Online Appendix

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

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A. Additional Description of Data

A.1 Collusion Data

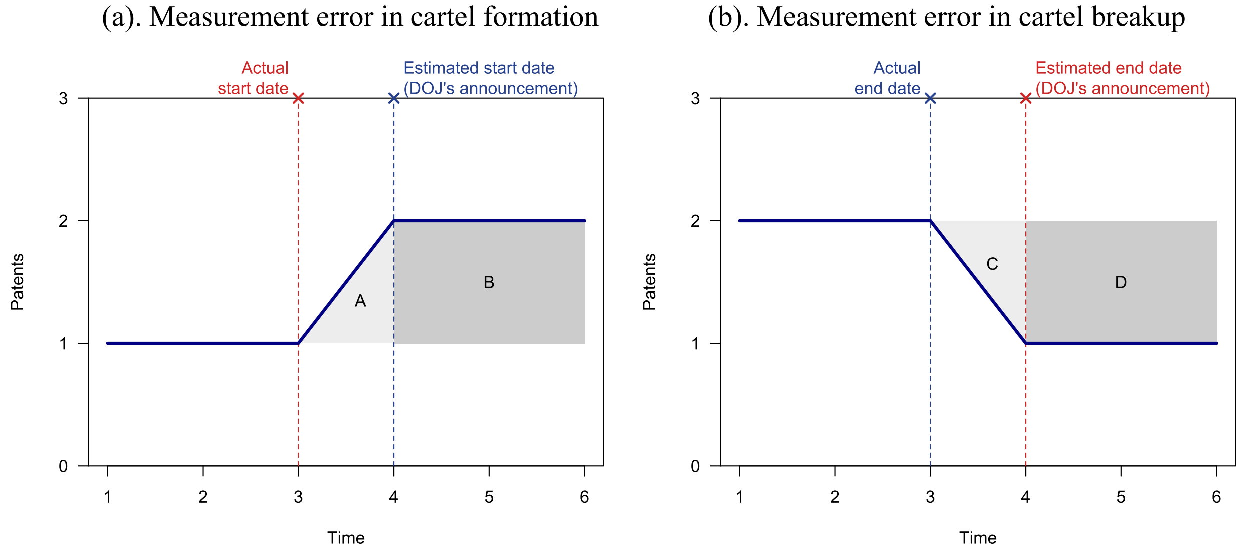
Figure A-2 and Figure A-3, respectively, show the first page of information (indictment) and plea agreement documents released by the Antitrust Division of the US Department of Justice. The most important information on collusion is the names of (co-)conspirators and the years of collusion formation 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. The DOJ should have robust and real evidence to claim the collusion period.

Yet, colluded firms have a strong incentive to understate the correct collusion period (unless the DOJ has strong evidence). This suggests that the DOJ’s estimation on 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 colluded 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 colluded 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 colluded. In Figure A-1(a), if the start date is negotiated, 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 colluded. In Figure A-1(b), if the end date is negotiated, the specification underestimates the effect size equal to the C area.

Figure A-1. Potential Measurement Error on Cartel Duration and Its Implications



Third, in Online Appendix C.6, I conduct sensitivity tests on the years of collusion and breakup.

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-2. 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.,	
Defendant.	San Francisco Venue

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 (colluded firm), collusion period, and detailed conduct are described. *Data*: The US DOJ.

Figure A-3. A Sample Plea Agreement (page 1 of 16)

Case3:11-cr-00162-WHA Document29 Filed05/17/11 Page1 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;

PLEA AGREEMENT - SAMSUNG SDI - PAGE 1

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.

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 firm-level match, I use 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).

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 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 colluded 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, 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 to 2015. 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 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 colluded 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.

