Mergers, Product Prices, and Innovation: Evidence from the Pharmaceutical Industry*

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Abstract

Using novel data from the pharmaceutical industry, we study the impact of mergers on product prices and innovation. Product prices increase approximately 5% more within acquiring versus matched non-acquiring firms. These price increases are more pronounced for horizontal mergers and for acquisitions of large and publicly traded targets, i.e., deals resulting in greater market power consolidation. Consistent with causal identification of enhanced market power around mergers, price increases are significantly greater within drug classes with acquirer/target overlap and absent for drugs already shielded from competition through patents and exclusivity rights. We find no evidence of mergers facilitating or incentivizing innovation—a potential tradeoff to higher product prices.

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1 Introduction

That mergers and acquisitions generate shareholder value is generally accepted (Betton, Eckbo, and Thorburn, 2008). How mergers benefit shareholders and the costs other stakeholders incur are less clear. Industry consolidation can create value through synergies, leading to efficiency gains and, potentially, lower product prices (as in Sheen (2014)). Mergers also result in technology sharing, which may spur beneficial innovation (as in Bena and Li (2014)). Alternatively, some mergers concentrate market power and may thus suppress competition. Reduced competition allows prices to drift upwards and innovation to wane.

This study examines whether the net effect of industry consolidation is increased production efficiency or, rather, increased market power by analyzing product prices and innovation around mergers and acquisitions (M&As) in the pharmaceutical industry. The pharmaceutical industry represents an ideal test case for several reasons, the first being the availability of comprehensive product-level price and new drug approval data. Another advantage of studying the pharmaceutical industry is the ability to easily identify substitute products—drugs in the same "class" or "therapeutic category" curing similar diseases. We can thus pinpoint specific shifts in product market competition around mergers joining producers of competing products. Additionally, a unique feature of this industry is that, through patents and exclusivity rights, some pharmaceutical products are essentially shielded from competition. This subsample provides us with an interesting control group. Finally, in other product markets, product quality likely also changes around mergers, confounding the effects of mergers on price. In the pharmaceutical industry, quality should be time invariant because products are classified according to precise doses of specific active ingredients.

We obtain detailed drug price data from the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS), which restricts our drug price sample to 2013–2018. NADAC survey drug prices represent the average unit cost of drugs to retail pharmacies. Because pharmacies are immediate customers of pharmaceutical manufacturers, these data capture the direct impact of mergers on drug prices. When we combine these price data with M&A announcements from the Securities Data Corporation (SDC), we identify 121 pharmaceutical mergers between 2013 and 2018 worth $438 billion total.

Do pharmaceutical mergers ultimately lead to cost efficiencies or, instead, price increases due

to the concentration of market power? At the product (i.e., individual drug) observation level, we regress winsorized annual percentage price changes on merger activity, controlling for firm-level characteristics and lagged price levels. Using percentage price changes as the dependent variable in our regressions controls for drug price levels fundamentally differing across merging and non-merging firms. Winsorizing these changes at the 1st and 99th percentiles eliminates the impact of extreme outliers. These initial results imply drug prices rise 4.7% more during firm-years associated with acquisitions than during other firm-years.

It is possible that drugs sold by merging firms tend to be those that increase in price, or that the observed price increase represents a continuation of an upward trend. We control for these concerns by adding fixed effects for each unique drug product. We find that drugs sold by merging firms are not simply drugs that generally increase in price during our sample period. Rather, drug prices increase *in particular* around merger years.

We first study concurrent (i.e., same-year) merger activity because anecdotal evidence suggests the effect of mergers on prices can be immediate. For example, the price of Celgene's top selling drug Revlimid rose 3.5% on the day its planned deal with Bristol-Myers Squibb was announced.[1] But we also examine the relation between prices and past (lagged one-year) merger activity. Lagging our merger indicator helps alleviate some endogeneity and reverse causality concerns: that an omitted variable simultaneously drives both merger activity and price increases, or that price increases cause mergers and not vice versa. Further, cost savings may take time to implement. Lagging merger activity allows us to determine whether efficiency gains are realized and passed along to consumers in the future, causing prices to revert to, or even fall below, pre-merger levels. Our estimates, however, suggest prices continue to increase 1.6–1.8% the following year, inconsistent with long-term cost cutting or mean reversion.

Because merger activity is not based upon random assignment, it could be that firms conducting mergers fundamentally differ from other firms. To control for selection into acquisition activity, we match each "treated" acquiring pharmaceutical firm with a similar "control" non-acquiring firm the year of the deal. A control firm is the non-acquiring firm closest to the treatment firm in propensity to acquire, estimated using the Harford (1999) acquisition likelihood model. We then construct a difference-in-differences analysis around the merger in which we test whether acquiring firms' drug

[1] "Pharmaceutical Industry CEOs Face Senate Hearing on Drug Prices," *The Wall Street Journal*, February 25, 2019.

prices increase more from the pre- to post-merger period than non-acquiring firms' drug prices. Depending upon the time frame around the merger examined, prices are 4.4% to 7.1% higher after mergers for acquiring firms than control firms.

Overall, our findings are more consistent with recent consolidation in the pharmaceutical industry leading to net market power concentration rather than net cost efficiencies. To further explore if and how marker power drives the relation between mergers and drug price, and to further reduce endogeneity concerns, we test the cross-sectional prediction that mergers increasing market share more should impact prices more. We create deal-level indicator variables for M&As involving targets that have established themselves as industry leaders, i.e., publicly traded targets; for large deals, defined as M&As with above-median deal values; and for horizontal mergers, with acquirers and targets that share the same 4-digit SIC code. We then interact these indicators with our merger indicator in our difference-in-differences model of drug prices to gauge the incremental impact of deals that concentrate market power the most. Prices increase 6.3%, 4.9%, and 6.0% more for acquisitions of public targets, large deals, and horizontal deals, respectively. These cross-sectional tests suggest that deals resulting in greater concentration of market power are associated with greater increases in drug price.

If deals that concentrate market power the most result in greater price increases, do shareholders benefit more from these deals? To test this question, we examine cumulative abnormal returns (CARs) around acquisition announcements, for all firms and for subsamples bifurcated on deal-level market power proxies. We find that pharmaceutical mergers are associated with positive three-day (five-day) CARs of 1.2% (1.4%), significant at the 10% level. Importantly, these shareholder gains are concentrated in deals that consolidate market power the most. Our most conservative estimates imply significant CARs of 2.3% around public deals, 1.9% around large deals, and 2.5% around horizontal mergers. By contrast, acquisitions of non-public targets, small targets, and targets operating in a different 4-digit SIC industry code are not associated with significant shareholder gains.

The above cross-sectional tests are performed at deal level. To more cleanly identify the impact of mergers on product prices, we exploit two unique features of pharmaceutical products to examine cross-sectional variation at the *product* level in the impact of mergers on prices. First, drug products are categorized into "therapeutic classes" according to the type of disease they are intended to cure.

Examples of these classifications include Anesthetics, Antidepressants, Cardiovascular Agents, and Immunological Agents (i.e., vaccines). This classification system provides a useful framework to identify similar products. The impact of mergers on product prices should be stronger if the target produces a related product because increases in market power should be greatest within these product lines. Second, we exploit the fact that a subsample of drugs is shielded from competition through patents or exclusivity rights. If market power consolidation causes price increases around mergers, then the impact of mergers on prices of drugs already protected from competition should be lower, if not nil.

We create an indicator for drugs whose manufacturers acquire target firms producing a drug in the same class or specializing in drugs curing the same symptom. We also use FDA data on patents and exclusivity rights to construct indicators for products facing little or no competition. Incorporating these indicators into our difference-in-differences analyses shows drug product lines shared by both the acquirer and the target experience significantly greater price increases around mergers than product lines with no acquirer/target overlap. We also show that drugs under patent or with exclusivity rights increase in price significantly less around mergers than unpatented or unprotected drugs; in fact, they are completely exempt from price hikes around mergers. These product-level cross-sectional tests significantly improve our identification by comparing the impact of mergers across groups of drugs within acquiring firms, thus ruling out the possibility that our results are strictly driven by drugs produced by merging firms fundamentally differing from other drugs. These findings point toward market power consolidation causing prices increases around mergers.

To conclude our study, we examine whether pharmaceutical mergers are associated with a potential benefit that may offset the negative impact on consumers of drug price increases: We investigate whether these mergers spur innovation. We depart from traditional innovation metrics based on patents because pharmaceutical patents are subject to concerns regarding "thicketing," a competition-blocking practice in which companies apply for multiple patents on the same drug. In fact, pharmaceutical industry experts claim patents fail to represent "true innovation."[2] We thus create two alternative innovation proxies. We first define innovation as the number of Type 1 (new molecular entities) and Type 2 (new active ingredients) new drugs approvals reported in

[2] "Pharma patent owners in the US are under pressure like they have never been before." *IAM.* November 26, 2018.

US Food and Drug Administration (FDA) data available from 2010 to 2018. New drug approvals captures output: the creation of new cures. Because drug development is a lengthy and risky process, another way to measure innovation is through input. Therefore, our second innovation proxy is research and development (R&D) expenditures. When we examine the impact of mergers on drug approval and R&D in difference-in-differences regressions with firm and year fixed effects, we find no evidence that mergers "push" innovation, i.e., that innovation increases after mergers.

Alternatively, mergers may incentivize innovation by rewarding *prior* innovation. In this case, we would not expect upticks new drug approvals during the post-merger period. Rather, this channel suggests companies innovate to increase their likelihood of being acquired. We study whether mergers indeed "pull" innovation in this manner by modeling acquisition likelihood as a function of concurrent and prior drug approval. We use both the full sample of firms with any type of FDA drug approval, which includes both public and private firms, and the subsample of publicly traded drug manufacturers with Compustat data, which allows us to control for firm characteristics. Regardless of the sample or time period studied, we find no link between prior innovation and the likelihood of being acquired.

We contribute to two strands of the M&A literature, one studying the source of shareholder value creation in mergers, the other examining the impact of mergers on stakeholders of the firm, in our case customers. Identifying the source of value generation matters because creating value through efficiency gains impacts stakeholders differently than through increased market power. Many studies focusing on stock returns to merging firms and their rivals tend to yield support for synergy creation (e.g., Healy, Palepu, and Ruback, 1992; Heron and Lie, 2002; Hoberg and Phillips, 2010; Maksimovic, Phillips, and Prabhala, 2011; Bena and Li, 2014; Phillips and Zhdanov, 2013; Sheen, 2014; Lee, Mauer, and Xu, 2018). Other studies focusing on the impact of mergers on consumer prices generally identify price jumps around mergers, more consistent with increases in market power (e.g., Kim and Singal, 1993; Prager and Hannan, 1998; Vita and Sacher, 2001; McCabe, 2002; Focarelli and Panetta, 2003; Taylor and Hosken, 2007; Dafny, 2009; Kwoka and Shumilkina, 2010; Hosken, Silvia, and Taylor, 2011; Ashenfelter, Hosken, and Weinberg, 2013; Luo, 2014; Miller and Weinberg, 2017; Cooper, Craig, Gaynor, and Van Reenan, 2019). Taken together, we can conclude that the effect of mergers is complex and likely product-market dependent.

