review of Economics and Statistics*, 90: 134–146.

B.2 The Stable Unit Treatment Value Assumption, Validity of the Control Groups, and Measurement Error

In this setting, the Stable Unit Treatment Value Assumption (SUTVA) may be violated if a formation or breakup of collusion affects firms in the control group. To address this concern, I exclude firms in the control group that share a six-digit NAICS code with the colluding firms.

Yet it is possible that the Antitrust Division of the DOJ did not indict some firms participating in collusion because they did not know they colluded, could not collect enough evidence to indict, or granted amnesty to some colluding firms (as per the Leniency Program). The control group consists of firms in the adjacent, but not same, market, so I do not expect that these omitted firms would affect the validity of the control group. Even if they are mistakenly included in the control group, it would work *against* my findings (i.e., introduce biases towards zero), leading to an underestimation, not an overestimation, of the effects.

Further, the event study DiD estimation, as in Equations (2) and (3) in the main paper, enables me to explicitly test for parallel trends by investigating yearly estimates for pre-event periods.

C. Additional Analyses, Figures, and Tables

Provided below are figures and tables not presented in the main paper.

C.1 Main Analyses

Table C-1 provides the main results based on Equation (2) in the main paper.

Table C-1. Effects of Collusion and Competition on Innovation: A Flexible Approach

(a). Collusion formation: Reduced competition and innovation

	Dependent variables ($\sinh^{-1}$):							
	Intensity of innovation				*Breadth of innovation*			
	Patents	Patents (Top 10%)	Citation-weighted patents	R&D expenditure	Unique technology classes	Tech-weighted patents	Patents in primary fields	Patents in peripheral fields
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × *Pre*	−0.049	−0.056	0.123	−0.033	−0.029	−0.028	−0.117**	−0.081
	(0.066)	(0.052)	(0.128)	(0.028)	(0.054)	(0.074)	(0.057)	(0.056)
Treat × $Post_A$	0.177**	0.129**	0.278**	0.109	0.106*	0.178**	0.130*	0.149**
	(0.068)	(0.054)	(0.134)	(0.074)	(0.058)	(0.078)	(0.075)	(0.067)
Treat × $Post_B$	0.287***	0.185**	0.400**	0.158**	0.166**	0.279**	0.251**	0.247***
	(0.105)	(0.075)	(0.181)	(0.060)	(0.081)	(0.115)	(0.106)	(0.086)
Observations	432,448	432,448	432,448	149,932	432,448	432,448	432,448	432,448
R^2	0.555	0.560	0.483	0.921	0.675	0.635	0.493	0.642
Adjusted R^2	0.442	0.449	0.353	0.910	0.460	0.394	0.365	0.552

(b). Collusion breakup: Increased competition and innovation

	Dependent variables ($\sinh^{-1}$):							
	Intensity of innovation				*Breadth of innovation*			
	Patents	Patents (Top 10%)	Citation-weighted patents	R&D expenditure	Unique technology classes	Tech-weighted patents	Patents in primary fields	Patents in peripheral fields
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × *Pre*	0.050	−0.040	0.115	0.041	0.015	0.045	0.036	−0.013
	(0.050)	(0.038)	(0.106)	(0.074)	(0.044)	(0.061)	(0.041)	(0.053)
Treat × $Post_A$	−0.0003	0.018	−0.157	−0.018	−0.014	−0.020	0.019	0.019
	(0.053)	(0.040)	(0.099)	(0.070)	(0.042)	(0.065)	(0.052)	(0.036)
Treat × $Post_B$	−0.099	0.054	−0.350***	−0.073	−0.113**	−0.141*	−0.068	−0.055
	(0.063)	(0.057)	(0.130)	(0.063)	(0.056)	(0.077)	(0.063)	(0.045)
Observations	432,993	432,993	432,993	150,025	432,993	432,993	432,993	432,993
R^2	0.561	0.569	0.483	0.921	0.526	0.512	0.500	0.652
Adjusted R^2	0.450	0.460	0.354	0.910	0.406	0.389	0.373	0.564

Notes. These tables report regression coefficients from eighteen separate regressions based on Equation (1). Panel A uses cartel formation as an event, and panel B uses cartel breakup as an event. Standard errors are in parentheses and are clustered by sector. *Data*: PatentsView and Compustat. *p < 0.1; **p < 0.05; ***p < 0.01.

Table C-2 provides the mechanism tests based on Equation (4) in the main paper.

Table C-2. Life Cycle of Collusion and the Intensity and Breadth of Innovation

	Dependent variables ($\sinh^{-1}$):							
	Intensity of innovation				*Breadth of innovation*			
	Patents (1)	Patents (Top 10%) (2)	Citation-weighted patents (3)	R&D expenditure (4)	Unique tech classes (5)	Tech-weighted patents (6)	Patents in primary fields (7)	Patents in peripheral fields (8)
$Treat \times Pre_1$	−0.082	0.008	−0.216**	−0.086	−0.061	−0.104*	−0.047	−0.027
	(0.052)	(0.046)	(0.096)	(0.086)	(0.041)	(0.059)	(0.051)	(0.046)
$Treat \times Collusion_1$	0.146	0.171**	−0.050	0.201**	0.064	0.128	0.160	0.122
	(0.103)	(0.073)	(0.153)	(0.095)	(0.064)	(0.100)	(0.108)	(0.093)
$Treat \times Collusion_2$	0.323***	0.237***	0.313	0.334***	0.197**	0.328***	0.313**	0.259***
	(0.121)	(0.070)	(0.226)	(0.116)	(0.081)	(0.123)	(0.121)	(0.088)
$Treat \times Post_1$	0.189	0.243***	−0.122	0.180	0.084	0.166	0.259**	0.145
	(0.106)	(0.090)	(0.157)	(0.141)	(0.070)	(0.109)	(0.111)	(0.097)
$Treat \times Post_2$	0.067	0.248**	−0.301*	0.262***	−0.0004	0.039	0.116	0.049
	(0.114)	(0.099)	(0.164)	(0.076)	(0.077)	(0.119)	(0.123)	(0.105)
$Treat \times Post_3$	−0.027	0.176**	−0.449**	0.205***	−0.064	−0.053	0.003	−0.031
	(0.138)	(0.087)	(0.193)	(0.077)	(0.095)	(0.139)	(0.146)	(0.136)
Observations	465,101	465,101	465,101	150,269	465,101	465,101	465,101	465,101
R^2	0.573	0.584	0.497	0.921	0.538	0.524	0.515	0.668
Adjusted R^2	0.458	0.472	0.361	0.910	0.414	0.396	0.383	0.578

Notes. This table reports regression coefficients from eight separate regressions based on Equation (4), where 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 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 firms that colluded and zero otherwise. Years are grouped into seven time periods, each representing the three-year period around the events of interest into one time group. Pre_1 means four to six years prior to the formation of collusion. Pre_2 means one to three years prior to the formation of collusion and serves as the baseline (an omitted category). $Collusion_1$ represents early collusion periods: one to three years after the formation of collusion. To account for varied collusion periods, $Collusion_2$ represents the fourth year of collusion and thereafter up to the year before the collusion breakup. $Post_1$ means one to three years after the breakup of collusion. $Post_2$ means four to six years after the breakup of collusion. $Post_3$ means seven to nine years after the breakup of collusion. Pre_2 serves as the baseline. The regression model controls for the assignee firm fixed effects and sector × year fixed effects. A sector is defined by the four-digit North American Industry Classification System (NAICS). Standard errors are in parentheses and are clustered by sector. *Data*: PatentsView and Compustat. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C-3 provides the mechanism tests based on Equation (2) in the main paper.

Table C-3. Effects of Collusion and Competition on Innovation: Analyses of Potential Mechanisms

(a). Collusion formation: Reduced competition and innovation

	Dependent variables ($\sinh^{-1}$):										
	Scope of Firms						*IP Strategy*	*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 × *Pre*	−0.056	−0.053	−0.055	−0.026	−0.070*	0.112***	0.034	−0.024	−0.101	−0.028	−0.043
	(0.112)	(0.112)	(0.049)	(0.069)	(0.037)	(0.037)	(0.065)	(0.063)	(0.153)	(0.040)	(0.041)
Treat × $Post_A$	0.290**	0.003	0.101*	0.110	0.239**	0.121	0.235***	0.209***	−0.176	0.159	0.018
	(0.112)	(0.106)	(0.052)	(0.069)	(0.092)	(0.091)	(0.090)	(0.064)	(0.129)	(0.109)	(0.053)
Treat × $Post_B$	0.290*	−0.019	0.234***	0.153	0.383**	−0.015	0.282**	0.265***	−0.038	0.213***	0.037
	(0.166)	(0.098)	(0.078)	(0.104)	(0.164)	(0.047)	(0.110)	(0.100)	(0.175)	(0.063)	(0.128)
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	0.297	0.909	0.910	0.488	0.442	0.425	0.910	0.909

(Table C-3 continued)