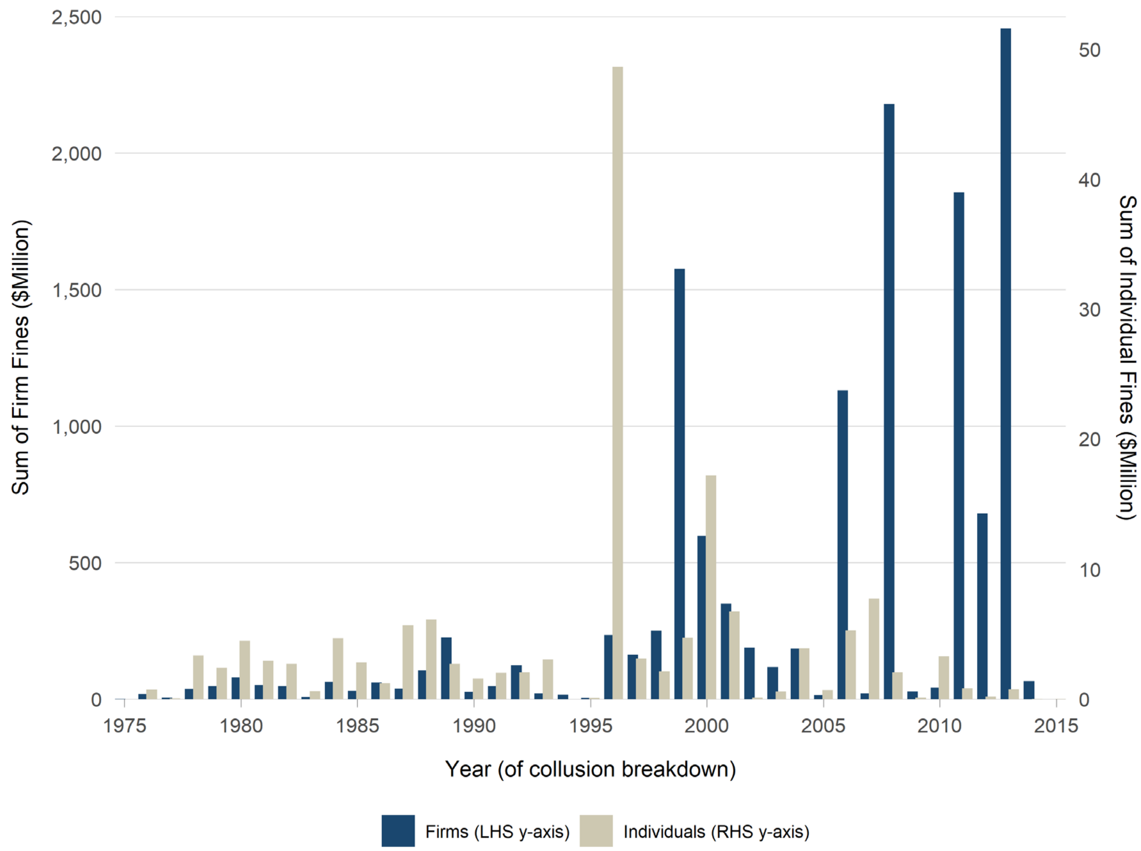
References.

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.

Figure B-1. Collusion Criminal Fines for Firms and Individuals, 1975–2015



Notes. This figure tracks the trend in antitrust punishment for collusion in the United States for 1975–2015. 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 2015 but have not yet been indicted due to ongoing closed investigations. *Sources*: The author's own data collection from the Antitrust Division of the US Department of Justice (DOJ) and the Antitrust Cases (formerly Trade Regulation Reporter) by the Commercial Clearing House (CCH).

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 colluded 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 colluded 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 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-weight patents	R&D expenditure	Unique tech classes	Tech-weighted patents	Patents in primary fields	Patents peripheral fields
	(1)	(2)	(3)	(5)	(6)	(7)	(8)	(9)
Treat × *Pre*	–0.035	–0.048	0.119	–0.033	–0.019	–0.014	–0.095*	–0.070
	(0.058)	(0.046)	(0.117)	(0.028)	(0.048)	(0.066)	(0.052)	(0.049)
Treat × $Post_A$	0.150**	0.111**	0.244*	0.109	0.091*	0.152**	0.115*	0.125**
	(0.061)	(0.050)	(0.124)	(0.074)	(0.053)	(0.072)	(0.065)	(0.060)
Treat × $Post_B$	0.235***	0.158**	0.335**	0.158**	0.134*	0.226**	0.213**	0.204***
	(0.090)	(0.067)	(0.159)	(0.060)	(0.071)	(0.100)	(0.088)	(0.076)
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)	(5)	(6)	(7)	(8)	(9)
Treat × *Pre*	0.052	–0.031	0.109	0.041	0.019	0.049	0.037	–0.007
	(0.047)	(0.036)	(0.101)	(0.074)	(0.041)	(0.058)	(0.038)	(0.050)
Treat × $Post_A$	–0.001	0.024	–0.146	–0.018	–0.014	–0.021	0.020	0.022
	(0.050)	(0.037)	(0.095)	(0.070)	(0.040)	(0.061)	(0.049)	(0.034)
Treat × $Post_B$	–0.089	0.053	–0.309**	–0.073	–0.102*	–0.127*	–0.060	–0.049
	(0.058)	(0.053)	(0.123)	(0.063)	(0.052)	(0.071)	(0.058)	(0.042)
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. 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 colluded firms and zero otherwise. Years are grouped into seven time periods, each representing the three-year period around the events of interest into one time group. 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: 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 × *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)