We contribute to this literature by quantifying the aggregate effects of mergers on prices and

innovation in the pharmaceutical industry, an industry whose products directly contribute to consumer welfare. Drug prices in the US have recently risen, prompting scrutiny from regulators, e.g., the February 2019 hearing during which pharmaceutical executives testified before the Senate Finance Committee. Our findings suggest that, even within this important and highly regulated industry, mergers are associated with significant price increases for the average product. Our most conservative, back-of-the-envelope estimate suggests that mergers contribute 0.95% to increases in drug prices each year.[3] Using the most recent figures on total drug spending from the Centers for Medicare and Medicaid Services (CMS), this translates into $1.4 billion in extra government spending per year.[4] Our findings inform policy around drug pricing by encouraging regulators concerned about high drug prices to consider antitrust enforcement as one potential solution. Importantly, our results isolate the types of deals that tend to be most harmful and the types of products most likely to increase in price around mergers: Price increases are greater around horizontal deals and acquisitions of large, publicly traded targets and within products shared by both the bidder and target. We conclude by showing that pharmaceutical mergers are not associated with an offsetting uptick in innovation, a common justification for high drug prices.[5] They neither facilitate nor incentivize the development of new drugs.

2 Related Literature and Contribution

The mergers and acquisitions (M&A) literature documents evidence of mergers creating shareholder value (Betton, Eckbo, and Thorburn, 2008). Findings are mixed regarding the source of this value creation, however. On one hand, synergy gains arising from improved operating performance could create value. On the other hand, mergers between rival firms could generate shareholder value by enhancing the merged firm's market power. While efficiency gains and increases in market power are not mutually exclusive merger outcomes, it is important to identify which effect dominates because they uniquely impact the stakeholders of the firm and thus differ in their welfare implications. In this section, we outline the literature documenting the sources of value creation in mergers. We

[3] Our calculations are based on our estimates that 21.5% of drugs are impacted by mergers each year, and mergers are associated with 4.4% prices increases (0.215*0.044 = 0.0095).

[4] Total CMS spending on drugs for 2017 was $150 billion (0.0095*$150 billion = $1.4 billion).

[5] For example, during his testimony before the Senate Finance Committee in February 2019, Sanofi's CEO Olivier Brandicourt referenced new medications and research and development expenses. (https://www.finance.senate.gov/imo/media/doc/26FEB2019BRANDICOURT-SANOFI.pdf)

then discuss the documented impacts of these outcomes on a particularly group of stakeholders: customers. We conclude by outlining our contributions to this literature.

Several studies find support for production efficiency gains using post-acquisition accounting performance or plant-level productivity data. For example, Healy, Palepu, and Ruback (1992) and Heron and Lie (2002) show that, relative to industry peers, merged firms exhibit superior operating performance after the merger. Using plant-level data for manufacturing firms, Maksimovic, Phillips, and Prabhala (2011) document that acquiring firms sell 27% and close 19% of target firms' plants after mergers. This evidence suggests that synergies obtained from the elimination of redundant assets are important sources of value creation.

Product market differentiation and human capital relatedness also contribute to merger synergies (Hoberg and Phillips, 2010; Lee, Mauer, and Xu, 2018), as do innovation and the ability to conduct R&D (Bena and Li, 2014; Phillips and Zhdanov, 2013). Using textual analysis, Hoberg and Phillips (2010) show that, when acquirers merge with a target whose products are similar to theirs but different from their rival's, the merger will help with product differentiation and thus improve profit margin. Instead of focusing on real assets, Lee, Mauer, and Xu (2018) document better post-merger performance when merged firms have related human capital since human capital relatedness can reduce labor costs. Bena and Li (2014) examine how pre-merger technology overlap affects merger outcomes: Technological overlap between the merged firms' innovation activities has a positive effect on future innovation, consistent with mergers improving innovation capabilities through synergies.

Alternatively, shareholder wealth may increase around mergers because of the concentration of market power. Consolidation of market power implies shareholders benefit due to transfers of wealth from other stakeholders, including customers, suppliers, or end-users of the products. A standard method to empirically quantify changes in market power around mergers involves studying stock returns to merging firms, rivals, customers, and suppliers around merger announcements. Fathollahi, Harford, and Klasa (2019) find that acquirer returns around merger announcements increase with industry-level product similarity, consistent with shareholders expecting to benefit more from deals that concentrate market power. The value of merging firms' competitors should also rise around merger announcements if mergers facilitate collusive, anti-competitive behavior. Yet, Eckbo (1983) and Stillman (1983) examine rival firms' returns around merger announcements

and do not find evidence consistent with mergers creating market power. Similarly, Fee and Thomas (2004) study announcement returns of rival firms, consumers, and suppliers; they find little evidence of collusive behavior but show increases in purchasing power with suppliers. Shahrur (2005) even documents *positive* mergers announcement returns to *customers*, concentrated within deals with positive cumulative wealth effects for acquirers and targets. In sum, the literature examining stock returns around merger announcement yields mixed results regarding the *sources* of value creation.

A more direct approach to identifying sources of value creation in mergers involves isolating mergers' impact on product prices. This approach is common and generally shows market power consolidation outweighing synergy gains, yielding a net negative impact of mergers on customers and suppliers. For example, using the industry-level Producer Price Index from the Bureau of Labor Statistics, Fathollahi, Harford, and Klasa (2019) document a positive price impact around horizontal mergers, particularly within industries with high product similarity, and Bhattacharyya and Nain (2011) show mergers exert price pressure on suppliers. Other studies focus on specific industries and document consistent effects. Airfares increase more on routes served by merging airlines relative to routes unaffected by mergers (Kim and Singal, 1993; Kwoka and Shumilkina, 2010). Hospital mergers are associated with increases in prices but not quality of care (Cooper, Craig, Gaynor, and Van Reenan, 2019; Dafny, 2009; Vita and Sacher, 2001). Rival hospitals increase prices around mergers as well (Dafny, 2009). Mergers in the banking industry lead to declines in deposit rates (Prager and Hannan, 1998), though these adverse price effects are temporary and ultimately reverse in the long-run (Focarelli and Panetta, 2003). Within the petroleum industry, mergers impact prices (Hosken, Silvia, and Taylor, 2011), in particular wholesale prices (Taylor and Hosken, 2007). In addition to the above industries, prior literature shows that mergers can positively impact the prices of academic journals (McCabe, 2002), household appliances (Ashenfelter, Hosken, and Weinberg, 2013), and beer (Miller and Weinberg, 2017).

Meanwhile, several studies find zero or negative changes in product prices around mergers. Luo (2014) re-examines the price effects of airline mergers focusing on the merger of Delta Airlines and Northwest Airlines; she finds no significant price changes after the merger. Sheen (2014) collects product quality and price data from *Consumer Reports* magazines and studies 88 mergers between 1980 and 2009. His key finding is that, when two firms selling common products merge, the quality of the related products converge and the price drops. However, these efficiency gains take two to

three years to be realized. These results provide evidence that mergers can enable efficiency gains, which lead to price decreases, and suggest that whether increases in market power or efficiency gains dominate may depend on the industry and product market in question.

We contribute to the above literature by examining the impact of mergers on prices in a large industry at the center of national policy debates—the pharmaceutical industry. As opposed to observing these effects indirectly by, for example, examining customer stock returns around supplier merger announcements, we measure the most direct impact of mergers on customers by studying product (i.e., drug) prices. Our study illustrates that one way recent mergers in the pharmaceutical industry may create shareholder value is by increasing prices charged to customers. We also document an important contributor to the recent rise in drug prices—industry consolidation—and identify the types of deals most harmful to customers and types of drugs most likely to increase in price around consolidation.

In addition, we examine a potential countervailing benefit to consolidation of the pharmaceutical industry: We study if mergers spawn innovation. We contribute to the literature on innovation around mergers by showing that pharmaceutical mergers neither facilitate the creation of future drugs, for example through technology sharing as in Bena and Li (2014), nor incentivize the creation of new drugs. Our innovation results are more consistent with Cunningham, Ederer, and Ma (2019), who focus on the impact of pharmaceutical mergers on the early stages of drug development. They show evidence of firms acquiring producers of competing drug products to subsequently discontinue development and thus squelch competition. While our focus is on the impact of mergers on drug *prices*, these so-called "killer acquisitions," which constitute 6% of pharmaceutical mergers, may be one of the mechanisms by which mergers decrease competition and thus allow prices to drift. Our study adds to the literature linking mergers and innovation by illustrating that pharmaceutical mergers neither "push" nor "pull" novel drugs through the development pipeline. Through this exercise, we are able to rule out the most obvious potential tradeoff to higher drug prices.

3 Data Sources, Sample Construction, and Summary Statistics

In this section, we describe the construction of our samples of data on drug prices, mergers and acquisitions (M&As), and innovation. We then summarize the main variables used in this study.

3.1 Drug price data and trends

Federal regulations require state Medicaid agencies to reimburse participating pharmacy providers for covered outpatient drugs dispensed to Medicaid beneficiaries. Reimbursement amounts are based on the agency's best estimate of the acquisition cost of a drug. Before 2011, many Medicaid agencies estimated acquisition costs using average wholesale prices. This benchmark, however, has been the subject of litigation over concerns that many wholesale prices were artificially inflated. To address these concerns, the National Association of State Medicaid Directors requested that the Centers for Medicare and Medicaid Services (CMS) develop a more credible drug pricing benchmark.

The CMS now contracts with Myers and Stauffer, a national certificated accounting firm, to conduct monthly surveys of retail pharmacy prices. Myers and Stauffer collects acquisition costs for covered outpatient drugs from a random sample of retail pharmacies designed to closely align with the composition of the population of US pharmacies, i.e., representing all 50 states and the District of Columbia and including both independent and chain pharmacies. Survey results allow for calculation of the average acquisition cost of drugs at the 11-digit National Drug Code (NDC) level, or the "National Average Drug Acquisition Cost (NADAC)."[6] Since drug acquisition cost is collected through monthly surveys, we observe multiple acquisition costs for a given drug within a year. Therefore, for each year, we calculate drug price as the weighed average of acquisition costs for a given drug, with weights corresponding to the number of days between effective prices. We adjust for inflation using the CPI and express all drug prices in 2018 dollars. We also winsorize drug prices at the 1^{st} and 99^{th} percentile to mitigate the impact of extreme outliers. The availability of drug prices from the NADAC survey restricts our drug price sample period to 2013 to 2018.