(b). Collusion breakup: Increased competition and innovation

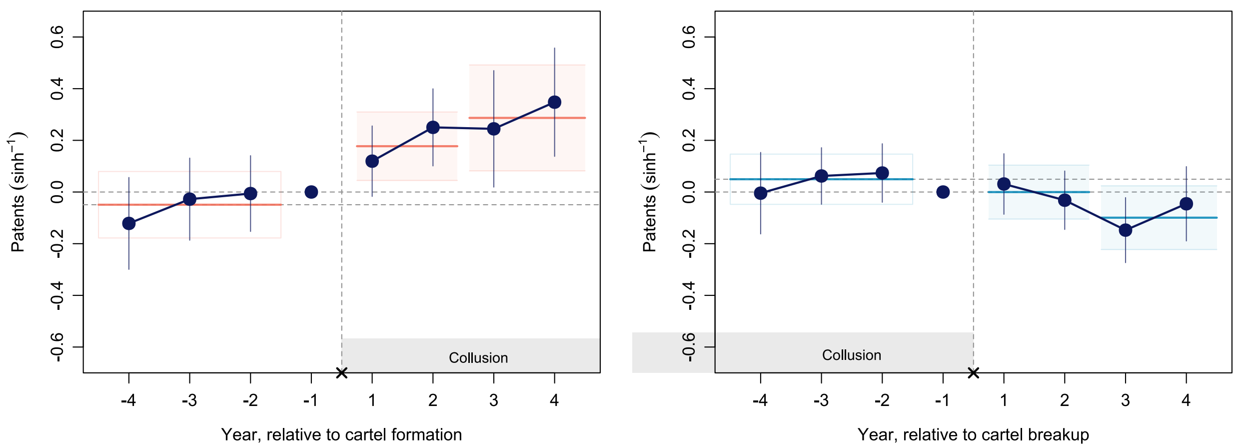
	Dependent variables ($\sinh^{-1}$):										
	Scope of Firms						*IP Strategy*	*Power of Collusion*			
	Split-sample		Patents in overlapping fields	Patents in distinct fields	Split-sample		Unique patent inventors	Split-sample			
	Patents by narrow firms	Patents by broad firms			R&D by narrow firms	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 × *Pre*	−0.026	0.164*	0.032	0.019	−0.049	0.180***	0.045	0.063	0.117	0.033	0.058
	(0.093)	(0.089)	(0.046)	(0.044)	(0.088)	(0.039)	(0.074)	(0.052)	(0.127)	(0.085)	(0.080)
$Treat \times Post_A$	0.067	−0.181**	0.006	0.037	−0.119	0.292**	−0.049	−0.037	0.318**	−0.026	−0.011
	(0.114)	(0.091)	(0.044)	(0.048)	(0.158)	(0.118)	(0.077)	(0.046)	(0.160)	(0.112)	(0.041)
$Treat \times Post_B$	0.041	−0.393***	−0.065	−0.019	−0.107	−0.051	−0.165	−0.125**	0.185	−0.016	−0.181***
	(0.135)	(0.132)	(0.056)	(0.063)	(0.124)	(0.196)	(0.101)	(0.059)	(0.206)	(0.106)	(0.057)
Observations	432,157	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 colluding firms (columns 2a and 8a), the number of patents in distinct fields among colluding firms (columns 2b and 8b), R&D expenditure (columns 3a, 3b, 6a, 6b, 9a, 9b, 12a, and 12b), and the unique number of inventors (columns 4 and 10), all of which are transformed by the inverse hyperbolic sine function in a firm × year. *Treat* is an indicator variable that takes the value of one for firms that colluded 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. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Figure C-1 shows how the formation and breakup changed the intensity of innovation measured by patents.

Figure C-1. Effects of Collusion and Price Competition on the Intensity of Innovation: Patents

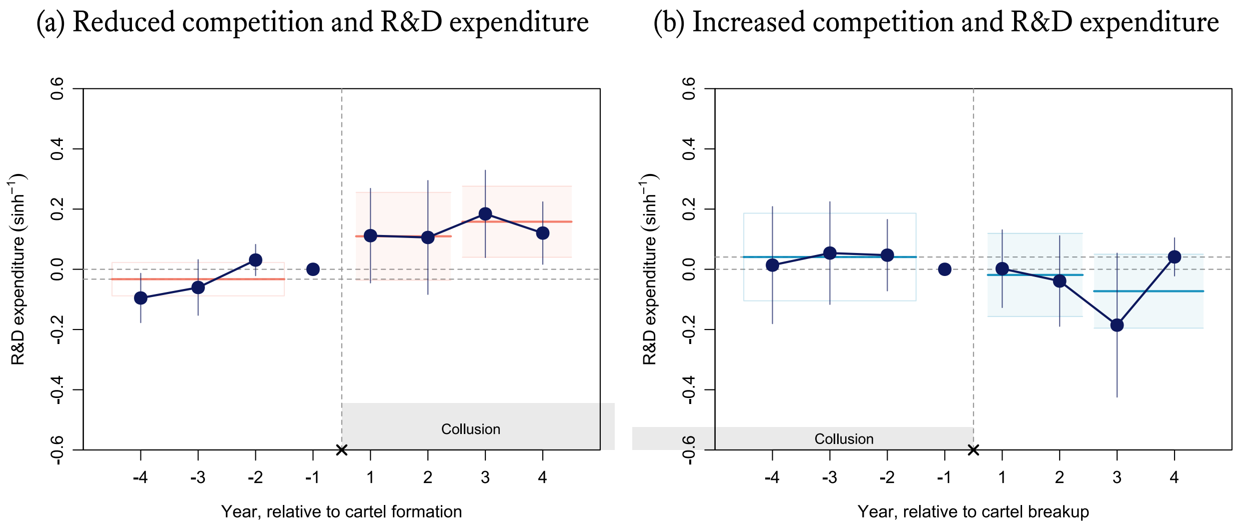
(a) Reduced competition and patents (b) Increased competition and patents



Notes. Plotted are the event-time coefficient estimates (dots) from a version of Equations (2) and (3), where the dependent variable consists of citation-weighted patents with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence intervals. Colored horizontal lines and the boxes around them represent the pooled difference-in-differences estimates and 95% confidence intervals from a version of Equation (2), grouped by two or three years around the event of interest. The regression model controls for assignee firm fixed effects and sector × year fixed effects. A sector is defined by the four-digit North American Industry Classification System. The year of collusion formation and breakup corresponds to year zero in the graphs and is omitted. Year –1 is used as the baseline. Standard errors are clustered at the sector level. *Data*: PatentsView.

Figure C-2 shows how the formation and breakup changed the intensity of innovation measured by the R&D expenditure of publicly traded firms.

Figure C-2. Effects of Collusion and Price Competition on the Intensity of Innovation: R&D expenditure

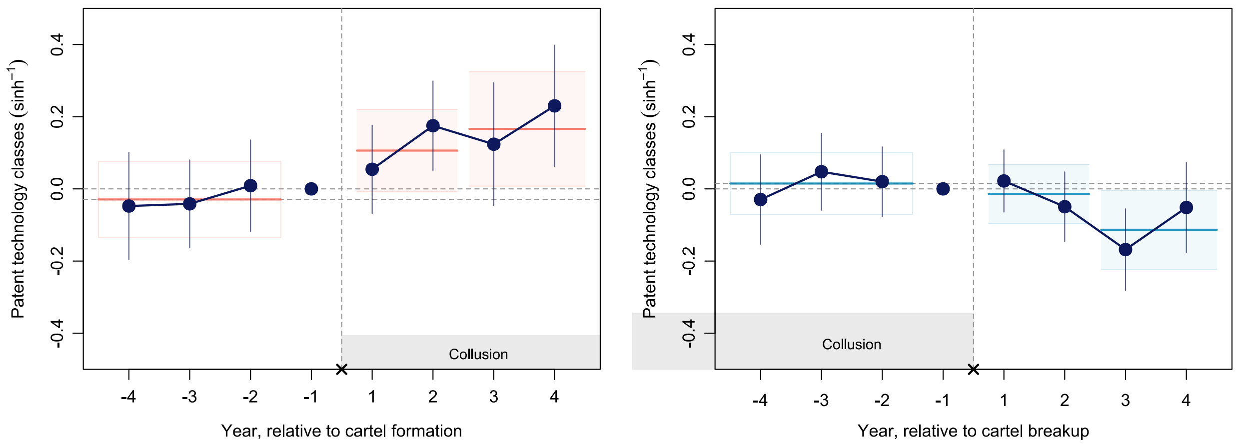


Notes. Plotted are the event-time coefficient estimates (dots) from a version of Equation (3), where the dependent variable consists of R&D expenditures (in millions of US dollars) with the inverse hyperbolic sine transformation in a firm × year. The vertical lines represent 95% confidence intervals. Colored horizontal lines and the boxes around them represent the pooled difference-in-differences estimates and 95% confidence intervals from a version of Equation (2), grouped by two or three years around the event of interest). The regression model controls for firm fixed effects and sector × year fixed effects. A sector is defined by the three-digit SIC. The year of collusion formation and breakup corresponds to year zero in the graphs and is omitted. Year −1 is used as the baseline. Standard errors are clustered at the sector level. Standard errors are clustered at the sector level. *Data*: Compustat.

