



Mergers, Industries, and Innovation: Evidence from R&D Expenditure and Patent Applications

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Executive Summary

For decades, there has been a broad consensus among policymakers, antitrust enforcers, and economists that most mergers pose little threat from an antitrust perspective and that mergers are generally procompetitive. However, over the past year, leadership at the FTC and DOJ has questioned whether mergers are, as a general matter, economically beneficial and asserted that mergers pose an active threat to innovation. The Agencies have also set the stage for a substantial increase in the scope of merger enforcement by focusing on new theories of anticompetitive harm such as elimination of potential competition from nascent competitors and the potential for cumulative anticompetitive harm from serial acquisitions.

Despite the importance of the question of whether mergers have a positive or negative effect on industry-level innovation, there is very little empirical research on the subject. Thus, in this study, we investigate this question utilizing, what is to our knowledge, a never before used dataset combining industry-level merger data from the FTC/DOJ annual HSR reports with industry-level data from the NSF on R&D expenditure and patent applications.

We find a strong positive and statistically significant relationship between merger activity and industry-level innovative activity. Over a three- to four-year cycle, a given merger is associated with an average increase in industry-level R&D expenditure of between \$299 million and \$436 million in R&D intensive industries. Extrapolating our results to the industry level implies that, on average, mergers are associated with an increase in R&D expenditure of between \$9.27 billion and \$13.52 billion per year in R&D intensive industries and an increase of between 1,430 and 3,035 utility patent applications per year. Furthermore, using a statistical technique developed by Nobel Laureate Clive Granger, we find that the direction of causality goes, to a substantial extent, directly from merger activity to increased R&D expenditure and patent applications.

Based on these findings we draw the following key conclusions:

- There is no evidence that mergers are generally associated with reduced innovation, nor do the results indicate that supposedly lax antitrust enforcement over the period from 2008 to 2020 diminished innovative activity. Indeed, R&D expenditure and patent applications increased substantially over the period studied, and this increase was directly linked to increases in merger activity.
- In previous research, we found that “trends in industrial concentration do not provide a reliable basis for making inferences about the competitive effects of a proposed merger” as “trends in concentration may simply reflect temporary fluctuations which have no broader economic significance” or are “often a sign of increasing rather than decreasing market competition.”¹ This study presents further evidence that previous consolidation in an industry or a “trend toward concentration” may reflect procompetitive responses to

¹ Robert Kulick & Andrew Card, *Industrial Concentration in the United States: 2002-2017*, NERA Economic Consulting (March 2022) at 24, available at <https://www.nera.com/publications/archive/case-project-experience/nera-economists-evaluate-claims-of-excessive-concentration-in-th.html> [hereafter “Kulick & Card (2022)”].

competitive pressures, and therefore should not play a role in merger review beyond that already embodied in the market-level concentration screens considered by the Agencies.

- The Agencies should proceed cautiously in pursuing novel theories of anticompetitive harm; our findings are consistent with the prevailing consensus from the previous decades that there is an important connection between merger activity and innovation, and thus, a broad “anti-merger” policy, particularly one pursued in the absence of strong empirical evidence, has the potential to do serious harm by perversely inhibiting innovative activity.
- Due to the link between mergers and innovative activity in R&D intensive industries where the potential for anticompetitive consequences can be resolved through remedies, relying on remedies rather than blocking transactions outright may encourage innovation while protecting consumers where there are legitimate competitive concerns about a particular transaction.
- The potential for mergers to create procompetitive benefits should be taken seriously by policymakers, antitrust enforcers, courts, and academics and the Agencies should actively study the potential benefits, in addition to the costs, of mergers.

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I. Introduction

Mergers are a ubiquitous part of the U.S. economy. From fiscal year 2011 to fiscal year 2020, an average of 1,739 transactions were reported to the Federal Trade Commission (FTC) and Department of Justice (DOJ, collectively the Agencies) per year under the Hart-Scott-Rodino (HSR) premerger notification program, which requires all transactions exceeding a specific financial threshold to be reported to the Agencies prior to closing.² Tens of thousands more transactions occur each year that fall below the HSR reporting threshold.³

For decades, there has been a broad consensus among policymakers, antitrust enforcers, and economists that most mergers pose little threat from an antitrust perspective and that mergers are generally procompetitive. For instance, of the 1,637 transactions reported to the Agencies in fiscal year 2020, only 48 or 2.9 percent were subject to a “Second Request” – a process in which the Agencies conduct a protracted inquiry into transactions identified as having the potential to be anticompetitive.⁴ Similarly, in fiscal year 2000, 2.0 percent of transactions were subject to a Second Request,⁵ and in fiscal year 2010, 3.9 percent of transactions were subject to a Second Request.⁶

However, under the Biden Administration, the Agencies have rejected the traditional consensus, viewing mergers as a source of pervasive economic harm without redeeming economic benefits.⁷ Agency leadership has blamed merger activity and industrial concentration for a host of economic ills, including inflation, lower wages for workers, and reduced innovation.⁸ From the standpoint of the previous economic consensus on antitrust policy, the Agencies’ growing belief that mergers

² Federal Trade Commission and Department of Justice, “Hart-Scott-Rodino Annual Report” (FY 2020) at 1, available at https://www.ftc.gov/system/files/documents/reports/hart-scott-rodino-annual-report-fiscal-year-2020/fy2020_-_hsr_annual_report_-_final.pdf [hereafter “HSR Annual Report (FY 2020)”].

³ WilmerHale, “M&A Report” (2022) at 2, available at <https://www.wilmerhale.com/insights/publications/2022-manda-report>.

⁴ HSR Annual Report (FY 2020), Appendix A at 1.

⁵ Federal Trade Commission and Department of Justice, “Annual Report to Congress” (FY 2000), Appendix A at 1, available at https://www.ftc.gov/sites/default/files/documents/reports_annual/23rd-report-fy-2000/annualreport2000_0.pdf.

⁶ Federal Trade Commission and Department of Justice, “Hart-Scott-Rodino Annual Report” (FY 2010), Appendix A at 1, available at https://www.ftc.gov/sites/default/files/documents/reports_annual/33st-report-fy-2010/1101hsrreport_0.pdf.

⁷ Christine S. Wilson, “An Update on FTC Merger Enforcement, Remarks at International Bar Associations 19th Annual International Mergers and Acquisitions Conference,” (June 15, 2022) at 9-10, available at https://www.ftc.gov/system/files/ftc_gov/pdf/CWilsonUpdateMergerEnforcement.pdf (“Current agency leadership takes a dim view of efficiencies. They argue that prior merger guidelines are inconsistent with the Clayton Act because they discuss procompetitive benefits and efficiencies from mergers. From a practical perspective, new leadership believes that mergers rarely, if ever, produce synergies or cost savings.”).

⁸ Lina Khan, “Remarks of Lina M. Khan Regarding the Request for Information on Merger Enforcement,” FTC Docket No. FTC-2022-0003 (January 18, 2022), available at https://www.ftc.gov/system/files/documents/public_statements/1599783/statement_of_chair_lina_m_khan_regardin_g_the_request_for_information_on_merger_enforcement_final.pdf.

pose a broad threat to innovation⁹ is striking, as one particularly salient point of agreement had been that mergers play an important role in fostering and encouraging innovation.¹⁰

While the *Request for Information on Merger Enforcement* issued by the Agencies in January 2022 posits that current policy “may underemphasize or neglect ... non-price elements of competition like innovation, quality, [and] potential competition,”¹¹ the 2010 *Horizontal Merger Guidelines* explicitly consider the potential for mergers to reduce innovation,¹² and the Agencies have opposed mergers based specifically on concerns regarding overlapping R&D portfolios and innovation in the past.¹³ Thus, what is new about the position taken by leadership at the Agencies is not recognition of the possibility that a particular merger may harm innovation. Rather, by focusing on new theories of anticompetitive harm, such as elimination of potential competition from nascent competitors¹⁴ or the creation of market power through “serial acquisitions,”¹⁵ the Agencies have set the stage for a substantial increase in the scope of merger enforcement. Specifically, under these new theories of anticompetitive harm, the purported harmful effects of mergers on innovation may manifest primarily at the industry-level rather than the firm-level, which has traditionally been the focus of merger review. As explained by FTC Commissioner Rebecca Kelly Slaughter:

Protecting innovation requires us to consider the impact of mergers on both the incentives of the merging firms, as well as on non-merging firms. For example, the incentives of non-merging firms may be relevant if a merger reduces the number of

⁹ See e.g., Debbie Feinstein, C. Scott Lent, and Matthew Tabas, “FTC Workshop Contemplates ‘New Approach’ to Pharmaceutical Mergers,” (July 13, 2022), available at <https://www.arnoldporter.com/en/perspectives/advisories/2022/07/ftc-contemplates-new-approach-to-pharmaceutical-mergers>.

¹⁰ See e.g., William J. Kolasky and Andrew R. Dick, “The Merger Guidelines and the Integration of Efficiencies into Antitrust Review of Horizontal Mergers,” (2015) at 58, available at <https://www.justice.gov/archives/atr/merger-guidelines-and-integration-efficiencies-antitrust-review-horizontal-mergers> (“Like allocative and productive efficiencies, achievement of dynamic efficiencies can be facilitated by antitrust and other public policies that permit efficient transactions in support of invention.”).

¹¹ Federal Trade Commission and Department of Justice, “Request for Information on Merger Enforcement,” (January 18, 2022) at 2, available at <https://www.regulations.gov/document/FTC-2022-0003-0001> [hereafter “FTC Merger RFI (2022)”].

¹² Federal Trade Commission and Department of Justice, “Horizontal Merger Guidelines,” (August 19, 2010) at 23-24, available at <https://www.justice.gov/sites/default/files/atr/legacy/2010/08/19/hmg-2010.pdf>.

¹³ See e.g., Department of Justice, “Applied Materials Inc. and Tokyo Electron Ltd. Abandon Merger Plans After Justice Department Rejected Their Proposed Remedy,” (April 27, 2015), available at <https://www.justice.gov/opa/pr/applied-materials-inc-and-tokyo-electron-ltd-abandon-merger-plans-after-justice-department>.

¹⁴ See e.g., Federal Trade Commission, “Statement of Chair Lina M. Khan, Commissioner Rohit Chopra, and Commissioner Rebecca Kelly Slaughter on the Withdrawal of the Vertical Merger Guidelines,” (September 15, 2021) at 8, available at https://www.ftc.gov/system/files/documents/public_statements/1596396/statement_of_chair_lina_m_khan_commissioner_rohit_chopra_and_commissioner_rebecca_kelly_slaughter_on.pdf.

¹⁵ See e.g., Federal Trade Commission, “Statement of Chair Lina M. Khan Joined by Commissioner Rebecca Kelly Slaughter and Commissioner Alvaro M. Bedoya in the Matter of JAB Consumer Fund/SAGE Veterinary Partners,” (June 13, 2022) at 3, available at https://www.ftc.gov/system/files/ftc_gov/pdf/2022.06.13%20-%20Statement%20of%20Chair%20Lina%20M.%20Khan%20Regarding%20NVA-Sage%20-%20new.pdf.

large firms that are the target sales audience for a new innovation being developed by a pharmaceutical startup, which may affect availability of capital to those startups.¹⁶

However, the previous consensus was built on a body of economic research and Agency experience suggesting that mergers play an important role in increasing productivity and innovation by, for instance, forcing rivals to invest more in R&D to compete with a more efficient firm or by attracting capital to firms hoping to become acquisition targets.¹⁷ Economic benefits of this sort will also generally be realized at the market and industry level, in addition to the firm level, and thus, an overly restrictive policy towards mergers has the potential to harm entire industries with potentially serious ramifications for consumers, competition, and economic growth.