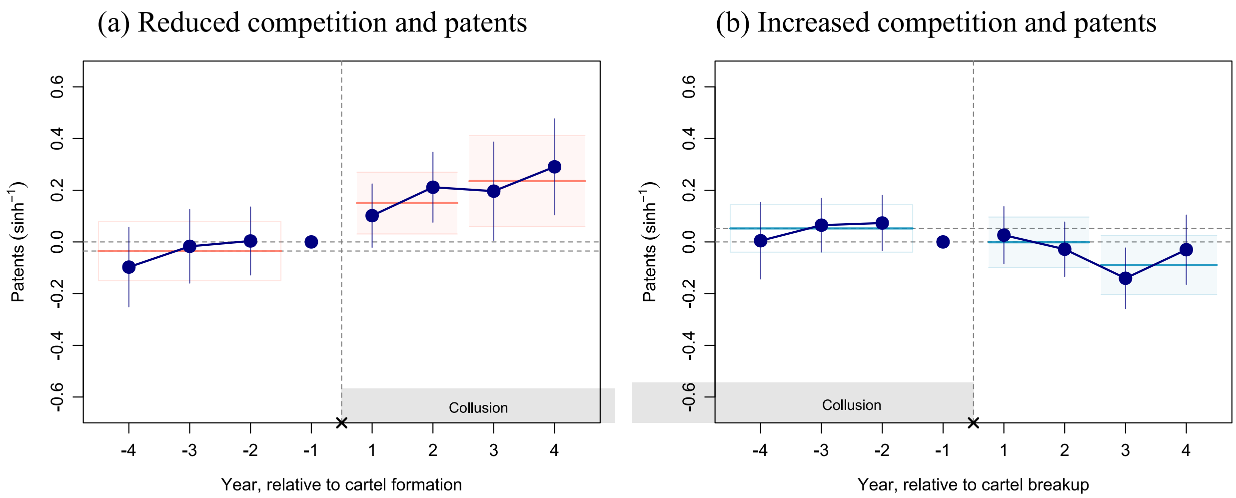
B. Collusion breakup: Increased competition and innovation

	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 × $Post_A$	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 × $Post_B$	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 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. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

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

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

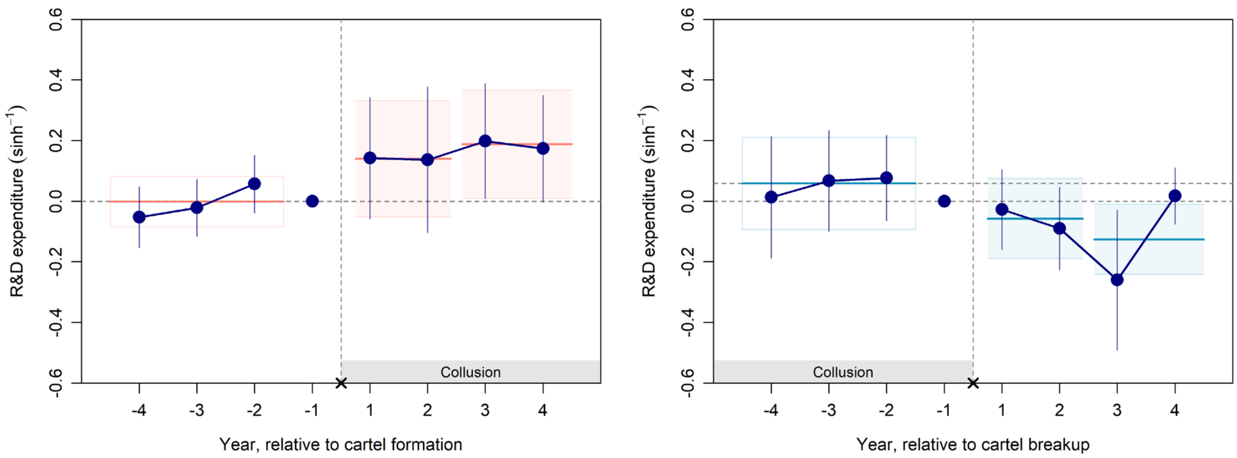


Plotted are the event-time coefficient estimates (dots) from a version of Equations (2) and (3), where the dependent variable consists of citation-weighted patents with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence intervals. Colored 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 R&D expenditure of publicly traded firms.