Figure C-3 shows how the formation and breakup changed the breadth of innovation measured by the unique number of patent technology classes.

Figure C-3. Effects of Collusion and Price Competition on the Breadth of Innovation: Technology Classes

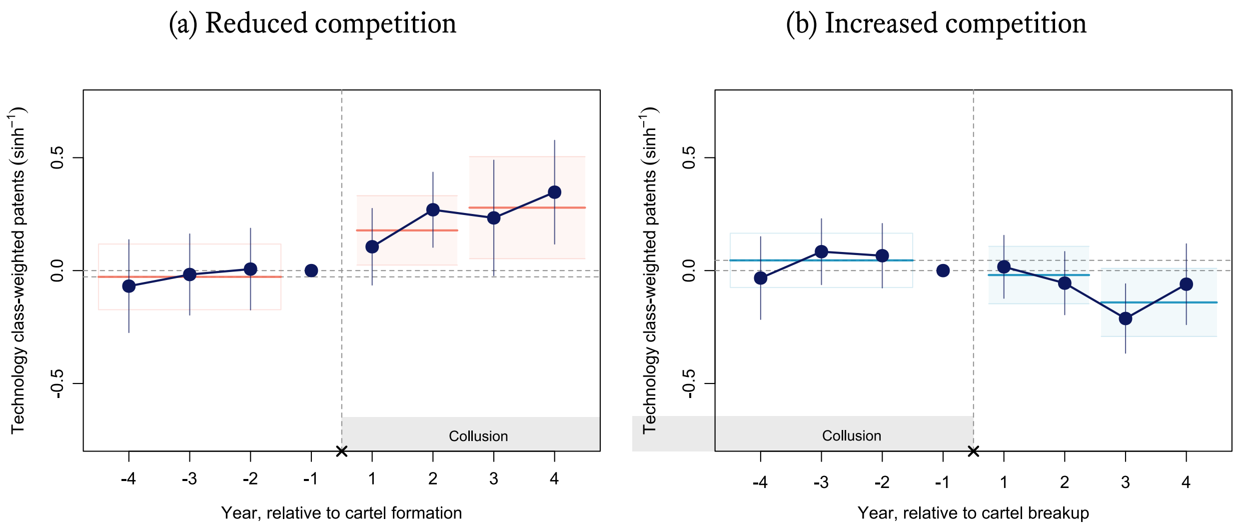
(a) Reduced competition and tech classes (b) Increased competition and tech classes



Notes. Plotted are the event-time coefficient estimates (dots) from a version of Equations (2) and (3), where the dependent variable consists of the unique number of patent technology classes with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence intervals. Colored horizontal lines and the boxes around them represent the pooled difference-in-differences estimates and 95% confidence intervals from a version of Equation (2), grouped by two or three years around the event of interest. The regression model controls for assignee firm fixed effects and sector × year fixed effects. A sector is defined by the four-digit North American Industry Classification System. The year of collusion formation and breakup corresponds to year zero in the graphs and is omitted. Year −1 is used as the baseline. Standard errors are clustered at the sector level. Standard errors are clustered at the sector level. Standard errors are clustered at the sector level. *Data*: PatentsView.

Figure C-4 shows how the formation and breakup changed the breadth of innovation measured by technology class-weighted patents.

Figure C-4. Effects of Collusion and Price Competition on the Intensity of Innovation: Technology Class-Weighted Patents

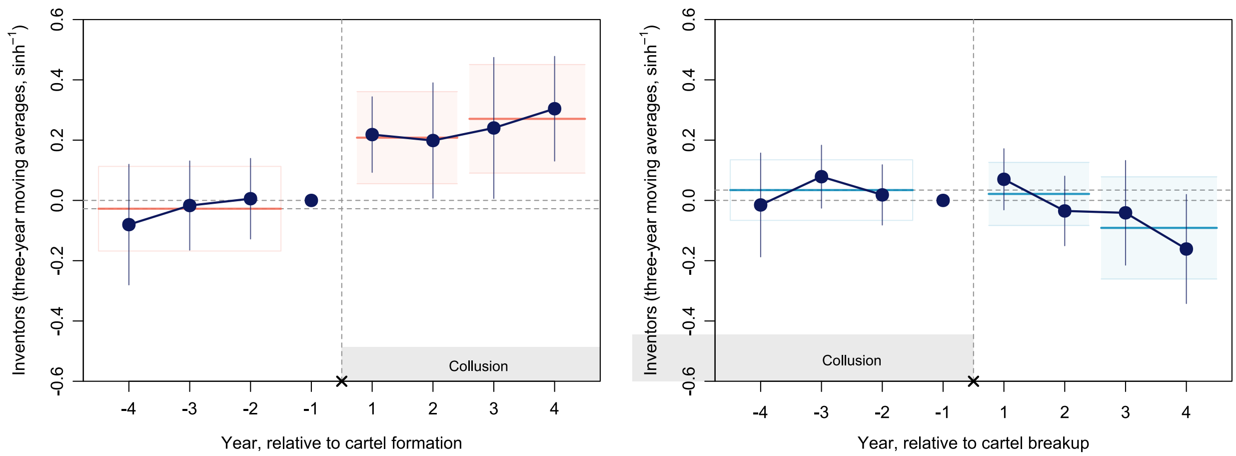


Notes. Plotted are the event-time coefficient estimates (dots) from a version of Equations (2) and (3), where the dependent variable consists of the technology class-weighted patents with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence intervals. Colored horizontal lines and the boxes around them represent the pooled difference-in-differences estimates and 95% confidence intervals from a version of Equation (2), grouped by two or three years around the event of interest. The regression model controls for assignee firm fixed effects and sector × year fixed effects. A sector is defined by the four-digit North American Industry Classification System. The year of collusion formation and breakup corresponds to year zero in the graphs and is omitted. Year −1 is used as the baseline. Standard errors are clustered at the sector level. Standard errors are clustered at the sector level. Standard errors are clustered at the sector level. *Data*: PatentsView.

Figure C-5 shows how the formation and breakup changed the number of unique patenting inventors.

Figure C-5. Effects of Collusion and Price Competition on the Intensity of Innovation: Inventors

(a) Reduced competition (b) Increased competition



Notes. Plotted are the event-time coefficient estimates (dots) from a version of Equations (2) and (3), where the dependent variable consists of the technology class-weighted patents with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence intervals. Colored horizontal lines and the boxes around them represent the pooled difference-in-differences estimates and 95% confidence intervals from a version of Equation (2), grouped by two or three years around the event of interest. The regression model controls for assignee firm fixed effects and sector × year fixed effects. A sector is defined by the four-digit North American Industry Classification System. The year of collusion formation and breakup corresponds to year zero in the graphs and is omitted. Year −1 is used as the baseline. Standard errors are clustered at the sector level. Standard errors are clustered at the sector level. Standard errors are clustered at the sector level. *Data*: PatentsView.

C.2 Poisson Pseudo-Maximum Likelihood Estimation

The main approach in the manuscript (inverse hyperbolic sine transformation; $\sinh^{-1}$ is well-defined at zero (unlike log transformation). The robustness check with Poisson models further mitigates the concern about zeros in the outcome variable. The Poisson regression results, provided in Table C-4, are highly consistent with the results from linear regressions. One challenge with the Poisson regression is that this non-linear model may fail to converge when there are high-dimensional fixed effects (e.g., firm and industry×year fixed effects). Fortunately, a new method has recently been developed which enables the estimation of Poisson pseudo maximum likelihood (PPML) regression (Correia, Guimarães, and Zylkin, 2020). I used the *PPMLHDFE* package (version 2.3.0; https://github.com/sergiocorreia/ppmlhdfe) in Stata 17. Standard errors are clustered at the sector level.

Table C-4, Panel (a) compares the innovation intensity results from the OLS (columns 1–3) and PPML (columns 4–5) models around cartel formation. Column 1 presents the OLS results with firm and year fixed effects; the corresponding Poisson results are shown in column 4. Column 2 presents the OLS results with firm and sector fixed effects; the corresponding Poisson results are shown in column 5. The two models produce highly consistent results. Note that the Poisson model failed to converge when I included firm fixed effects and sector×year fixed effects. Still, the estimates from the Poisson regressions are highly consistent with those from OLS regressions.

The Poisson regression results on the breadth of innovation and the corresponding OLS results are presented in Table C-5. In Panel (a), the breadth of innovation increased after the formation of the cartel, and the results are highly consistent across all five specifications.