Despite the importance of the question of whether mergers have a positive or negative effect on industry-level innovation, there is very little empirical research on the subject. Thus, in this study, we investigate this question utilizing, what is to our knowledge, a never before used dataset combining industry-level merger data from the FTC/DOJ annual HSR reports with industry-level data from the National Science Foundation (NSF) on R&D expenditure and patent applications. We then employ simple and widely used econometric techniques to assess the relationship between industry-level merger activity and innovative activity, as measured by R&D expenditure and patent applications, in subsequent years. We find a strong positive and statistically significant relationship between merger activity and industry-level innovative activity. Furthermore, using a statistical technique developed by Nobel Laureate Clive Granger, we find that the direction of causality goes, to a substantial extent, directly from merger activity to increased R&D expenditure and patent applications. Based on these general findings, and the specific details discussed below, we believe our findings support five primary policy conclusions.

First, there is no evidence that mergers are generally associated with reduced innovation, nor do the results indicate that supposedly lax antitrust enforcement over the period from 2008 to 2020 diminished innovative activity.¹⁸ Indeed, R&D expenditure and patent applications increased substantially over the period, and this increase was directly linked to increases in merger activity.

Second, in previous research, we found that “trends in industrial concentration do not provide a reliable basis for making inferences about the competitive effects of a proposed merger” as “trends in concentration may simply reflect temporary fluctuations which have no broader economic

¹⁶ Rebecca Kelly Slaughter, “Keynote Remarks of Commissioner Rebecca Kelly Slaughter at the FTC/DOJ Pharmaceutical Task Force Workshop,” (June 14, 2022) at 3, available at https://www.ftc.gov/system/files/ftc_gov/pdf/Keynote-Remarks-Pharma-Workshop.pdf.

¹⁷ Federal Trade Commission and Department of Justice, “Commentary on the Horizontal Merger Guidelines,” (March 2006) at v, available at <https://www.justice.gov/atr/file/801216/download> (“The vast majority of mergers pose no harm to consumers, and many produce efficiencies that benefit consumers in the form of lower prices, higher quality goods or services, or investments in innovation.”); *Id.* at 48 (“As the Guidelines state, efficiencies ‘can enhance the merged firm’s ability and incentive to compete, which may result in lower prices, improved quality, enhanced service, or new products.’ ... Moreover, when a merged firm achieves such efficiencies, it may induce competitors to strive for greater efficiencies in order to compete more effectively.”).

¹⁸ See e.g., Daniel A. Crane, *Has the Obama Justice Department Reinvigorated Antitrust Enforcement?* 65 STANFORD LAW REVIEW (July 2012) 13-20 (discussing perceived laxity in antitrust enforcement during the George W. Bush and Obama administrations).

significance” or are “often a sign of increasing rather than decreasing market competition.”¹⁹ This study presents further evidence that previous consolidation in an industry or a “trend toward concentration”²⁰ may reflect procompetitive responses to competitive pressures, and therefore should not play a role in merger review beyond that already embodied in the market-level concentration screens considered by the Agencies.

Third, the Agencies should proceed cautiously in pursuing novel theories of anticompetitive harm; our findings are consistent with the prevailing consensus from the previous decades that there is an important connection between merger activity and innovation, and thus, a broad “anti-merger” policy, particularly one pursued in the absence of strong empirical evidence, has the potential to do serious harm by perversely inhibiting innovative activity.

Fourth, due to the link between mergers and innovative activity in R&D intensive industries where the potential for anticompetitive consequences can be resolved through remedies, relying on remedies rather than blocking transactions outright may encourage innovation while protecting consumers where there are legitimate competitive concerns about a particular transaction.

Fifth, the potential for mergers to create procompetitive benefits should be taken seriously by policymakers, antitrust enforcers, courts, and academics and the Agencies should actively study the potential benefits, in addition to the costs, of mergers.

Due to the importance of the topic and the paucity of previous research, we subject the results to a series of robustness tests. We find that the results are highly robust to different timing assumptions, different definitions of the dataset (balanced versus unbalanced panels); different weightings, and different ways of estimating the models. Nevertheless, to simplify the exposition and provide succinct quantitative results, after considering the tradeoffs of the various modelling approaches, we designate one set of estimates as our primary results. These primary results are presented in the body of the text and summarized below, while the various robustness tests are presented in Appendices B, C and D. Specifically:

- There is a strong statistically significant association between innovation, as measured by R&D expenditure and patent applications, and merger activity in the previous years.
- Increases in R&D expenditure associated with mergers begin, on average, in the second year after HSR filing and peak in the third year. Increases in patent application activity are strongest in the fourth year after HSR filing.
- Over a three- to four-year cycle, each merger is associated with an average increase in industry-level R&D expenditure of between \$299 million and \$436 million. These estimates are conservative as they only capture the effect of mergers in industries associated with acquiring firms. However, we also find evidence of “spillover” benefits,

¹⁹ Kulick & Card (2022) at 24.

²⁰ FTC Merger RFI (2022) at 2.

such as increased investment by firms seeking to be purchased, in industries associated with acquired firms.

- Extrapolating our results to the industry level implies that, on average, mergers are associated with an increase in R&D expenditure of between \$9.27 billion and \$13.52 billion per year in the most R&D intensive industries (without accounting for spillover effects) and an increase of between 1,430 and 3,035 utility patent applications per year.
- Controlling for temporal trends, mergers and previous R&D expenditure account for over 91 percent of the within-industry variation in R&D expenditure.
- Statistical tests for “Granger Causality” consistently show that the direction of causality goes, to a significant extent, from mergers to increased innovative activity.

It is important to note that mergers are driven by a wide variety of factors which cannot be fully controlled for through econometric means. Thus, we caution that the results presented here should not be interpreted as indicating that a policy leading to more mergers will necessarily increase innovative activity. The results also cannot tell us whether any particular merger that occurred during the sample period increased or decreased innovation or whether a proposed merger being considered by the Agencies will be beneficial. However, the results show that, on net, there has been a powerful connection between merger activity and innovation in recent years, that the relationship is highly robust, that this relationship cannot be dismissed as a mere correlation due to general economic trends or differences across industries, and that to a significant extent, mergers, or economic factors associated with merger activity, play an active role in fueling innovation.

The remainder of this paper is organized as follows. In Section II, we briefly review the literature concerning the relationship between mergers and innovation, highlighting mechanisms through which mergers may, in theory, incentivize or disincentivize innovative activity, and discuss our study’s contribution to the economic literature. In Section III, we describe the construction of our unique industry-level dataset and outline our empirical methodology. In Section IV, we present our primary empirical results, consisting of a series of econometric models assessing the industry-level impact of merger activity in previous years on two different measures of innovation, R&D expenditure and patent applications, and discuss the implications of our findings. Section V concludes.

II. Economic Theory and Empirical Context

Economic theory has identified a variety of mechanisms through which mergers may increase or decrease innovation at both the industry and firm levels. Empirical work investigating these mechanisms is limited, and has primarily assessed firm-level outcomes, small sets of transactions, and/or limited datasets (for instance, restricted to publicly-traded firms). The first part of this section provides a brief overview of mechanisms through which mergers may affect innovation. The second part of this section discusses the contribution of this paper in the context of the existing literature.

A. Mechanisms

Merger activity may foster industry-level innovation for several reasons. Industries with robust merger activity may attract higher levels of investment, increasing access to capital for merged and non-merged firms.²¹ Innovation may increase in industries where acquisition potential exists, as smaller firms and startups adopt “entry for buyout” strategies²² and enter and innovate with the goal of eventually being acquired.²³ Competitors may also be spurred to innovate simply to remain competitive with merged/acquiring rivals.

Mergers can also increase the incentive and ability to innovate at the firm level. Mergers may significantly reduce the costs of (or barriers to) collaboration across firms and improve R&D efficiency,²⁴ as consolidated entities are often better able to profitably facilitate the shared use of intellectual property and leverage economies of scale and scope in R&D.²⁵ Consolidated firms may also be better positioned to capture profits from successful innovation,²⁶ and therefore willing

²¹ See Naomi Hausman, Daniel C. Fehder & Yael V. Hochberg, *The Virtuous Cycle of Innovation and Capital Flows*, (October 28 2020), available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3714727; Joe Kennedy, *Monopoly Myths: Is Big Tech Creating Antitrust ‘Kill Zones’?*, Information Technology & Innovation Foundation (November 9, 2020), available at <https://itif.org/publications/2020/11/09/monopoly-myths-big-tech-creating-kill-zones/> [hereafter “Kennedy (2020)”] (noting that in many merger-heavy industries, “venture capital investment, especially in early-stage deals, has grown significantly over the last decade[.]”).

²² See Ginger Ze Jin, Marco Leccese & Liad Wagman, *How Do Top Acquirers Compare in Technology Mergers? New Evidence from an S&P Taxonomy*, NBER Working Paper 29642 (November 2022) at 46, available at <https://www.nber.org/papers/w29642>.

²³ See Brett Hollenbeck, *Horizontal Mergers and Innovation in Concentrated Industries*, 18 QUANTITATIVE MARKETING AND ECONOMICS 1-37 (2020) (“[T]he prospect of being bought out by an incumbent with deep pockets may also encourage entry into the market by new firms, encouraging development of new products and technologies.”); Gordon M. Phillips & Alexei Zhdanov, *R&D Investment and the Incentives from Merger and Acquisition Activity*, 26(1) THE REVIEW OF FINANCIAL STUDIES 34-78 at 34 (2012) [hereafter “Phillips & Zhdanov (2012)”] (“Recent articles describe how acquisitions are often attempts by large firms to grow by buying innovation. This acquisition potential provides stronger incentives for small firms to engage in R&D.”); Kennedy (2020).

²⁴ See Guido Federico, Fiona Scott Morton & Carl Shapiro, *Antitrust and Innovation: Welcoming and Protecting Disruption*, in INNOVATION POLICY AND THE ECONOMY 20, Josh Lerner and Scott Stern, eds. (University of Chicago Press, 2020) 125-190 at 133 [hereafter “Federico, Scott Morton & Shapiro (2020)”]; Ard-Pieter de Man & Geert Duysters, *Collaboration and Innovation: A Review of the Effects of Mergers, Acquisitions and Alliances on Innovation*, 25 TECHNOVATION 1377-1387 at 1379 (2005) [hereafter “de Man & Duysters (2005)”] (“M&A may stimulate innovation for a number of reasons. Technological know how is often tacit and can therefore not be easily transmitted from one firm to another. In order to avoid high transaction costs, firms may be inclined to engage in an acquisition in order to solve problems related to the transmission of tacit knowledge. . . Furthermore, firms having complementary knowledge can combine their specific strengths and develop new technologies or products that each partner on its own would not have been able to create.”).

²⁵ See Federico, Scott Morton & Shapiro (2020) at 127, 134; Mahdiyeh Entezarkheir & Saeed Moshiri, *Mergers and Innovation: Evidence from a Panel of U.S. Firms*, 27(2) ECONOMICS OF INNOVATION AND NEW TECHNOLOGY 132-153 (June 2016) [hereafter “Entezarkheir & Moshiri (2016)”]; de Man & Duysters (2005) at 1379.