To identify drug manufacturers, we refer to the National Drug Code Directory. The NDC Directory provides information submitted to the Food and Drug Administration (FDA) including product ID, product NDC, and labeler name. We match our drug price sample with the pharmaceutical manufacturer (i.e., labeler) by product NDC. We further restrict our sample to drugs produced by publicly traded US pharmaceutical companies by manually matching the drug price data with Compustat by company name.

[6] A more detailed description of the survey process and CMS's methodology to calculate the NADAC can be found at: https://www.medicaid.gov/medicaid-chip-program-information/by-topics/prescription-drugs/ful-nadac-downloads/nadacmethodology.pdf.

We also collect patent and exclusivity rights from the publication *Approved Drug Products with Therapeutic Equivalence Evaluations*, commonly known as the "Orange Book." Patents and exclusivity rights both decrease competition but have several important differences. Namely, patents are broader property rights issued anytime during the development period, while exclusivity rights are issued only upon drug approval and refer to specific delays and prohibitions on rival drug approval. Also, patents generally span 20 years, though they can be extended, whereas exclusivity rights last 180 days to 7 years, depending on the type of drug.[7] We match patent and exclusivity information to our sample using new drug application type and number, as well as ingredients. If the same drug is associated with multiple dates, we use the most recent date as the drug's patent or exclusivity expiration. We classify a drug as patented or covered under exclusivity rights if its patent or exclusivity has not yet expired.

To investigate how merger and acquisition (M&A) activity affects drug prices, we obtain M&A announcements from Securities Data Company (SDC) Platinum. Following prior literature (e.g., Bena and Li, 2014), we identify M&As using deal codes corresponding to a merger, an acquisition of majority interest, or an acquisition of assets. We require acquirers to own less than 50% of the target firm prior to the deal and at least 90% after the deal. We condition on completed deals and require the acquirer to be a public firm listed on the Center for Research in Security Prices (CRSP) and Compustat databases during the event window. Then, we focus on deals with acquirers belonging to one of the four pharmaceutical industries: Health Care, Medical Equipment, Pharmaceutical Products, and Chemicals, classified according to the acquirer's Fama-French 48 industry specification. We match the SDC data with our drug price data, and create an indicator equal to one if the drug manufacturer conducted an M&A during the current fiscal year. With this newly combined data set, we are able to observe, at the *drug-year* level, whether a drug's manufacturer conducts any acquisition or not. Last, we obtain all firm-level accounting information from Compustat. Our final drug price sample consists of 21,213 drug-year observations associated with 5,883 unique drugs and 75 unique pharmaceutical firms from 2013 to 2018.

We conclude by collecting two additional pieces of information on each drug product. First, we assign each drug to its Major Therapeutic Class Code by merging on NDC, or, if unsuccessful, on

[7]For more details on the differences between patents and exclusivity rights, see https://www.fda.gov/drugs/development-approval-process-drugs/frequently-asked-questions-patents-and-exclusivity.

drug name. Second, through extensive web searches, we hand-collect data on the symptom each drug is intended to treat. To check our research, we verify our symptom data designations with industry professionals.

Figure 1 graphs the annual inflation-adjusted average winsorized drug price per unit (NADAC) from 2013 to 2018. It illustrates a strong, upward price trend. After inflation adjustments, drug prices average $8.44 per unit in 2013 but $10.75 per unit by 2018. Table 1 reports the full distribution of drug prices. The mean drug price per unit is approximately $10, and the mean price change (the natural logarithm of this year's price divided by last year's price) is -1.3% per year. An average percentage price decrease coupled with upward-trending average price levels is consistent with more expensive drugs increasing in price but cheaper drugs declining in price. We confirm this prediction in untabulated results: Drugs with prices above our sample mean increase in price by almost 8% per year while drugs associated with below-average costs decrease in price by almost 3% per year on average. Among all drugs in our sample, 11% are under patent, 2.5% are exclusivity protected, 89% are brand-name (as opposed to generic), 84% are prescription (as opposed to over-the-counter), and 10% treat life-threatening diseases.

Figure 2 bifurcates drug prices into two groups: drugs produced by firms that participate in at least one acquisition during our sample period and drugs sold by firms that do not. The annual average cost of drugs produced by merging firms is greater than non-merging firms and increases monotonically from around $11 per unit in 2013 to over $15 per unit in 2018. Panel B of Table 1 provides a univariate comparison of drug prices across drug-years associated with a merger and drug-years not associated with a merger. As suggested by Figure 2, merging firms sell significantly more expensive drugs and experience greater price changes than non-merging firms; in fact, while drugs produced by merging firms tend to increase in price, non-merging firms' drugs decline in price on average. We also note that drugs associated with acquirers are more likely to be patented and have exclusivity rights but less likely to be brand name (versus generic) and prescription (versus over-the-counter).

We next examine M&A activity within the pharmaceutical industry from 2013 to 2018. Figures 3 and 4 give an overview of the number of pharmaceutical M&A deals and the dollar amounts invested in these deals. Figure 3 shows the number of deals is highest with 38 deals in 2015 and decreases to 12 deals in 2017. Deal values follow a similar pattern in Figure 4: The aggregate deal

value peaks in 2015 at $174 billion and bottoms out in 2017 at $18 billion.

Table 2 Panel A presents summary statistics of the full sample of 121 merger and acquisition deals worth $438 billion total. As shown in Figure 5, these deals are conducted by 40 unique acquirers. The median firm acquirers 2.5 targets during the sample period, and the maximum number of acquisitions by a single firm is 10 by Valeant Pharmaceuticals International Inc. Table 2 Panel B shows the average deal size is $3.6 billion, but the distribution in skewed: The median deal is worth $774 million. Within these pharmaceutical mergers, acquisitions of publicly traded targets, private targets, and subsidiaries are fairly evenly distributed. Following Harford (1999), we calculate acquiring firms' cumulative abnormal returns (CARs) surrounding the acquisition announcement date by constructing a market model using the CRSP value-weighted market returns over the 200-day period ending 11 days before the announcement date. We estimate three-day (five-day) CARs of 1.2% (1.4%). These abnormal returns are statistically different from zero at the 10% level, thus indicative of these mergers creating shareholder value on average.

Finally, from Compustat data we generate firm-level control variables that may relate to pricing strategies. We define and summarize these variables in the Appendix. Table A1 Panel A summarizes firm characteristics for all pharmaceutical companies with drug prices reported in the NADAC survey. Panel B splits the sample on acquisition activity. Acquiring firms tend to be larger, hold more cash, and be more profitable. While acquiring firms tend to have lower leverage ratios, non-acquiring firms tend to have higher Z-scores, which may suggest better financial health.

3.2 Innovation data and trends

Though studies of other industries generally rely on patent volume and citations to measure innovation, these metrics are problematic within the pharmaceutical industry. Pharmaceutical companies have been accused of "patent thicketing," a competition-blocking practice of applying for multiple patents on the same drug or extending patents on existing drugs. For example, AbbVie, the maker of the world's best selling drug Humira, has obtained over 100 patents on this one drug.[8] This practice is not uncommon. On average, the US's 12 best-selling drugs hold 71 patents per drug, with exclusivity lasting 38 years, almost twice the standard 20-year exclusivity period for core

[8] "By Adding Patents, Drugmaker Keeps Cheaper Humira Copies Out of U.S." *The Wall Street Journal*, October 16, 2018.

patents.[9] According to Rachel Sher, the deputy general counsel of the the Association for Accessible Medicines (AAM), which represents generic drug companies: "Too often branded companies are seeking to patent features of the drugs that don't represent true innovation."[10]

To deal with the aforementioned "patent thicketing" problem, we create an arguably cleaner innovation proxy using new drug approval data from the US Food and Drug Administration (FDA). The FDA provides reports of all approved drug applications each month. Monthly reports include original and supplemental approvals, allowing us to see approval dates, the applying companies (i.e., manufacturers), the active ingredients, the submission classification, and the submission status for each drug. The FDA categorizes new drug products by submission classification.[11] We define innovation as approvals of new molecular entities or new ingredients (i.e., Type 1, Type 2, Type 1/4, Type 2/3, and Type 2/4). We restrict our sample to new drug product applications from pharmaceutical companies with publicly traded stock in the US by manually matching the drug innovation data with Compustat by company name. Our sample period spans from 2010 to 2018.

Figure 6 presents the total number of Type 1 (new molecular entity) and Type 2 (new active ingredient) drug approvals by year. Aggregate innovation in this industry ranges between 11 and 30 new drugs per year. Next, we combine our innovation sample with SDC merger data, now including deals back to 2010 to match the innovation sample period. We segment our data into two groups based on whether the firm applying for new drug approval conducted an acquisition during our sample period. Figure 7 presents the average number of new drug approvals each year by merger activity. Innovation is more prevalent within firms conducting acquisitions, but new drug approvals are still infrequent. Even within acquiring firms, which tend to innovate more frequently, the average firm introduces between 0.10 and 0.25 drugs per year, or one new drug every 4 to 10 years.

While new drug development is at the heart of pharmaceutical innovation, we recognize that new drug approvals are infrequent and new drug development takes time. An alternative approach

[9] "Overpatented, Overpriced: How Excessive Pharmaceutical Patenting is Extending Monopolies and Driving up Drug Prices." *Initiative for Medicines, Access & Knowledge (I-MAK).* August 2018.

[10] "Pharma patent owners in the US are under pressure like they have never been before." *IAM.* November 26, 2018.

[11] E.g., new molecular entity (Type 1), new active ingredient (Type 2), new dosage form (Type 3), new combination (Type 4), new formulation or other differences (Type 5), new indication or claim (Type 6), previously marketed but without an approved FDA (Type 7), Rx to OTC (Type 8), new indication or claim, drug not to be marketed under type 9 NDA after approval (Type 9), new indication or claim, drug to be marketed under type 10 NDA after approval (Type 10), a Type 1 and Type 4 combination (Type 1/4), a Type 2 and Type 3 combination (Type 2/3), a Type 2 and Type 4 combination (Type 2/4), and a Type 3 and Type 4 combination (Type 3/4).

to gauging innovation through new drug output is to quantify input, i.e., investments in the research and development of new drug products. Thus, we also combine our pharmaceutical merger sample and control firms with Compustat data to examine changes in R&D around mergers.