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

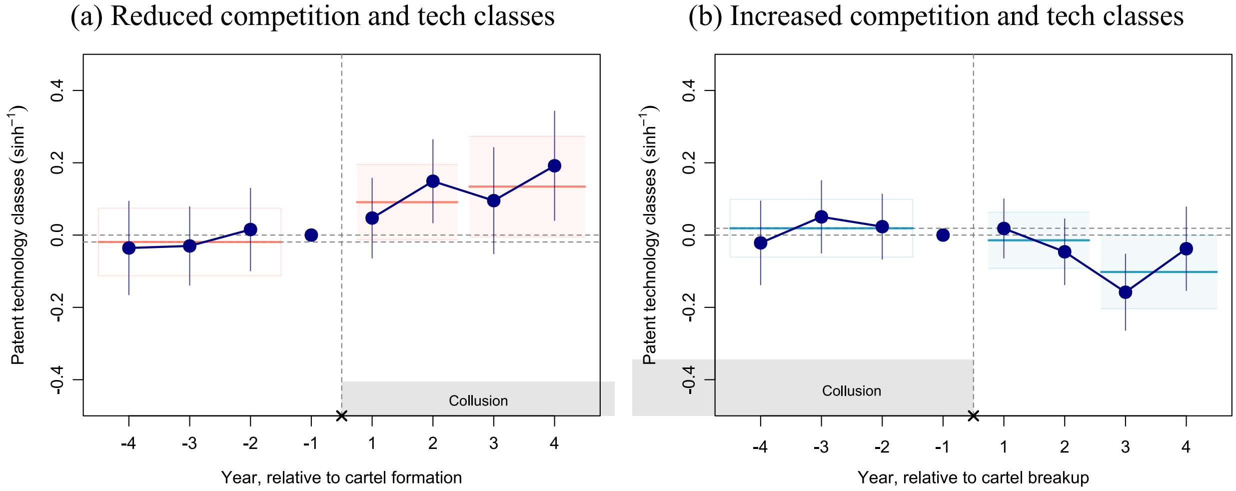
(a) Reduced competition and R&D expenditure (b) Increased competition and R&D expenditure



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

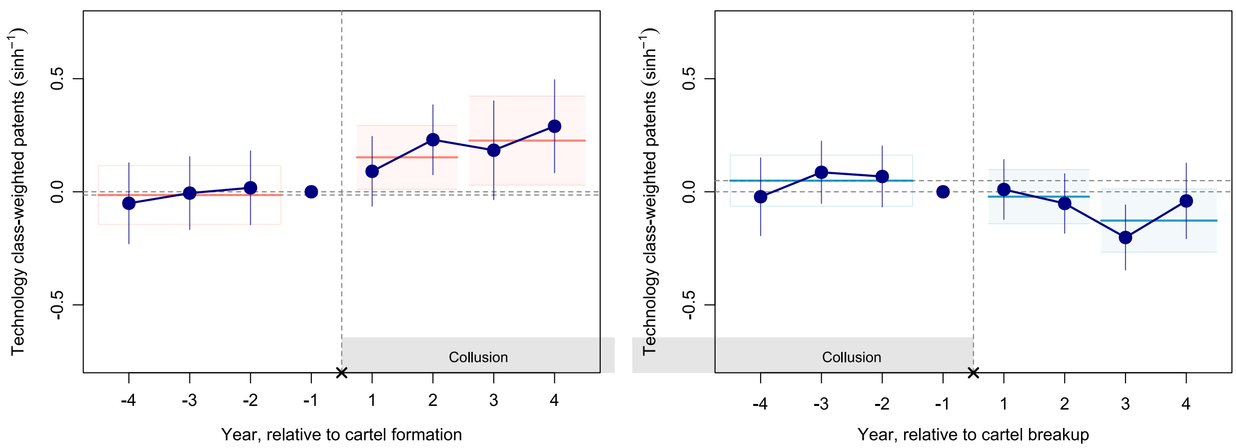


Plotted are the event-time coefficient estimates (dots) from a version of Equations (2) and (3), where the dependent variable consists of the unique number of patent technology classes with the inverse hyperbolic sine transformation in an assignee firm × year. The vertical lines represent 95% confidence 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

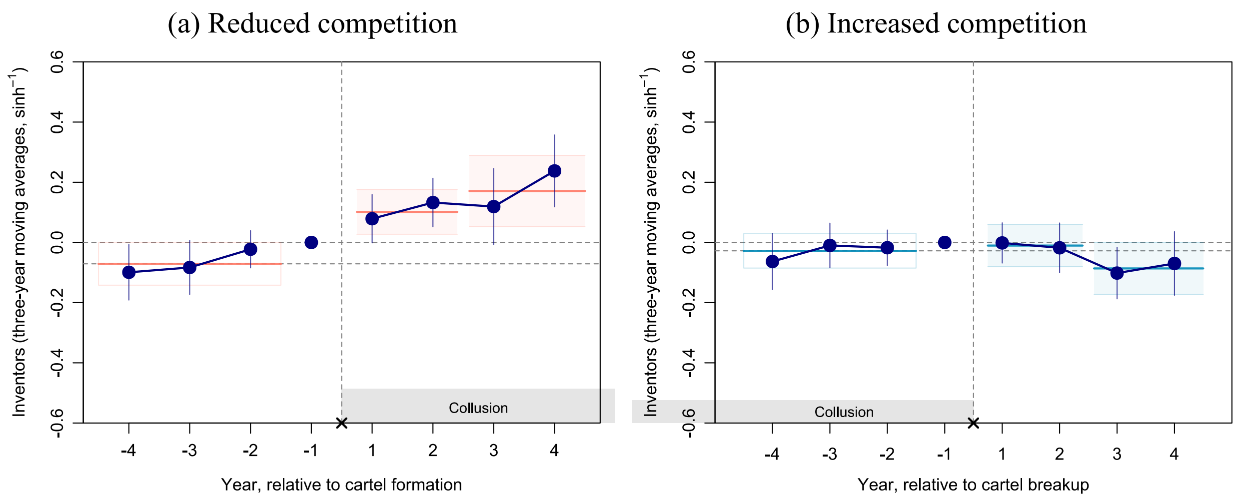
(a) Reduced competition (b) Increased competition



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



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 Quality of Innovation: The Long-term Influence of Patents

I tested using the long-term patent influence measure (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-4 shows the descriptive statistics of the measure.