²⁶ Richard J. Gilbert & Hillary Green, *Merging Innovation into Antitrust Agency Enforcement of the Clayton Act*, 83 GEORGE WASHINGTON LAW REVIEW 1919-1947 at 1925-26 (2015) (“A merger can increase the combined firm’s ability to appropriate the benefits from innovation in two ways. First, if the benefit from an innovation is proportional to the scale of operations that employ the innovation, a merger can increase appropriation by increasing the size of the operations that profit from the innovation. Second, by increasing the merged firm’s market share, a merger can increase

and able to undertake more complex, expensive and potentially riskier innovation projects.²⁷ In addition, technological spillovers may allow non-merging firms to build on innovations by others.²⁸

Researchers have also postulated mechanisms through which merger activity may decrease industry- or firm-level innovation. Specifically, merger activity may have a chilling effect on innovation if consolidation allows a firm to invest less in costly innovation post-merger due to reduced competition or to exclude or impair innovative rivals.²⁹ A firm that gains market power through acquisitions may be incentivized to adopt exclusionary tactics to deter innovative competitors and preserve rents.³⁰ Industry-level innovation may decrease if incumbent firms acquire start-ups for the express purpose of terminating disruptive innovations (“killer acquisitions”) or if serial acquisitions in industries deter entry and investment by potential competitors (“kill zones”).³¹

Because mergers have the potential to both increase or decrease innovation, investigating the non-price effects of mergers on innovation is consistent with the “consumer welfare standard,” which is the guiding principle of U.S. antitrust law.³² For decades, in accordance with the consumer welfare standard, the Agencies have actively considered the potential for transactions to harm

appropriation by reducing the share of the market that may imitate the innovation without compensating the innovator.”). Higher innovation may also result from the demand expansion effect of consolidation, whereby mergers may allow merged firms to increase margins, providing incentives to innovate to increase demand. See Bruno Jullien & Yassine Lefouili, *Horizontal Mergers and Innovation*, 64 JOURNAL OF COMPETITION LAW AND ECONOMICS 364-392 at 367 (2018) [hereafter “Jullien & Lefouili (2018)”].

²⁷ See de Man & Geert Duysters (2005) at 1379; Michael Katz & Howard A. Shelanski, *Merger Policy and Innovation: Must Enforcement Change to Account for Technological Change?*, in INNOVATION POLICY AND THE ECONOMY (Volume 5), Adam B. Jaffe, Josh Lerner & Scott Stern, eds. (MIT Press, January 2005) 109-165 at 131, 136; Federico, Scott Morton & Shapiro (2020) at 126 (observing that “process innovations that lower costs can be most valuable at the largest firms, and market leaders often invest substantial sums to introduce new generations of products.”).

²⁸ See Jullien & Lefouili (2018) at 367 (“As has been emphasized in the literature, a given firm’s investment in R&D may not only benefit the firm itself but also its rivals through technological spillovers. When such a positive innovation externality exists, it creates another channel through which a merger can lead to more innovation.”).

²⁹ See Federico, Scott Morton & Shapiro (2020) at 127.

³⁰ *Id.* at 158.

³¹ See Colleen Cunningham, Florian Elder & Song Ma, *Killer Acquisitions*, 129(3) JOURNAL OF POLITICAL ECONOMY (March 2021) [hereafter “Cunningham, Elder & Ma (2021)”] (“This paper argues incumbent firms may acquire innovative targets solely to discontinue the target’s innovation projects and preempt future competition. We call such acquisitions “killer acquisitions.”); Kennedy (2020); Sai Krishna Kamepalli, Raghuram Rajan & Luigi Zingales, *Kill Zone*, NBER Working Paper 27146 (2022), available at https://www.nber.org/system/files/working_papers/w27146/w27146.pdf [hereafter “Kamepalli, Rajan & Zingales (2022)”].

³² See e.g., Herbert Hovenkamp, *Is Antitrust’s Consumer Welfare Principle Imperiled*, 64(1) THE JOURNAL OF CORPORATION LAW 65-94 at 67 (2019) (“The overall goal is clear, however, which is to encourage markets in which output, measured by quantity, quality, or innovation, is as large as possible consistent with sustainable competition. To the extent antitrust intervention furthers this goal it is justified on purely economic grounds.”).

innovation, and where relevant, have opposed mergers on that basis.³³ Thus, what is new in today's debate is not whether the Agencies should consider the effects of mergers on innovation during the merger review process, but whether antitrust enforcement should be expanded based on novel legal theories of anticompetitive harm which posit systemic harm to innovation due to mergers.

B. Empirical Context

The empirical literature on the relationship between mergers and innovative activity is limited and has primarily assessed firm-specific effects, while relying on data covering small sets of transactions and/or samples with significant limitations such as restriction to publicly-traded firms, firms in the manufacturing sector, or firms within a single industry.³⁴ Despite the present focus of the Agencies on the broader relationship between mergers and innovative activity in the U.S. economy, including the industry-level consequences of merger activity, we are aware of no studies that evaluate the relationship between mergers using economy-wide, industry-level data.

Thus, in this study we investigate the industry-level relationship between mergers and R&D, relying on a (to our knowledge) unique dataset combining data on merger activity with industry-level data on R&D expenditure and patent applications. This dataset has several features which allow us to contribute to the existing literature. In particular, our analyses allow us to examine the relationship between merger activity and innovation at the industry level (thus including merging firms, rival firms, and firms in related industries) using data from publicly-traded and private U.S. firms in manufacturing and non-manufacturing industries. This broad scope means that we are able to investigate the relationship between mergers and innovation from an economy-wide perspective. The data also allow us to employ multiple measures of innovative activity (R&D expenditure and patent applications) and to assess the relationship between mergers and innovative activity over an extended and recent time period (2008 to 2020 for R&D expenditure, 2008 to 2018 for patent applications).

³³ The Agencies long history of protecting innovation has been recognized by Commissioner Slaughter. See Rebecca Kelly Slaughter, "Dissenting Statement of Commissioner Rebecca Kelly Slaughter," Docket No. 191-0061 (November 15, 2019) at 1, available at https://www.ftc.gov/system/files/documents/public_statements/1554283/17_-_final_rks_bms-celgene_statement.pdf; Rebecca Kelly Slaughter, "Dissenting Statement of Commissioner Rebecca Kelly Slaughter," Docket No. 191-0169 (May 5, 2020) at 2, available at https://www.ftc.gov/system/files/documents/public_statements/1574577/191_0169_dissenting_statement_of_commissioner_rebecca_kelly_slaughter_in_the_matter_of_abbvie_and_0.pdf ("Since the 2010 Guidelines, the Commission has brought several cases that include allegations of harm to innovation.").

³⁴ See Entezarkheir & Moshiri (2016); Olivier Bertrand, *Effects of Foreign Acquisitions on R&D Activity: Evidence from Firm-Level Data for France*, 38(6) RESEARCH POLICY 1021-1031 (2009); Bruno Cassiman, Massimo G. Colombo, Paola Garrone & Reinilde Veugelers, *An Empirical Analysis of the Role of Technological- and Market-Relatedness*, 34 RESEARCH POLICY 195-220 (2005); Phillips & Zhdanov (2012); Florian Szucs, *M&A and R&D: Asymmetric Effects on Acquirers and Targets*, 43(7) RESEARCH POLICY 1264-1273 (September 2014) [hereafter "Szucs (2014)"]; Carmine Ornaghi, *Mergers and Innovation in Big Pharma*, 27 INTERNATIONAL JOURNAL OF INDUSTRIAL ORGANIZATION 70-79 (2009); Justus Haucap, Alexander Rasch & Joel Stiebale, *How Mergers Affect Innovation: Theory and Evidence*, 63 INTERNATIONAL JOURNAL OF INDUSTRIAL ORGANIZATION 283-325 (2019); Cunningham, Elder & Ma (2021); Kamepalli, Rajan & Zingales (2022).

III. Data and Methodology

This study relies on a dataset which is, to our knowledge, new to the economic literature. This dataset allows us to provide new insights about the relationship between mergers and innovation while relying solely on simple econometric techniques. Part A, below, provides a high-level overview of our data and methodological approach. Readers interested primarily in the results of our empirical analyses are invited to proceed directly from Part A of this section to Section IV. Those interested in more detail regarding the construction of our dataset, summary statistics, and initial exploratory analyses, as well as an in-depth description of our primary methodology and the motivation behind our selection of robustness tests, are invited to refer to Parts B-D of this section.

A. Overview of Data and Methodology

To create the panel dataset we use for our empirical analyses in Section IV, we combine publicly-available data from four sources:

- 1) Annual data on pre-merger Hart-Scott-Rodino Act (HSR) filings aggregated to the three-digit North American Classification System (NAICS) code level available from the Agencies;
- 2) Annual data on R&D expenditure (domestic and foreign) by U.S. entities by three-digit NAICS code available from the NSF;
- 3) Annual data on patent applications filed by U.S. entities by three-digit NAICS code available from the NSF; and
- 4) Data on industry revenue/sales receipts by three-digit NAICS code, drawn from the Census Bureau's most recent Economic Census in 2017.

We utilize these data to perform a series of regressions where the dependent variables of interest – annual R&D expenditure and annual patent applications – are regressed against the primary independent variables of interest – merger activity quantified through HSR filings in prior years. Our regression specifications include industry and time fixed effects, and the primary results are weighted by 2017 industry revenue.

Although controlling for industry and time fixed effects means that any relationship discovered between mergers and innovation goes beyond mere correlation, it cannot be said to be causal due to the multitude of time-varying industry- and firm-specific factors that are correlated with merger activity. However, by supplementing the basic regression analysis with a methodology known as Vector Autoregression (VAR), which involves including in the regression analysis lags of the dependent variable in addition to the independent variables of interest, we can assess whether any relationship identified between mergers and each measure of innovation reflects a specific directional relationship from mergers to innovation. To the extent there is evidence that the direction of causality runs, at least in part, from mergers to one or both measures of innovation, such results would imply that the competitive processes that underlie merger activity play an active role in the determination of future innovative activity. Thus, to test the direction of causality, we

use an econometric procedure known as the “Granger Causality” test, which was first developed by Nobel Laureate Clive Granger in a seminal article published in 1969.³⁵

Our primary results in Section IV show a strong positive relationship between merger activity in prior years and both R&D expenditure and patent applications, and demonstrate that mergers “Granger Cause” both R&D expenditure and patent activity. These results are confirmed by a series of robustness checks presented in Appendices B-D, which indicate that the results are highly robust to different definitions of the data sample, econometric estimation techniques, and weighting structures.

As noted above, the data construction and empirical methodology are discussed in greater detail in the remainder of this section.

B. Data

We combine data from four publicly-available sources to examine the relationship between merger activity and innovation in the U.S. economy.

