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

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Abstract

Using novel data from the pharmaceutical industry, we study product prices and innovation around mergers. Exploiting within-deal variation in product market consolidation, we show prices increase more within drugs in consolidating markets than within matched control drugs. Estimates indicate a 2% average price effect that persists for about one year. Price increases are more pronounced for drugs in concentrated markets and without generic competition. Examination of trade-offs reveals these deals generate significant shareholder value and spur labeling and other manufacturing-related innovation, but not new drug approvals.

JEL Codes: G34, G30, O30, L11
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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 (Sheen, 2014). Mergers also result in technology sharing, which stimulates innovation (Bena and Li, 2014). Alternatively, some mergers may concentrate market power and suppress competition (Cunningham, Ederer, and Ma, 2021). Reduced competition allows prices to drift upwards and innovation to wane.

This study examines the effect of industry consolidation on product prices and innovation in the pharmaceutical industry. Understanding the drivers of prices and innovation in the pharmaceutical industry is valuable because its products directly and undoubtedly contribute to social welfare. For this reason, policymakers make ensuring access to pharmaceutical products a top priority. Rising drug prices in the US prompted the February 2019 hearing during which pharmaceutical executives testified before the Senate Finance Committee and the July 2021 Senate Antitrust Subcommittee hearing with industry experts and patient advocates. During the latter, Senator Mike Lee argued that "innovation, competition, and affordable prices are arguably more important to prescription drug markets than almost any other consumer market we can think of." Therefore, determining if consolidation in this industry tends to enable or decelerate rising prices and new drug development informs policy debates at the highest level of politics.

In addition to the pharmaceutical industry being important in its own right, it represents an ideal laboratory for testing the effects of mergers on product markets in general. To begin, comprehensive and reliable pharmaceutical price and innovation data are available at the product-level, as opposed to the firm- or industry-level. Another advantage of this industry is its standardized product classification systems, which allow us to pinpoint shifts in product market competition around mergers joining producers of competing products. Finally, in other product markets, quality also changes around mergers, conflating the effects of mergers on price. In the pharmaceutical industry, however, quality is held constant because product codes correspond to precise doses of specified ingredients. These unique features of the pharmaceutical industry thus enable more precise identification of the effects of mergers on product market outcomes than in other industries.

Are pharmaceutical mergers ultimately associated with cost efficiencies or, instead, price increases due to the concentration of market power? To test this research question, 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 sample to 2013–2019. NADAC survey drug prices represent the average unit cost of drugs to retail pharmacies, the customers of pharmaceutical manufacturers. When we combine these price data with M&A announcements from the Securities Data Corporation (SDC), we identify 202 pharmaceutical deals, worth $687 billion total, in which the acquirer produces drugs with available price data.

Our identification strategy hinges on exploiting within-deal variation in expected product market consolidation. We construct a difference-in-differences (DID) setting comparing price changes of drugs whose product markets consolidate with simultaneous price changes of matched control drugs whose product markets are not directly affected by the merger. Consolidation should occur when the acquirer and the target share a product market. We define product markets using Anatomical Therapeutic Chemical (ATC) codes from the World Health Organization (WHO). To control for observable differences between acquirer drugs with versus without consolidating product markets, we match on prescription/over-the-counter and brand name/generic statuses using NADAC data and on patent and exclusivity rights coverage using data from the US Food and Drug Administration (FDA) "Orange Book." We then select the matched control product with the closest lagged reimbursement volume, a proxy for demand, from Medicaid's State Drug Utilization Database (SDUD). We confirm that there are no significant differences in pre-merger price trends across sample and control products, consistent with the parallel trends assumption being satisfied.

We then construct our DID regression with the natural logarithm of drug prices as the dependent variable. Our coefficient of interest corresponds to the interaction of an indicator variable for drugs with product market consolidation and an indicator corresponding to post-merger time periods. It measures the difference in (approximate percentage) price changes around mergers between drugs whose product markets consolidate and matched control drugs whose product markets are unaffected by the merger. Being our DID sample is constructed at the deal level, we "saturate" product and time fixed effects with deal indicators. Product-deal-level fixed effects net out differences in price levels across products, and deal-event-time facilitate price comparison with drugs produced by the same acquiring firm at the same time.

Prices increase significantly more for acquirer drugs whose product market overlaps with a product market of the target firm than for matched control drugs. Drug prices increase 2.2%

more at time of the merger announcement and for approximately one year after the merger if the drug belongs to a product market shared by the acquirer and target. Closer analysis of the price dynamics reveals that price trends are not significantly different across drugs from affected product markets and their matched control drugs leading up to the merger (consistent with parallel trends) but diverge as early as the quarter of the merger. Quick price responses are consistent with anecdotal evidence suggesting that price changes around mergers can be immediate.[1] A significant, positive price difference continues for approximately one year post-merger. Overall, our findings show acquiring pharmaceutical firms raise prices more within product markets in which they gain market power. These results are inconsistent with synergy gains from mergers benefiting customers.

Our findings withstand a battery of robustness tests. We first verify the robustness of our results to alternative methods of identifying acquirer/target product overlap. We exploit the nested, hierarchical nature of the ATC code system to narrow our definition of acquirer/target overlap. Our baseline tests identify overlap using therapeutic subgroups from 3-digit or "2^{nd} level" ATC codes, but in robustness tests we redefine overlap using codes for pharmacological subgroups ("3^{rd} level"), chemical subgroups ("4^{th} level"), and the chemical substance ("5^{th} level"). Not only do our main findings withstand alternative overall definitions, but we also observe that price differences expand with product similarity. For instance, when we narrow our overlap threshold to the highest ATC code level, our coefficient of interest increases, implying price effects up to 4.1%. These finding provide us with some confidence our results are not spurious because we would expect price differences to increase with product similarity if they are driven by gains in market power. We further examine our estimates' sensitivity to constructing product markets based on a drug's mechanism of action ("MoA") or established pharmacological class ("EPC"). Our results hold. We also verify robustness to alternate samples of drugs as well as an alternate pool of control drugs: We eliminate drugs involved in multiple mergers in close proximity for our sample and exclude drugs associated with other mergers from controls. We obtain estimates similar to those in our baseline regressions.

[1]For example, Celgene increased the price of its top selling drug Revlimid 3.5% on the day its planned deal with Bristol-Myers Squibb was announced. ("Pharmaceutical Industry CEOs Face Senate Hearing on Drug Prices," *The Wall Street Journal*, February 25, 2019.) Another example involves Ovation Pharmaceuticals' Indocin IV price hike from $109 per treatment to $1,500 per treatment two days after purchasing competing drug NeoProfen from Abbott Laboratories. (Klobuchar, Amy, 2020, *Antitrust: Taking on Monopoly Power from the Gilded Age to the Digital Age* (Alfred A. Knopf, New York)).

Next, we investigate cross-sectional heterogeneity in price changes around acquisitions using a triple differences model. If market power drives the relation between mergers and drug prices, then price increases should be greater within less competitive product markets, in which firms could more easily exert market power. Indeed, prices increase more within markets with fewer participants and with no generic competitors, suggesting that consolidation within less competitive markets is more detrimental to consumers. In fact, we observe no price effect of mergers within disperse product markets. In addition to providing further evidence that our results are not spurious, these findings identify the types of product markets—those lacking competition, specifically from generics—most susceptible to price hikes around mergers.

Our results suggest pharmaceutical mergers are associated with significant welfare costs in the form of higher drug prices. We conclude our study by quantifying two potential trade-offs. The first involves shareholder value creation. To study changes in shareholder wealth, we examine cumulative abnormal returns (CARs) around acquisition announcements, for all pharmaceutical mergers in our sample and for subsamples bifurcated on proxies for market power consolidation. On average pharmaceutical merger announcements are associated with positive and significant five-day acquirer CARs of 1.5%, consistent within substantial shareholder value creation. Of interest, these shareholder gains are greater around deals that consolidate market power the most: Abnormal returns around horizontal mergers exceed those around diversifying mergers, and returns are significantly greater within deals with more economically meaningful acquirer/target product market overlap. If mergers generate shareholder wealth through synergistic cost-cutting such as eliminating redundancies in administrative or distribution, then we would not expect merger announcement returns to vary with proxies for market power consolidation, as we find. Our findings instead lend support to the story that mergers benefit shareholders more when they increase market power.

The second trade-off we examine is whether pharmaceutical mergers spur innovation. We depart from traditional innovation metrics based on patents because pharmaceutical patents are subject to concerns regarding "thicketing," applying for multiple patents on the same drug to block competition.[2] We thus create alternative innovation proxies based on FDA New Drug Approval data. Unlike prices, innovation metrics are measured at the firm level. We must adjust our

[2]Pharmaceutical industry experts claim patents fail to represent "true innovation." ("Pharma patent owners in the US are under pressure like they have never been before." *IAM*. November 26, 2018.)

methodology accordingly. We create an innovation DID model analogous to our price models, except comparing innovation changes within acquiring firms and to innovation changes within matched non-acquiring firms. To control for selection into acquisition activity, we pair each acquiring firm with the non-acquiring firm closest in propensity to acquire, estimated using the Harford (1999) acquisition likelihood model. We run regressions at the deal-level, including deal and deal-event-time fixed effects as well as time-varying firm-level controls.

We find some evidence that new drug applications increase more within acquiring firms than control firms. This increase, however, is driven by follow-on applications, the majority of which relate to changing an existing product's label or manufacturing process. Initial new drug applications—which include arguably the most innovative applications, such as applications for FDA approval of new molecules and new active ingredients—do not increase around mergers. Because developing new drugs is a risky and lengthy process, we extend our sample to examine new drug applications up to ten years post-merger. Even over this longer time frame, we continue to find no difference in initial new drug application patterns between acquiring and matched non-acquiring firms.