4 Baseline Drug Price Regressions

In this section, we investigate how merger and acquisition (M&A) activity in the pharmaceutical industry relates to drug prices. Our baseline regression, run at the product-year (i.e., drug-year) level, is as follows:

$$\Delta Price_{i,j,t} = \beta_e Merger_{i,j,t} + \theta X_{i,t-1} + Price_{j,t-1} + \epsilon_{i,j,t} \tag{1}$$

where the dependent variable $\Delta Price$ is the natural logarithm of the ratio of the year t price to the year *t-1* price at the 11-digit National Drug Code (NDC) level. The main variable of interest, $Merger_{i,j,t}$, is an indicator variable that equals one if pharmaceutical firm i producing drug j conducted at least one merger in year t. If acquirers exploit synergies to increase production efficiency and thus reduce drug prices, we expect the coefficient β to be negative. Alternatively, if mergers increase acquirers' market power and they in turn increase drug prices, we expect β to be positive. X represents firm-level controls for firm size, cash holdings, ROA, leverage, and Z-score (all defined in the Appendix), and $Price_{j,t-1}$ represents the prior year's drug price. We winsorize all continuous variables at the 1^{st} and 99^{th} percentiles to mitigate the effects of outliers.

Table 3 presents our results. The coefficient on $Merger_t$ suggests that drugs produced by acquiring firms increase in price 4.7% more than other drugs. Acquirer-level controls generally impact price changes. Large drug manufacturers tend to raise prices less than small drug manufacturers. Cash and operating performance (ROA) tend to be positively related to price changes, as are leverage and financial health (greater Z-scores). The coefficient on $Price_{t-1}$ is negative and marginally significant, suggesting that prices increase less if beginning-of-year prices were already high.

The observed positive relation between price changes and merger activities may simply reflect a continuation of an upward trend in price, unrelated to mergers. Further, drugs produced by firms that tend to make acquisitions may fundamentally differ from other types of drugs. To address

these concerns, we include National Drug Code (NDC) fixed effects for each unique drug product j, as follows:

$$\Delta Price_{i,j,t} = \beta_e Merger_{i,j,t} + \theta X_{i,t-1} + Price_{j,t-1} + \delta_j + \epsilon_{i,j,t} \quad (2)$$

The positive coefficient on $Merger_t$ in Model (2) suggests that drugs sold by merging firms are not simply drugs that generally increase in price during our sample period. Rather, within the same drug, prices increase 3.0% more around merger years that non-merger years.

Though we observe greater drug price increases the year of the merger, prices may drop after the merger if efficiency gains in development and production take time to realize. Alternatively, prices may continue to increase if firms implement new pricing strategies over time. Thus, we next examine how merger activity affects future (next-year) drug price changes. The estimated coefficient on $Merger_{t-1}$ in Model (3) without drug fixed effects suggests that, compared to drugs produced by non-merging firms, merging firms' drugs increase in price 1.7% more the following year. Model (4) yields a similar magnitude of 1.5% with the inclusion of drug fixed effects. Our results are inconsistent with mean-reversion; rather, they suggest drug prices increase around mergers and remain high.

5 Difference-in-differences analyses

Because the decision to acquire another firm is not random, in this section we take steps towards more explicitly controlling for firm characteristics driving merger activity. Specifically, we assign each firm-year observation a propensity to acquire score using the Harford (1999) model. This model predicts merger bidding using abnormal returns, sales growth, noncash working capital, leverage, market-to-book, price-to-earnings, size, and year fixed effects. We then match each firm-year associated with an acquisition (i.e., each *deal*) to the drug manufacturer with the closest predicted acquisition likelihood that did not conduct an acquisition that year. Then, using only drugs from acquiring firms and control firms, we estimate the following difference-in-differences equation:

$$\frac{Price_{i,j,t}}{InitialPrice_{i,j}} = \theta Treatment * Post_{i,j,t} + \beta Treatment_{i,j} + \zeta Post_{i,j,t} + \gamma X_{i,t-1} + \delta_j + \epsilon_{i,j,t} \quad (3)$$

where $Price_{i,j,t}$ is the price of drug j produced by company i at time t, which we scale by *Initial* $Price_{i,j}$, the first price of the drug used in our analysis. *Treatment* equals one if the drug is associated with an acquiring firm and zero if the drug is associated with a matched control firm. *Post* equals zero before the merger year and one during and after the merger year, for both the treated and matched control firms' drugs. Our coefficient of interest is θ, which captures the difference in relative price from the pre-merger to post-merger periods (first difference) between drugs whose manufacturers conduct an acquisition and drugs made by very similar manufacturers that do not conduct an acquisition (second difference). X represents firm-level controls for firm size, cash holdings, ROA, leverage, and Z-score (defined in the Appendix), and δ_j is a drug-level fixed effect.

Table 4 presents our difference-in-differences analyses with varying windows around the merger event year. Regardless of the number of years around the merger we include, we observe positive and significant coefficients on the post/treatment interaction term. Our estimates range from 4.4% using the three-year period spanning from one year prior to the merger until one year after the merger to 7.1% when we focus on the five-year period from two years pre-merger to two years post-merger. Expanding the window to three years pre and post or fully to all years in the sample yields price hikes 5.3% and 5.7% greater for acquiring firms than matched control firms. These findings suggest that drugs whose producers acquire another firm increase in price 4.2% to 7.1% more than drugs produced by matched firms that do not acquire other firms.

6 Cross-sectional Predictions and Results

We have established that prices tend to increase around mergers. Our fixed effects models help rule out alternative stories regarding price trends within individual drugs and our difference-in-differences analyses help alleviate sample selection concerns. In this section we take additional steps towards alleviating endogeneity concerns using cross-sectional tests. Specifically, we test if price increases are greater within deals concentrating market power more and within product markets directly impacted by mergers. We also test if prices of drugs already protected from competition under patents or exclusivity rights are less sensitive to mergers. In addition to bolstering our argument that the link between mergers and drug prices is not a spurious correlation, these cross-

sectional analyses provide important insights for regulators scrutinizing these deals: They allow us to identify the types of mergers most harmful to consumers as well as the types of drugs most impacted by mergers.

6.1 Do deals that concentrate market power more impact prices more?

If our results reflect acquisitions causing drug price increases, then we expect the effect of mergers on prices to be more pronounced among deals that concentrate market power the most. We hypothesize that deals involving a publicly traded target (implying the merger of two publicly traded companies because all of our acquirers are publicly traded), large deals, horizontal mergers, and mergers of two firms making competing drugs should consolidate market power the most and thus lead to the greatest increases in drug prices. To test these predictions, we augment our baseline difference-in-difference regressions of relative prices on merger activity with indicators for public targets, large deals, and horizontal mergers. *Public target* equals one if the drugmaker acquires a publicly traded firm during the year; *Large deal* equals one if at least deal the firm conducts that year exceeds the median deal value of pharmaceutical mergers in our sample; and *Horizontal merger* equals one if the drugmaker acquires a target sharing the same 4-digit SIC code.[12] Because these indicators can only equal one if a merger occurs, they are analogous to an interaction term, and their coefficients can be interpreted as the *incremental* price impact of each deal type. For the sake of brevity, we restrict our sample period to the five-year period spanning from two years before to two years after the merger. All models include controls from Table 3 and product (NDC) fixed effects.

Table 5 results are consistent with deals concentrating market power the most being associated with greater price increases around mergers. Acquisitions of public targets are associated with price increases 6.3% greater than acquisitions of private targets or subsidiaries, and acquisitions of large targets are associated with price increases 4.9% greater than deals involving small targets. Further, horizontal mergers are associated with prices that increase 6.0% more than diversifying mergers. Our evidence thus suggests mergers resulting in a greater degree of market concentration are associated with larger price increases. These findings are consistent with our prediction that

[12] Appendix Table A2 provides the breakdown of industry composition by 4-digit acquirer and target SIC codes. Acquirers are concentrated in the Pharmaceutical Preparations business line; acquirers in 99 of our 121 deals come from this industry classification. Using a strict, same 4-digit SIC code definition of horizontal mergers, slightly over half (68 of 121) of deals in our sample are horizontal mergers.

mergers positively impact drug prices by consolidating market power.

6.2 Shareholder value creation by merger type

The results documented above suggest the effect of mergers on price changes is more pronounced among deals that concentrate market power the most. Because shareholder value creation may be greater for deals that increase market power, here we investigate the stock market's reaction to merger announcements. We follow Harford (1999) and calculate three-day and five-day acquiring firms' cumulative abnormal returns (CARs) surrounding the acquisition announcement date. Using deal-level observations, we compare the acquirer's three-day and five-day CARs between deals that concentrate market power the most and other deals.

Table 6 presents merger announcement CARs. Aggregating all deals in Panel A, we observe positive three-day and five-day CARs of 1.2% and 1.4%, respectively, statistically different from zero at the 10% level. Panel B shows subsample analyses by market power proxy. Consistent with our prediction that shareholders of firms making acquisitions that concentrate market power more benefit more, both three-day CARs and five-day CARs for deals involving public targets, large targets, and horizontal mergers are significantly positive and of economic importance. Surrounding announcements of public (large) deals, three-day and five-day CARs are 2.3% and 2.9% (1.9% and 1.9%), respectively. Horizontal mergers are associated with three-day (five-day) CARs of 2.5% (3.1%). In contrast, other deals are not associated with abnormal returns statistically different from zero. While abnormal returns across public versus private and subsidiary targets, and large versus small deals are not statistically different, horizontal mergers are associated with three-day (five-day) abnormal returns 3.4% (4.2%) greater than diversifying mergers, a statistically significant difference. Overall, our evidence is consistent with mergers that consolidate market power the most significantly benefiting shareholders but with other deals not generating significant shareholder wealth.

6.3 Competition at the drug level

If market power consolidation is the channel through which mergers are associated with greater price increases, then prices should increase more for drugs produced by both the acquiring firm and the target firm. On the other hand, mergers should have a lesser impact on prices of drugs

protected from competition. We thus predict prices of patented drugs and drugs with exclusivity rights will be less sensitive to mergers because they already face less competition than other drugs.

To test whether price changes around mergers vary with competition, Table 7 augments our difference-in-differences regressions with interactions between merger activity and indicators for acquirer/target drug overlap as well as product-level competition. *Drug overlap* equals one if the firm acquires a target producing a drug in the same Major Therapeutic Drug Class or specializes in the production of drugs curing the same symptom. *Drug overlap* can only equal one if a merger occurs and is hence analogous to an interaction term. *Patent* (*Exclusivity*) equals one if the drug is under patent (exclusivity protected), as noted in the FDA database. For brevity we restrict our sample period to the five-year period spanning from two years before to two years after the merger. We include controls from Table 3 and product (NDC) fixed effects.