First, to quantify merger activity, we use data compiled by the Agencies from annual premerger HSR filings made pursuant to the Hart-Scott-Rodino Act of 1976 and made public in annual reports (HSR Annual Reports).³⁶ The number of transactions reported in each HSR Annual Report represents a useful measure of economically significant merger activity in the year – particularly merger activity with the potential for significant anticompetitive effects – as HSR filings are a mandatory precursor for mergers of significant dollar value.³⁷

In the HSR Annual Reports, the Agencies assign each transaction to an “industry group” defined using three-digit North American Industrial Classification System (NAICS) codes.³⁸ Because transactions may involve firms in different industries, each HSR Annual Report contains two distinct tables assigning mergers to industries. Table X of each HSR Annual Report presents the total number of transactions by industry where each transaction is assigned to the industry

³⁵ Clive W. J. Granger, *Investigating Causal Relations by Econometric Models and Cross-Spectral Methods*, 37(3) *ECONOMETRICA* 424-438 (1969) [hereafter “Granger (1969)”].

³⁶ Federal Trade Commission, *Hart-Scott-Rodino Antitrust Improvements Act of 1976*, available at <https://www.ftc.gov/legal-library/browse/statutes/hart-scott-rodino-antitrust-improvements-act-1976>.

³⁷ The HSR Act generally requires premerger notification for transactions valued above a certain dollar threshold, which is revised annually by the Agencies based on changes in the U.S. gross national product. The reporting threshold for 2008, the first year for which we have R&D expenditure and patent application data, was \$63.1 million. Federal Trade Commission and Department of Justice, “Hart-Scott-Rodino Annual Report” (FY 2008), at 1, n. 2, available at https://www.ftc.gov/sites/default/files/documents/reports_annual/31st-report-fy-2008/hsrreport_0.pdf. The reporting threshold for 2020, the final year for which we have R&D expenditure data, was \$94 million. United States Federal Trade Commission, “HSR threshold adjustments and reportability for 2020,” available at <https://www.ftc.gov/enforcement/competition-matters/2020/01/hsr-threshold-adjustments-reportability-2020>.

³⁸ The NAICS classifies economic activity in the U.S. economy using a hierarchical system of numerical codes. Business are grouped within codes “according to similar[ities] in the processes used to produce goods or services.” Executive Office of the President, Office of Management and Budget, “North American Industry Classification System, United States, 2017,” at 3, available at https://www.census.gov/naics/reference_files_tools/2017_NAICS_Manual.pdf. Following the HSR Annual Reports, we refer to a given three-digit NAICS code as an “industry group” or “industry.”

associated with the acquiring firm or buyer.³⁹ We refer to the data in Table X organized by the buyer's industry as the "Buyer's Industry Sample." Table XI of each HSR Annual Report presents the total number of transactions by industry where each transaction is assigned to the industry associated with the acquired firm or seller.⁴⁰ We refer to the data in Table XI organized by the seller's industry as the "Seller's Industry Sample."

The second source we rely on contributes our primary measure of innovation, consisting of annual data from the NSF capturing worldwide R&D expenditure by U.S. firms, by NAICS code. Specifically, the data is derived from the NSF's Business Enterprise Research and Development Survey (BERD), and its predecessors, the Business R&D and Innovation Survey (BRDS), and the Business R&D and Innovation Survey (BRDIS), which provide comprehensive R&D expenditure data for the U.S. from 2008 to 2020.⁴¹

The third source we rely on is data on utility patent applications by NAICS code derived from NSF's BERD/BRDS/BRDIS surveys, available for U.S. firms from 2008 to 2018.⁴² Utility patents

³⁹ Specifically, each transaction is assigned to the industry group from which the buyer derived the majority of its revenue. *See e.g.*, "HSR Annual Report (FY 2020)", Table X.

⁴⁰ Specifically, each transaction is assigned to industry group from which the seller derived the majority of its revenue. *Id.*, Table XI.

⁴¹ *See* United States National Science Foundation, "Business Enterprise Research and Development Survey," available at <https://www.nsf.gov/statistics/srvyberd/>. Annual worldwide R&D expenditure by U.S. firms from 2009 to 2019 are available for download from the NSF website as a single file. *See* United States National Science Foundation, "Business Enterprise Research and Development: 2019, Table 66 – Worldwide R&D paid for by the company and others and performed by the company, by industry and company size: 2009-2019," available at https://nces.nsf.gov/pubs/nsf22329#technical-notes_. For 2008 R&D expenditure data, *see* United States National Science Foundation, "Business Research and Development Innovation: 2008-10, Table 4 - Worldwide R&D paid for by the company and performed by the company and others: 2008, by industry and company size," available at https://www.nsf.gov/statistics/nsf13332/content.cfm?pub_id=4160&id=2. Data for 2020 (forthcoming publicly) were obtained directly from the NSF at the request of the authors. As explained by the NSF, these data constitute "the primary source of information on R&D expenditure and R&D employees of for-profit, publicly or privately held, nonfarm businesses with 10 or more employees in the United States that performed or funded R&D either domestically or abroad." *See* United States National Science Foundation, "Business Enterprise Research and Development Survey," available at <https://www.nsf.gov/statistics/srvyberd/>.

⁴² United States National Science Foundation, "Business Research and Development Innovation: 2008-10, Table 37 - U.S. patent applications and patents issued, by industry and company size," available at https://www.nsf.gov/statistics/nsf13332/content.cfm?pub_id=4160&id=2; United States National Science Foundation, "Business Research and Development Innovation: 2008-10, Table 86 - U.S. patent applications and patents issued, by industry and company size," available at https://www.nsf.gov/statistics/nsf13332/content.cfm?pub_id=4160&id=2; United States National Science Foundation, "Business Research and Development Innovation: 2008-10, Table 131 - U.S. patent applications and patents issued, by industry and company size," available at https://www.nsf.gov/statistics/nsf13332/content.cfm?pub_id=4160&id=2; United States National Science Foundation, "Business Research and Development Innovation: 2008-10, Table 131 - U.S. patent applications and patents issued, by industry and company size," available at https://www.nsf.gov/statistics/nsf13332/content.cfm?pub_id=4160&id=2; United States National Science Foundation, "Business Research and Development Innovation: 2012, Table 51 - U.S. patent applications and patents issued, by industry and company size," available at <https://www.nsf.gov/statistics/2016/nsf16301/#chp2>; United States National Science Foundation, "Business Research and Development Innovation: 2013, Table 60 - U.S. patent applications and patents issued, by industry and company size," available at

represent “patents for invention” and constitute approximately 90 percent of the patents issued by the U.S. Patent and Trademark Office.⁴³ We use patent application data rather than patent issuance data⁴⁴ as a measure of innovation because the average “pendency period” for a utility patent (the time between when a utility patent application is filed and it is granted) is approximately 32 months,⁴⁵ and therefore, “the date that an application was filed more accurately reflects when the technology was developed.”⁴⁶

Finally, we obtain industry-level data on total receipts/revenue by three-digit NAICS code from the U.S. Census Bureau’s most recent Economic Census (2017).⁴⁷

The Agencies assign HSR transactions to industries using three-digit NAICS codes. Thus, we match these data to the NSF R&D expenditure and patent application data available at the three-digit NAICS code level.⁴⁸ In constructing the data, we begin by matching the NSF data for a given

<https://www.nsf.gov/statistics/2016/nsf16313/#chp2>; United States National Foundation, “Business Research and Development Innovation: 2014, Table 54 - U.S. patent applications and patents issued, by industry and company size,” available at <https://www.nsf.gov/statistics/2018/nsf18302/#chp2>; United States National Foundation, “Business Research and Development Innovation: 2015, Table 57 - U.S. patent applications and patents issued to companies located in the United States that performed or funded R&D, by industry and company size: 2015,” available at <https://nces.nsf.gov/pubs/nsf18313/#data-tables>; United States National Foundation, “Business Research and Development Innovation: 2016, Table 60 - U.S. patent applications and patents issued to companies located in the United States that performed or funded R&D, by industry and company size: 2016,” available at <https://nces.nsf.gov/pubs/nsf19318/#data-tables>; United States National Foundation, “Business Research and Development Innovation: 2017, Table 60 - U.S. patent applications and patents issued to companies located in the United States that performed or funded R&D, by industry and company size: 2017,” available at <https://nces.nsf.gov/pubs/nsf20311/#data-tables>; United States National Foundation, “Business Research and Development Innovation: 2018, Table 62 - U.S. patent applications and patents issued to companies located in the United States that performed or funded R&D, by industry and company size: 2018,” available at <https://nces.nsf.gov/pubs/nsf21312/#data-tables>.

⁴³ United States Patent and Trademark Office, “Types of Patents,” (March 31, 2016) available at <https://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/patdesc.htm> (“Utility Patent – Issued for the invention of a new and useful process, machine, manufacture, or composition of matter, or a new and useful improvement thereof, it generally permits its owner to exclude others from making, using, or selling the invention for a period of up to twenty years from the date of patent application filing, subject to the payment of maintenance fees. Approximately 90% of the patent documents issued by the USPTO in recent years have been utility patents, also referred to as ‘patents for invention.’”).

⁴⁴ The NSF does not maintain data on issued patents by application date over the time period covered by this study. However, patent applications are frequently used in the economic literature as a proxy for innovation. Indeed, because all patent filings are public, even patents that are not granted are still potentially valuable in promoting innovation.

⁴⁵ United States Patent and Trademark Office, “U.S. Patenting Trends by NAICS Category, Utility Patent Grants, Calendar Years 1963-2012,” available at https://www.uspto.gov/web/offices/ac/ido/oeip/taf/naics/doc/naics_info.htm.

⁴⁶ United States Patent and Trademark Office, “U.S. Patenting Trends by NAICS Category, Utility Patent Grants, Calendar Years 1963-2012,” available at https://www.uspto.gov/web/offices/ac/ido/oeip/taf/naics/doc/naics_info.htm.

⁴⁷ United States Census Bureau, “EC1700SIZECONCEN.dat,” available at <https://www2.census.gov/programs-surveys/economic-census/data/2017/sector00/EC1700SIZECONCEN.zip>.

⁴⁸ As a result of this matching procedure, R&D expenditure and patent application data only available at higher levels of industrial aggregation from the NSF, *i.e.*, several three-digit NAICS industries grouped together or two-digit NAICS sectors, are necessarily excluded. Data for four-digit NAICS codes 5413, 5415, and 5417 were summed to quantify R&D expenditure and patent applications for the three-digit NAICS code 541 – Professional, scientific, and technical services.

year to transaction data from the HSR Annual Reports for the previous year.⁴⁹ We offset the data for several reasons. First, transaction counts from the HSR Annual Reports are reported based on the date of initial filing rather than the date of consummation. Second, following the completion of a merger, integration of the merged entities typically occurs over an extended time period.⁵⁰ Third, the economic literature has found that there is typically a lag between the time a given merger occurs and any innovation attributable to the merger.⁵¹

NSF data for R&D expenditure and/or patent applications may be missing for a given industry in a given year.⁵² As a result, the industries that can be included in the analysis for any given year will differ for each measure of innovative activity. Furthermore, as explained above, mergers can either be assigned to the buyer's industry or the seller's industry. Thus, the combination of the data sources described in this section gives rise to four distinct samples:

- Data on annual R&D expenditure by industry from 2008 to 2020 matched to annual HSR transaction data assigned to the industry associated with the buyer (“R&D Buyer’s Industry Sample”).
- Data on annual R&D expenditure by industry from 2008 to 2020 matched to annual HSR transaction data assigned to the industry associated with the seller (“R&D Seller’s Industry Sample”).
- Data on annual patent applications by industry from 2008 to 2018 matched to annual HSR transaction data assigned to the industry associated with the buyer (“Patent Application Buyer’s Industry Sample”).
- Data on annual patent applications by industry from 2008 to 2018 matched to annual HSR transaction data assigned to the industry associated with the seller (“Patent Application Seller’s Industry Sample”).