This study contributes to the national debate on rising drug prices by quantifying the aggregate effects of mergers on pharmaceutical prices. Our findings suggest that, even within this important and highly regulated industry, mergers are associated with significant price increases. A back-of-the-envelope estimate suggests that mergers contribute to $1.5 billion in extra US government spending per year on prescription drugs alone.[3] Importantly, we also show that pharmaceutical mergers are not associated with an offsetting uptick in new drug approval, a common justification for high drug prices.[4] Our findings therefore inform policy around drug pricing by proposing careful antitrust enforcement as one potential remedy for rising drug prices. Even so, the welfare costs from higher drug prices associated with these mergers should be weighed against their benefits to the owners of the firm as well as the costs associated with increasing enforcement.

We also contribute to the academic literature on the winners and losers in mergers and acquisitions. Many other studies focus on specific industries and document positive price effects,

[3] In 2019 prescription drug spending for Medicare Part B, Medicare Part D, and Medicaid reached $37 billion, $183 billion, and $69 billion, respectively, for a total of $289 billion. In our sample drugs involved in a merger impacting their product market account for of 23.1% reimbursement dollars, and these drugs are associated with 2.2% prices increases. This translates into $1.5 billion (0.231∗0.022∗$289 billion) in extra US government spending per year.

[4] 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)

consistent with our findings. 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 Reenen, 2019; Dafny, 2009; Vita and Sacher, 2001). Rival hospitals increase prices around mergers as well (Dafny, 2009). Eliason, Heebsh, McDevitt, and Roberts (2020) show how recent consolidation within the dialysis industry is associated with increased reimbursements but worse patient outcomes, consistent with a decline in value. Deposit rates decline following bank mergers, though these adverse price effects are temporary (Prager and Hannan, 1998; Focarelli and Panetta, 2003; Garmaise and Moskowitz, 2006). Around mergers petroleum companies increase oil prices (Hosken, Silvia, and Taylor, 2011), especially wholesale prices (Taylor and Hosken, 2007). Mergers are also associated with price hikes of academic journals (McCabe, 2002), household appliances (Ashenfelter, Hosken, and Weinberg, 2013), and beer (Miller and Weinberg, 2017).

In contrast, several studies find null effects or product price declines around mergers. Spienza (2002) documents that interest rates charged by banks decrease after consolidation, but, as market shares increase, these efficiency gains disappear and credit supply to small borrowers declines. Reexamining the price effects of airline mergers, Luo (2014) finds no significant price changes after the merger of Delta Airlines and Northwest Airlines. Using *Consumer Reports* data, Sheen (2014) finds that, when two firms selling common products merge, the quality of the related products converges and the price drops, though these efficiency gains take two to three years to be realized. In sum, whether market power or efficiency gains dominate in mergers is an unresolved issue and likely depends on the industry and product market in question.

The impact of mergers on stakeholders also appears sensitive to research method and time period. For example, a standard method to quantify changes in market power around mergers involves studying stock returns to merging firms, rivals, customers, and suppliers around merger announcements. Although Fathollahi, Harford, and Klasa (2022) 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, Eckbo (1983) and Stillman (1983) examine rival firms' returns around merger announcements and do not find evidence consistent with mergers creating market power. Similarly, when 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.

We contribute to the above literature by quantifying changes in product prices, innovation, and shareholder value around mergers in a large industry at the center of national policy debates—the pharmaceutical industry. Given the substantial welfare benefits of pharmaceutical products, understanding their price determinants is valuable in its own right. Moreover, relative to other industries, the pharmaceutical industry has the advantages of granular product-level price data, products with relatively time-invariant quality, a widely-accepted product grouping system, and unique innovation milestones. These industry attributes thus allow us to better identify changes in product prices, innovation, and shareholder value around mergers.

Our paper closely relates to, but is nonetheless distinct from, several recent studies on pharmaceutical mergers. Haucap, Rasch, and Stiebale (2019) and Cunningham, Ederer, and Ma (2021) both document declines in innovation around pharmaceutical mergers. Studying large pharmaceutical mergers in Europe, Haucap, Rasch, and Stiebale (2019) show a drop in patent applications by merging firms and their rivals, albeit to a lesser extent. Discrepancies in our results may likely stem from different merger samples and time periods as well as different innovation metrics. While Haucap, Rasch, and Stiebale (2019) do not include acquisitions of small biotech firms, Cunningham, Ederer, and Ma (2021) explicitly focus on drugs in the early stages of development. They show evidence of firms acquiring competing drug manufacturers to discontinue development and thus squelch competition. These so-called "killer acquisitions" constitute between 5.3% and 7.4% of pharmaceutical mergers, according to their most conservative estimates. Our study complements theirs because we instead mainly focus on drug *prices*. In a subsequent working paper, Hammoudeh and Nain (2020) also study pharmaceutical mergers. Although their univariate tests are consistent with price increases around mergers, as we find, parts of their multivariate analysis suggest reductions in price. The most likely explanations for these results are differences in data sources and empirical strategies.[5] Other unique features of our study include our examinations of changes in

[5]Hammoudeh and Nain (2020) estimate prices using Medicaid reimbursements from states to pharmacies. States historically overpaid for reimbursements, which prompted the CMS to collect price estimates using the NADAC survey, our data source. Furthermore, we model the effect of mergers on prices and innovation using difference-in-differences specifications whereas Hammoudeh and Nain (2020) use OLS regressions. They infer acquirer/target product market overlap using textual analysis to calculate similarity scores between descriptions of therapeutic area

new drug applications and shareholder value around mergers.

The remainder of the paper is organized as follows. Section 1 formalizes our hypotheses. Section 2 describes our data sources and sample construction and presents summary statistics. Section 3 motivates our identification strategy and presents our main results along with robustness tests and cross-sectional analyses. Sections 4 and 5 examine tradeoffs to higher drug prices, namely, shareholder value creation and enhanced innovation. Section 6 concludes.

1 Hypothesis Development

The M&A literature documents evidence of mergers creating shareholder value (Betton, Eckbo, and Thorburn, 2008). The two primary sources of this value creation are efficiency gains or "synergies" and enhanced market power. Several studies find support for post-acquisition efficiency gains using accounting performance or plant-level productivity data. For example, Healy, Palepu, and Ruback (1992) and Heron and Lie (2002) show that merged firms exhibit superior post-merger operating performance relative to industry peers. 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). Hoberg and Phillips (2010) show that, when acquirers merge with a target whose products are similar to theirs but different from their rivals' products, the merger will help with product differentiation and thus improve profit margin. Hammoudeh and Nain (2020) also show product market similarity increases the likelihood of a deal. 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. Further, Bena and Li (2014) show that pre-merger technology overlap has a positive effect on future innovation, consistent with mergers improving innovation capabilities

and mechanism of action whereas we directly match drugs using ATC codes and MoA or EPC for robustness. Finally, we match affected drugs to control drugs within the same firms with identical characteristics; their controls come from non-acquiring firms.

through synergies.

These studies motivate our first hypothesis, the *Synergistic Gains Hypothesis*. Because mergers can lead to synergistic gains through the elimination of redundancies and the sharing of technology, firms may pass along gains to consumers in the form of lower prices. The empirical predictions associated the *Synergistic Gains Hypothesis* are that product prices decline around mergers. Because redundancies are more likely when firms making similar products merge, price declines should be greatest within product markets shared across the bidder and target. The other empirical prediction is that technology sharing should lead to more innovation.

Alternatively, mergers strengthen market power, which can negatively impact customers and suppliers. For example, using the industry-level Producer Price Index from the Bureau of Labor Statistics, Fathollahi, Harford, and Klasa (2022) document price increases around horizontal mergers, particularly within industries with high product similarity, and Bhattacharyya and Nain (2011) show mergers allow firms to exert price pressure on suppliers.

Thus, our second hypothesis, the *Market Power Hypothesis*, states that, because mergers consolidate market power, they may adversely impact stakeholders. The broad prediction of the *Market Power Hypothesis* is that merging firms exploit enhanced market power by charging higher prices to customers. Price impacts should be greatest within product markets in which market power is consolidated the most, specifically, product markets the acquirer and target have in common.

Because the synergies and enhanced market power are not mutually exclusive, our empirical estimates capture the *net* impact of mergers on customers and reveal which force dominates.

2 Data Sources, Sample Construction, and Summary Statistics

This section describes the construction of our samples of drug prices, other drug features, innovation metrics, and mergers and acquisitions. We also summarize and discuss our main variables.

2.1 Drug price data and trends

Our drug price proxy is based on data from the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS). Prior to the NADAC survey, the CMS allowed states to independently estimate drug costs for Medicaid reimbursements.

Most states based cost estimates on average wholesale prices (AWP). In 2011 the Office of Inspector General reported that AWP-based reimbursement rates were "fundamentally flawed," leading to inflated estimates, and recommended a single national benchmark that more accurately reflects actual pharmacy costs and thereby "eliminate[s] States' reliance on the inflated published prices that cause Medicaid and its beneficiaries to pay too much for certain drugs."[6] To develop a credible pricing benchmark, in 2012 the CMS began contracting with Myers and Stauffer, a national certified accounting firm, to survey retail pharmacies. 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.[7] As shown in Figure 1, NADAC prices are derived from invoices from pharmaceutical manufacturers and wholesalers to pharmacies and do not reflect off-invoice discounts or rebates.