Table C-4. OLS and Poisson Pseudo Maximum Likelihood Estimations: Intensity of Innovation

(a). Collusion Formation

	Dependent variables: patents				
	OLS with $\sinh^{-1}$ *transformation*			*Poisson Pseudo Maximum Likelihood*	
	(1)	(2)	(3)	(4)	(5)
Treat × *Post*	0.269*** (0.088)	0.294*** (0.087)	0.249*** (0.078)	0.331*** (0.106)	0.489*** (0.110)
Fixed effects	Firm+Year	Firm+Sector	Firm+Year×Sector	Firm+Year	Firm+Sector
Observations	432,448	432,448	432,448	432,448	432,448
R^2	0.539	0.532	0.555	–	–
Adjusted R^2	0.438	0.429	0.442	–	–
Pseudo R^2	–	–	–	0.710	0.699

(b). Collusion Breakup

	Dependent variables: patents				
	OLS with $\sinh^{-1}$ *transformation*			*Poisson Pseudo Maximum Likelihood*	
	(6)	(7)	(8)	(9)	(10)
Treat ×	0.023	0.085	−0.076	−0.128*	0.026
Post	(0.057)	(0.059)	(0.056)	(0.070)	(0.073)
Fixed effects	Firm+Year	Firm+Sector	Firm+Year×Sector	Firm+Year	Firm+Sector
Observations	432,993	432,993	432,993	432,993	432,993
R^2	0.546	0.538	0.561	–	–
Adjusted R^2	0.446	0.437	0.450	–	–
Pseudo R^2	–	–	–	0.750	0.741

Table C-5. OLS and Poisson Pseudo Maximum Likelihood Estimations: Breadth of Innovation

(a). Collusion Formation

	Dependent variables ($\sinh^{-1}$): patent technology classes				
	OLS with $\sinh^{-1}$ *transformation*			*Poisson Pseudo Maximum Likelihood*	
	(1)	(2)	(3)	(4)	(5)
Treat ×	0.152**	0.169***	0.147***	0.192***	0.268***
Post	(0.059)	(0.058)	(0.054)	(0.066)	(0.070)
Fixed effects	Firm+Year	Firm+Sector	Firm+Year×Sector	Firm+Year	Firm+Sector
Observations	432,448	432,448	432,448	432,448	432,448
R^2	0.506	0.498	0.522	–	–
Adjusted R^2	0.397	0.388	0.401	–	–
Pseudo R^2	–	–	–	0.409	0.404

(b). Collusion Breakup

	Dependent variables ($\sinh^{-1}$): patent technology classes				
	OLS with $\sinh^{-1}$ *transformation*			*Poisson Pseudo Maximum Likelihood*	
	(6)	(7)	(8)	(9)	(10)
Treat ×	0.008	0.056	−0.067	−0.150***	−0.029
Post	(0.041)	(0.043)	(0.043)	(0.044)	(0.048)
Fixed effects	Firm+Year	Firm+Sector	Firm+Year×Sector	Firm+Year	Firm+Sector
Observations	432,993	432,993	432,993	432,993	432,993
R^2	0.510	0.503	0.526	–	–
Adjusted R^2	0.403	0.394	0.406	–	–
Pseudo R^2	–	–	–	0.422	0.418

References.

Correia, S., Guimarães, P. and Zylkin, T., 2020. Fast Poisson estimation with high-dimensional fixed effects. *The Stata Journal*, 20(1), 95–115.

MacKinnon, J. G., and Magee, L. 1990. Transforming the Dependent Variable in Regression Models. *International Economic Review*, 31(2), 315–339.

C.3 Quality of Innovation: The Long-term Influence of Patents

I then checked the effects of price competition on the long-term patent influence (Corredoira and Banerjee 2015). This measure incorporates *indirect* forward citations as well as direct forward citations. In other words, with a discounting factor (α), this measure counts how many times the focal patent was cited (the first generation), how many times the patents that cite the focal patent were cited (the second generation), and tracks these indirect forward citations for all later (descendent) generations. The long-term influence measure is essentially the alpha centrality with direction (Bonacich and Lloyd, 2001; Corredoira and Banerjee, 2015). I calculated this measure for all USPTO patents. Table C-6 shows the descriptive statistics of the measure.

Table C-7 provides the results. The point estimates are positive but not statistically different from zero. I do not find evidence that price competition meaningfully affected the *average* long-term influence of patents at the firm-year level. It may be because "exploration" is risky and does not always turn out to be successful. To check this, I also checked the *number* of the top 25 percent patents in terms of their long-term influence. The top 25 percent is assessed at the three-digit CPC-year level. The point estimates are positive, but I cannot reject the null hypothesis that they are different from zero.

Table C-6. Descriptive Statistics of Long-term Patent Influence (All US Patents, 1976–2020)

	Mean	Min	First Quartile	Median	Third Quartile	Max
Long-term influence						
$\alpha = 0.8$	52,238.0	0.0	0.0	14.0	4211.0	4,476,620.0
$\alpha = 0.6$	4,919.9	0.0	0.0	8.0	696.2	548,642.5
$\alpha = 0.4$	407.0	0.0	0.0	3.9	101.8	66,986.6
Nodes (generations)	10.6	0.0	0.0	4.0	17.0	70.0

Table C-7. Reduced Competition and Long-term Patent Influence

	Dependent variables ($\sinh^{-1}$): Long-term patent influence						
	Average influence			Count of top 25% influential patents			Average nodes
	$\alpha = 0.8$	$\alpha = 0.6$	$\alpha = 0.4$	$\alpha = 0.8$	$\alpha = 0.6$	$\alpha = 0.4$	
Treat × *Post*	0.117	0.064	0.031	0.021	0.028	0.027	0.051
	(0.241)	(0.198)	(0.153)	(0.234)	(0.194)	(0.154)	(0.078)
Observations	211,301	211,301	211,301	211,301	211,301	211,301	211,044
R^2	0.883	0.878	0.867	0.881	0.876	0.864	0.807
Adjusted R^2	0.804	0.796	0.778	0.802	0.793	0.773	0.681

There are two potential concerns about using this measure in the sample that spans several decades: (1) the measure is highly dispersed and (2) patents are treated differently by their registered year even if we compare the patents of the same cohort. First, for $\alpha = 0.8$, the mean is 52,238, whereas the median is 14. Half of the sample patents have a value equal to or less than 14, but the top quartile patents have a value equal to or higher than 4,221, and the maximum value reaches 4,476,620. Second, a patent registered in 1995 has had a much greater opportunity of being cited than a patent registered in 2015. Even if we compare patents registered in the same year, their potential to have been cited across many descendent patents hasn't been realized. Thus it is not possible to distinguish long-term influential patents from patents that have no long-term influence until they are cited across at least several generations. Patents are in different stages of their own "influence life cycle." Since the sample spans 1976 through 2020, early patents (and their assignee firms) have had a chance to be cited across 70 generations (maximum number of nodes in the sample), whereas later patents haven't even started the citation race and get no chance to be cited (minimum number of nodes in the sample).

Additional notes on the patent long-term influence measure.

I have spent significant time and effort creating this measure for all USPTO patents. The computation of this measure for all the patents in the USPTO was computationally demanding. I spent about six months coding the program in different statistical tools and running it. Corredoira and Banerjee (2015) used *R* and the package, *igraph*, to measure the long-term influence of patents: *"we calculate $Influence_{\alpha}$ with α-centrality algorithm from R (command: alpha.centrality; package: igraph version 0.6).*" The *igraph* package takes the citation matrix as an input and uses matrix operations to calculate the alpha centrality, or long-term influence. The package handles this computation well for their limited sample of *"12,332 patents assigned to semiconductor main classes (i.e., 257, 326, 438 and 505) (Hall et al., 2001) with granting year between 1990 and 1994."*

For this study, I use almost all patents registered by USPTO due to the wide range of control firms. I tried the same approach as used by Corredoira and Banerjee (2015) but encountered several critical errors. The resulting dimension of the direct citation matrix for my data is 113,129,137 × 113,129,137 ("A"). The package then tried to calculate $A + A^2 + A^3 + A^4 + \cdots$. After many trials and errors, I realized that *R* could not handle the matrix operations of this large matrix. I then divided the matrix into smaller chunks, using the fact that the whole network consists of many smaller local networks that are not (or are only loosely) connected to each other. It turns out that *R* cannot even handle the matrix for the smallest local network. I then tried the matrix operations with different statistical tools, including *MATLAB*, *Julia*, *Stata*, and *Python*, all of which failed to do the job.

Therefore, I manually programmed to calculate the alpha centrality *for each patent*, using vector (not matrix) operations. For patent A, I identified the list of direct forward citations ("List 1") out of 113,129,137 direct citation ties. I then identified the list of direct forward citations to all patents in List 1 ("List 2"). I repeated this process until I ended up with no items in the list (no further forward citations); the farthest indirect link stopped at List 79—i.e., the focal patent was cited across 79 descendent generations. I then calculated the alpha centrality for Patent A with different weights (α). I repeated this for all 7,720,592 patents registered in USPTO. After optimizing the code for the fastest calculation, the computation took about four months with four independent instances running in two latest computers (one with the 10th generation Intel i9 processor with 128 Gb memory and another with an Intel Xeon W-2145 processor with 128 Gb memory).

C.4 R&D Collaboration

If firms formed the R&D consortia while colluding on the price, this non-price collaboration might confound the test of the relationship between price competition and innovation. I collected information on R&D collaboration from the SDC Platinum database and checked whether non-price collaboration drove the results.

I find that seven colluding firms participated in R&D collaboration. Yet, in most cases, R&D collaboration occurred outside of the collusion period; thus, the participation in R&D consortia should not affect—in particular, magnify—the results. One notable exception is an R&D collaboration between Mitsubishi Electric Corp and Sharp Corp. They entered into six different alliances in 1990, 1996, 2000 (two times), 2001, and 2007.