C. Summary Statistics

As discussed in the next section, we use the data samples described above in a series of regression analyses in which industry-level R&D expenditure and patent applications are used as measures of innovation and are regressed against merger activity in previous years.

⁴⁹ The HSR Annual Reports pertain to fiscal years (for example, HSR filings data in the Fiscal Year 2020 HSR Annual Report correspond to the period October 1, 2019 through September 30, 2020). *See e.g.*, “HSR Annual Report (FY 2020)” at 1.

⁵⁰ *See* Szucs (2014) at 1265 (“Restructuring R&D activities is a protracted affair that can take a number of years to complete.”).

⁵¹ *See e.g.*, Entezarkheir & Moshiri (2016); Phillips & Zhdanov (2012).

⁵² Missing observations in the NSF data are either labelled “D” (data withheld to avoid disclosing operations of individual companies) or “NA” (not available). Beginning in 2017, the NSF began presenting ranges to provide more information in cases where redaction would otherwise be necessary. In such instances, we adopt the following rule: if the difference between the high and low values in the range is less than or equal to five percent of the high-end value, the observation is included using the midpoint of the range; otherwise the observation is treated as missing.

Due to the presence of missing data, for each sample we consider two data structures, a “balanced panel” structure, where attention is restricted to industries with data in all years, and an “unbalanced panel” structure with no restrictions on the industries that are included. For our primary analysis, we present results based on the balanced panel data because this approach allows us to compare results across specifications and models with a consistent set of industries observed at consistent points in time; as discussed below, these industries are also the most relevant for evaluating the relationship between mergers and innovation. Having a substantial time dimension for each observation is also useful for estimating some of the models presented in Section IV. However, the unbalanced panel results are also informative as they allow for a larger sample size of industries. Thus, unbalanced panel results mirroring our primary balanced panel results are presented in Appendix B.

Table 1 shows the industries included in the balanced and unbalanced panels for the R&D expenditure samples and patent application samples, respectively.⁵³

**TABLE 1:
THREE-DIGIT NAICS INDUSTRIES INCLUDED
BY SAMPLE**

NAICS Industry	NAICS Code	Balanced R&D	Unbalanced R&D	Balanced Patent Applications	Unbalanced Patent Applications
Food Manufacturing	311		X	X	X
Beverage and Tobacco Product Manufacturing	312		X		X
Wood Product Manufacturing	321		X	X	X
Paper Manufacturing	322		X	X	X
Printing and Related Support Activities	323	X	X	X	X
Petroleum and Coal Products Manufacturing	324		X		X
Chemical Manufacturing	325	X	X	X	X
Plastics and Rubber Products Manufacturing	326	X	X	X	X
Nonmetallic Mineral Product Manufacturing	327	X	X	X	X
Primary Metal Manufacturing	331	X	X	X	X
Fabricated Metal Product Manufacturing	332	X	X	X	X
Machinery Manufacturing	333	X	X	X	X
Computer and Electronic Product Manufacturing	334	X	X	X	X
Electrical Equipment, Appliance, and Component Manufacturing	335	X	X		X
Transportation Equipment Manufacturing	336	X	X	X	X
Furniture and Related Product Manufacturing	337		X	X	X
Miscellaneous Manufacturing	339		X		X
Publishing Industries (except Internet)	511	X	X		X
Telecommunications	517		X	X	X
Data Processing, Hosting, and Related Services	518	X	X	X	X
Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	533		X		X
Professional, Scientific, and Technical Services	541		X	X	X
Total Industries		12	22	16	22

For R&D expenditure, if attention is restricted to three digit-NAICS industries with non-missing data from 2008 to 2020, we obtain a sample of 12 industries for which we have R&D data for all 13 years. As shown in Appendix A, in each year, these industries account for over 80 percent of R&D expenditure at the three-digit industry level. For patent applications, for which data are

⁵³ Where transaction data for an industry is missing from the HSR Annual Reports, we infer that there were no transactions in the industry in that year. Thus, the transaction variables are always assigned a value of zero rather than missing in such cases. Because the transaction variables are never missing, for a given measure of innovative activity, the same industries are included in both the Buyer’s Industry Sample and the Seller’s Industry Sample. That is, what differs between the samples is not the set of industries included or the industry-level R&D or patent application levels, but the number of HSR transactions reported per industry.

available from 2008 to 2018, there are 16 industries with consistent annual data. In each year, these industries account for 75 percent or more of utility patent applications at the three-digit industry level. Importantly, mergers and innovative activity in key industries that have been the focus of scrutiny are captured in either the R&D balanced panel, the patent application balanced panel, or both. For example, pharmaceutical firms and agricultural chemical firms are included in three-digit NAICS industry “325 – Chemical Manufacturing;”⁵⁴ the three-digit NAICS industry “511 – Publishing” includes software/gaming publishers;⁵⁵ and major internet platforms are included in the three-digit NAICS industry “518 – Data Processing, Hosting, and Related Services.”⁵⁶

Summary statistics for the R&D Buyer’s Industry Sample and R&D Seller’s Industry Sample are presented in Table 2 for both the balanced and unbalanced panels:

**TABLE 2:
SUMMARY STATISTICS:
R&D EXPENDITURE**

R&D Data	Balanced Panel					Unbalanced Panel				
	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs
Dependent Var										
R&D (\$mil)	\$26,500	\$33,516	\$198	\$126,102	156	\$18,678	\$28,725	\$6	\$126,102	263
Independent Var										
Mergers (Buyer Industries)	31	29	0	145	156	29	29	0	145	263
Mergers (Seller Industries)	34	28	0	130	156	32	33	0	215	263

Summary statistics for the Patent Application Buyer’s Industry Sample and Patent Application Seller’s Industry Sample are presented in Table 3 for both the balanced and unbalanced panels:

**TABLE 3:
SUMMARY STATISTICS:
PATENT APPLICATIONS**

Patent Data	Balanced Panel					Unbalanced Panel				
	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs
Dependent Var										
Patent Applications	5,892	8,720	36	40,845	176	5,600	7,974	0	40,845	231
Independent Var										
Mergers (Buyer Industries)	29	29	0	145	176	27	28	0	145	231
Mergers (Seller Industries)	32	31	0	155	176	30	30	0	155	231

As shown in Tables 2 and 3, comparison of the balanced panel and unbalanced panel summary statistics indicate that for a given industry in a given year, R&D expenditure and patent application data are more likely to be missing for industries that tend to have lower R&D expenditure, fewer patent applications, and less merger activity.

⁵⁴ U.S. Census Bureau, “North American Industry Classification System,” available at <https://www.census.gov/naics/?input=325&year=2012>.

⁵⁵ U.S. Census Bureau, “North American Industry Classification System,” available at <https://www.census.gov/naics/?input=511&year=2012>.

⁵⁶ U.S. Census Bureau, “North American Industry Classification System,” available at <https://www.census.gov/naics/?input=518&year=2012>.

D. Motivation and Methodology

As a starting point for our analysis, Figure 1 presents data on total R&D expenditure by U.S. firms and the number of HSR transactions in the previous year from 2008 to 2020.

**FIGURE 1:
R&D EXPENDITURE V. MERGER ACTIVITY
IN THE PREVIOUS YEAR, 2008-2020**

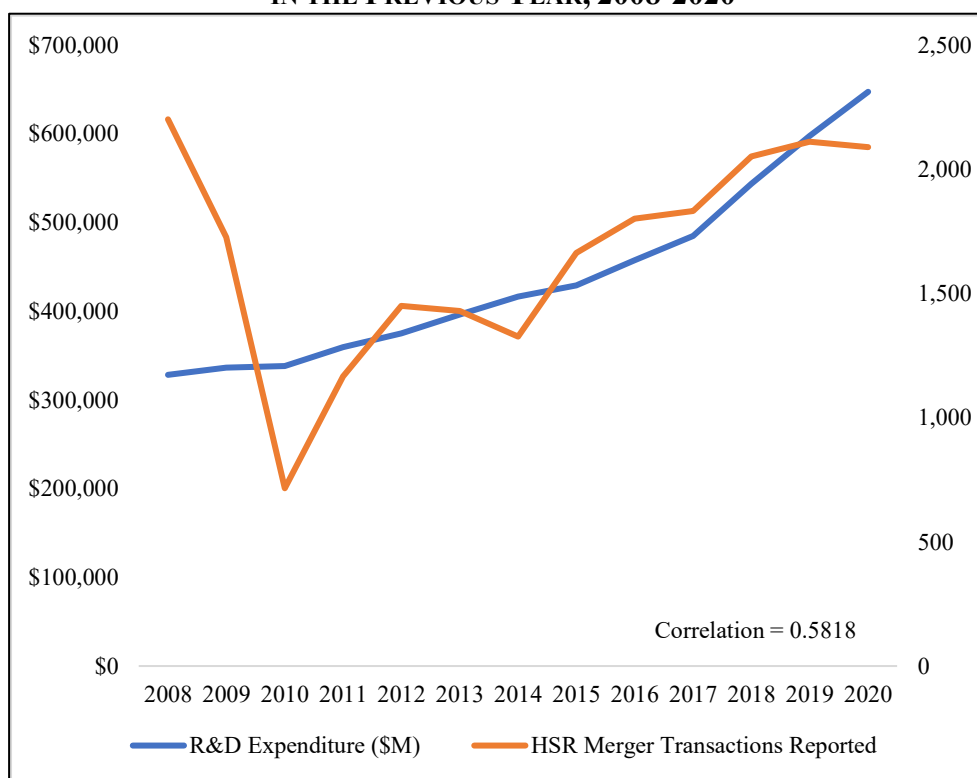


Figure 1 shows that R&D expenditure has increased steadily since 2008 and that there is a strong correlation between R&D expenditure and merger activity in the previous year. However, this correlation may reflect the effects of confounding factors rather than a specific, industry-level relationship between mergers and innovation. In particular:

- The relationship may reflect the effects of time-related trends common to both variables, including those arising from overall macroeconomic conditions.
- The relationship may be driven by differences in industry characteristics, such as production technology or relative size, rather than representing a direct link between merger activity within an industry and industry-level innovative activity.
- The timing of the simple correlational analysis does not allow for the possibility that the relationship between mergers and R&D expenditure may change over time.

Thus, to account for these factors, we use regression analysis to assess the relationship between innovation and merger activity in previous years. Specifically, we estimate models where the dependent variables are measures of innovation – industry-level R&D expenditure and patent applications – and the independent variables are a series of regressors capturing industry-level merger activity in the previous years. Each regression is then estimated controlling for industry and year fixed effects to eliminate the potentially confounding effects of differences in industry characteristics and common time trends.