Figure C-4 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 tested the *number* of 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 estimate are positive, but I cannot reject the null hypothesis that they are different from zero.

Table C-4. 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-5. 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 then 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 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 is not possible to distinguish long-term influential patents from the 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 to create 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 $\times$ 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). I will make this measure and all other patent-based measures used in this study publicly available to researchers.

C.3 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 colluded 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 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-6, column 2, empirical analysis excluding firms that participated in R&D collaboration provides results consistent to 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-6. Intensity of Innovation: Excluding Firms in R&D Collaboration

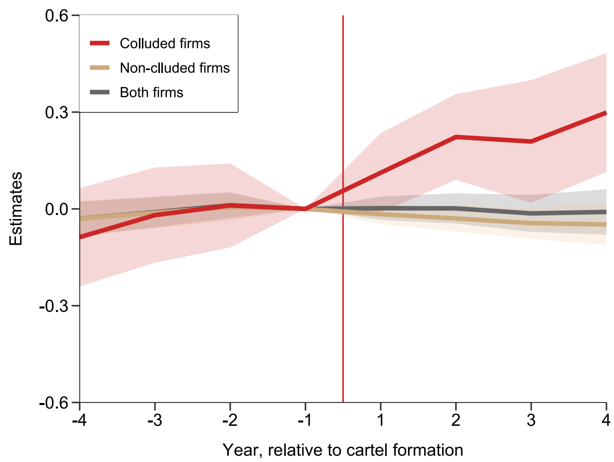
	Dependent variables ($\sinh^{-1}$):		
	R&D Expenditure		
	Full Sample (1)	Excluding All R&D Collaborators (2)	Excluding Two Repeat Collaborators (3)
$Treat \times Post$	0.152**	0.176**	0.212***
	(0.069)	(0.069)	(0.066)
Observations	149,932	149,868	149,887
R^2	0.921	0.921	0.921
Adjusted R^2	0.910	0.909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

C.4 Non-Colluded Firms

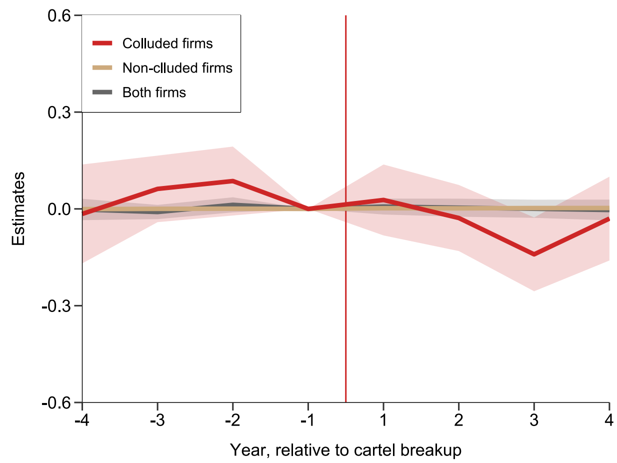
Figure C-6(a-b) shows the flexible difference-in-differences results for patent filings for (1) colluded firms (a red line), (2) non-colluded firms (a brown line), and (3) both firms as the treatment group (a gray line) around cartel formation and breakup, respectively. Figure C-6(c) compares the estimates for key outcomes—patent filings and the unique number of technology classes—for the three groups. For the groups other than the colluded firms, I cannot reject the null hypothesis that there was no effect. One explanation for the negligible spillover effect is that non-colluded firms tend to be smaller and have negligible power in the market.

Figure C-6. Collusion and Innovation: Comparison by Group

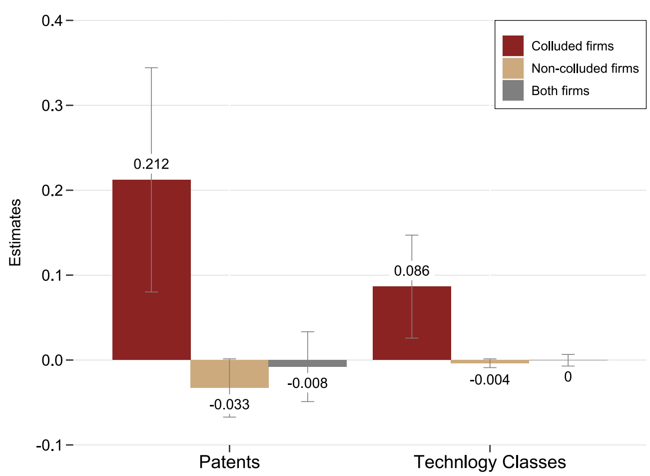
(a). Cartel formation and patents by group