Table 7 tabulates our cross-sectional results on competition at the drug level. Model (1) suggests that, from the pre- to post-merger period, prices of drugs produced by both the acquirer and the target firm increase 3.5% more than other drugs around mergers. This finding supports market power consolidation as the channel through which mergers impact prices: The products most directly impacted by the merger experience greater price hikes than other products. Next, we estimate the impact of mergers on drugs facing limited competition in Models (2) and (3). Consistent with our predictions, we find that mergers impact prices of drugs covered under patents or with exclusivity rights significantly less. In fact, prices of patented drugs and drugs with exclusivity protection do not increase around mergers at all. This finding that products already dominating the market and protected from competition are unaffected by mergers is also consistent with increases in market power being the channel through which mergers impact drug prices.

7 Innovation

Our results thus far are consistent with mergers, particularly those concentrating market power, being associated with higher prices. Consumers and regulators may tolerate higher prices if mergers are associated with offsetting advantages. In particular, it may be the case that drug prices increase around mergers (a disadvantage to consumers) but that merged pharmaceutical companies develop more new drugs (an advantage to consumers). Examining how pharmaceutical mergers impact

innovation helps us clarify potential trade-offs and quantify their welfare implications.

In this section we explore two ways in which mergers may impact innovation. Bena and Li (2014) conclude that mergers improve innovation, particularly in cases in which the merging firms overlap in technology prior to the merger. Because a newly formed merged firm may innovate more due to technology sharing, we begin by testing whether mergers spur *future* innovation. This channel implies mergers "push" innovation. A separate but non-mutually-exclusive channel through which mergers may encourage innovation is by "pulling" new drugs through the development pipeline, or rewarding *past* innovation. The idea behind this second channel is that companies develop new drugs to increase their likelihood of being acquired.

7.1 Mergers and future innovation: Do mergers "push" innovation?

As explained in Section 3, though many prior studies of other industries use patent volume and citations to proxy for innovation, patents are problematic in the pharmaceutical industry due to the common practice of "patent thicketing" in which drug makers apply for multiple patents on the same product. The general consensus among pharmaceutical experts is that patents do not represent "true innovation."[13] We thus use two alternative definitions of innovation. We first define innovation as the number of US Food and Drug Administration (FDA) new drug approvals per firm-year. To capture novel products, as opposed to variations of existing treatments such as new dosage forms, we restrict this innovation definition to approvals of new molecular entities (Type 1) and new active ingredients (Type 2). An obvious downside to using new drug approval as an innovation proxy is the long time frame necessary to develop new treatments. Therefore, in addition to focusing on output, we study innovation input through research and development (R&D) expenditures. While it may take years to develop a new drug, the impact of mergers on R&D could be immediate.

To investigate how merger and acquisition activity in the pharmaceutical industry affects drug product innovation, we again employ a difference-in-differences model: At the deal level, we match each "treated" acquiring firm with a "control" non-acquiring firm with the closest estimated propensity to acquire from the Harford (1999) model during the year of the deal. We address the concern

[13] "Too often branded companies are seeking to patent features of the drugs that don't represent true innovation." Rachel Sher, the deputy general counsel of the the Association for Accessible Medicines (AAM). ("Pharma patent owners in the US are under pressure like they have never been before." *IAM*. November 26, 2018.)

that firms that apply for new drug products can be fundamentally different from firms that do not by restricting our sample to US publicly traded firms that have applied for at least one type of new drug product during the sample period of 2010 to 2018. We then examine whether mergers lead to more innovation using the following model:

$$Innovation_{i,t} = \theta Treatment * Post_{i,t} + \beta Treatment_i + \zeta Post_{i,t} + \gamma X_{i,t-1} + \gamma_i + \delta_t + \epsilon_{i,t} \quad (4)$$

Our coefficient of interest is θ, which we expect to be positive if mergers spur innovation. We control for firm size, cash holdings, ROA, leverage, and Z-score, and include firm and year fixed effects in all models.

Table 8 presents our innovation difference-in-differences analyses. Models (1), (2), and (3) present results on whether M&A activities affect the number of drugs approved using ± 2 years around the merger, ± 3 years around the merger, and all available years in the sample, respectively. Models (4)–(6) present analogous regressions using R&D expenditures as the innovation proxy. The post/treatment interaction coefficients are not statistically different from zero in any model, suggesting that firms do not innovate significantly more after mergers.

7.2 Past innovation and acquisition likelihood: Do mergers "pull" innovation?

Although our evidence suggests mergers do not "push" *future* innovation, mergers may encourage companies to innovate by rewarding *past* innovation. This alternative channel suggests companies innovate more to increase the likelihood of becoming an attractive target. Using the following regression, we study whether mergers indeed "pull" new drugs through the development pipeline by testing whether innovation influences the likelihood of becoming a target:

$$Target_{i,t+n} = \beta DrugApproval_{i,t} + \gamma_i + \delta_t + \epsilon_{i,t} \quad (5)$$

The dependent variable is an indicator equal to one if the firm becomes a target in year $t+n$. We vary n from zero to three years. The main variable of interest, $Drug\ Approval_{i,t}$, equals the number of new Type 1 (new molecular entity) and Type 2 (new active ingredient) FDA drug approvals. γ and δ represent firm and year fixed effects. We study two samples, both spanning from 2010

to 2018. The first sample includes all firms with any type of drug approval from the FDA. This sample captures all active drug manufacturers in the US, both public and private. Our second sample uses all Compustat firms categorized as operating in the Healthcare, Medical Equipment, Pharmaceutical Products, and Chemicals according to the Fama-French 48 industry classifications. For the Compustat sample, we include firm-level control variables defined in the Appendix.

Table 9 presents our acquisition likelihood models. We learn that innovation does not significantly impact the likelihood of becoming a target in a merger. This result holds for up three years in the future. It is robust to using the full sample of both public and private drug manufacturers and as well as within the subsample of public firms, which allows for firm controls. Our evidence suggests that mergers neither push nor pull innovation. In sum, we document higher prices around pharmaceutical mergers but are unable to identify a countervailing positive impact on new drug development.

8 Conclusion

We exploit novel drug price data to find that drug prices rise significantly around mergers. Our estimates of the price impact hover around 5%. The effect is strongest within deals that concentrate market power the most and within drugs produced by the both acquirer and target. It is attenuated for drugs already shielded from competition through patents and exclusivity rights. Prior studies document and this study confirms that M&As generally create value for shareholders. Our results suggest that mergers within the pharmaceutical industry display little evidence of efficiency gains or synergies; rather, any benefit to shareholders appears to be at the cost of other stakeholders, in our case, customers.

We also examine if pharmaceutical mergers offer a potentially offsetting benefit: innovation resulting from synergistic technology sharing. We find no evidence of upticks in new drug approval or R&D expenses after mergers. Nor do we observe a positive link between drug approval and the likelihood of becoming a merger target in the future.

Our findings have potential policy implications. The average merger in our sample is associated with increases in product prices but not offsetting increases in innovation, suggestive of these mergers having adverse effects on competition and potentially restricting access to medication for

the marginal consumer. Our results suggest the Federal Trade Commission and Department of Justice should place increased scrutiny on deals joining established market leaders, large deals, and horizontal mergers, in particular, as well as within product markets.

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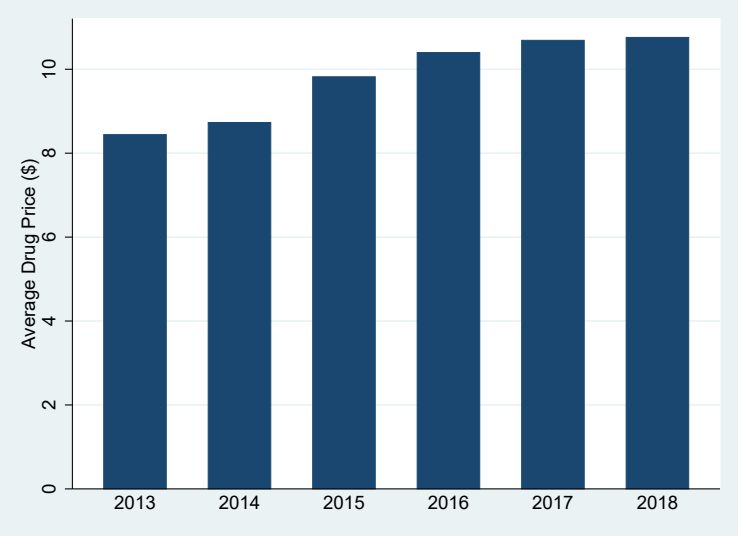

Figure 1
Average Drug Prices
This figure presents the average unit price in 2018 dollars of drugs sold to retail pharmacies in our sample each year. We source drug prices from the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS).

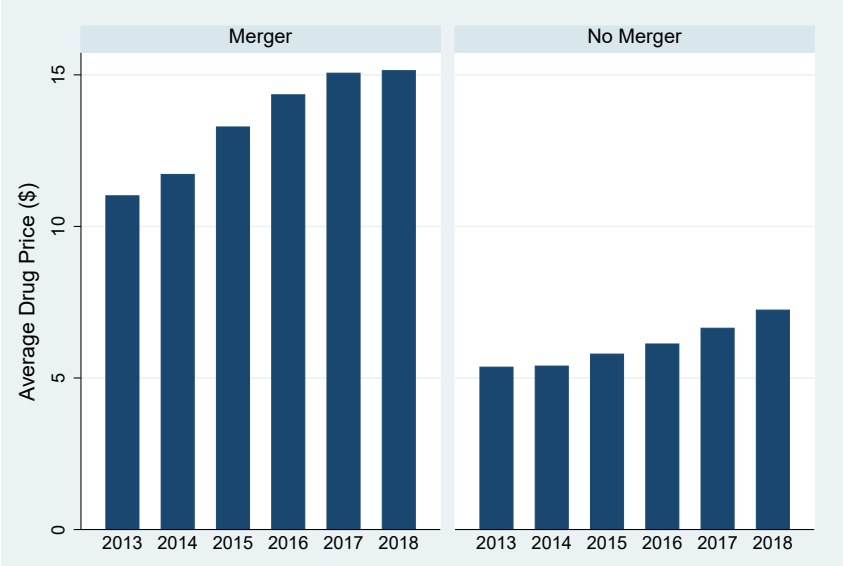

Figure 2
Average Drug Prices by Merger Activity
This figure presents the average unit price in 2018 dollars of drugs sold to retail pharmacies each year, bifurcated on whether the drug manufacturer acquired another firm during the sample period. "Merger" firms participate in at least one merger during our sample period. We source drug prices from the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS) and merger announcements from the Securities Data Corporation (SDC).