Although controlling for industry and time fixed effects means that any relationship discovered between mergers and innovation goes beyond mere correlation, the relationship still cannot be said to be causal due to the multitude of time-varying industry and firm-specific factors that are correlated with merger activity. Indeed, the fundamentally endogenous nature of mergers and the lack of exogenous variation in merger activity always place limitations on the degree to which econometric relationships between merger activity and economic outcomes can be considered causal. However, by supplementing the basic regression analysis with a methodology known as Vector Autoregression (VAR), which involves including in the regression analysis lags of the dependent variable in addition to the independent variables of interest, we can assess whether any relationship identified between mergers and each measure of innovation reflects a specific directional relationship from mergers to innovation, as distinct from a more general association where mergers are an endogenous part of the process of innovation. To the extent there is evidence that the direction of causality runs, at least in part, from mergers to one or both measures of innovation, such results would imply that the competitive processes that underlie merger activity play an active role in the determination of future R&D expenditure and patent applications. Thus, to test the direction of causality, we use an econometric procedure known as the “Granger Causality” test, which was first developed by Nobel Laureate Clive Granger in a seminal article published in 1969.⁵⁷

In estimating VAR models with panel data, the standard estimation procedure used to estimate fixed-effects regressions may provide biased estimates of the relationships of interest.⁵⁸ However, this potential bias is mitigated as the time dimension of a panel increases.⁵⁹ Due to the relatively long time period covered by our samples, for our primary analysis, we use the standard fixed effects “within” estimator to estimate the VAR models in the next section. Econometricians have also developed more complex procedures using Generalized Methods of Moments (GMM) estimation to control for potential biases in dynamic panel regressions. In particular, the Arellano-Bond estimator has become widely used in the literature.⁶⁰ While we apply this method as a robustness test in Appendix D, we have opted not to use this estimation procedure for our primary analysis because the large number of instruments involved has the potential to lead to estimation problems in a sample like ours and because the procedure requires additional assumptions which

⁵⁷ See Granger (1969).

⁵⁸ Stephen Nickell, *Biases in Dynamic Models with Fixed Effects*, 49(6) *ECONOMETRICA* 1417-1426 (1981).

⁵⁹ David Roodman, *How to do xtabond2: An Introduction to Difference and System GMM in Stata*, 9(1) *THE STATA JOURNAL* 86-136 at 128 (2009) [hereafter “Roodman (2009)”] (“If T is large, dynamic panel bias becomes insignificant, and a more straightforward fixed-effects estimator works.”).

⁶⁰ Manuel Arellano & Stephen Bond, *Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations*, 58 *REVIEW OF ECONOMIC STUDIES* 277-297 (1991) [hereafter “Arellano & Bond (1991)”].

may be invalid.⁶¹ As shown in Appendix D, both approaches yield very similar results. Indeed, our primary results are generally conservative relative to the magnitudes estimated using the Arellano-Bond estimator.

We also conduct a number of additional robustness tests. For instance, while our primary regression results are weighted by each industry’s revenue from the 2017 Economic Census, we find that there is little difference between the weighted results presented in the next section and the unweighted results presented in Appendix C. In addition, our results are robust to the use of balanced or unbalanced panels, as discussed above and presented in Appendix B, and the use of alternative lag-lengths, as shown in the next section.

IV. Empirical Analysis and Findings

The empirical analysis in this section begins with the presentation of our econometric results for R&D expenditure. We then report results for patent applications and conclude with a discussion of our findings and their policy implications.

A. R&D Expenditure Results

We begin our analysis of the relationship between merger activity and industry-level R&D expenditure by assessing the effect of mergers on R&D expenditure in the first, second, and third years following HSR filing.⁶² The results are presented in Table 4.

⁶¹ In implementing the Arellano-Bond estimator, we have estimated the results using both the “difference GMM” estimator and the “systems GMM” estimator. We have opted to report the difference estimator results in Appendix D because use of the difference estimator involves fewer instruments, requires fewer assumptions, and generally performs better on the post-estimation autocorrelation tests we have examined. The results, however, are directionally similar if the systems estimator is used instead. We also note that, even with the reduced number of instruments involved in using the difference estimator, and after imposing significant additional restrictions on the instrument set, we still find very high values for the Hansen statistic across all estimates, providing further support for our decision to use the fixed-effects results as our primary estimates. *See* Roodman (2009) at 128-129.

⁶² All regression analyses presented in this section and the next are weighted by industry revenue from the 2017 Economic Census. Unweighted results are presented in Appendix C.

**TABLE 4:
EXPLORATORY R&D REGRESSION
RESULTS (\$MILLIONS)**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Merger (T-1)	50.1390	53.3958	24.5572	-17.1251
Merger (T-2)	185.6946***	78.4396	87.2692	109.7758
Merger (T-3)	-	-	318.1813***	276.8547***
Sum	235.8336***	131.8354*	430.0077***	369.5054***
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industries	12	12	12	12
Observations	144	144	132	132
Within R ²	0.4333	0.3866	0.5956	0.512

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

The first panel of Table 4 presents the results of a “two-lag” specification of the regression model where for R&D expenditure in a given year T , the independent variables of interest are merger activity in year $T-1$ (the prior year) and year $T-2$ (two years prior). With this structure, the coefficients on the merger variables of interest can be interpreted as the average effect of a merger on R&D expenditure in the first and second years following HSR filing. The first regression presents the results when the model is estimated using the Buyer’s Industry Sample. The second regression presents the results when the model is estimated using the Seller’s Industry Sample. In the second panel, the analysis is repeated adding a third lag of the merger variable to capture the average effect of a merger on R&D in the three years following HSR filing.

In each regression, the sum of the merger variables is positive and statistically significant, indicating a strong positive relationship between merger activity and subsequent R&D activity. There is however, no evidence of statistically significant effects in the first year after HSR filing in either the two-lag or the three-lag specification of the model and the three-lag specification indicates substantial positive effects in the third year, suggesting the addition of an additional lag for year $T-4$ may be warranted.

However, the inclusion of an excessive number of lags or irrelevant lags raises two potential problems with respect to the VAR models employed below to assess the direction of causality. First, the inclusion of too many lags may cause the Granger Causality test to spuriously reject the null hypothesis, leading to unwarranted inferences of Granger Causality. Second, to avoid arbitrary lag-length specifications and maintain uniformity across models, we limit ourselves to consideration of specifications with a symmetric number of lagged dependent and independent variables. Consequently, each additional lag reduces the sample size by removing a full year of data from consideration.

Nevertheless, adding a fourth-lag to the regressions presented in Table 4 results in a statistically significant positive coefficient for the year $T-4$ merger variable for the Seller’s Industry Sample, while the first year merger variables remain positive but not statistically significant in both samples. Due to these considerations, in our primary model presented below in Table 5, we re-estimate the model matching R&D expenditure in year T to merger activity in year $T-2$, allowing us to consider

the relationship between mergers and R&D up to four years after HSR filing, while limiting the risk of false positive results and preserving the size of the sample.

**TABLE 5:
PRIMARY R&D REGRESSION
RESULTS (\$MILLIONS)**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Merger (T-2)	61.7122	17.8951	115.4202*	90.4024
Merger (T-3)	237.3406***	268.8175***	237.2457***	217.6872***
Merger (T-4)	-	-	110.4936*	164.5499**
Sum	299.0528***	286.7126***	463.1595***	472.6395***
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industries	12	12	12	12
Observations	144	144	132	132
Within R ²	0.4928	0.4633	0.6079	0.5407

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

The results for the Buyer’s Industry Sample (regressions one and three) provide evidence of a positive relationship between mergers and industry-level R&D beginning in the second year after HSR filing with a larger and uniformly statistically significant relationship arising in the third year after HSR filing. The three-lag specification of the model also shows that statistically significant positive effects extend into the fourth year after HSR filing. Overall, the results indicate that for the Buyer’s Industry Sample, each merger is associated with an average increase in R&D expenditure of between \$299 million and \$463 million.

For evaluating the economic significance of these results, it is useful to consider the industry-level magnitudes implied by coefficients from Table 5 and the summary statistics from Table 2. As indicated in Table 2, on average, there were 31 mergers annually per industry in the (balanced) Buyer’s Industry Sample. Multiplying the average number of mergers per year by the average increase in R&D expenditure per merger of between \$299 million and \$436 million yields an average annual industry-level effect of between \$9.27 billion and \$13.52 billion relative to average annual industry-level R&D in the sample of \$26.5 billion. Thus, the coefficient estimates imply that the relationship between mergers and R&D is economically significant in addition to being statistically significant.

Of course, mergers may also affect innovative activity in industries associated with sellers as well as buyers. When a merger involves firms in different industries, the effect on the industry associated with the seller may be negative, due to the reduction in the number of firms associated with the industry and/or anticompetitive effects, or positive, due to “spillover effects” such as increased investment in the industry. Thus, it is important to also assess the effect of mergers in the Seller’s Industry Sample (regressions two and four). The results indicate that for the Seller’s Industry Sample, mergers are also associated with a substantial, statistically significant increase in R&D expenditure, with large, statistically significant effects beginning in the third year following HSR filing and continuing into the fourth year. Overall, the results indicate that for the Seller’s Industry Sample, each merger is associated with an average increase in R&D expenditure of

between \$287 million and \$473 million. Performing the same industry-level calculation as that conducted for the Buyer’s Industry Sample in the previous paragraph yields an average annual industry-level effect of between \$9.75 billion and \$16.07 billion.

As discussed in the previous section, although the relationships estimated thus far go beyond mere correlation, due to the endogenous nature of mergers, the results cannot be described as causal. However, by using the VAR methodology described above, we can assess whether the direction of causality runs, at least in part, from mergers to R&D.

Table 6 presents the VAR results estimated on both the Buyer’s Industry and Seller’s Industry Samples. Each model is identical to the corresponding model in Table 5, except that the VAR models include as regressors a symmetric number of lags of the dependent variable (R&D expenditure).

**TABLE 6:
PRIMARY R&D VAR
RESULTS (\$MILLIONS)**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
R&D (T-1)	0.8993***	0.9481***	0.8848***	1.0183***
R&D (T-2)	0.0906	0.0924	0.0916	0.0211
R&D (T-3)	-	-	-0.0494	-0.0612
Merger (T-2)	61.9510**	66.2123***	61.8280**	55.5891**
Merger (T-3)	109.4457***	90.7126***	106.3637***	89.9479**
Merger (T-4)	-	-	44.4538	27.7225
Sum	171.3967***	156.9249***	212.6455***	173.2595***
Granger	P = 0.0000	P = 0.0000	P = 0.0000	P = 0.0004
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industries	12	12	12	12
Observations	132	132	120	120
Within R ²	0.9323	0.9241	0.9298	0.9182

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

As shown in Table 6, as with our baseline regressions, the VAR estimates indicate that mergers are associated with economically and statistically significant increases in R&D expenditure even after controlling for R&D expenditure in prior years. Table 6 also includes the p-values associated with the Granger Causality test for each model. In each case, we reject the “null hypothesis” of no causality and conclude that past merger activity “Granger Causes” future R&D expenditure. The coefficients also indicate that a substantial share of the relationship between mergers and R&D is explained by mergers and variables correlated with merger activity, but not prior R&D activity. Together, lagged merger and R&D activity, in conjunction with the time fixed effects, account for over 91 percent of the within variation in industry-level R&D, indicating that these factors alone explain the vast majority of future industry-level R&D activity.

B. Patent Application Results

Next, we apply the same empirical methodology to examine the relationship between merger activity and an alternative measure of innovation – annual utility patent applications. As discussed above, we use patent applications in a given year rather than patent issuance, as patent applications are more closely associated with when the relevant innovative activity occurred.

As in the case of R&D expenditure, we begin our analysis of the relationship between merger activity and industry-level patent activity by assessing the effect of mergers on patent applications in second, third, and fourth years following HSR filing. The primary regression results are presented in Table 7.