(b). Cartel breakup and patents by group



(c). Comparing key outcomes by group

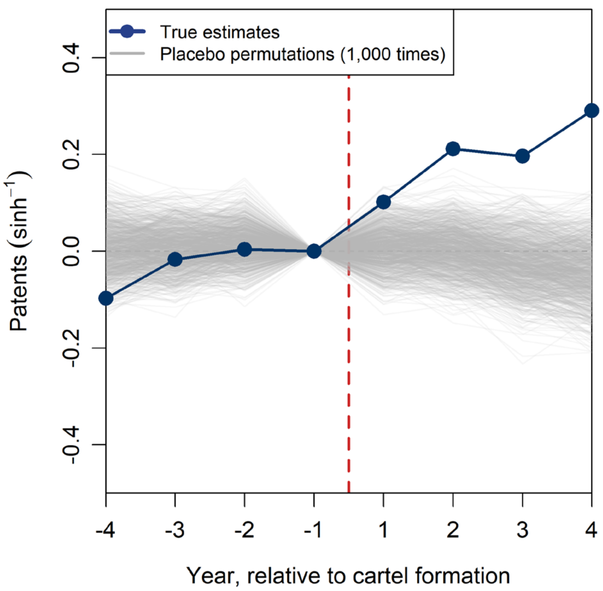


C.5 Placebo Permutation Tests

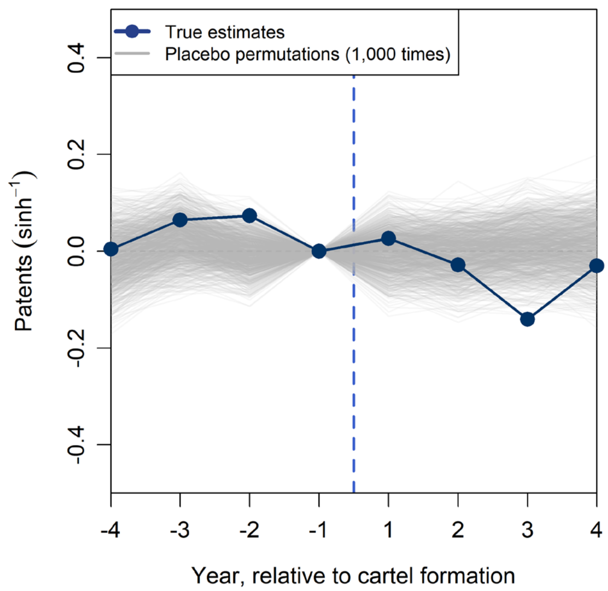
Figure C-7 illustrates the placebo tests for patents separately for the formation and breakup of collusion.

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

(a) Reduced competition and patents



(b) Increased competition and patents

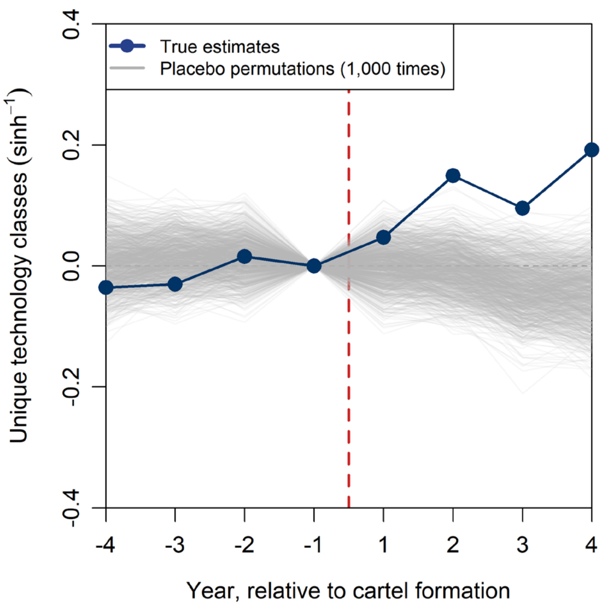


Plotted are the event-time coefficient estimates (dots) from a version of Equation (3), where the dependent variable consists of citation-weighted patents with the inverse hyperbolic sine transformation in a firm × year. Blue dots and lines represent the real treatment group (colluded firms), and 1,000 gray lines represent the results for 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.