The NADAC therefore represents the average cost retail pharmacies pay for drugs. This measure of drug prices clearly has advantages and disadvantages. The NADAC is ideal for testing our research question—how mergers of pharmaceutical manufacturers impact customers—because retail pharmacies are drug makers' customers. The NADAC is less appropriate for precisely quantifying the price consumers ultimately pay, which depends on retail pharmacies' profit margins as well as patients' insurance coverage. Even so, it seems plausible to assume that pharmacies will pass along at least a portion of price changes to end users. We also note that CMS reimbursement rates are based on NADAC prices, and all taxpayers bear the cost of government reimbursements.

The NADAC survey results allow for calculation of retail pharmacies' average acquisition cost per unit at the National Drug Code (NDC) level. Visual inspection of the data suggests that "units" generally represent one individual tablet or capsule, tube of cream/gel/ointment, bottle of spray, or vial of medicine, ordinarily associated with a specified dose. We are careful to ensure quantities remain constant over time.

Because the NADAC survey reports unit price data with irregular frequencies, we aggregate prices to the quarterly level by weighting the NADAC by the number of days between reported

[6] https://oig.hhs.gov/oei/reports/oei-03-11-00060.pdf

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

price changes. Figure 2 presents an example of our quarterly price measure using 2018Q3 NADAC prices for the 40 mg Lipitor tablet. First, we calculate the number of days between effective dates associated with each NADAC price and divide by the number of days in the quarter to obtain a time weighting for each price. For example, a new price ($14.83) is posted at the beginning of the quarter on July 1, 2018. We assume this price is valid for 15 days until the next price ($13.55) becomes effective on July 16, 2018. This second price is then effective for 37 days until August 22, 2018, when the final price ($13.65) is posted. Our weights are thus 0.163 (15/92), 0.402 (37/92), and 0.435 (40/92). We multiply each price by its weight and sum the weighted prices to obtain the time-weighted average quarterly price for each drug product. Finally, we adjust for inflation using the CPI and express all prices in 2019 dollars. The availability of drug prices from the NADAC survey restricts our drug price sample period to 2013–2019. The full NADAC sample consists of 805,155 drug-quarter observations between 2013-2019 associated with 41,395 unique NDCs.

Figure 3 graphs the average annual, inflation-adjusted drug price per unit. It illustrates a strong, upward trend. After inflation adjustments, drug prices within the full sample average $6.46 per unit in 2013 but $9.91 per unit by 2019. To ensure observed price increases are not driven by market entry and exit, we examine price trends within a balanced sample of drugs with price data available all seven years. Indeed, prices increase monotonically within the balanced sample as well. For the balanced sample, inflation-adjusted unit drug prices average $6.46 in 2013 but grow to $9.94 by 2019.

Table 1 Panel A reports summary statistics on drug prices and characteristics for the full NADAC sample. The mean price per unit is approximately $9.16, and the median is $0.24. The distribution is right-skewed, indicative of a small percentage of drugs in our sample being quite expensive. For example, the 90th percentile of drug price is $6.59 per unit, and the 99th percentile hovers around $96.57 per unit.[8] The NADAC survey also distinguishes between brand name versus generic and prescription versus over-the-counter drugs: Among all drugs in the full NADAC sample, 14% are brand-name (as opposed to generic) and 86% are prescription (as opposed to over-the-counter). We obtain additional drug characteristics from several other sources. We collect patent

[8]Our findings are not driven by extreme outliers such as the 2015 scandal involving "Pharma Bro" Martin Shkreli, whose company Turing Pharmaceuticals acquired the drug Daraprim, which treats the a life-threatening parasitic infection, and increased its price over 5,000% ("Drug Goes From $13.50 a Tablet to $750, Overnight," *The New York Times*, September 20, 2015). Our results are similar in magnitude and significance when we winsorize prices at the 1st and 99th percentile. See Internet Appendix Table IA5.

and exclusivity rights from the FDA's Approved Drug Products with Therapeutic Equivalence Evaluations database, commonly known as the "Orange Book." We match patent and exclusivity data with the NDC Directory by new drug application type and number, and then merge to our drug acquisition cost data using NDC. We classify a drug as patented or covered under exclusivity rights if its patent or exclusivity has not yet expired. We observe that 10% of drugs in the full NADAC sample are under patent, and 3% are exclusivity protected.[9] Ideally, we would like to control for demand with drug-level sales volume. But drug manufacturers are not required to report sales at the product-level. We instead turn to Medicaid's State Drug Utilization Database (SDUD), which reports total units and amounts reimbursed by NDC by state. We aggregate these state-level figures to reflect the total units of each product reimbursed by Medicaid each year. If Medicaid reimbursement units are correlated with total units sold, our reimbursement metric should serve as a proxy for demand. Medicaid reimburses 302,000 units of the average drug product in our sample, but this metric is highly skewed: The median reimbursement represents only 4,000 units while the 90$^{\text{th}}$ percentile is nearly half a million units.

Our identification strategy, which we describe in Section 3, hinges upon within-deal variation in product market consolidation. We must therefore identify each drug's product market. To do this, we draw upon two well-established drug classification systems. Our primary product market definition is based on Anatomical Therapeutic Chemical (ATC) codes from the World Health Organization (WTO). ATC codes are a widely-accepted classification system with five nested levels: main anatomical groups (1$^{\text{st}}$ level or 1-digit), therapeutic subgroups (2$^{\text{nd}}$ level or 3-digit), pharmacological subgroups (3$^{\text{rd}}$ level or 4-digit), chemical subgroups (4$^{\text{th}}$ level or 5-digit), and chemical substance (5$^{\text{th}}$ level or 7-digit). Internet Appendix Table IA1 provides an example. We are able to merge ATC codes with NADAC prices using NDCs for 71% of our sample. Our merge rate increases to 87% by filling missing ATC codes with ATC codes of drugs with identical active ingredients from the NDC description. We also infer product markets from pharmacological class categories reported in the NDC directory. These categories, i.e., Mechanism of Action (MoA) and Established Pharmacologic Class (EPC), correspond to the listed drug's active moieties. Our

[9]Patents are broader property rights issued any time 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. For more details, see https://www.fda.gov/drugs/development-approval-process-drugs/frequently-asked-questions-patents-and-exclusivity.

baseline overlap measure is acquirer/target 3-digit ATC overlap, but we verify robustness to more narrowly defined ATC overlap and MoA/EPC overlap as well.

To address the concern that acquirers stop competition before it begins, as in Cunningham, Ederer, and Ma (2021), we supplement 3-digit ATC overlap with "pipeline" overlap. If a target firm has no drugs listed in the FDA Orange Book database, we identify the type of drugs the target is developing by conducting Google searches for news articles released around the merger announcement date containing the names of the acquirer and target firms. For example, Merck's drug Temodar corresponds to ATC3 code L01 for "Antineoplastic Agents," drugs intended to prevent or slow the progress of a neoplasm (tumor). When Merck acquired Israel-based biopharmaceutical firm cCAM Biotherapeutics in 2015, news reports revealed the cCAM deal included several early-stage drugs that were similar. In one report Merck Research Laboratories president Dr Roger Perlmutter said: "The acquisition of cCAM supports our objective to advance the care of patients with cancer by stimulating tumor-directed immune responses."[10] Because the drug Temodar's ATC code description closely resembles the description of cCAM's pipeline, we assume Temodar shares a product market with the target firm. Our results, however, are robust to ignoring such pipeline overlap.[11]

2.2 Innovation metrics

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 instance, AbbVie has obtained over 100 patents on Humira, the world's best selling drug, alone.[12] 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 patents.[13] According to Rachel Sher, the deputy general counsel of the the Association for Accessible Medicines, which represents generic drug companies: "Too often branded companies are seeking to patent features

[10] "Merck to acquire Israe"s cCAM Biotherapeutics for $605m." *Pharmaceutical Technology*, July 29, 2015.
[11] See Internet Appendix Table IA6.
[12] "By Adding Patents, Drugmaker Keeps Cheaper Humira Copies Out of U.S." *The Wall Street Journal*, October 16, 2018.
[13] "Overpatented, Overpriced: How Excessive Pharmaceutical Patenting is Extending Monopolies and Driving up Drug Prices." *Initiative for Medicines, Access & Knowledge (I-MAK).* August 2018.

of the drugs that don't represent true innovation."[14]

To deal with the aforementioned "patent thicketing" problem, we use new drug approval data from the FDA to create a cleaner innovation proxy. The FDA reports all approved drug applications and categorizes them as initial versus secondary applications, and by submission classification. Initial, or "original," applications represent first-time applications whereas secondary, or "supplemental," applications request a change to an FDA approved applications. Submission classifications (illustrated in Table IA8) broadly cover the creation of new drugs (e.g., new molecules, new active ingredients, or new combinations), labeling changes, and other applications, with the most common "other" category being a process optimization known as "chemistry, manufacturing, and control" or "CMC." All new drug applications are contained within initial applications, and all labeling applications are considered secondary applications. Other and missing submission codes appear in both initial and secondary applications.

We aggregate drug applications (total and by category) at the firm-year level and present summary statistics in Panel B of Table 1. On average, drugs manufacturers submit 33.5 applications per year, of which 3.6 are first-time applications and 29.8 are follow-on applications for existing products. The average firm submits only 0.5 applications per year corresponding to new drugs. The bulk of applications instead relate to labeling (19.6 per firm-year on average) or manufacturing and other process changes (13.3 per firm-year). Arguably, initial applications are more innovative than supplemental applications and new drug applications are more innovative than labeling or manufacturing changes. If so, true innovation is rare. Only 10% of all applications are initial applications, of which only 1.6% correspond to new drug products.