**TABLE 7:
PRIMARY PATENT
APPLICATION RESULTS**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Merger (T-2)	-8.7881	3.0389	7.8128	31.6581**
Merger (T-3)	58.1001***	19.7301	45.8163**	-16.7469
Merger (T-4)	-	-	51.0094***	83.2348***
Sum	49.312**	22.769	104.6385***	98.146***
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industries	16	16	16	16
Observations	160	160	144	144
Within R ²	0.4049	0.3589	0.4218	0.4538

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

As in the previous section, the first panel of Table 7 presents the results of a “two-lag” specification of the regression model where for patent applications in a given year T , the independent variables of interest are merger activity in year $T-2$ (two years prior) and year $T-3$ (three years prior). The first regression presents the results when the model is estimated using the Buyer’s Industry Sample and the second regression presents the results when the model is estimated using the Seller’s Industry Sample. In the second panel, the analysis is repeated adding a third lag of the merger variable of interest to capture the average effect of a merger on patenting activity in the fourth year after HSR filing.

For the Buyer’s Industry Sample, the sum of the merger variables in each regression is positive and statistically significant. For the Seller’s Industry Sample, while the overall effect of mergers on patent applications is positive but not significant in the two-lag model, the net effect of merger activity becomes large and statistically significant in the three-lag model, with particularly sizable effects realized in the fourth year after HSR filing. In contrast, R&D expenditure experiences the largest increase in the third year after HSR filing, consistent with the notion that R&D activity leads patenting activity.

In terms of industry-level magnitudes, the coefficients from the Buyer’s Industry regressions in Table 7 imply that, on average, each merger is associated with an increase of 49 to 105 patent

applications. Multiplying the average number of mergers per year in the Buyer’s Industry Sample (29) by the average increase in patent applications per merger of between 49 and 105, yields an average annual increase of between 1,430 and 3,035 patent applications across industries, relative to the average annual industry-level patent application total of 5,829. For the Seller’s Industry Sample, multiplying the average number of mergers per year in the sample (32) by the average increase in patent applications per merger of between 23 and 98, yields an average annual industry-level increase of between 729 and 3,141 patent applications. Thus, like the R&D results, the coefficient estimates imply that the effect of mergers on patent applications is economically significant in addition to being statistically significant.

Table 8 presents the results of applying the VAR methodology to the patent application data.

**TABLE 8:
PRIMARY PATENT
APPLICATION VAR RESULTS**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Patents (T-1)	0.5607***	0.4852***	0.4306***	0.4065***
Patents (T-2)	-0.3075***	-0.2516***	-0.1103	-0.0389
Patents (T-3)	-	-	-0.1562	-0.1762**
Merger (T-2)	-30.2669*	4.1301	-10.1591	31.6402**
Merger (T-3)	78.7768***	24.8631	49.1510**	-11.867
Merger (T-4)	-	-	50.8297**	94.0882***
Sum	48.5099**	28.9932*	89.8216***	113.8614***
Granger	P = 0.0000	P = 0.1756	P = 0.0007	P = 0.0000
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No of Industries	16	16	16	16
Observations	144	144	128	128
Within R ²	0.5508	0.4792	0.5865	0.6464

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

As shown in Table 8, the VAR estimates indicate that mergers are associated with economically and statistically significant increases in patenting activity in all cases after controlling for patenting activity in prior years. For the Buyer’s Industry results, we find that merger activity “Granger Causes” patent activity in both the two-lag and three-lag models. For the Seller’s Industry results, the two-lag model Granger Causality test approaches statistical significance, and the three-lag model is highly significant. Furthermore, the patent application VAR results indicate that the direction of causality is primarily from mergers to patent activity.

C. Discussion

To our knowledge, this study is the first to present evidence of a strong positive, industry-level relationship between mergers and innovative activity. A significant implication of this finding is that there is no evidence that, mergers are, in general, an impediment to innovation or that more aggressive antitrust enforcement over the period would have increased innovation. Indeed, the results suggest that overly aggressive antitrust enforcement could significantly reduce innovation.

However, like all econometric analyses assessing the economic consequences of merger activity, this study has important limitations. Mergers are complex economic phenomena driven by a multitude of factors, and each merger is unique in terms of its potential for anticompetitive harm and procompetitive benefits. Thus, the results presented here can only speak to the net relationship between the mergers and each measure of innovation over the sample period. Furthermore, the results should not be taken to imply that policies leading to increased merger activity will necessarily increase innovation; the results only describe retrospectively the overall relationship between the mergers that occurred and each measure of innovation within the extant policy environment. Nevertheless, the results are certainly relevant for today’s debates about the future of antitrust policy, as they document a strong positive relationship between merger activity within industries and industry-level measures of innovative activity and imply that there is a direct link between merger activity itself, holding constant prior innovative activity, and innovation.

With regard to the quantitative interpretation of our findings, because within-industry mergers are common to both the Buyer’s Industry and Seller’s Industry Samples, the quantitative relationship between mergers and each measure of innovation cannot be calculated by adding together the regression coefficient estimates for each sample. Due to the overlap in the samples, we therefore use the results from the Buyer’s Industry Sample to estimate that each merger, on average, is associated with an increase in R&D expenditure of between \$299 million and \$436 million and an increase in patent applications of between 49 and 105 over a three- to four-year cycle. However, these estimates are likely conservative as the large effects observed for the Seller’s Industry Sample (in some cases, larger overall than the Buyer’s Industry Sample) suggest that at least part of the relationship between mergers and R&D is driven by spillover effects realized in industries associated with acquired firms.

In terms of policy implications, our results provide further evidence that the Agencies should not consider trends in industrial concentration in reviewing transactions as proposed in the January 2022 *Request for Information on Merger Enforcement*.⁶³ In previous research, we found that “trends in industrial concentration do not provide a reliable basis for making inferences about the competitive effects of a proposed merger” as “trends in concentration may simply reflect temporary fluctuations which have no broader economic significance” or are “often a sign of increasing rather than decreasing market competition.”⁶⁴ While the results presented here do not establish whether it is mergers *per se* that increase innovation, or factors associated with the competitive processes that drive merger activity, the direct link between merger activity and innovation provides further evidence that previous consolidation in an industry, or a “trend toward concentration” at the industry-level, may indicate increasing competition rather than a tendency towards monopoly. Trends in concentration are not only unreliable for assessing the potential anticompetitive harm of mergers, but, as increased innovation is positively associated with merger activity, focusing on trends in industrial concentration, beyond the information already embodied in the *market-based* concentration screens considered by the Agencies, has the potential to perversely discourage, rather than encourage, innovation. Furthermore, not only should the Agencies eschew consideration of previous trends in industrial concentration in the merger review process, but they should also proceed cautiously in pursuing novel theories of anticompetitive

⁶³ FTC Merger RFI (2022) at 2.

⁶⁴ Kulick & Card (2022) at 24.

harm – such as enforcement targeting serial acquisitions or the protection of potential competition in nascent industries. These theories have the potential to vastly increase the scope of merger enforcement because every merger has the potential to affect the evolution of competition in markets that do not yet exist, particularly in innovative industries, and large numbers of transactions occur in most industries in a given year. As there is a strong link between mergers and innovation, an overly-restrictive antitrust policy has the potential to do serious harm to innovation and, more broadly, economic growth.

These results also have implications with regard to the current debate over the use of remedies in the merger review process. Leadership at the Agencies has expressed doubts about the efficacy of behavioral remedies and indicated a preference for blocking transactions outright rather than attempting to ameliorate the potential anticompetitive effects of mergers through remedies in general.⁶⁵ However, due to the link between mergers and innovative activity, in R&D intensive industries, where the potential for anticompetitive consequences can be resolved through remedies, relying on remedies rather than blocking transactions outright may encourage innovation while protecting consumers.

Finally, while most economic research today focuses on the potential for mergers to create anticompetitive effects, our results suggest that much more attention should be paid to the potential benefits of merger activity. As discussed above, extrapolating our results to the industry level implies that mergers, on average, are associated with an increase in R&D expenditure of between \$9.27 billion and \$13.52 billion per year in the most R&D intensive industries (without accounting for spillover effects). With evidence of such large increases in innovative activity linked directly to merger activity, the potential for mergers to create procompetitive benefits should be taken very seriously by policymakers, antitrust enforcers, and academics.

V. Conclusion

For decades, there has been a broad consensus among policymakers, antitrust enforcers, and economists that most mergers pose little threat from an antitrust perspective and that mergers are generally procompetitive. However, over the past year, leadership at the FTC and DOJ has questioned whether mergers are, as a general matter, economically beneficial and asserted that mergers pose an active threat to innovation. The Agencies have also set the stage for a substantial increase in the scope of merger enforcement by focusing on new theories of anticompetitive harm such as elimination of potential competition from nascent competitors and the potential for cumulative anticompetitive harm from serial acquisitions.

Despite the importance of the question of whether mergers have a positive or negative effect on industry-level innovation, there is very little empirical research on the subject. Thus, in this study, we investigate this question utilizing, what is to our knowledge, a never before used dataset combining industry-level merger data from the FTC/DOJ annual HSR reports with industry-level data from the NSF on R&D expenditure and patent applications. We find that there is a strong,

⁶⁵ See e.g., Lina Khan, “Letter to the Honorable Elizabeth Warren, Federal Trade Commission Office of the Chair,” (August 6, 2021), available at https://www.warren.senate.gov/imo/media/doc/chair_khan_response_on_behavioral_remedies.pdf.

statistically significant association between innovation, as measured by R&D expenditure and patent applications, and merger activity in previous years and that over a three- to four-year cycle, each merger is associated with an average increase in industry-level R&D expenditure of between \$299 million and \$436 million. Extrapolating our results to the industry level implies that, on average, mergers are associated with an increase in R&D expenditure of between \$9.27 billion and \$13.52 billion per year in the most R&D intensive industries, and an increase of between 1,430 and 3,035 utility patent applications per year. Overall, the results show that, on net, there has been a powerful connection between merger activity and innovation in recent years, that the relationship is highly robust, that this relationship cannot be dismissed as a mere correlation due to general economic trends or differences across industries, and that to a significant extent, mergers, or economic factors associated with merger activity, play an active role in fueling innovative activity.

Appendix A: R&D Expenditure and Patent Applications by Dataset

As discussed in Section III, our primary empirical analyses utilize “balanced panels,” which for the R&D expenditure regressions consist of industries which have non-missing R&D expenditure data from 2008 to 2020, and for the patent application regressions consist of industries with non-missing patent application data from 2008 to 2018. Table A1 shows the percentage of total R&D expenditure across all three-digit NAICS industries in the NSF R&D data accounted for by industries included in our balanced panel, by year.