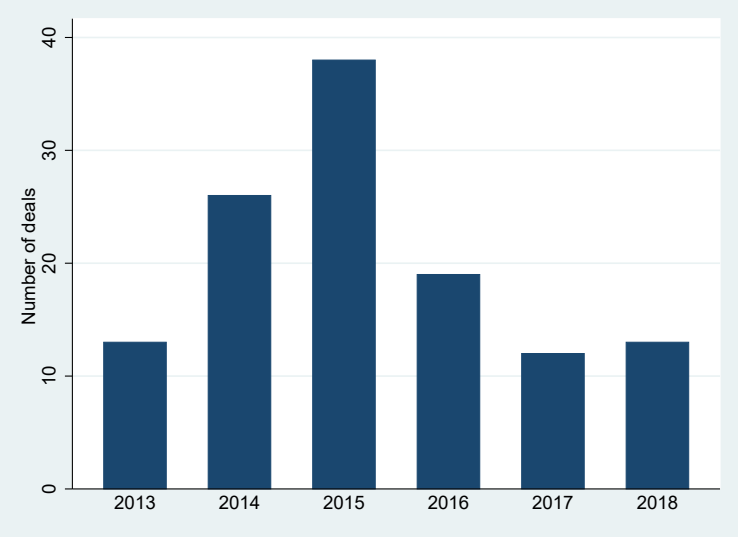

Figure 3
Number of Pharmaceutical Mergers and Acquistions
This figure presents the number of pharmaceutical mergers and acquisitions (M&As) each year. Our merger sample consists of firms with M&A announcements in the Securities Data Corporation (SDC) database between 2013 and 2018 and with drug prices reported in the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS).

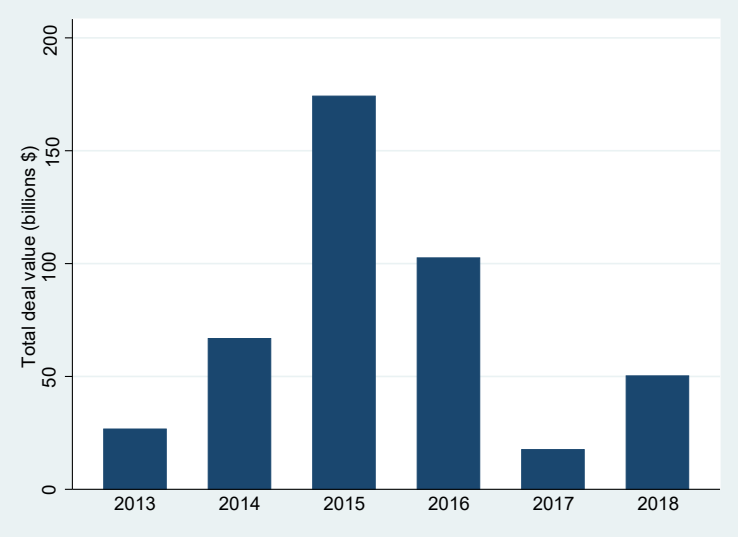

Figure 4
Aggregate Deal Value of Pharmaceutical Mergers and Acquistions
This figure presents the total deal value in billions of US dollars of pharmaceutical mergers and acquisitions (M&As) each year. Our merger sample consists of firms with M&A announcements in the Securities Data Corporation (SDC) database between 2013 and 2018 and with drug prices reported in the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS).

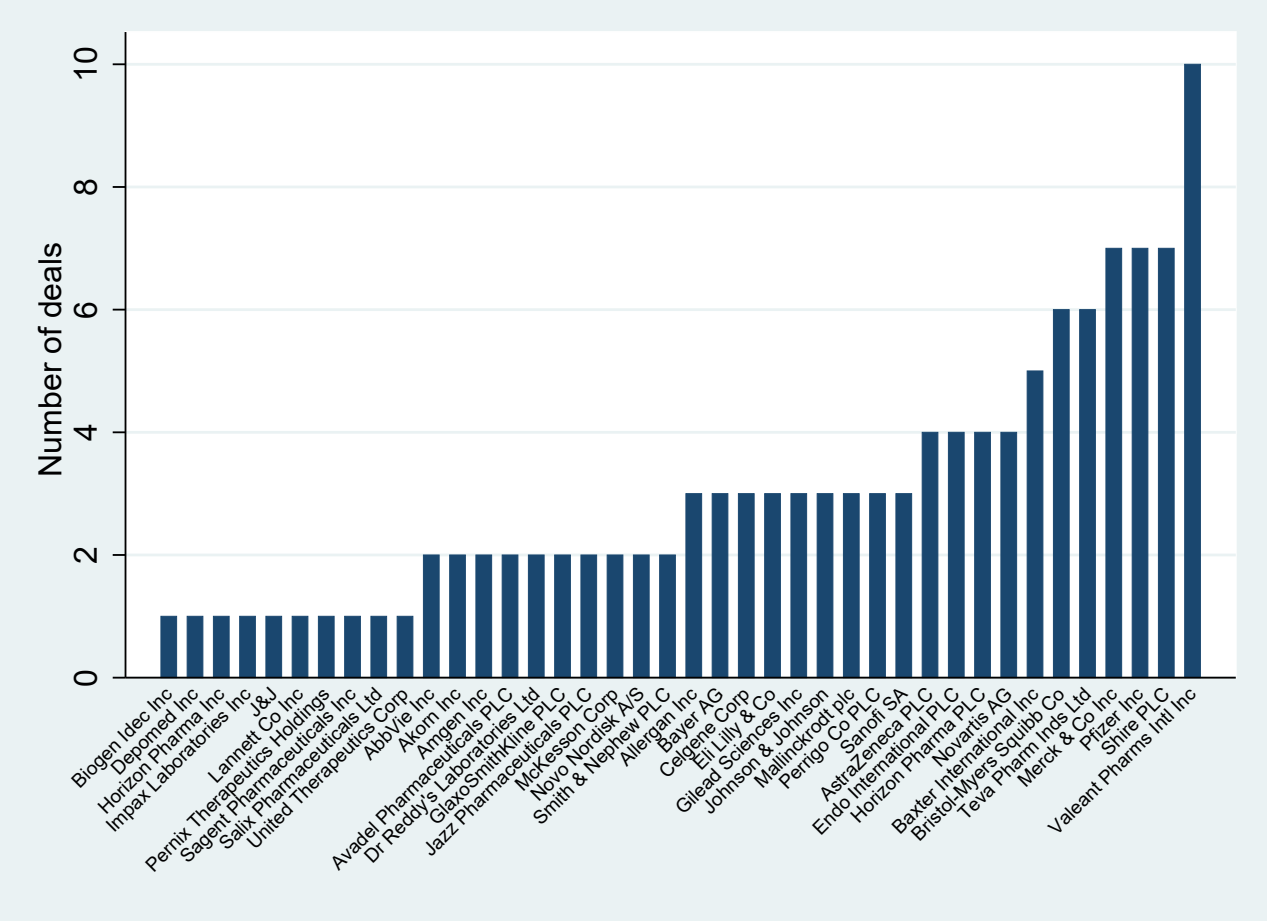

Figure 5
Number of Acquisitions per Firm
This figure presents the number of pharmaceutical mergers and acquisitions (M&As) by acquirer. Our merger sample consists of firms with M&A announcements in the Securities Data Corporation (SDC) database between 2013 and 2018 and with drug prices reported in the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS).

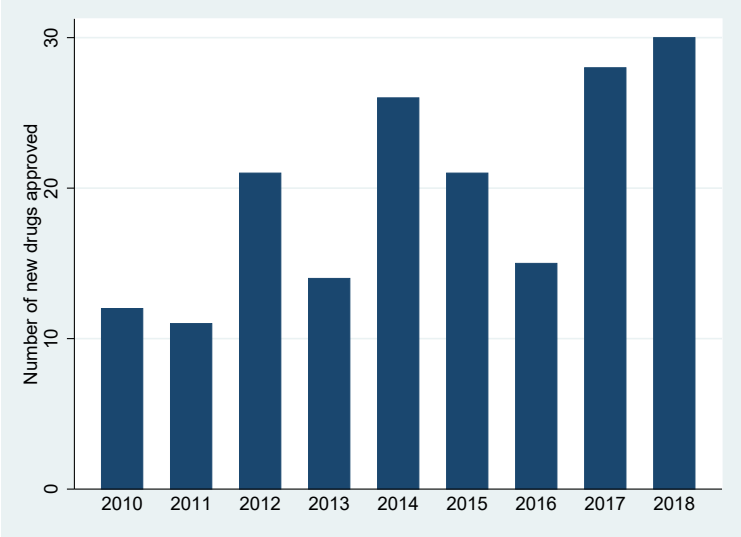

Figure 6
Number of New Drugs Approved
This figure presents the total number of US Food and Drug Administration (FDA) new drug approvals from 2010–2018. We restrict our definition of new drugs to Type 1 (new molecular entity) and Type 2 (new active ingredient) approvals.

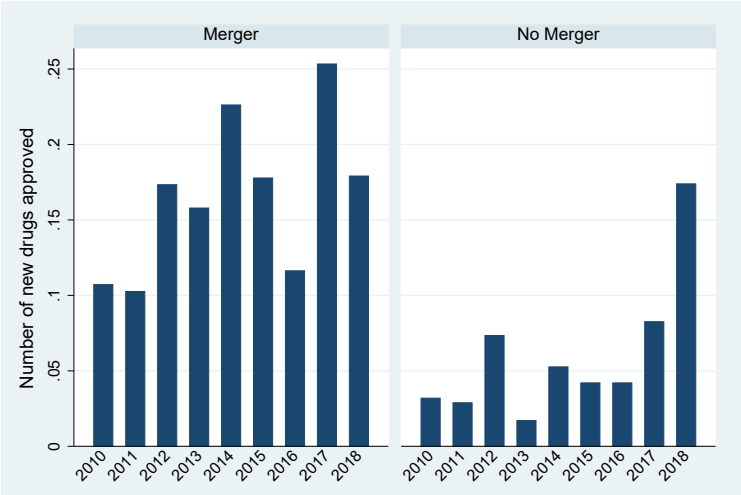

Figure 7
Average Drug Approval by Merger Activity
This figure presents the average number of US Food and Drug Administration (FDA) new drug approvals per firm from 2010–2018 by merger activity. "Merger" firms participate in at least one merger during our sample period. We restrict our definition of new drugs to Type 1 (new molecular entity) and Type 2 (new active ingredient) approvals.