2.3 Pharmaceutical mergers

To investigate drug prices and pharmaceutical innovation around mergers, 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 condition on completed deals in which the acquirer owned less than 50% of the target firm prior to the deal and at least 90% after the deal. To merge our drug price data with SDC, we first identify drug manufacturers (i.e., "labelers") using

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

the NDC Directory, which provides information submitted to the FDA on labeler names for each product. If necessary, we identify the parent company associated with the labeler through web searches. For example, Johnson & Johnson is the parent company of the labeler Janssen Pharmaceuticals. We use a fuzzy name match to link drug manufacturers directly to acquirer names in SDC or indirectly by first matching with company names in the Center for Research in Security Prices (CRSP)/Compustat merged database then merging with SDC on CUSIP. The CRSP/Compustat merged database also serves as the source of our firm-level accounting and stock price data.

Figure 4 gives an overview of M&A activity within the pharmaceutical industry from 2013 to 2019. Deal volume peaks at 45 deals in 2015, decreases to 22 deals in 2017, and rebounds some in 2018 and 2019. Deal values follow a similar pattern: The aggregate deal value spikes in 2015 at $184 billion and bottoms out in 2017 at $31 billion. The aggregate value of the 202 M&As in our sample is $687 billion. These deals are conducted by 67 unique acquirers. Table 1 Panel C shows these deals are substantial in size: The average deal is worth $3.4 billion, and even deals at the 10^{th} percentile are valued at $95 million. Acquisitions of publicly traded targets, private targets, and subsidiaries are fairly evenly distributed. Internet Appendix Table IA2 provides the breakdown of industry composition by acquirer and target SIC codes. Acquirers are concentrated in Pharmaceutical Preparations, with 162 deals having an acquirer belonging to this industry classification. Acquirers and targets share the same 4-digit SIC code in slightly over half (107) of deals.

3 Drug Price Changes Around Pharmaceutical Mergers

This section investigates changes in drug prices around mergers. We begin by describing our empirical strategy, including how we identify drugs whose product markets consolidate around mergers and how we match them with control products. We then motivate our difference-in-differences (DID) model and verify its assumptions. Next, we perform our baseline tests. We conclude by validating the robustness of our results and examining their cross-sectional variation.

3.1 Difference-in-differences model and assumptions

Our empirical strategy for testing how product prices move around mergers is to compare changes in prices of drugs influenced by mergers to simultaneous price changes of drugs unaffected by a merger, but otherwise similar. Because mergers are not based on random assignment, we must carefully control for the firm and product characteristics that may drive merger activity or impact product pricing. We hold firm characteristics constant by exploiting within-deal variation in produce market consolidation. In other words, our sample and control drug product both belong to the same firm (the acquirer). We control for product characteristics through a careful matching process. We elaborate on our identification strategy below.

Figure 5 illustrates how we select sample drugs whose product markets consolidate as a result of the merger. The large circle depicts the drug portfolio of the acquiring firm while the small circle illustrates target firm drugs. The shaded intersection of these circles represents an overlapping product market. The acquiring firm's drugs belong to our sample if one of the target firm's drugs shares their product market. In our example, acquirer drug A1 is sampled because it shares a product market with target drug T1. Empirically, we use Anatomical Therapeutic Chemical (ATC) codes to identify product markets and assume consolidation occurs in overlapping product markets; an acquiring firm's drug is sampled if its 3-digit ATC code corresponds to the same code as at least one of the target firm's drugs.[15] Often target firms do not yet sell drugs. In these mergers, we sample an acquirer drug if its ATC code description closely resembles the description of the target firm's pipeline, as described in Section 2.1.

At the time of the merger, the average acquirer manufactures 324 individual products with prices in the NADAC database while the average target only manufactures 26 such drugs. This suggests that, as is typical in mergers, acquirers in our sample tend to be substantially larger than their target firms. Of the 202 pharmaceutical mergers that occur during our sample period, 85 deals involve at least one overlapping product market. Because we use within-deal variation in product market consolidation for identification, we must condition on deals with overlapping product markets. Within these remaining deals, 23.6% of acquirer drugs overlap with target product

[15] The majority of drugs in our sample (65%) correspond to only one ATC3 code. If a drug corresponds to more than one code, we sample the drug if at least one of its codes corresponds to at least one of the target drug's codes. Internet Appendix Table IA3 provides a hypothetical example.

markets. 90.6% of overlap is attributable to target drugs already in distribution while the remaining 9.4% of overlapping target drugs are still in the development pipeline.

Next, we must select appropriate control drugs. We limit potential controls to the pool of acquirer drugs without product market overlap. This allows us to exploit variation in market power consolidation, all the while holding firm characteristics constant. Controlling for drug-level characteristics is also important. We match each drug in our sample to an acquirer drug unaffected by the merger on the following dimensions: brand name/generic, prescription/over-the-counter, and patent and exclusivity rights status. We then select the drug with the closest total units reimbursed by Medicaid last year, a proxy for lagged demand. If we obtain more than one match, we select the drug closest in unit price.[16] In Figure 5 sample drug A1 is matched with control drug A2, and we will compare change in the price of drug A1 around the merger to simultaneous changes in the price of drug A2.

Table 2 reproduces drug-level summary statistics for acquirer drugs the quarter prior to the acquisition. We then summarize our difference-in-differences sample. Relative to the full NADAC drug sample presented in Table 1, acquirer drugs tend to be more expensive. Acquirer drugs also are more likely to be brand name and covered under patents or exclusivity rights. But more importantly for our empirical strategy, acquirer drugs with product market overlap are different: They are cheaper than the average acquirer drug and more likely to be generic and prescription but less likely to be patented or associated with exclusivity rights. Though descriptive in nature, this table points to the importance of carefully selecting control drugs. Because we exactly match sample and control drugs on brand name/generic, prescription/over-the-counter, patent and exclusivity rights status, differences in the sample and control groups along these dimensions equal zero. Sample and control drugs are also statistically and economically similar in terms of reimbursement rates. The only meaningful difference between sample and control drugs is price (difference = \$2.80, t-stat = 2.49). We do not explicitly match on price levels because imposing prices bands around controls restricts our pool of potential controls even further and could bias DID coefficient estimates.[17] This slight baseline difference nonetheless emphasizes the importance of controlling for price levels by examining within-product changes in (log) price, which we do.

[16] Our results are robust to propensity score matching instead of exact matching. See Internet Appendix Table IA4.

[17] In our setting, for instance, we may inadvertently select controls with recent price increases that will experience (downward) reversion to the mean in the near future, which would bias our DID coefficient estimate upward.

After successfully matching sample and control drugs along observables, we need to remove common time trends. The following DID equation allows us to identify the impact of mergers on prices by comparing price changes across acquirer drugs whose product market overlaps with the target firm and matched control drugs produced by the same company at the same time:

$$ln(Price_{i,k,t}) = \theta Consolidate * Post_{i,k,t} + \delta_{i,k} + \eta_{k,t} + \epsilon_{i,k,t} \tag{1}$$

where $Price_{i,k,t}$ is the price of drug i produced by the acquiring firm associated with deal k at event quarter t. *Consolidate* equals one if the drug belongs to a product market that is consolidating due to the merger, and zero for matched control drugs. *Post* equals zero before deal k and one during and after the merger announcement quarter. Our coefficient of interest is θ, which is associated with the interaction term between *Consolidate* and *Post*. This coefficient captures the relative difference in log price from the pre-merger to post-merger periods (first difference) between drugs directly affected by the merger and control products (second difference). Otherwise stated, it is the difference in approximate percentage price change in drugs with product market consolidation due to the merger and similar drugs, produced by the same manufacturer conducting the acquisition, without product market consolidation. As our DID sample is constructed at the deal level, we "saturate" product and time fixed effects with deal indicators. $\delta_{i,k}$ is a drug-deal fixed effect, which controls for time-invariant differences in price levels across products. $\eta_{k,t}$ represents a deal-event-time fixed effect, which serves several purposes. It nets out time-invariant firm (drug manufacturer) characteristics as well as simultaneous changes in price in matched control drugs. We present t-statistics based on robust standard errors clustered at the product level.

A key identifying assumption when using the DID approach is parallel trends. It requires that, in the absence of a merger, the difference in prices between sample and control drugs would be constant over time. To provide support for this assumption, we estimate the following equation:

$$Ln(Price_{i,k,t}) = \sum_{\substack{t=-6 \\ t\neq -1}}^{+6} \theta_t Qtr_t * Consolidate_{i,k} + \delta_{i,k} + \eta_{k,t} + \epsilon_{i,k,t}. \tag{2}$$

This equation is equivalent to our baseline DID model, except we replace the post-merger indicator with multiple indicators for event time: Qtr_t equals one if the observation corresponds to quarter

t relative to the merger quarter. We use one quarter prior to the merger as the base quarter.

For the parallel trends assumption, we are interested in whether the coefficients associated with the interactions between consolidating product markets and pre-merger event times are significantly different from zero. Figure 6 plots estimates of differences in price trends between sample and control drugs around mergers. All pre-merger θ coefficients are statistically indistinguishable from zero, consistent with parallel trends.