TABLE A1:
PERCENT OF TOTAL R&D EXPENDITURE
IN INCLUDED INDUSTRIES

Year	Balanced Panel			Unbalanced Panel		
	R&D in Included Industries (\$M)	%	Total (\$M)	R&D in Included Industries (\$M)	%	Total (\$M)
2008	\$264,528	86.0%	\$307,588	\$307,588	100.0%	\$307,588
2009	\$248,726	84.3%	\$294,901	\$294,901	100.0%	\$294,901
2010	\$260,265	84.7%	\$307,184	\$307,184	100.0%	\$307,184
2011	\$272,670	96.2%	\$283,499	\$283,499	100.0%	\$283,499
2012	\$281,254	85.9%	\$327,276	\$327,276	100.0%	\$327,276
2013	\$298,393	82.4%	\$362,256	\$362,256	100.0%	\$362,256
2014	\$317,635	83.6%	\$379,797	\$379,797	100.0%	\$379,797
2015	\$314,615	81.6%	\$385,528	\$385,528	100.0%	\$385,528
2016	\$330,703	91.9%	\$359,873	\$359,873	100.0%	\$359,873
2017	\$345,233	82.1%	\$420,603	\$420,603	100.0%	\$420,603
2018	\$375,244	81.2%	\$462,366	\$462,366	100.0%	\$462,366
2019	\$393,248	80.2%	\$490,619	\$490,619	100.0%	\$490,619
2020	\$431,531	81.3%	\$530,805	\$530,805	100.0%	\$530,805

As shown above, industries in our R&D balanced panel account for between 80 and 96 percent of total annual R&D expenditure in reported three-digit NAICS industries from 2008 to 2020. Table A2 presents analogous calculations for the patent application data.

**TABLE A2:
PERCENT OF TOTAL PATENT APPLICATIONS
IN INCLUDED INDUSTRIES**

Year	Balanced Panel			Unbalanced Panel		
	Patent Applications in Included Industries	%	Total	Patent Applications in Included Industries	%	Total
2008	92,313	75.2%	122,762	122,762	100.0%	122,762
2009	85,029	80.1%	106,183	106,183	100.0%	106,183
2010	86,739	80.1%	108,345	108,345	100.0%	108,345
2011	82,272	95.9%	85,770	85,770	100.0%	85,770
2012	86,710	76.3%	113,620	113,620	100.0%	113,620
2013	98,971	75.7%	130,753	130,753	100.0%	130,753
2014	81,026	75.2%	107,770	107,770	100.0%	107,770
2015	93,882	81.4%	115,272	115,272	100.0%	115,272
2016	100,144	82.3%	121,732	121,732	100.0%	121,732
2017	110,119	82.3%	133,786	133,786	100.0%	133,786
2018	119,707	81.1%	147,596	147,596	100.0%	147,596

As shown in Table A2, industries included in our balanced panel account for between 75 and 96 percent of annual patent application activity across three-digit NAICS industries from 2008 to 2018.

Appendix B: Unbalanced Panel Regression Results

Below, we present the results of estimating the regressions in Section IV using unbalanced panels.

**TABLE B1:
UNBALANCED PANEL
R&D REGRESSION RESULTS (\$MILLIONS)**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Merger (T-2)	138.551***	31.5235	169.7081***	67.0423**
Merger (T-3)	163.442***	182.543***	134.1106***	103.3466***
Merger (T-4)	-	-	169.7457***	138.4753***
Sum	301.993***	214.0665***	473.5644***	308.8642***
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No of Industries	22	22	22	22
Observations	243	243	225	225
Within R ²	0.5146	0.5172	0.6445	0.6043

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

**TABLE B2:
UNBALANCED PANEL
R&D VAR RESULTS (\$MILLIONS)**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
R&D (T-1)	0.8506***	0.8935***	0.6885***	0.9414***
R&D (T-2)	0.0986*	0.1178*	0.1971*	0.0765
R&D (T-3)	-	-	0.0099	0.0032
Merger (T-2)	-2.201	-7.7594	-19.4444	-49.8195**
Merger (T-3)	130.1796***	65.3835**	141.5735***	52.6810
Merger (T-4)	-	-	55.9048*	14.7423
Sum	127.9786***	57.6241***	178.0339***	17.6038
Granger	P = 0.0000	P = 0.0196	P = 0.0000	P = 0.1166
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No of Industries	22	22	22	22
Observations	197	197	171	171
Within R ²	0.9063	0.8958	0.9028	0.8829

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

As shown in Tables B1 and B2, the R&D expenditure unbalanced panel results are generally consistent with the results from the balanced panel results presented in Section IV. The sum of the coefficients on the merger variables are positive and statistically significant in all of the results presented in Table B1 and in all but one regression in Table B2.

**TABLE B3:
UNBALANCED PANEL
PATENT APPLICATION REGRESSION RESULTS**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Merger (T-2)	-4.7236	6.2217	13.2360	33.3513**
Merger (T-3)	49.1878***	20.8975	39.4649**	-14.2796
Merger (T-4)	-	-	33.4313**	77.4006***
Sum	44.4642***	27.1192*	86.1322***	96.4723***
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No of Industries	22	22	22	22
Observations	210	210	189	189
Within R ²	0.3110	0.2742	0.3151	0.3578

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

**TABLE B4:
UNBALANCED PANEL
PATENT APPLICATION VAR RESULTS**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Patents (T-1)	0.5637***	0.4943***	0.3900***	0.3833***
Patents (T-2)	-0.3133***	-0.2467***	-0.1190	-0.0478
Patents (T-3)	-	-	-0.1560*	-0.1573**
Merger (T-2)	-27.3645*	8.5502	-9.3436	31.2687**
Merger (T-3)	72.8166***	22.1969	46.3304***	-11.8446
Merger (T-4)	-	-	48.7945**	92.7115***
Sum	45.4521**	30.7471*	85.7813***	112.1356***
Granger	P = 0.0000	P = 0.1342	P = 0.0004	P = 0.0000
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No of Industries	22	22	21	21
Observations	175	175	148	148
Within R ²	0.4978	0.4327	0.5739	0.6380

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

As shown in Tables B3 and B4, the patent application unbalanced panel results are again consistent with the results from the balanced panel specifications presented in Section IV. The sum of the coefficients on the merger variables is positive and statistically significant in all regressions.

Appendix C: Unweighted Regression Results

Our primary regression specifications in Section IV are weighted by 2017 industry revenue. For robustness, below we present unweighted versions of the balanced panel regression results presented in Section IV.

**TABLE C1:
UNWEIGHTED
R&D REGRESSION RESULTS (\$MILLIONS)**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Merger (T-2)	136.5239*	69.9261	159.4195**	134.2719**
Merger (T-3)	159.1629**	248.9094***	270.136***	203.2094***
Merger (T-4)	-	-	23.8637	136.5817**
Sum	295.6868***	318.8355***	453.4192***	474.063***
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No of Industries	12	12	12	12
Observations	144	144	132	132
Within R ²	0.3965	0.4225	0.496	0.4955

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

**TABLE C2:
UNWEIGHTED
R&D VAR RESULTS (\$MILLIONS)**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
R&D (T-1)	0.9419***	0.9579***	0.9633***	0.9975***
R&D (T-2)	0.1160*	0.1108	0.1200	0.1106
R&D (T-3)	-	-	-0.0593	-0.0826
Merger (T-2)	52.0614*	56.235**	39.9675	43.5378*
Merger (T-3)	84.0256***	60.1660**	103.6596***	58.6476*
Merger (T-4)	-	-	9.513	35.2345
Sum	136.087***	116.4016***	153.1401***	137.4199***
Granger	P = 0.0001	P = 0.0003	P = 0.0005	P = 0.0062
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No of Industries	12	12	12	12
Observations	132	132	120	120
Within R ²	0.9263	0.924	0.9222	0.9176

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

As shown in tables C1 and C2, the sum of the coefficients on the merger variables is positive and statistically significant in each regression.

**TABLE C3:
UNWEIGHTED
PATENT APPLICATION REGRESSION RESULTS**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Merger (T-2)	-4.7582	13.6376	8.1682	35.6745**
Merger (T-3)	60.3981***	20.241	50.4197***	-3.9005
Merger (T-4)	-	-	23.0596	45.1451**
Sum	55.6399***	33.8786*	81.6475***	76.9191***
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No of Industries	16	16	16	16
Observations	160	160	144	144
Within R ²	0.2538	0.1965	0.2526	0.2471

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

**TABLE C4:
UNWEIGHTED
PATENT APPLICATION VAR RESULTS**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Patents (T-1)	0.5822***	0.5291***	0.5612***	0.5136***
Patents (T-2)	-0.2961***	-0.2705***	-0.1139	-0.0722
Patents (T-3)	-	-	-0.0613	-0.1123
Merger (T-2)	-16.9624	17.4617	-8.1221	28.7778*
Merger (T-3)	71.9863***	18.6495	58.5001***	0.5602
Merger (T-4)	-	-	14.2396	49.5707***
Sum	55.0239***	36.1112**	64.6176**	78.9087***
Granger	P = 0.0001	P = 0.1091	P = 0.0038	P = 0.0066
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No of Industries	16	16	16	16
Observations	144	144	128	128
Within R ²	0.4509	0.3792	0.4879	0.4818

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

As shown in tables C3 and C4, the sum of the coefficients on the merger variables is positive and significant in each of the regressions.

Appendix D: Arellano-Bond Regression Results

Because our R&D expenditure and patent application data samples span significant time periods (2008 to 2020 and 2008 to 2018, respectively), our primary results presented in Section IV utilize a standard fixed effects “within” estimator. As an additional robustness check, we apply a “difference GMM” estimator developed in Arellano and Bond (1991) correcting for small-sample standard errors, which is commonly utilized in the literature to correct for potential bias in dynamic panel estimation.⁶⁶ As shown in Tables D1 and D2, below, this approach yields similar results to those presented in Section IV.⁶⁷

**TABLE D1:
ARELLANO-BOND ESTIMATOR
R&D EXPENDITURE VAR (\$MILLIONS)**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
R&D (T-1)	0.8136***	0.8658***	0.5579**	0.7230**
R&D (T-2)	0.1039	0.1025	0.3066	0.1975
R&D (T-3)	-	-	-0.0057	-0.0070
Merger (T-2)	69.4949**	88.5577	66.2666*	66.2498
Merger (T-3)	104.5782***	96.6497	106.4205***	137.6818
Merger (T-4)	-	-	88.4447*	50.0417
Sum	174.0731***	185.2074**	261.1318***	253.9733***
Granger Test	P = 0.0014	P = 0.1346	P = 0.0006	P = 0.0443
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No
No of Industries	12	12	12	12
Observations	120	120	108	108

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.

⁶⁶ See Arellano & Bond (1991)

⁶⁷ Due to the length of the time dimension of the panel, in applying the Arellano-Bond estimator, we restrict the instrument set to two lags.

**TABLE D2:
ARELLANO-BOND ESTIMATOR
PATENT APPLICATION RESULTS**

	2 Lag Model		3 Lag Model	
	Buyer's Industry Sample	Seller's Industry Sample	Buyer's Industry Sample	Seller's Industry Sample
Patents (T-1)	0.3842***	0.4067***	0.1445	0.2953***
Patents (T-2)	-0.3505***	-0.3241***	-0.1124**	-0.0917
Patents (T-3)	-	-	-0.3124	-0.3391***
Merger (T-2)	-1.8377	17.2875	29.6927	52.0474*
Merger (T-3)	90.4434***	27.2004***	60.3918***	-7.8282
Merger (T-4)	-	-	76.9684	108.4240***
Sum	88.6057***	44.4879***	167.0529**	152.6432***
Granger Test	P = 0.0000	P = 0.0007	P = 0.0000	P = 0.0007
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No
No of Industries	16	16	16	16
Observations	128	128	112	112

[1] Results indicated with a triple asterisk (***) are significant at the one percent level. [2] Results indicated with a double asterisk (**) are significant at the five percent level. [3] Results indicated with a single asterisk (*) are significant at the ten percent level.