In Table C-8, column 2, empirical analysis excluding all seven collusive firms that participated in R&D collaboration provides results consistent with the main findings. In column 3, the results remain qualitatively the same after excluding only Mitsubishi Electric Corp and Sharp Corp. In sum, I do not find any evidence that collaboration on non-price dimensions drives or confounds the result.

Table C-8. Intensity of Innovation: Excluding Firms in R&D Collaboration

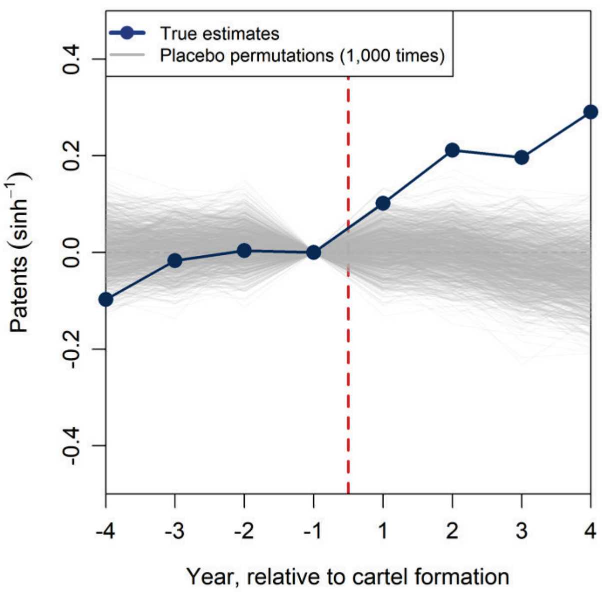
	Dependent variables ($\sinh^{-1}$):		
	R&D Expenditure		
	Full Sample	Excluding All R&D Collaborators	Excluding Two Repeat Collaborators: Mitsubishi and Sharp
	(1)	(2)	(3)
Treat × *Post*	0.152** (0.069)	0.176** (0.069)	0.212*** (0.066)
Observations	149,932	149,868	149,887
R^2	0.921	0.921	0.921
Adjusted R^2	0.910	0.909	0.910

C.5 Placebo Permutation Tests

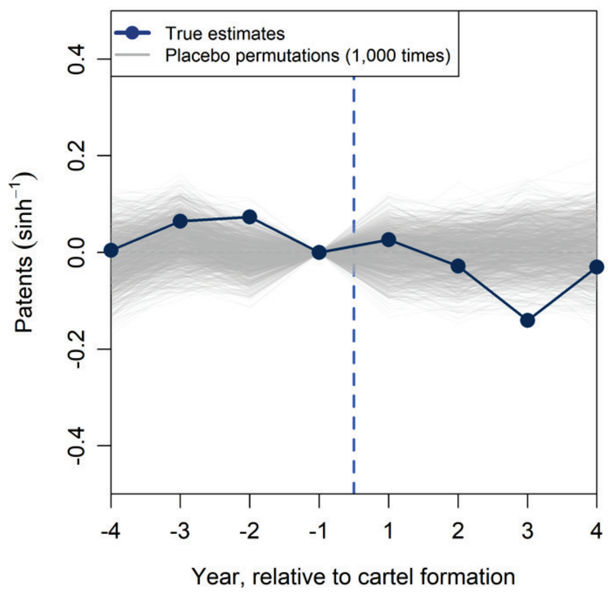
Figure C-6 illustrates the placebo tests for patents separately.

Figure C-6. Effects of Collusion and Price Competition: Placebo Permutation Tests on Patents

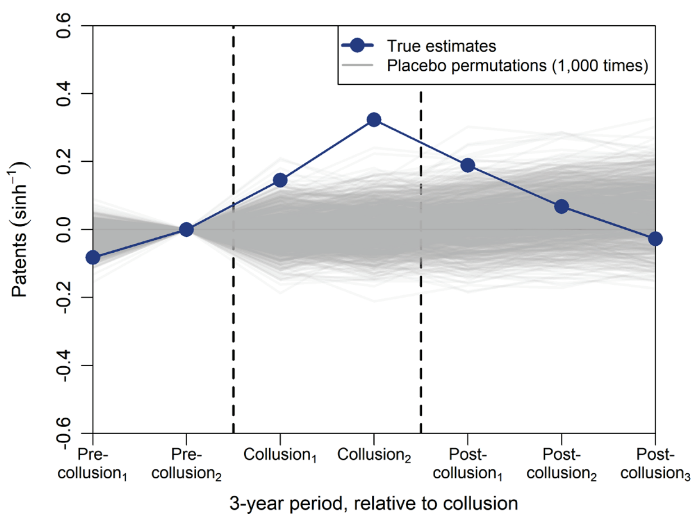
(a) Reduced competition and patents



(b) Increased competition and patents



(c) The life cycle of collusion and technology classes

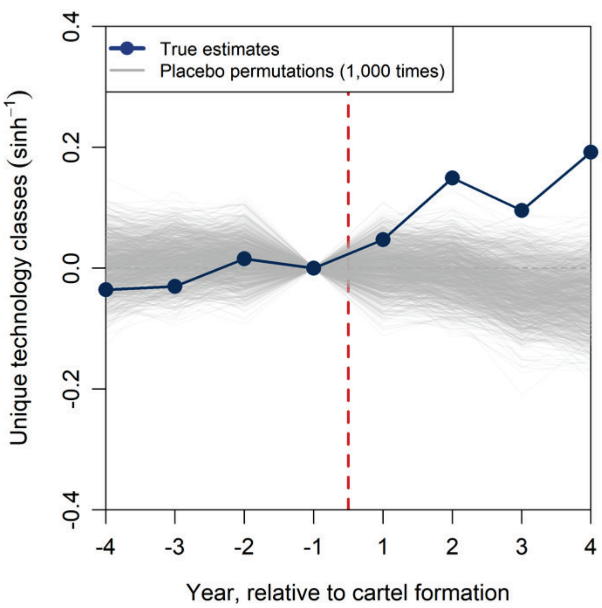


Notes. Plotted are the event-time coefficient estimates (dots) from a version of Equation (3), where the dependent variable consists of citation-weighted patents with the inverse hyperbolic sine transformation in a firm × year. Blue dots and lines represent the real treatment group (colluding firms), and 1,000 gray lines represent the results of placebo tests. The regression model controls for firm fixed effects and sector × year fixed effects. A sector is defined by the four-digit North American Industry Classification System. The year of collusion formation and breakup corresponds to year zero in the graphs and is omitted. Year –1 is used as the baseline. Standard errors are clustered at the sector level. *Data*: PatentsView.

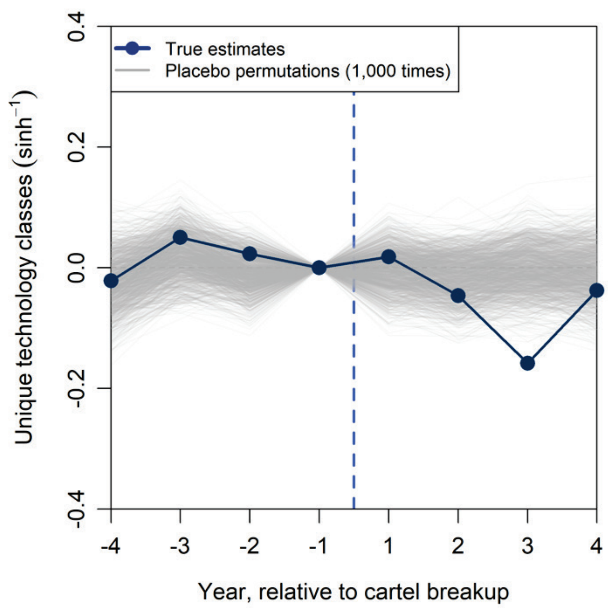
Figure C-7 illustrates the placebo tests for the unique number of patented technology classes separately.

Figure C-7. Effects of Collusion and Price Competition: Placebo Permutation Tests on Technology Classes

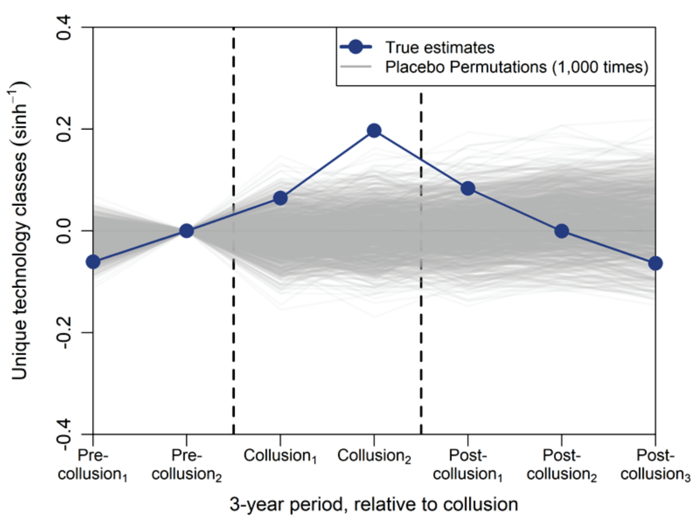
(a) Reduced competition and technology classes



(b) Increased competition and technology classes



(c) The life cycle of collusion and technology classes



Notes. Plotted are the event-time coefficient estimates (dots) from a version of Equation (3), where the dependent variable consists of citation-weighted patents with the inverse hyperbolic sine transformation in a firm × year. Blue dots and lines represent the real treatment group (colluding firms), and 1,000 gray lines represent the results of placebo tests. The regression model controls for firm fixed effects and sector × year fixed effects. A sector is defined by the four-digit North American Industry Classification System. The year of collusion formation and breakup corresponds to year zero in the graphs and is omitted. Year –1 is used as the baseline. Standard errors are clustered at the sector level. *Data*: PatentsView.