One potential concern is that drugs in consolidating product markets appear to increase in price relative to control drugs as early as the quarter prior to the merger. The mostly likely explanation for these anticipatory effects is that corporate insiders charged with product pricing decisions are likely aware of the merger well before its public announcement. In fact, a six month lag from merger inception to consummation is not uncommon.[18] Rambachan and Roth (2021) note that anticipatory effects are a common issue in parallel trends analysis and propose re-normalizing the definition of pre-treatment period. Noting that our time cutoff likely produces conservative estimates, we retain the merger quarter as our baseline time threshold. Nevertheless, we confirm robustness to re-normalizing our pre/post cutoff to include the merger negotiation period in Internet Appendix Table IA7.

In addition to examining the validity of the parallel trends assumption, this figure begins to teach us about the changes in prices around mergers. Prices of drugs experiencing product market consolidation increase about 2% more than control drugs at the time of the merger and remain significantly higher for four quarters. Taken as a whole, these findings reveal few significant differences in price movements between sample and control drugs in the pre-period (consistent with parallel trends) but provide evidence of drugs affected by the merger increasing in price significantly more at the time of the merger and remaining elevated for almost one year.

3.2 Difference-in-differences regressions results and discussion

Table 3 presents our DID analyses with varying windows around the merger quarter. Regardless of the number of quarters around the merger we include, we observe positive and significant coefficients on the consolidation/post-merger interaction term. Our estimates range from 1.3% using the period

[18] "What You Need To Know About Mergers & Acquisitions: 12 Key Considerations When Selling Your Company." *Forbes*. August 27, 2018.

spanning from one quarter prior to the merger until one quarter after the merger to 2.2% when we focus on four to six quarters pre and post merger. These findings suggest that drugs whose product markets are directly impacted by the merger increase in price significantly more than matched control drugs, whose product markets are unaffected. Though gains in synergy may also be realized, overall, the prevailing price change around mergers is positive. This evidence supports the *Market Power Hypothesis* over the *Synergistic Gains Hypothesis*.

According to the Federal Trade Commission, when approving a merger, "the key question the Agency asks is whether the proposed merger is likely to create or enhance market power or facilitate its exercise."[19] How, then, do we identify price increases associated with deals approved by regulators? Several factors could come into play. The first is the magnitude of the price increase. While the effects we document are statistically significant, their economic magnitude may be insufficient to garner the attention of regulators. An additional point of consideration in the merger approval process is the time it would take a competitor to enter the market, or "timeliness of entry." Entry is generally considered "timely" if achieved within two years, and the Agencies challenge mergers only if they determine entry by competitors would not be timely. Our time trends results in Figure 6 show that price increases are only sustained for three to four quarters post-merger. A final reason these mergers may be approved relates to the difficulty of predicting demand within the pharmaceutical industry. Because pharmaceutical products have high switching costs (e.g., because of side effects), they are likely associated with low price elasticity and low demand-side substitutability. Therefore, prices may remain inflated longer than they would in other industries, rendering predicting the impact of mergers on prices within this industry particularly challenging. Otherwise stated, as researchers we have the benefit of hindsight.

3.3 Difference-in-differences robustness checks

This section verifies the robustness of our baseline difference-in-differences analyses to several alternative specifications. We begin by altering our definition of acquirer/target overlap, which is how we identify drugs with product market consolidation. We originally define overlap as cases in which either the target firm produces a drug with the same 3-digit ATC code or the target firm's pipeline includes products with similar descriptions to the ATC code descriptions. ATC codes are

[19] https://www.ftc.gov/tips-advice/competition-guidance/guide-antitrust-laws/mergers.

7-digit codes representing five nested levels of classifications: main anatomical groups (1st or 1-digit level), therapeutic subgroups (2nd or 3-digit level), pharmacological subgroups (3rd or 4-digit level), chemical subgroups (4th or 5-digit level), and the chemical substance (5th or 7-digit level).[20]

Models (1)–(6) in Table 4 condition on same 4-digit, 5-digit, or 7-digit ATC code acquirer/target overlap. For brevity, we restrict our time windows to correspond to plus or minus four or six quarters around the merger. Because conditioning on higher degrees of ATC code matching is increasingly restrictive, the number of drugs we identify with product market consolidation falls. Our sample size decreases accordingly. Nonetheless, in all cases our coefficients of interest are positive and significant. In fact, they slightly larger than coefficients in our baseline regressions and are increasing in product similarity. Coefficient estimates range from 0.025 to 0.037 four quarters pre- and post-merger and from 0.027 to 0.041 six quarters pre- and post-merger. These estimates imply that acquirer drugs with target product market overlap increase in price significantly more than control drugs, even—and especially when—product markets are more narrowly defined.

Models (7) and (8) of Table 4 use an alternative definition of overlap. Hammoudeh and Nain (2020) and Cunningham, Ederer, and Ma (2021) infer acquirer/target overlap using mechanism of action (MoA) or established pharmacologic class (EPC).[21] To verify robustness to this alternative product market definition, we consider acquirer and target product markets overlapping if they share a MoA or EPC. While MoA/EPC overlap almost always implies ATC3 overlap (96% of drugs with MoA/EPC overlap also share an ATC3 code with a target drug), only approximately half of ATC3 overlap cases also have MoA/EPC overlap. This implies that drugs with MoA/EPC overlap roughly represent a subset of drugs with ATC3 code overlap. Within this subset our results not only hold but are also stronger. Acquirer drugs with an MoA or EPC equivalent to the MoA or EPC of a target drug increase in price 3.0% to 3.1% more than matched control drugs.

We continue our robustness checks in Table 5 by examining price changes around mergers within substantially smaller, but possibly cleaner, subsamples. One concern with our sample construction is that our observations occur at the deal-drug level. This means we allow a drug to appear in our DID sample each time it overlaps with a target drug in a merger; therefore, if the acquiring

[20] We present an example in Internet Appendix Table IA1.

[21] Hammoudeh and Nain (2020) use textual analysis to calculate similarity scores between descriptions of therapeutic area and mechanism of action whereas Cunningham, Ederer, and Ma (2021) directly match drugs on therapeutic areas and mechanisms of action, as we do.

firm conducts multiple mergers (and many do), a drug could appear in our sample multiple times. Models (1) and (2) present our baseline results across varying time windows for the subsample of acquirer drugs that only experience product market overlap once. Our sample size drops, as expected, but our coefficients of interest rise. The coefficient from the model using four quarters pre- and post-merger increases from our baseline estimate of 0.022 to 0.034. The coefficients in the second model with a longer time window increase similarly. In sum, weighting drug-level observations by the number of mergers with which they are associated, as we do in our baseline models in Table 3, does not drive our positive price estimates.

We also examine how our choice of controls impacts our findings. Our baseline results allow drugs with product market overlap in one merger to serve as control drugs in other mergers. The main benefit to this approach is that drugs with overlap probably tend to be more similar to one another than to drugs that never experience product market consolidation. In general, broadening the pool of potential control products allows for more similar matches. Nonetheless, this approach may be problematic if mergers occur in quick succession. To learn how our control sample impacts our findings, we first limit potential control drugs to acquirer drugs that never experience product market overlap with a target firm. Our sample size drops slightly as we are now unable to identify controls for several drugs. Models (3) and (4) continue to show positive coefficients of interest, though statistically insignificant and somewhat lower in magnitude compared to those found in our baseline models.

We conclude our robustness in Table 5 by combining the two robustness checks above. That is, we match our subsample of acquirer drugs that experienced product market consolidation only once with controls that were never affected by a merger. Models (5) and (6) show these results. The coefficients associated with the interaction of *Consolidate* and *Post* remain positive and significant, even increasing in magnitude from our baseline models to 3.5% and 3.4%. We infer from these robustness checks that our choices of sample and control drugs do not appear drive our main findings.

3.4 Competition and drug prices around mergers

This section uses cross-sectional tests to strengthen identification and explore the mechanisms behind the link between mergers and price increases. Specifically, we test if price increases are

greater within less competitive product markets. In addition to bolstering our argument that the link between mergers and drug prices is not a spurious correlation, this cross-sectional analysis provides important insights for regulators scrutinizing these deals.

If our results reflect firms exploiting market power concentration around mergers to inflate drug prices, then we expect price increases around mergers to be more pronounced within concentrated product markets. To test our prediction, we augment our baseline DID regressions of log prices with the indicator *Concentrated*, which equals one if the drug belongs to a concentrated product market. We assume a market is concentrated if the number of unique labelers in the product market the year before the merger falls below the median. If a drug belongs to more than one product market (ATC3 code), we associate it with the least competitive market. When we interact *Concentrated* with our indicators for product market consolidation and the post-merger period, we can interpret the coefficient on the triple interaction as the difference in price change around mergers between sample and control drugs across, in concentrated versus disperse product markets.

Models (1) and (2) of Table 6 show that prices increase more within concentrated product markets than disperse product markets. Concentrated product markets that experience further consolidation due to a merger are associated with price increases around 5% greater than consolidating product markets with more competitors. These findings are consistent with our prediction that merger-induced market power consolidation allows prices to rise and provide further support for the *Market Power Hypothesis*.

Our second cross-section test is motivated by the observation that pricing power should be easier to establish in the absence of generic competition. We therefore create an indicator *No generic*, which equals one if the drug faces no generic competition in the same ATC7 code space. About one-quarter (26%) of drugs in our DID sample have no generic competition. Models (3) and (4) of Table 6 document coefficients on the triple interaction of *No generic*, *Consolidate*, and *Post* equal to 0.027 and 0.077. As expected, drugs in less competitive product markets, those without generic competition, increase in price more around mergers than other drugs experiencing product market consolidation.