Table 1. Drug Price Summary Statistics

This table presents summary statistics on our full sample of drug prices reported in the Centers for Medicare and Medicaid Services (CMS) survey between 2013 and 2018. *Price* is the National Average Drug Acquisition Cost (NADAC) per unit reported by surveyed retail pharmacies, averaged over the fiscal year of the drug manufacturer and expressed in 2018 dollars. $\Delta Price$ approximates the annual percentage change in *Price* as the natural log of the ratio of current to prior price. *Patent* (*Exclusivity*) is an indicator equal to one if the drug is under patent (exclusivity protected), as noted in the FDA database. *Brand name* (*Prescription*) is an indicator variable for brand name (prescription) drugs, created from the NADAC database. Panel A presents summary statistics for the full sample. Panel B bifurcates the sample on whether or not the producer of the drug conducted an acquisition during the year. Continuous variables are winsorized at the 1st and 99th percentiles.

Panel A: Full sample

	Mean	Std. Dev.	P10	Median	P90
Price	9.887	40.734	0.036	0.577	13.508
ΔPrice	-0.013	0.206	-0.223	-0.006	0.171
Patent	0.111	0.314	0	0	1
Exclusivity	0.025	0.158	0	0	0
Brand name	0.887	0.317	0	1	1
Prescription	0.838	0.368	0	1	1

Panel B: Merger firms versus no merger firms

	Merger		No merger			
	Mean	N	Mean	N	Difference	t-stat
Drug price	13.478	16,117	6.194	15,669	7.284	16.003
ΔPrice	0.004	12,996	-0.031	11,744	0.034	13.168
Patent	0.154	16,117	0.065	15,669	0.089	25.554
Exclusivity	0.037	16,117	0.013	15,669	0.024	13.802
Brand name	0.812	16,117	0.963	15,669	-0.150	-43.537
Prescription	0.798	16,117	0.879	15,669	-0.081	-19.611

Table 2. Pharmaceutical Mergers and Acquisitions

This table presents summary statistics of firms with M&A announcements in the Securities Data Corporation (SDC) database between 2013 and 2018 and with drug prices reported in the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS).

Panel A: Aggregate deal volume and values

Year	N	Average deal value ($ millions)	Total deal value ($ millions)
2013	13	2,056	26,722
2014	26	2,569	66,806
2015	38	4,584	174,197
2016	19	5,397	102,540
2017	12	1,467	17,603
2018	13	3,866	50,259
Total	121	3,621	438,126

Panel B: Deal characteristics

	Mean	Std. Dev.	P10	Median	P90
Deal value (in $millions)	3,621	7,604	125	774	9,693
Public target	0.331	0.472	0	0	1
Private target	0.339	0.475	0	0	1
Subsidiary	0.331	0.472	0	0	1
$CAR_{[-1,1]}$	0.012	0.066	-0.029	0.004	0.081
$CAR_{[-2,2]}$	0.014	0.072	-0.036	0.005	0.094

Table 3. Mergers and Drug Prices

This table presents regressions of price changes on merger activity at the drug-year level. The dependent variable is $\Delta Price$, which equals the natural log of the ratio of current to prior price. $Merger_t$ ($Merger_{t-1}$) is an indicator equal to one if the drug manufacturer conducted a merger or acquisition during fiscal year t (*t-1*). We include control variables, defined in the Appendix and product (NDC) fixed effects when noted. All continuous variables are winsorized at the 1st and 99th percentiles. We present robust standard errors.

	(1)	(2)	(3)	(4)
Merger_t	0.047***	0.013***		
	(14.612)	(3.677)		
Merger_{t-1}			0.018***	0.016***
			(6.333)	(5.427)
Ln(Assets)	-0.003*	-0.115***	-0.001	-0.120***
	(-1.753)	(-17.366)	(-0.652)	(-17.902)
Cash	0.073***	-0.125***	0.093***	-0.117***
	(5.825)	(-6.191)	(7.392)	(-5.863)
ROA	0.326***	0.329***	0.346***	0.316***
	(16.770)	(13.362)	(17.586)	(12.585)
Leverage	0.175***	0.073***	0.154***	0.077***
	(11.222)	(3.411)	(9.795)	(3.607)
Z-score	0.016***	0.002	0.015***	0.003
	(8.376)	(0.353)	(8.131)	(0.606)
Price_{t-1}	-0.003*	-0.325***	-0.003*	-0.326***
	(-1.782)	(-16.893)	(-1.921)	(-17.009)
Constant	-0.115***	1.411***	-0.121***	1.450***
	(-6.836)	(19.144)	(-7.124)	(19.600)
Observations	21,213	21,213	21,213	21,213
Adjusted R^2	0.0410	0.148	0.0330	0.149
Product fixed effects	N	Y	N	Y

Table 4. Difference-in-Differences Analyses

This table presents difference-in-differences analyses that explicitly control for selection into the merger sample using the Harford (1999) acquisition likelihood model. At the deal level, we match each "treated" acquiring firm with the "control" non-acquiring firm closest in predicted acquisition likelihood the year of the merger. The dependent variable is *Scaled price*, which equals the annual drug price divided by the initial drug price. *Post* corresponds to the years of and after the merger. Each model varies the number of included years around the merger, as noted. We include Table 3 control variables, defined in the Appendix, and product (NDC) fixed effects. All continuous variables are winsorized at the 1st and 99th percentile. We present robust standard errors.

	± 1 year	± 2 years	± 3 years	All years
	(1)	(2)	(3)	(4)
Post*Treatment	0.044***	0.071***	0.053***	0.057***
	(3.877)	(5.751)	(4.791)	(5.947)
Post	0.049***	0.080***	0.125***	0.145***
	(6.898)	(10.921)	(17.336)	(17.879)
Treatment	-0.012*	-0.031***	-0.028***	-0.031***
	(-1.759)	(-3.647)	(-1.460)	(-1.373)
Controls	Ln(Assets), Cash, ROA, Leverage, Z-score			
Observations	20,098	30,952	38,483	46,315
Adjusted R^2	0.037	0.062	0.075	0.080
Product fixed effects	Y	Y	Y	Y

Table 5. Do Deals that Concentrate Market Power the Most Impact Prices More?
This table presents difference-in-differences analyses with deal-level market power interactions. We restrict the sample to ± 2 years around the merger. These models explicitly control for selection into the merger sample using the Harford (1999) acquisition likelihood model. At the deal level, we match each "treated" acquiring firm with the "control" non-acquiring firm closest in predicted acquisition likelihood the year of the merger. The dependent variable is *Scaled price*, which equals the annual drug price divided by the initial drug price at year *t-2*. *Post* corresponds to the years of and after the merger. *Public target* equals one if the firm acquires at least one publicly traded target firm, as reported in SDC. *Large deal* equals one if the firm conducts at least one acquisition whose deal value exceeds our sample median. *Horizontal merger* equals one if the firm acquires at least one target sharing the same 4-digit SIC code. We include Table 3 control variables, defined in the Appendix, and product (NDC) fixed effects. All continuous variables are winsorized at the 1st and 99th percentile. We present robust standard errors.

	(1)	(2)	(3)
Public target*Post*Treatment	0.063***		
	(7.685)		
Large deal*Post*Treatment		0.049***	
		(6.323)	
Horizontal merger*Post*Treatment			0.060***
			(6.180)
Post*Treatment	0.044***	0.045***	0.034***
	(3.743)	(3.605)	(3.045)
Post	0.080***	0.078***	0.078***
	(11.120)	(10.637)	(10.726)
Public target	-0.015***		
	(-3.643)		
Large deal		-0.001	
		(-0.256)	
Horizontal merger			-0.037***
			(-5.430)
Treatment	-0.030***	-0.031***	-0.044***
	(-3.470)	(-3.758)	(-4.685)
Controls	Ln(Assets), Cash, ROA, Leverage, Z-score		
Observations	30,952	30,952	30,952
Adjusted R^2	0.065	0.065	0.064
Product fixed effects	Y	Y	Y

Table 6. Merger Announcement Returns

This table presents three-day and five-day cumulative abnormal returns (CARs) to acquirers around M&A announcements. Panel B segments on market power proxies. *Public target* equals one if the target firm is publicly traded, as reported in SDC. *Large deal* equals one if the deal value exceeds the sample median deal value. *Horizontal merger* equals one if the acquirer and target share the same 4-digit SIC code. t-statistics are presented below.

Panel A: Full sample

	$CAR_{[-1,1]}$	$CAR_{[-2,2]}$
All deals	0.012*	0.014*
	(1.83)	(1.94)

Panel B: Subsample analyses

	$CAR_{[-1,1]}$	Difference	$CAR_{[-2,2]}$	Difference
By public target status:				
Public target	0.023**	0.016	0.029***	0.023
	(2.228)	(1.114)	(2.540)	(1.495)
Non-public target	0.007		0.007	
	(0.831)		(0.728)	
By target size:				
Large	0.019**	0.013	0.019**	0.009
	(2.320)	(1.018)	(2.201)	(0.632)
Small	0.006		0.010	
	(0.543)		(0.826)	
By deal type:				
Horizontal	0.025***	0.034***	0.031***	0.042***
	(2.984)	(2.556)	(3.310)	(2.978)
Diversifying	-0.008		-0.012	
	(-0.848)		(-1.125)	

Table 7. Cross-section Variation in Mergers' Impact on Prices at the Drug Level
This table presents difference-in-differences analyses with drug-level market power interactions. We restrict the sample to ± 2 years around the merger. These models explicitly control for selection into the merger sample using the Harford (1999) acquisition likelihood model. At the deal level, we matched each "treated" acquiring firm with the "control" non-acquiring firm closest in predicted acquisition likelihood the year of the merger. The dependent variable is *Scaled price*, which equals the annual drug price divided by the initial drug price at year *t-2*. *Post* corresponds to the years of and after the merger. *Drug overlap* equals one if the target firm produces a drug from the same class or specializes in drugs curing the same symptom. *Patent* (*Exclusivity*) is an indicator equal to one if the drug is under patent (exclusivity protected), as noted in the FDA database. We include Table 3 control variables, defined in the Appendix, and product (NDC) fixed effects. All continuous variables are winsorized at the 1st and 99th percentile. We present robust standard errors.