C.6 Heterogeneity Checks with Leave-one-out Iterations at the Cartel Level

The leave-one-out iterations at the firm level are provided in Section 5.4 of the main paper (pp. 15–16). In this part, I performed analyses at the cartel level by removing one cartel each time. Table C-9 shows the results.

Table C-9. Top cartels that magnify or shrink the patent filing estimate

(a). Summary statistics across all iterations

	mean	sd	min	median	max
Patent filings	0.216	0.014	0.148	0.217	0.252

(b). Top 5 cartels that magnified the estimate

Order	Cartel	Estimate *without* this cartel
1	TFT-LCD Panels	0.148
2	Auto Parts (Automotive Electrical Components)	0.184
3	Optical Disk Drives (ODD)	0.200
4	Marine Products (Marine Hose)	0.203
5	Vitamins	0.210

(c). Top 5 cartels that shrank the estimate

Order	Cartel	Estimate *without* this cartel
1	Graphite Electrodes	0.252
2	Industrial Chemicals (Monochloroacetic Acid)	0.237
3	Methyl Glutamine	0.236
4	Automotive Air Conditioning Systems and Body Sealing Products	0.234
5	Food Service Equipment (Kitchen Hardware)	0.227

A general pattern from the firm- and cartel-level exercises is that firms in high-tech sectors such as pharmaceutical, display, or semiconductor industries contributed to magnifying the estimates.

C.7 Heterogeneity: Firm Scope and East Asian firms

Below I explain (1) how I treated large firms when deciding market segments and CPC patent classes and (2) if the results are robust to the exclusion of East Asian firms.

First, for patent analysis, I used the most granular patent assignee unit. Large conglomerates have different patenting entities within their corporations. For example, Samsung Group files patents by business units that are sufficiently narrow. I picked the patent assignee firms closest to those specified in the DOJ cases. When *Samsung SDI* colluded, the treated unit is *Samsung SDI Co., Ltd*. Other Samsung-affiliated assignee firms excluded are: *Samsung Electronics Co., Ltd.*; *Samsung Display Co., Ltd*; *Samsung Electro-mechanics Co., Ltd.*; *Samsung Techwin, Co., Ltd.*; *Samsung LED Co., Ltd*; *Samsung Petrochemical Co., Ltd.*; *Samsung Engineering Co., Ltd.*; *Samsung Medison Co., Ltd*; *Samsung Heavy Industries Co., Ltd.*; *Samsung Corning Advanced Glass, LLC*; and *Samsung Precision Ind. Co, Ltd*.

In addition, as reported in Table 5, columns 1a–1b, the patent results are driven by narrower firms that have above-median HHI of patent technology classes, mitigating a concern that the effects are driven by the multi-business conglomerates I selected.

Further, I performed the patent analysis on overlapping technology fields among colluding firms; here, *all* colluding firms in each cartel were taken into account. This analysis picked up to five overlapping patent technology fields (three-digit CPC) among all colluding firms in each cartel. This approach removes any idiosyncratic patenting activities of large firms that are not related to the collusive market because I removed their patenting activities in the non-overlapping technology fields. The results reported in Table 5, columns 2a–2b and 8a–8b, suggest that the effects are primarily driven by patents in overlapping fields. In other words, even if there's a firm with a broad business scope, its impact on the estimate is limited.

Second, for public company analysis, I used Compustat North America to minimize the idiosyncratic variations in company size, scope, and regulations they face. Most East Asian firms thus are excluded from the sample. Plus, in a more granular analysis using the segment data, I find that the effects are primarily driven by firms that have only 1–2 segments (Table 5, column 3a–3b), mitigating the concern that a small number of multi-unit, multinational firms drive the entire results.

Third, as reported in Table 4 of the paper, East Asian firms did not disproportionately influence the estimates in one direction. Three Japanese firms are found to magnify the estimates (in Panel a), and the same number of Japanese firms are found to shrink the estimates (in Panel b).

Taken together, firms with a narrow focus show greater effects, suggesting that the results are not driven entirely by multi-business firms reallocating resources across their units.

To further check this idea, Table C-10 shows the regression results (split-sample analyses) for East

Asian firms and non-East Asian firms. In column 4, the breadth of the patent effect is more precisely estimated for non-East Asian firms (p<0.05), although the point estimates are similar for East Asian and non-East Asian firms.

Table C-10. Split-Sample Analysis on East Asian Firms and Others

(a). Formation of collusion

	Dependent variables ($\sinh^{-1}$): patent counts			
	Intensity of innovation (patent filings)		*Breadth of innovation (technology classes)*	
	East Asian firms	Non-East Asian Firms	East Asian firms	Non-East Asian Firms
	(1)	(2)	(3)	(4)
Treat ×	0.319**	0.203**	0.156	0.153**
Post	(0.149)	(0.086)	(0.100)	(0.062)
Observations	431,684	431,609	431,684	431,609
R^2	0.548	0.532	0.517	0.515
Adjusted R^2	0.435	0.429	0.395	0.393

Notes. Restricted the treatment group to East Asian firms in columns (1) and (3). This includes China, Japan, South Korea, and Taiwan. Note that East Asia also includes Hong Kong, Mongolia, and North Korea, but firms from these countries are not found in the treated group.

(b). Breakup of collusion

	Dependent variables ($\sinh^{-1}$): patent counts			
	Intensity of innovation (patent filings)		*Breadth of innovation (technology classes)*	
	East Asian firms	Non-East Asian Firms	East Asian firms	Non-East Asian Firms
	(1)	(2)	(3)	(4)
Treat ×	0.056	−0.177**	0.024	−0.142**
Post	(0.068)	(0.076)	(0.047)	(0.062)
Observations	431,816	432,022	431,816	432,022
R^2	0.553	0.548	0.520	0.516
Adjusted R^2	0.441	0.434	0.399	0.394

Notes. Restricted the treatment group to East Asian firms in columns (1) and (3). This includes China, Japan, South Korea, and Taiwan. Note that East Asia also includes Hong Kong, Mongolia, and North Korea, but firms from these countries are not found in the treated group.

C.8 Corporate Scope: Market Profitability and Corporate Financial Reallocation

It is important to check whether the increased innovation activities happened in the market where firms colluded (through market profitability) or in different markets in which the colluding firms operate (through firm-level profitability and financial reallocation). I used the granular Compustat Segment data to check the market versus firm mechanism and verify the control group. Table C-11 shows the results.

For instance, I restricted 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. Table C-11, column 3, shows the results that the colluding firms increased R&D expenditure by 23.6 percent.

Table C-11. Cartel Formation and the Intensity of Innovation by Business Segments

	Dependent variables ($\sinh^{-1}$): R&D expenditure								
	Single segment		>75% sales from one segment		Matched segment	Firm scope			
						Narrow firms		Broad firms	
	(1a)	(1b)	(2a)	(2b)	(3)	(4a)	(4b)	(5a)	(5b)
Treat × *Post*	0.262**	0.431***	0.236**	0.250**	0.236**	0.347***	0.406***	−0.017	−0.098
	(0.120)	(0.107)	(0.099)	(0.108)	(0.117)	(0.124)	(0.136)	(0.100)	(0.170)
Sample	Split	Split	Split	Split	Full	Split	Split	Split	Split
Restrictions applied to	Treated	Treated & Control	Treated	Treated & Control	–	Treated	Treated & Control	Treated	Treated & Control
Observations	149,798	64,372	149,808	99,366	149,932	149,833	99,727	149,815	39,697
R^2	0.920	0.921	0.920	0.923	0.919	0.920	0.910	0.921	0.929
Adjusted R^2	0.909	0.906	0.909	0.911	0.908	0.909	0.896	0.910	0.917

C.9 Financial Constraint and East Asian Firms

The analyses on publicly traded firms in the main paper used Compustat North America to mitigate the concern that non-US firms have idiosyncratic characteristics; for example, they have only a limited presence in the U.S. market and face different regulations on internal financial transfers. This mitigates a concern that East Asian conglomerates have easier access to capital through their affiliated financial institutions.

I further checked Compustat North America and performed additional analyses by excluding firms with headquarters in East Asia. These excluded firms include *Mitsubishi Electric Corp* (Japan), *Eisai Co., Ltd.* (Japan), *Sharp Corp.* (Japan), *LG Display Co. Ltd.* (South Korea), and *AU Optronics Corp.* (Taiwan).