Cunningham, Ederer, and Ma (2021) examine so-called "killer acquisitions" in which firms acquire competitors to halt development. Using data from the pharmaceutical industry, they show that acquirers are more likely to halt the development of target firm drugs if the acquirer shares

the product market. Further, drugs are less likely to advance from Phase 1 to Phase 2 if they are acquired by a firm competing in the same product market. They also show that "killer" deals disproportionately occur beneath regulatory thresholds, thus skirting scrutiny. If deals that occur earlier—when the target's drug is in the development as opposed to production phase—are more likely to suppress competition, then the price impact of these deals may be greater. We test this prediction by adding an indicator for pipeline overlap to our DID regressions. *Pipeline* equals one if the drug shares a product market with drugs in the target firm's pipeline. Because this indicator can only equal one for drugs with overlapping product markets, the coefficient associated with the triple interaction term *Pipeline*Consolidate*Post* can be interpreted as the incremental price impact of pipeline overlap. We therefore do not need (and cannot specify a model with) an independent *Pipeline* indicator because, by definition, no control drug has overlap of any type.

Our estimates in Models (5)–(6) of Table 6 show that pipeline overlap is not associated with greater price increases. Our evidence complements the findings of Cunningham, Ederer, and Ma (2021). Although acquisitions curb the production of future products (as they show), we show acquisitions potentially motivated by suppressing future competition are not associated with large price increases for existing products, at least not in the short-run.

4 Shareholder Value Creation

In this section we examine the stock market's reactions to pharmaceutical mergers. Our first goal is to quantify tradeoffs associated with these mergers. Examining abnormal returns around merger announcements clarifies whether these transactions generally generate value for shareholders. Our second goal is to examine whether shareholder value creation varies with market power concentration. If mergers generate shareholder value through synergistic cost-cutting like eliminating redundancies in administration or streamlining distribution channels, then we would not expect merger announcement returns to vary with proxies for market power concentration. Alternatively, if mergers tend to benefit shareholders because they increase market power, then we would expect higher stock returns around announcements of mergers that concentrate market power more.

Table 7 presents merger announcement CARs. Panel A examines the full sample of pharmaceutical mergers. Following Harford (1999), we calculate acquiring firms' cumulative abnormal returns

(CARs) surrounding the acquisition announcement by constructing a market model using the CRSP value-weighted market returns over the 200-day period ending 11 days before the announcement. We observe positive five-day CARs of 1.5%, statistically different from zero at the 1% level. These CARs indicate mergers in our sample create shareholder value on average.

Although all of our deals take place within the pharmaceutical industry, there is heterogeneity in the extent to which acquirers and targets are similar. If mergers tend to benefit shareholders through gains in market power, then deals involving more similar acquirers and targets should generate more shareholder value. Because announcement returns correspond to the entire firm, not individual products, we generate proxies capturing acquirer/target similarity at the deal level. Our first proxy distinguishes between horizontal and diversifying deals. We define *horizontal* deals as those whose acquirer and target share the same 4-digit SIC code. In contrast, *diversifying* deals join firms with different 4-digit SIC codes. Industry composition analysis in Internet Appendix Table IA2 reveals that our deals are fairly evenly distributed between horizontal and diversifying deals. Consistent with shareholders of acquiring firms benefiting more from deals that concentrate market power more, five-day CARs around horizonal mergers are positive and significantly greater than CARs around diversifying deals. Surrounding announcements of horizontal deals, CARs average 2.9%, significantly greater than CARs around diversifying deals that are statistically and economically indistinguishable from zero. Our second proxy captures whether any acquirer drugs overlap, i.e., share the same 3-digit ATC code, with a target drug's product market. Interestingly, we find that the mere presence of product market overlap in a merger does not significantly impact returns. Deals with acquirer/target product market overlap are associated with abnormal returns of 1.6% on average, close to the average returns of 1.5% around deals without overlap.

To further explore if and how product market overlap is associated with merger returns, in Panel B we condition on deals with at least some acquirer/target product market overlap and then segment on the economic importance of the overlap or the type of overlap. To gauge the economic importance of the product market overlap, we sum the total dollars reimbursed by Medicaid in the prior year across all acquirer drugs sharing a 3-digit ATC code with the target firm. We then scale this aggregate reimbursement amount of overlapping drugs by firm size. *High (Low) overlap* denotes mergers whose economic importance of drug overlap falls above (below) the mean or median, as noted. We find that mergers associated with above-average overlap tend to create

significantly more wealth for the acquiring firm's shareholders: Five-day CARs average 5.0% for deals associated with above-average overlap but only 0.9% for other deals. Because our metric for the economic importance of acquirer/target overlap is right-skewed (only 17% of observations are considered above-average), we also split the sample evenly along the median. The difference between stock returns around above-median and below-median overlap deals is lower, albeit still statistically significant and economically meaningful at 2.2%.

We conclude by splitting our overlap deal subsample on whether the acquirer drugs overlap with products in the target's pipeline or with those already being sold. Our product-level price analysis reveals that acquirer drugs with pipeline overlap are associated with greater price increases around the merger, consistent with greater market power gains. Although overlap type is associated with price changes, it does not appear to correlate strongly with acquirer returns around merger announcements. The most likely explanation for this result is that deals with pipeline overlap tend to be much smaller, both in absolute terms and relative to the acquirer's market value, and smaller deals impact acquirer stock prices less.

5 Innovation

This section examines whether pharmaceutical mergers spur innovation. That merged companies will develop more new drugs together than separately is an oft cited advantage to pharmaceutical mergers. Bena and Li (2014) conclude that mergers improve innovation, particularly if the merging firms overlap in technology prior to the merger. If pharmaceutical mergers also improve innovation, consumers and regulators may tolerate the higher prices they tend to be associated with. Examining innovation around pharmaceutical mergers thus helps us clarify potential trade-offs and welfare implications.

5.1 Innovation DID model and assumptions

To investigate pharmaceutical innovation activity around mergers, we again employ a DID model. Unlike prices, innovation occurs at the *firm*, not the *product*, level. Therefore, we now include in our sample all pharmaceutical manufacturers conducting an acquisition in the given year. To identify control firms, we assign each firm-year observation a propensity to acquire score using

the Harford (1999) model. This model (shown in Internet Appendix Table IA9) predicts merger bidding using abnormal returns, sales growth, noncash working capital, leverage, market-to-book, price-to-earnings, size, and year fixed effects. Then, at the deal level, we match each acquiring firm with the non-acquiring firm with the closest predicted acquisition likelihood the year of the deal.

Table 8 examines how well our matching process selects control firms. It displays t-tests on differences in means across all variables in the Harford (1999) model. Our acquiring and control firms are well balanced. They do not significantly differ along any observables related to acquisition likelihood. We also achieve common support. Control firms' average propensity to acquire is not significantly different from acquiring firms.

To net out common time trends, we turn to the following DID regression of innovation from firm j around merger k at year t:

$$Innovation_{j,k,t} = \theta Merger * Post_{k,t} + \gamma X_{j,t-1} + \gamma_k + \delta_{k,t} + \epsilon_{j,k,t} \tag{3}$$

Innovation equals the natural log of one plus the number of FDA new drug applications. The first model uses all FDA new drug applications. We then bifurcate drug applications into initial versus secondary applications. Initial (or "original") applications are first-time new drug applications whereas secondary (or "supplemental") applications are changes to an FDA approved application. Finally, we create three groups based on submission classification codes (illustrated in Table IA8): new drug approvals, labeling changes, and all other codes, including missing values. Our coefficient of interest is θ, which compares acquiring firms' changes in innovation around mergers to innovation changes within matched non-acquiring firms at the same time. We expect θ to be positive if mergers spur innovation. We control for firm size, cash holdings, ROA, leverage, Z-score, and M/B, and include deal and deal-event-time fixed effects in all models.

The above DID approach depends upon the assumption that the difference in innovation between acquirers and control firms would be constant over time in the absence of a merger. To examine this parallel trends assumption, we regress innovation metrics on indicator variables capturing time relative to the merger event and their interaction with an indicator for merging firms as follows:

$$Innovation_{k,t} = \sum_{\substack{t=-3 \\ t\neq -1}}^{+3} \theta_t Year_{k,t} * Merger_k + \gamma X_{j,t-1} + \gamma_k + \delta_{k,t} + \epsilon_{j,k,t} \tag{4}$$

This equation is otherwise equivalent to our main DID equation. The base year is one year before the merger, and we are interested in whether the coefficients associated with the interaction between the indicators for events years and mergers are significantly different from zero during the years prior to the merger year.

Figure 7 graphs the innovation regression coefficients associated with all merger/year interactions, along with their 95% confidence intervals. For all innovation metrics, the confidence intervals associated with the interaction coefficients before the merger contain zero. Hence, we observe no significant difference in pre-merger price trends across acquiring firms and matched control firms and can assume the parallel trends assumption is satisfied.

Furthermore, these trends reveal how innovation changes within acquiring firms, relative to matched control firms. While new drug applications increase during the merger year and one year after, these increases appear to be driven by secondary applications. Secondary applications increase up to 45%, but primary applications remain stagnant. Labeling applications and applications related to other changes such as manufacturing process improvements rise, but not new drug approvals related to new molecules, new active ingredients, or new combinations, etc. We confirm these results in a streamlined regression setting below.

5.2 Mergers and innovation

Table 9 presents our innovation DID regression analyses. Our models examine whether new drug applications increase more within acquiring firms than matched non-acquiring firms within the seven-year time frame spanning from three years pre-merger to three years post-merger. Given that our dependent variable is the natural log of (one plus) the number of applications, we can interpret coefficients of interest as approximate incremental percentage change in applications.