	(1)	(2)	(3)
Drug overlap*Post*Treatment	0.035**		
	(2.441)		
Patent*Post*Treatment		-0.111***	
		(-8.439)	
Exclusivity*Post*Treatment			-0.122***
			(-5.143)
Post*Treatment	0.062***	0.091***	0.077***
	(5.430)	(6.891)	(6.186)
Post	0.080***	0.048***	0.071***
	(10.925)	(6.148)	(9.755)
Treatment	-0.017**	-0.034***	-0.032***
	(-2.316)	(-3.982)	(-3.798)
Patent*Post		0.176***	
		(12.695)	
Exclusivity*Post			0.165***
			(7.251)
Controls	Ln(Assets), Cash, ROA, Leverage, Z-score		
Observations	30,952	30,952	30,952
Adjusted R^2	0.064	0.070	0.064
Product fixed effects	Y	Y	Y

Table 8. Pharmaceutical Mergers and Innovation

This table models innovation around mergers from using difference-in-differences analyses that explicitly control for selection into the merger sample using the Harford (1999) acquisition likelihood model. At the deal level, we match each "treated" acquiring firm with the "control" non-acquiring firm closest in predicted acquisition likelihood the year of the merger. *Post* corresponds to the years of and after the merger. We vary the number of years included around the merger, as noted. The dependent variable in Models (1)–(3) equals the number of new drugs approved. The sample spans 2010 to 2018 and includes firms with any type of drug approval from the FDA during our sample period. We restrict our definition of innovation to Type 1 (new molecular entity) and Type 2 (new active ingredient) FDA new drug approvals. The dependent variable in Models (4)–(6) is research and development (R&D) expenses, divided by total assets. This sample matches our prior sample and spans 2013 to 2018. Control variables are defined in the Appendix. All continuous variables are winsorized at the 1st and 99th percentile. Observations are at the firm-year level. We include firm and year fixed effects in all models and present robust standard errors.

	Drug approval			R&D		
	± 2 years	± 3 years	All years	± 2 years	± 3 years	All years
	(1)	(2)	(3)	(4)	(5)	(6)
Post*Treatment	-0.049	-0.026	-0.031	-0.000	-0.005	-0.010
	(-0.879)	(-0.683)	(-0.857)	(-0.009)	(-0.570)	(-1.169)
Post	0.019	-0.005	0.008	0.003	0.004	0.005
	(0.402)	(-0.154)	(0.302)	(0.396)	(0.638)	(0.893)
Treatment	0.048	0.020	0.017	0.001	0.003	0.006
	(0.925)	(0.710)	(0.845)	(0.156)	(0.518)	(1.172)
Ln(Assets)	0.015	0.011	0.008	-0.005	-0.006	-0.005
	(0.366)	(0.234)	(0.197)	(-0.460)	(-0.629)	(-0.558)
Cash	-0.191	-0.155	-0.157*	0.005	-0.006	-0.014
	(-1.573)	(-1.375)	(-1.751)	(0.342)	(-0.368)	(-0.797)
ROA	0.134	0.170	0.092	-0.140***	-0.133***	-0.123***
	(0.521)	(0.682)	(0.493)	(-3.148)	(-3.220)	(-4.357)
Leverage	0.051	0.106	0.114	-0.111***	-0.112***	-0.109***
	(0.400)	(0.850)	(1.070)	(-3.067)	(-3.404)	(-3.632)
Z-score	-0.023	-0.038	-0.014	0.013	0.012	0.012**
	(-0.862)	(-1.305)	(-0.681)	(1.656)	(1.476)	(2.122)
Observations	1,206	1,569	2,335	1,206	1,569	2,335
Adjusted R^2	0.387	0.412	0.400	0.787	0.769	0.717
Firm & year FE	Y	Y	Y	Y	Y	Y

Table 9. Drug Approval and Acquisition Likelihood: Do Mergers "Pull" Innovation? This table models the likelihood of being acquired as a function of innovation. The dependent variable equals one if the firm is a target in the current year or subsequent year, two years, or three years, as noted. The variable of interest is *Drug approval*, which equals the number of new Type 1 (new molecular entity) and Type 2 (new active ingredient) FDA drug approvals. The sample spans 2010 to 2018 and includes firms (i) with any type of drug approval from the FDA during our sample period or (ii) categorized as operating in the Fama-French 48 Healthcare, Medical Equipment, Pharmaceutical Products, and Chemicals industries based 4-digit SIC codes in Compustat. Control variables from Compustat are measured in year *t-1* and defined in the Appendix. All continuous variables are winsorized at the 1st and 99th percentile. Observations are at the firm-year level. We include firm and year fixed effects in all models and present robust standard errors.

	Target_t		Target_{t+1}		Target_{t+2}		Target_{t+3}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drug approval	0.009	0.019	-0.005	-0.019	0.009	0.010	0.002	-0.001
	(0.638)	(0.954)	(-0.511)	(-1.284)	(0.840)	(0.584)	(0.221)	(-0.074)
Ln(Assets)		-0.001		0.009*		0.010**		-0.004
		(-0.181)		(1.695)		(2.025)		(-0.793)
Cash		-0.036***		-0.041***		0.012		0.013
		(-3.009)		(-3.238)		(0.763)		(1.222)
ROA		-0.000		-0.001		-0.001		0.001
		(-0.604)		(-0.757)		(-1.354)		(0.559)
Leverage		-0.001		0.000		-0.001		0.001
		(-0.859)		(0.038)		(-0.727)		(0.996)
Z-score		0.000		-0.000		-0.000		0.000
		(0.346)		(-0.000)		(-0.577)		(0.376)
Market-to-book		-0.000		0.000***		-0.000		-0.000
		(-0.802)		(2.900)		(-0.379)		(-0.475)
Tangibility		-0.079**		-0.087**		0.025		0.025
		(-2.149)		(-2.341)		(0.780)		(0.864)
Sales growth		-0.000		-0.000		-0.000		0.000
		(-0.852)		(-1.472)		(-0.884)		(0.087)
Observations	8,102	2,081	8,102	2,081	8,102	2,081	8,102	2,081
Adjusted R^2	0.004	0.085	0.001	0.077	0.001	0.065	0.002	0.036
Firm & year FE	Y	Y	Y	Y	Y	Y	Y	Y

Appendix: Variable Definitions, Summary Statistics, and M&A Industry Composition

A.1 NADAC and hand-collected drug characteristics

Brand-name: An indicator equal to one for brand-name drugs.

Drug approval: The total number of Type 1 (new molecular entity) and Type 2 (new active ingredient) drug approvals during the fiscal year.

Drug overlap: An indicator equal to one if the target firm produces a drug from the same class or specializes in drugs curing the same symptom.

Exclusivity: An indicator equal to one if the drug is exclusivity protected, as noted in the FDA database.

Patent: An indicator equal to one if the drug is under patent, as noted in the FDA database.

Prescription: An indicator equal to one for prescription drugs.

Price: The National Average Drug Acquisition Cost (NADAC) per unit, averaged over the fiscal year of the drug manufacturer and expressed in 2018 dollars.

ΔPrice: The annual percentage change in drug price, calculated as the natural log of the ratio of the current year price to prior year price.

A.2 SDC deal characteristics

Deal value: The total transaction value of all acquisitions of a firm conducted during a given year.

Diversifying: An indicator equal to one if the acquirer and target have different 4-digit SIC code.

Horizontal: An indicator equal to one if the firm acquires at least one target sharing the same 4-digit SIC code.

Large deal: An indicator equal to one if at least one deal value during the year exceeds the median deal value of pharmaceutical mergers in our sample.

Merger$_t$: An indicator equal to one if the drug manufacturer conducted a merger or acquisition during the current fiscal year.

Merger$_{t-1}$: An indicator equal to one if the drug manufacturer conducted a merger or acquisition during the prior fiscal year.

Private: An indicator equal to one if the target being acquired is private.

Public: An indicator equal to one if the firm acquires at least one publicly traded target firm.

Subsidiary: An indicator equal to one if the target being acquired is subsidiary of another firm.

A.3 Compustat firm characteristics

Cash: Cash and cash equivalents, scaled by total assets.

Leverage: The sum of long-term debt and debt in current liabilities divided by the book value of total assets.

Ln(Assets): The natural log of total assets.

Market-to-book: Total assets less book value of equity plus market value of equity, divided by total assets.

R&D: Research and development expense, scaled by total assets.

ROA: Operating income before depreciation (EBITDA) divided by the book value of total assets.

Sales growth: Percentage change in sales.

Tangibility: Net property, plant and equipment scaled by total assets.

Z-score: Modified Altman's (1968) Z-score, defined as (1.2*Working capital + 1.4*Retained earnings + 3.3*EBIT + 0.999*Sales)/Total assets.

Table A1. Firm-level Summary Statistics

This table presents summary statistics of pharmaceutical companies with drug prices reported in the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS) between 2013 and 2018. Firm characteristics are based on Compustat data and defined in the Appendix. Panel A presents summary statistics for the full sample. Panel B bifurcates the sample on whether or not the producer of the drug conducted an acquisition during the year. All variables are winsorized at the 1st and 99th percentiles.

Panel A: Full sample

	Mean	Std. Dev.	P10	Median	P90
Ln(Assets)	9.784	1.714	7.209	10.424	11.739
Cash	0.197	0.192	0.039	0.138	0.407
ROA	0.040	0.092	-0.005	0.041	0.123
Leverage	0.344	0.180	0.100	0.373	0.583
Z-score	1.790	1.290	0.556	1.309	3.883

Panel B: Merger firms versus no merger firms

	Merger		No merger			
	Mean	N	Mean	N	Difference	t-stat
Ln(Assets)	10.287	15,736	9.154	12,742	1.133	58.093
Cash	0.210	14,894	0.187	12,616	0.023	9.170
ROA	0.044	15,736	0.031	12,742	0.013	8.578
Leverage	0.321	15,736	0.376	12,742	-0.055	-25.267
Z-score	1.711	15,691	1.817	12,727	-0.105	-5.971

Table A2. Industry Composition

This table presents industry composition based on 4-digit SIC codes of firms with M&A announcements in the Securities Data Corporation (SDC) database between 2013 and 2018 and with drug prices reported in the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS).

	Acquirer SIC							
Target SIC	Med Chem (2833)	Pharma Prep (2834)	Bio Prod (2836)	Chem & Chem Prep (2899)	Surgical (3841)	Ortho & Pros (3842)	Wholesale Drugs (5122)	Bio Research (8731)
Med Chem (2833)	0	1	0	0	0	0	0	0
Pharma Prep (2834)	1	63	2	2	3	0	0	1
Bio Products (2836)	1	24	4	0	1	0	0	0
Ag Chem (2879)	0	0	0	1	0	0	0	0
Electronic Comp's (3679)	0	1	0	0	0	0	0	0
Surgical (3841)	0	2	0	0	0	1	0	0
Electro Med (3845)	0	2	0	0	0	0	0	0
Opthalmic (3851)	0	1	0	0	0	0	0	0
Med, Dent, & Hosp (5047)	0	0	0	0	0	1	0	0
Wholesale Drugs (5122)	0	2	0	0	0	0	1	0
Drug Stores (5912)	0	0	0	0	0	0	1	0
Comp Sys Design (7373)	0	0	0	0	1	0	0	0
Bio Research (8731)	0	4	0	0	0	0	0	0