The results are presented in Table C-12. Columns 1–2 include all firms, whereas columns 3–4 exclude East Asian firms present in Compustat North America data. It happens to be the case that all these East Asian firms fall into the "Low revenue growth" category. Their exclusion did not significantly change the interpretation, although the point estimate had increased for the low-revenue-growth group.

Table C-12. Financial Constraints and R&D Expenditure: Robustness check around East Asian Firms

	Dependent variables ($\sinh^{-1}$): R&D expenditure			
	All firms		*Excluding East Asian Cartelists*	
	High revenue growth (1)	Low revenue growth (2)	High revenue growth (3)	Low revenue growth (4)
Treat × *Post*	0.303*** (0.087)	0.021 (0.077)	0.303*** (0.087)	0.104 (0.083)
Observations	149,086	149,084	149,086	149,078
R^2	0.920	0.920	0.920	0.920
Adjusted R^2	0.910	0.910	0.910	0.910

Notes. Columns (2) and (4) show the regression results after excluding East Asian firms from the treated group.

This suggests that East Asian firms did not invest much in R&D activities when their revenue growth is low (If they have better and easier access to internal capital, we would expect the opposite since their R&D expenditure should not have been affected much).

My interpretation is that many East Asian countries have stringent rules on the separation of industrial and financial capital. South Korea, for example, has long enforced that "industrial businesses can hold only up to a 4-percent stake in a bank, while banks can own up to 15 percent stake in an industrial business (https://business.inquirer.net/353497/removing-hurdles-bank-ownership)." Thomson Reuters' Practical Law summarizes in its article titled *Banking Regulation in South Korea*:

> *A bank must not hold more than 15% of the voting stock issued by another company unless it has been allowed to by the FSC … A non-financial organisation cannot hold more than 4% of total and outstanding voting*

shares of a bank (https://uk.practicallaw.thomsonreuters.com/w-032-4691)

Japan also has a similar regulation that the stock ownership by individual banks and other financial institutions should not exceed 5 percent since 1977 (a ten-year grace period was given; the limit was 10 percent before 1977) (Morck, Nakamura, and Shamdasani, 2000). In an article titled *Banking Regulation in Japan*, Thomson Reuters' Practical Law summarizes:

> *"In principle, banks and their subsidiaries cannot acquire or hold voting rights in domestic companies (other than companies falling into the permitted business categories for the bank's subsidiary) which, in total, exceed 5% of the total voting rights … In addition, bank holding companies and their subsidiaries are generally prohibited from acquiring or holding voting rights in domestic companies (other than companies falling into the permitted business categories for bank's subsidiary) which, in total, exceed 15% of the total voting rights* (https://uk.practicallaw.thomsonreuters.com/w-007-5339)

C.10 Industry Growth Rate

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., the 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. Table C-13 shows the top five Fast-growing industries. I ran regressions as in Equation (1) on key measures of innovation activities.

Figure C-8 graphically summarizes the results. The effects are greater for markets that exhibited high growth rate before cartel formation. They increased patenting activities by 40 percent, the top 10 percent of high-quality patents by 43 percent, and the number of unique technology classes 20 percent. However, firms in the mature markets did not increase their innovation activities as much.

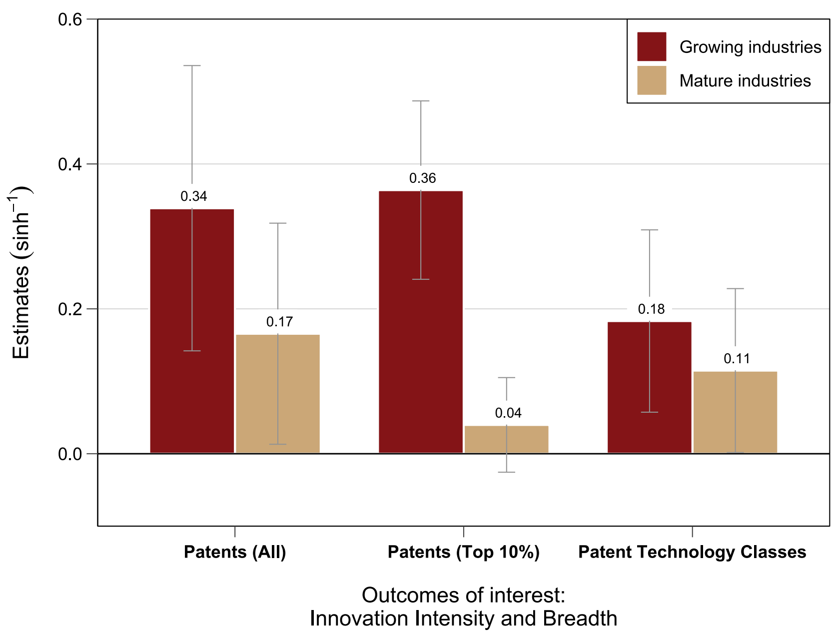
The results suggest that the increase in the breadth of innovation was not driven by firms in mature markets that try to escape the colluding market; the estimates are greater for firms in rapidly growing markets. Furthermore, if firms sought to escape the mature colluding market, it is expected that 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 4(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 (rather than trying to escape the mature market).

Table C-13. Fast-growing industries for five years before cartel formation

Order	NAICS4	NAICS4 definition	NAICS6	NAICS6 definition	Cartel formation year
1	5417	Scientific Research and Development Services	541714	Research and Development in Biotechnology (except Nanobiotechnology)	1988
2	3341	Computer and Peripheral Equipment Manufacturing	334112	Computer Storage Device Manufacturing	1999
3	3363	Motor Vehicle Parts Manufacturing	336310	Motor Vehicle Gasoline Engine and Engine Parts Manufacturing	1996
4	3344	Semiconductor and Other Electronic Component Manufacturing	334419	Other Electronic Component Manufacturing [e.g., CRT (cathode ray tube) manufacturing; LCD (liquid crystal display) unit screens manufacturing]	2001
5	3342	Communications Equipment Manufacturing	334220	Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing	2001

Notes. A few examples in squared brackets added by the author from the NAICS definition document (https://www.census.gov/naics/).

Figure C-8. Intensity and Breadth of Innovation by Pre-Collusion Industry Growth Rate

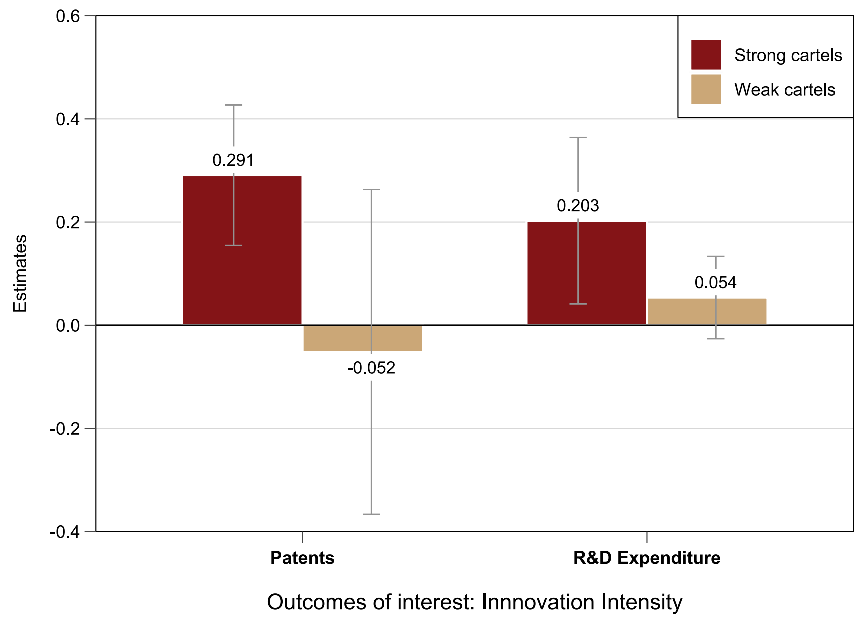


Notes. Plotted are the difference-in-differences coefficient estimates from six separate regressions based on Equation (1), with the formation of collusion as an event of interest. Average annual innovation growth rates are calculated for five years prior to cartel formation at the industry group level (four-digit NAICS). Each colluding firm (along with its counterfactual firms) is divided into two groups based on the median, 37%. 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 90% confidence intervals. The regression model controls for assignee firm fixed effects and industry group (four-digit NAICS) × year fixed effects. *Data*: PatentsView.

C.11 The Strength of Collusion

To better understand the coverage of collusion and its innovation implications, I investigated how the strength of collusion is associated with the relationship between price competition and innovation. I measure the strength of collusion by the patent share (for patent analysis) and sales share (for R&D analysis) of colluding firms. Figure C-9 graphically summarizes the results (based on the results presented in Table 5 of the main paper). From the split-sample analysis on strong collusion (that have an above-median share) and weak collusion (that have a below-median share), I find that firms in strong collusion on average increased their patenting activities by 24.5 percent and R&D expenditure by 20.3 percent, whereas those in weak collusion exhibit negligible effects that are not statistically distinguishable from zero.