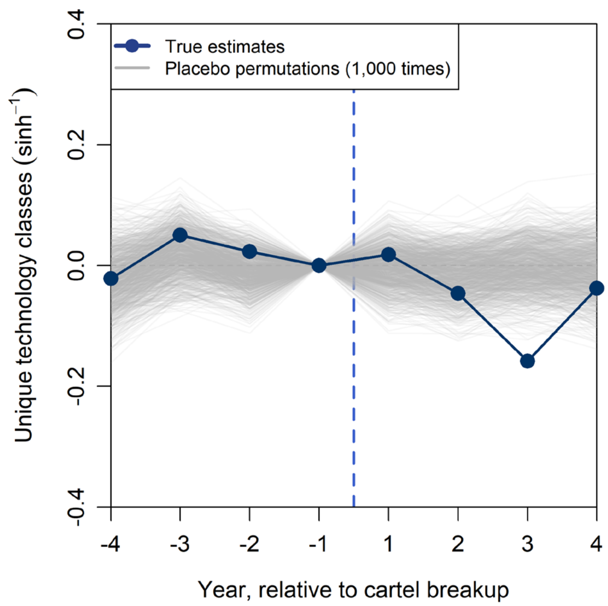
Figure C-8 illustrates the placebo tests for the unique number of patented technology classes separately.

Figure C-8. Effects of Collusion and Price Competition: Placebo Permutation Tests on Technology Classes

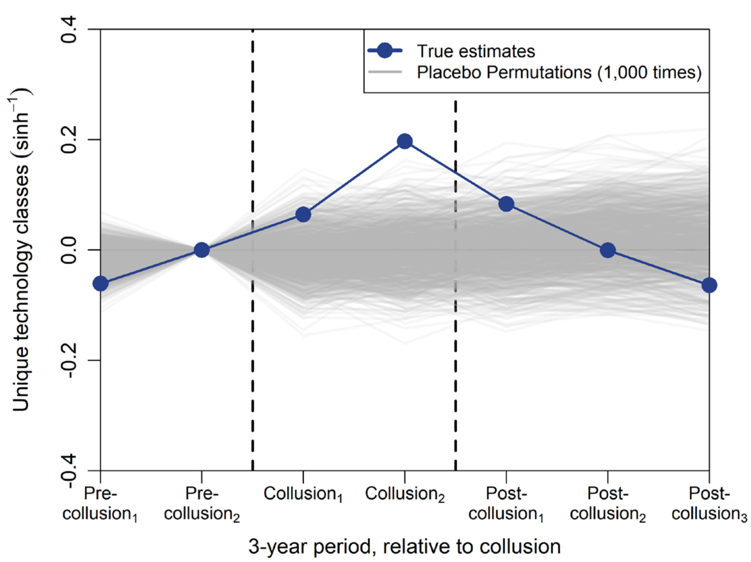
(a) Reduced competition and technology classes



(b) Increased competition and technology classes



(c) The life cycle of collusion and technology classes

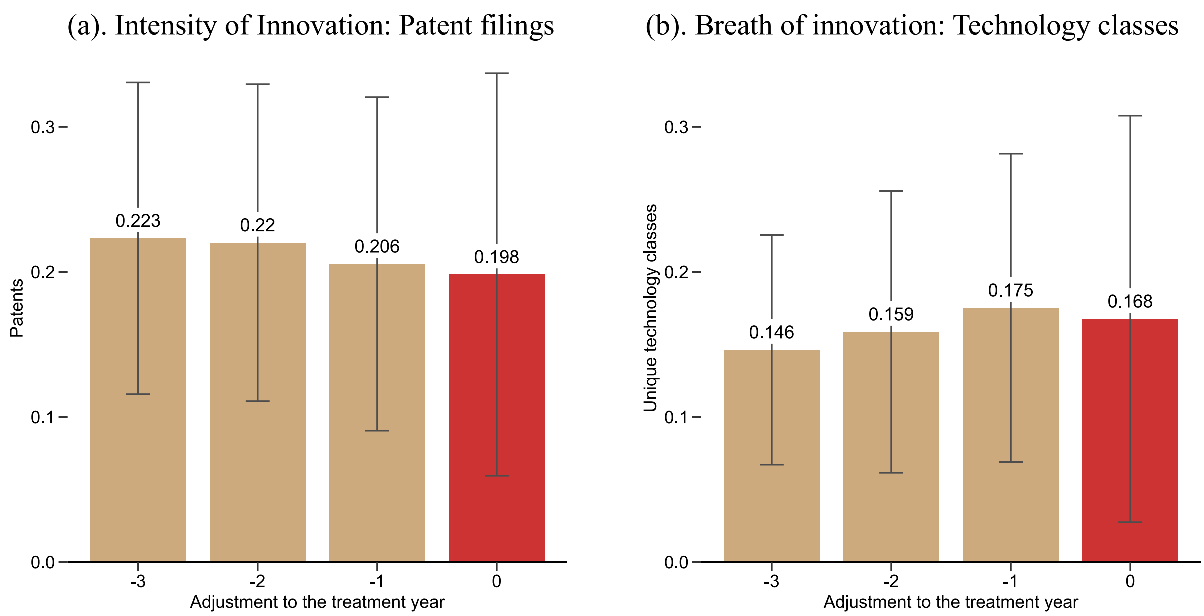


Plotted are the event-time coefficient estimates (dots) from a version of Equation (3), where the dependent variable consists of citation-weighted patents with the inverse hyperbolic sine transformation in a firm × year. Blue dots and lines represent the real treatment group (colluded firms), and 1,000 gray lines represent the results for 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 Sensitivity Test of Cartel Formation by Year