Our coefficient of interest in Model (1) shows that acquiring firms increase applications 31.0% more than matched non-acquiring firms. At first glance, this result seems to suggest that mergers are associated with increased innovation. But segmenting applications on initial versus secondary submissions in Models (2) and (3) and on submission classifications in Models (4)–(6) shows that the increase in new applications is driven by secondary applications and by applications related to labeling and manufacturing process changes. Initial applications and new drug applications do not increase significantly more within acquiring firms than matched control firms.

Our above innovation analyses use the same time period and sample as our drug price analysis, limiting us to a short time period beginning in 2013. Yet, new drug development takes time. For this reason, this section examines the robustness of our innovation results to longer time periods around the merger. We extend our sample of merging firms and potential control firms to include all FDA new drug applicants between 1990 and 2020. We then merge this larger and longer sample of firm-years with Compustat to obtain firm controls and with SDC to identify mergers. As before, we match acquiring firms with non-acquiring control firms based on their propensity to acquire score generated from the Harford (1999) model.

Using this larger sample and extending the time period to ten years before and after the merger, Figure 8 presents innovation differences between acquiring and non-acquiring firms using a model adapted from Equation 4, and Table 10 presents regression results analogous to those in Table 9. Even over this longer time period, we fail to identify significant upticks in innovation with acquiring firms relative to non-acquiring firms. In fact, we no longer observe jumps in secondary applications or labeling and manufacturing-related applications.

Taken as a whole, our innovation results suggest that any increase in innovation around mergers is a recent phenomenon concentrated within follow-on applications to relabel products or streamline manufacturing. Although this sort of innovation likely benefits shareholders by increasing sales or leading to cost efficiencies, it is unlikely to serve consumers. Furthermore, reexamining innovation over an extended sample period calls into question whether mergers are associated with even the least innovative drug applications and confirms that mergers are not associated with the creation of new drugs, even up to ten years after the merger.

6 Conclusion

Prior studies document that mergers and acquisitions tend to generate wealth for shareholders. We confirm this finding in the context of recent mergers in the pharmaceutical industry and explore whether shareholder value creation tends to stem from synergies or market power gains on net. We find that pharmaceutical mergers are generally accompanied by increases in product prices—particularly within uncompetitive product markets that experience further consolidation as a result of the merger. We also examine innovation around mergers and find that any innovative activity is

limited to labeling and manufacturing process changes, not new drug creation. These findings are inconsistent with synergistic gains being passed along to consumers through lower prices or better products.

Our study has implications for policymakers, who often claim ensuring affordable access to medication for constituents is a top priority. We show that one contributor to rising drug prices is recent consolidation in the pharmaceutical industry. Understanding the nature of competitive forces in this industry provides insights into how to better regulate this important industry and contain drug prices.

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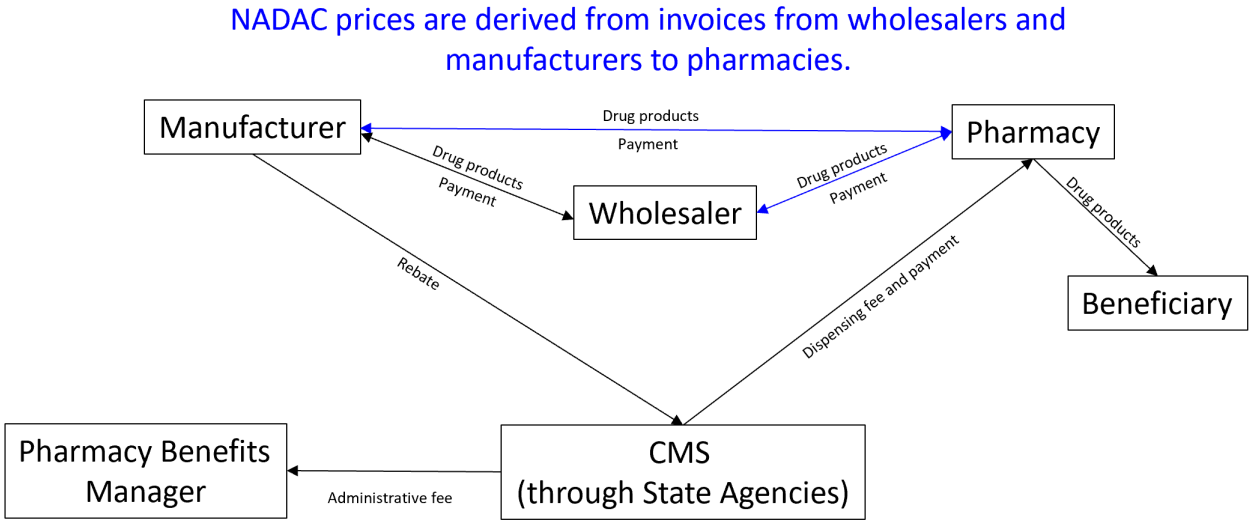
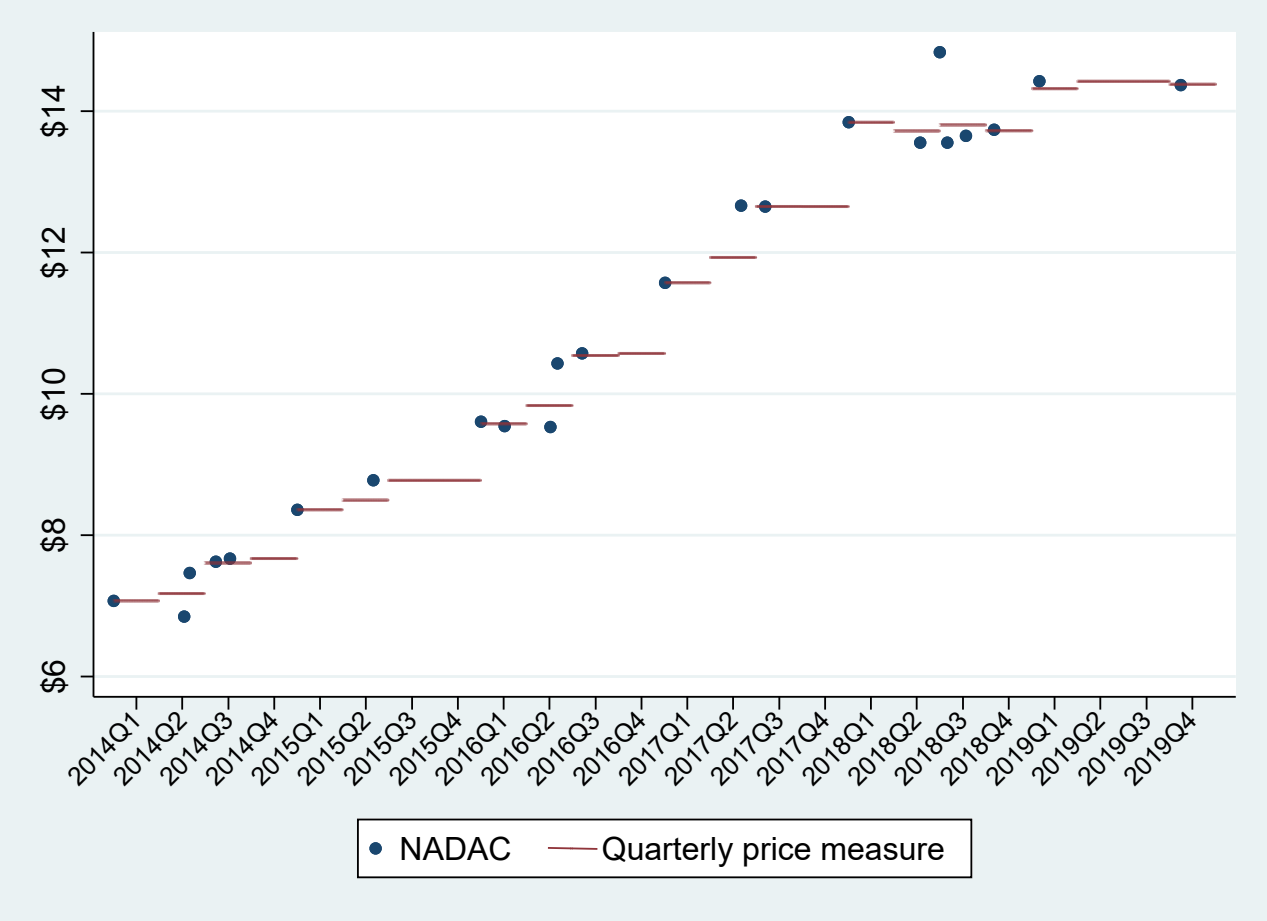


Figure 1
Pharmaceutical Industry Structure and Main Players
This chart describes the payment and supply chain for prescription drug benefits through the Center for Medicaid Services (CMS). National Average Drug Acquisition Cost (NADAC) prices are derived from invoices from manufacturers and wholesalers to pharmacies, denoted by the blue lines. NADAC prices do not reflect off-invoice discounts, rebates or price concessions. Sources: https://www.kff.org/medicaid/issue-brief/pricing-and-payment-for-medicaid-prescription-drugs/ and https://www.medicaid.gov/medicaid/prescription-drugs/downloads/retail-price-survey/nadac-overview-operations.pdf



NDC Description	NADAC Per Unit ($)	Effective Date	Days Effective in 2018Q3	Weight (Days Eff./ Total days)	NADAC * Weight
LIPITOR 40 MG TABLET	14.83	7/1/2018	15	0.163	2.4187
LIPITOR 40 MG TABLET	13.55	7/16/2018	37	0.402	5.4515
LIPITOR 40 MG TABLET	13.65	8/22/2018	40	0.435	5.9352
Weighted average quarterly price:					13.81

Figure 2
Quarterly Drug Price Measure: An Example
This figure illustrates our method of calculating quarterly drug prices using Lipitor as an example. Using drug prices and effective dates from the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS), we create a time-weighted average drug price each quarter (top). Our weightings are based on the number of days in which the price was effective during the quarter, scaled by the total number of days in the quarter. We provide an example of the calculation of Lipitor's 2018Q3 price (bottom).