Figure C-9. Intensity and Breadth of Innovation by the Strength of Collusion



Notes. Plotted are the difference-in-differences coefficient estimates from four separate regressions based on Equation (1), with the formation of collusion as an event of interest. The strength of collusion was measured by the patent share (for patent analysis) and sales share (for R&D analysis) of colluding firms. The dependent variable consists of the number of patent filings (red-colored bars) and R&D expenditure (brown-colored 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.

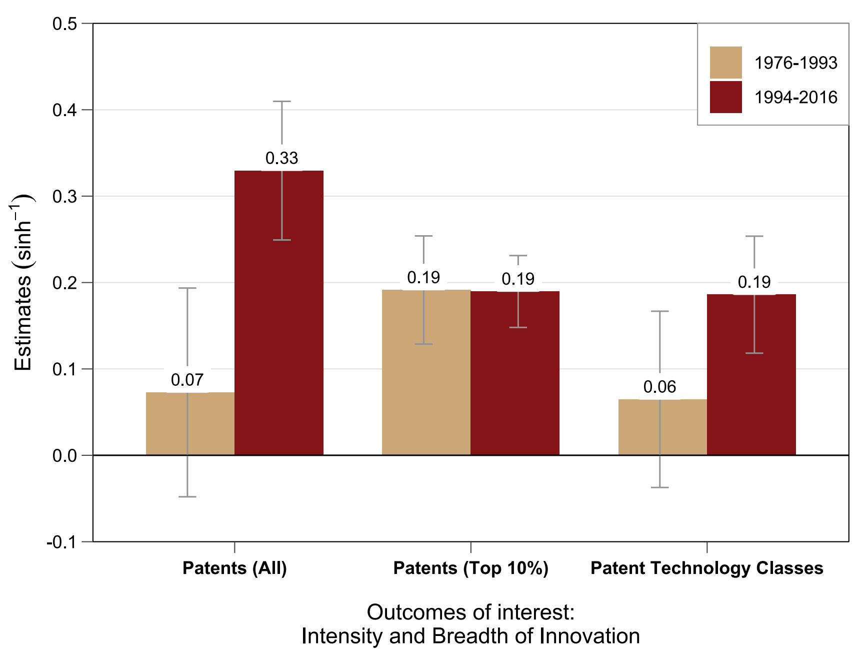
C.12 Temporal Heterogeneity (Antitrust Policy Changes)

An important source of heterogeneity is a temporal change in competition, collusion, and innovation. During the sample period, the US antitrust policy experienced a major change: the revision of the leniency program in 1993–1994. Advances in communication technologies and transportation may also have affected how colluding firms discuss price levels and share information. Furthermore, patterns of technological innovation have also changed.

It is therefore vital to check whether my main results change over time. I ran regressions based on Equation (1) separately for periods before and after the leniency policy change, based on the breakup year of collusion. This roughly divides my sample period into two large bins: 1976–1993 and 1994–2016.

Figure C-10 graphically presents the results. The effect on patent filings and patent technology classes are higher for 1994–2016, but I did not find a noticeable, systematic difference in the high-quality patents between the two time periods. This suggests that, despite new competition policies and advancements in technologies, the main findings—particularly those of high-quality patents—remain robust and are not driven by specific time-varying factors.

Figure C-10. Temporal Heterogeneity:
The Intensity and Breadth of Innovation over Time



C.13 Patents by Colluding and Non-colluding Firms in the Vitamin Cartel:

The vitamin cartel is known to have overcharged up to 100% of the benchmark price (Bernheim, 2008; Igami and Sugaya, 2022). In Figure 2 of the main paper, colluding firms increased their patent filings after the cartel's formation, and the patenting level reverted to the bench market level after the cartel breakup. Non-colluding firms in the same market followed a similar pattern, but the magnitude was much smaller.

Table C-14 summarizes the selected well-cited patents registered by colluding firms during the vitamin cartel. Panel (a) shows patents directly related to vitamins (i.e., that represent the intensity of vitamin innovation), whereas Panel (b) lists those patents loosely related to vitamins (i.e., that could potentially show the broadening innovation around vitamins).

The vitamin cartel example suggests that colluding firms indeed increased the intensity and breadth of innovation during collusion in this technology and patent-intensive sector.

Table C-14. Selected Well-Cited Patents by Colluding Firms in the Vitamin Cartel

(a). Patents directly related to vitamins

US Patent Number	Title	Filing date	Assignee firm ("filed by")	Forward citations (cited by)	Relatedness to Vitamin
5,501,861	Fast dissolving tablet and its production	1994-09-06	Takeda Pharmaceutical Co Ltd	209	"The present invention relates to a fast dissolving tablet comprising a pharmacologically active ingredient, such as a **vitamin**"
5,356,636	Stable vitamin and/or carotenoid products in powder form, and the preparation thereof	1992-12-16	BASF SE	82	"A process for preparing stable dry powders which are insoluble in hot water and which contain fat-soluble **vitamins** and/or carotenoids"
4,966,779	Stable, water miscible emulsion comprising a fat-soluble vitamin	1989-12-21	BASF Corp	63	"The present invention pertains to fat-soluble **vitamins**, more specifically, to stable, water-miscible, emulsified formulations thereof"
6,254,886	Multilayer tablet	1998-09-11	Merck Patent GmbH	63	"The invention relates to multilayer tablets which are constructed of two, three or more layers, one layer containing probiotic microorganisms, while the other layers contain foodstuff ingredients valuable in nutritional physiology, such as **vitamins**, minerals, etc."
5,428,029	Vitamin D3 fluorinated analogs	1993-11-24	Hoffmann La Roche Inc	47	"**Vitamin** D3 fluorinated analogs"
6,020,003	Method of making spray-dried powders with high edible-oil	1998-02-23	BASF Corp	39	"The present invention relates to a method for making spray-dried tablettable powders with high

	loadings based on non-hydrolyzed gelatin				edible oil loadings based on non-hydrolyzed gelatin. Said edible oils can be **vitamin**, flavor and fragrance oils."
5,516,640	Method of determination of pivka	1994-04-18	Eisai Co Ltd	26	"To provide a simple immunochemical assay of a PIVKA of every kind (PIVKA-VII, -IX, -X, -C, -S or -Z: protein induced by **vitamin** K absence) corresponding to a vitamin K-dependent protein."

(b). Patents loosely related to vitamins

US Patent Number	Title	Filing date	Assignee firm ("filed by")	Forward citations (cited by)	Description
5,210,015	Homogeneous assay system using the nuclease activity of a nucleic acid polymerase	1990-08-06	Hoffmann La Roche Inc	1,256	"The present invention is directed to a process of detecting a target **nucleic acid** using labeled oligonucleotides."
5,120,548	Swelling modulated polymeric drug delivery device	1989-11-07	Merck and Co Inc	880	"… the degree of polymer swelling can be regulated for a prolonged period to achieve either desired constant or intermittent **drug delivery**"
5,514,718	Heterocyclic compounds, processes for their preparation and pharmaceutical compositions containing them	1994-04-15	Merck Sharp and Dohme Ltd	205	"This invention relates to a class of **heterocyclic compounds** which are useful as tachykinin receptor antagonists. The tachykinins are a group of naturally-occurring **peptides**…"
5,487,972	Nucleic acid detection by the 5′-3′exonuclease activity of polymerases acting on adjacently hybridized oligonucleotides	1993-01-05	Hoffmann La Roche Inc	1,256	"A process of detecting a target **nucleic acid** using labeled oligonucleotides which uses the 5′ to 3′ nuclease activity of a nucleic acid polymerase to cleave annealed labeled oligonucleotide …"
4,957,681	Preparation of pharmaceutical mixtures	1989-04-03	BASF SE	128	"The present invention relates to a process for the preparation of **pharmaceutical mixtures** by continuous weighing of the individual components."
5,333,675	Apparatus and method for performing automated amplification of nucleic acid sequences and assays using heating and cooling steps	1993-02-22	Hoffmann La Roche Inc	211	"The invention pertains to the field of chain reactions for amplifying DNA or RNA (**nucleic acids**), and, more particularly, to the field of machines for automatically performing this process through temperature cycling."
5,418,149	Reduction of non-specific amplification glycosylase using DUTP and DNA uracil	1991-07-23	Hoffmann La Roche Inc	173	"This invention relates to improved methods for amplifying **nucleic acids** using methods such as the polymerase chain reaction (PCR) procedure."

5,478,337	Medicine container	1993-04-28	Otsuka Pharmaceutical Co Ltd; Takeda Chemical Industries Ltd	157	"The present invention relates to **medicine containers** which comprise a container having an **antibiotic or like medicine** hermetically accommodated therein and another container joined thereto and similarly containing a liquid for dissolving the medicine …"
5,026,560	Spherical granules having core and their production	1998-01-14	Takeda Chemical Industries Ltd	232	"This invention relates to spherical granules having a core excellent in hardness and disintegration, and to their production … such as benzimidazoles described below … and vitamin drugs such as **vitamin B1, vitamin B2, vitamin B6, vitamin C**, and fursultiamine."

Notes. The most recent patent information was acquired from Google Patents (https://patents.google.com/), accessed on October 15, 2022. Vitamin-related descriptions are excerpted from the patent title, abstract, or description.