I performed a sensitivity analysis around the start date of the collusion (T). I run 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-9(a) shows the sensitivity test for patent filings (the intensity of innovation). We see that the point estimate increases as the treatment year is adjusted by one to three years earlier. This is consistent with the argument to be made in the next point that the effects are underestimated in the presence of term negotiation. Figure C-9 (b) shows the same sensitivity test for the unique number of technology classes (the breadth of innovation). The size of the effect increases as I adjust the treatment year by one year. It then begins to decrease for further adjustments. Overall, the results are robust to these adjustments.

Figure C-9. Sensitivity test of cartel formation by year



Notes. This figure shows the regression estimates using different years of treatment. For example, "–1" indicates that one year before the cartel formation is used as the treatment year. "0" with a red bar indicates the estimates of the main analysis without any adjustment. The vertical lines represent the 95% confidence interval.

C.7 Markets versus Firms

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 colluded firms operate (through firm-level financial constraint and profitability). I used the granular Compustat Segment data to check the market versus firm mechanism and verify the control group. Table C-7 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-7, column 3, shows the results that the colluded firms increased R&D expenditure by 23.6 percent.

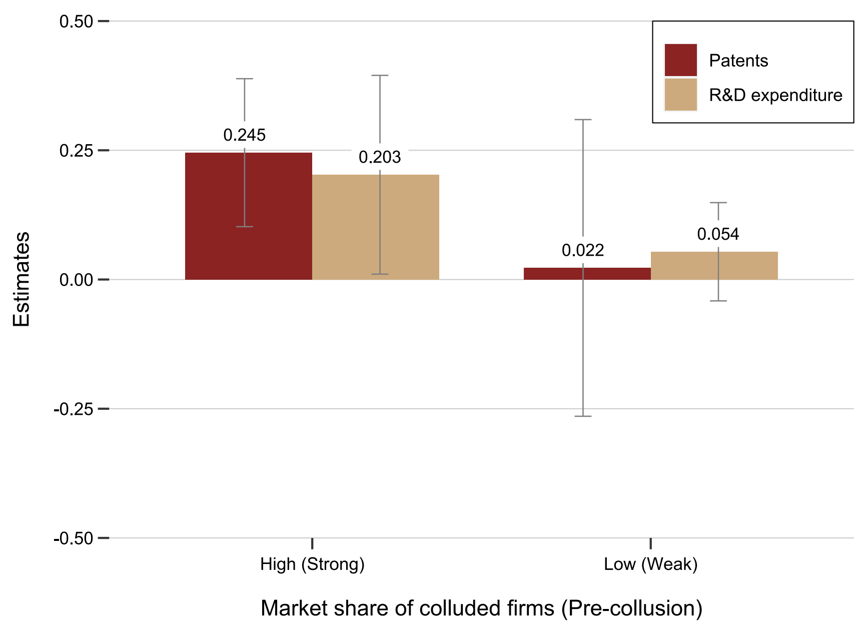
Table C-7. Cartel Formation and the Intensity of Innovation by Business Segments

	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.8 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 colluded firms. Figure C-10 graphically summarizes the results. From the split-sample analysis on strong collusion (that have above-median share) and weak collusion (that have 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-10. 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 colluded 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.9 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 two major changes: the revision of the leniency program in 1993–1994 and the enactment of Antitrust Criminal Penalty Enhancement and Reform Act in 2004 (Ghosal and Sokol, 2020). Advances in communication technologies and transportation may also have affected how colluded firms discuss price levels and share information. Furthermore, patterns of technological innovation have also changed. For example, we have witnessed rapid growth in the artificial intelligence and machine learning fields, and the role of competition in these fields may be different from the role of competition in the emerging fields in the 1970s and 1980s.

It is therefore vital to check whether my main results change over time. I ran regressions based on Equation (1) separately for periods before and after the two significant policy changes, based on the breakup year of collusion. This roughly divides my sample period into two large bins: 1976–1993 and 1994–2016. Figure C-11 graphically presents the results. The effect on patent filings is higher for 1994–2016 but, in general, I did not find a noticeable, systematic difference in innovation activities between the two time periods. This suggests that, despite new competition policies and advancements in technologies, the main findings remain robust and are not driven by specific time-varying factors.

Figure C-11. Temporal Heterogeneity:
The Intensity and Breadth of Innovation over Time