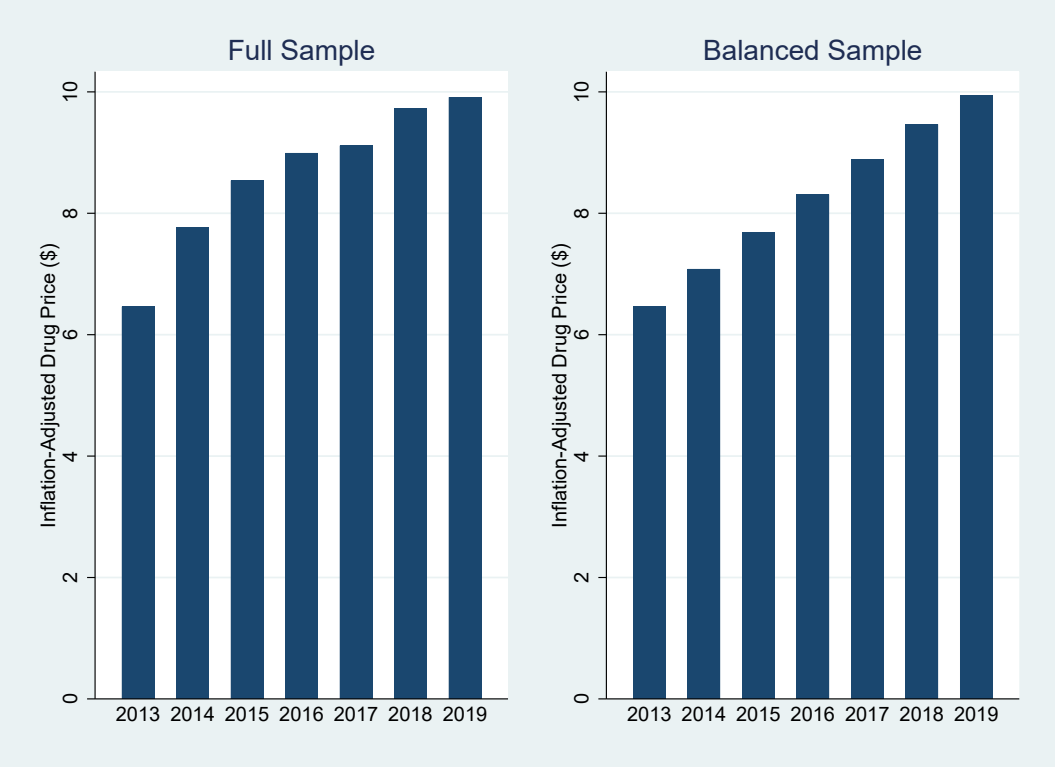


Figure 3
Drug Price Trends
This figure presents the average year-end (4th quarter) unit price (in 2019 US dollars) of drugs sold to retail pharmacies for our full sample of drug prices (left) and for a balanced sample requiring available price data each year (right). We source drug prices from the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS).

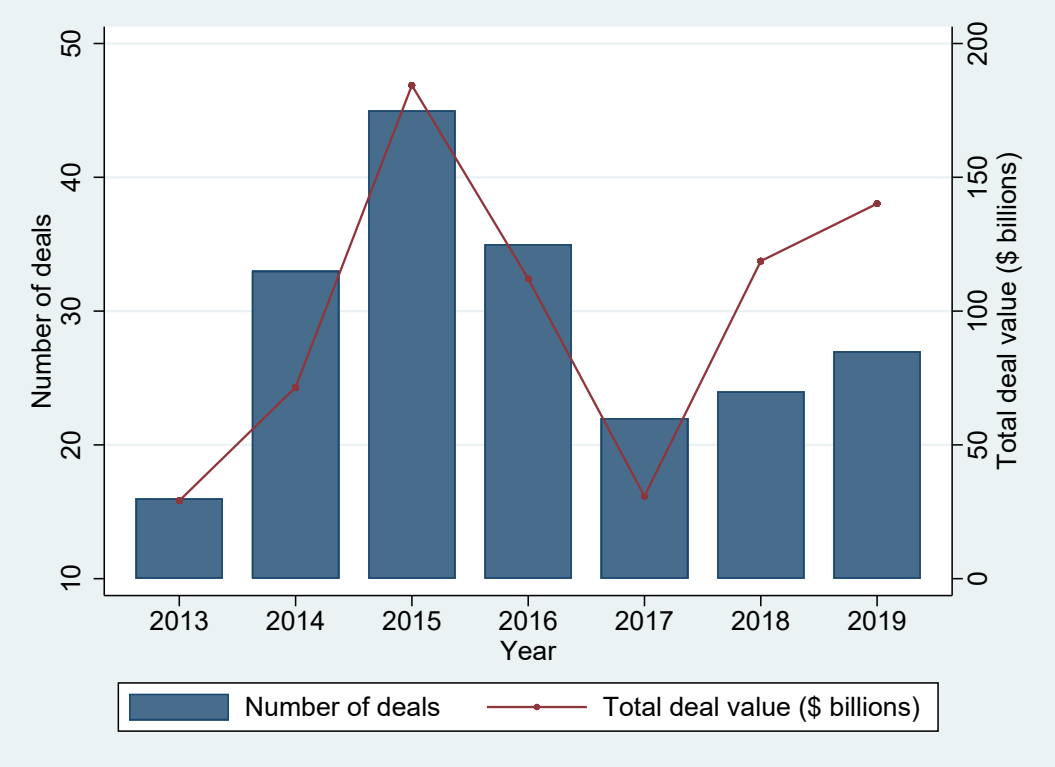


Figure 4
Pharmaceutical Mergers and Acquisitions
This figure presents the number (left axis) and total deal value in billions of US dollars (right axis) of pharmaceutical mergers and acquisitions (M&As) each year. Our merger sample consists of firms with M&A announcements in the Securities Data Corporation (SDC) database between 2013 and 2019 and with drug prices reported in the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS).

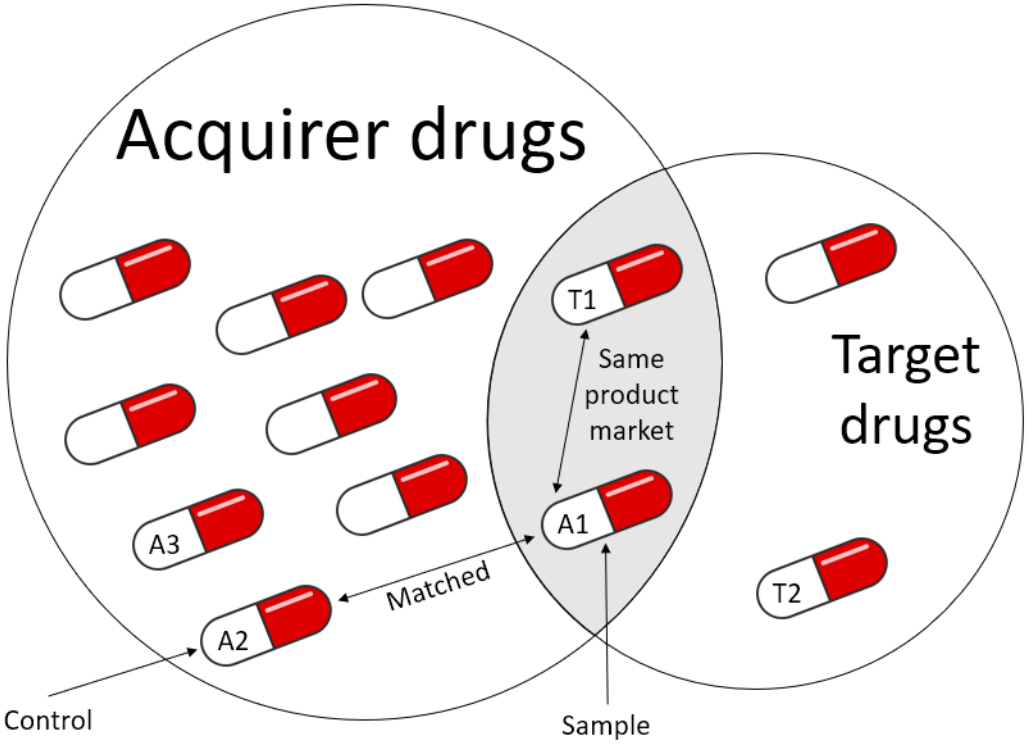


Figure 5
Identification Strategy
We examine how product prices change around mergers by exploiting within-deal variation in product market consolidation to compare changes in prices of sample products directly impacted by the merger to simultaneous price changes of similar control products. This figure illustrates how we select sample and control drugs. The large circle depicts the drug portfolio of the acquiring firm A while the small circle illustrates drugs belonging to target firm T. Their shaded intersection represents an overlapping product market, shared by acquirer drug A1 and target drug T1. Potential control drugs are acquirer drugs whose product market does not overlap with any of the target's product market (A2, A3, etc.). We match sample drug A1 to these potential controls on brand name/generic, prescription/over-the-counter, patent and exclusivity rights statuses, then select the drug with the closest total units reimbursed by Medicaid last year, represented by drug A2 in this example.

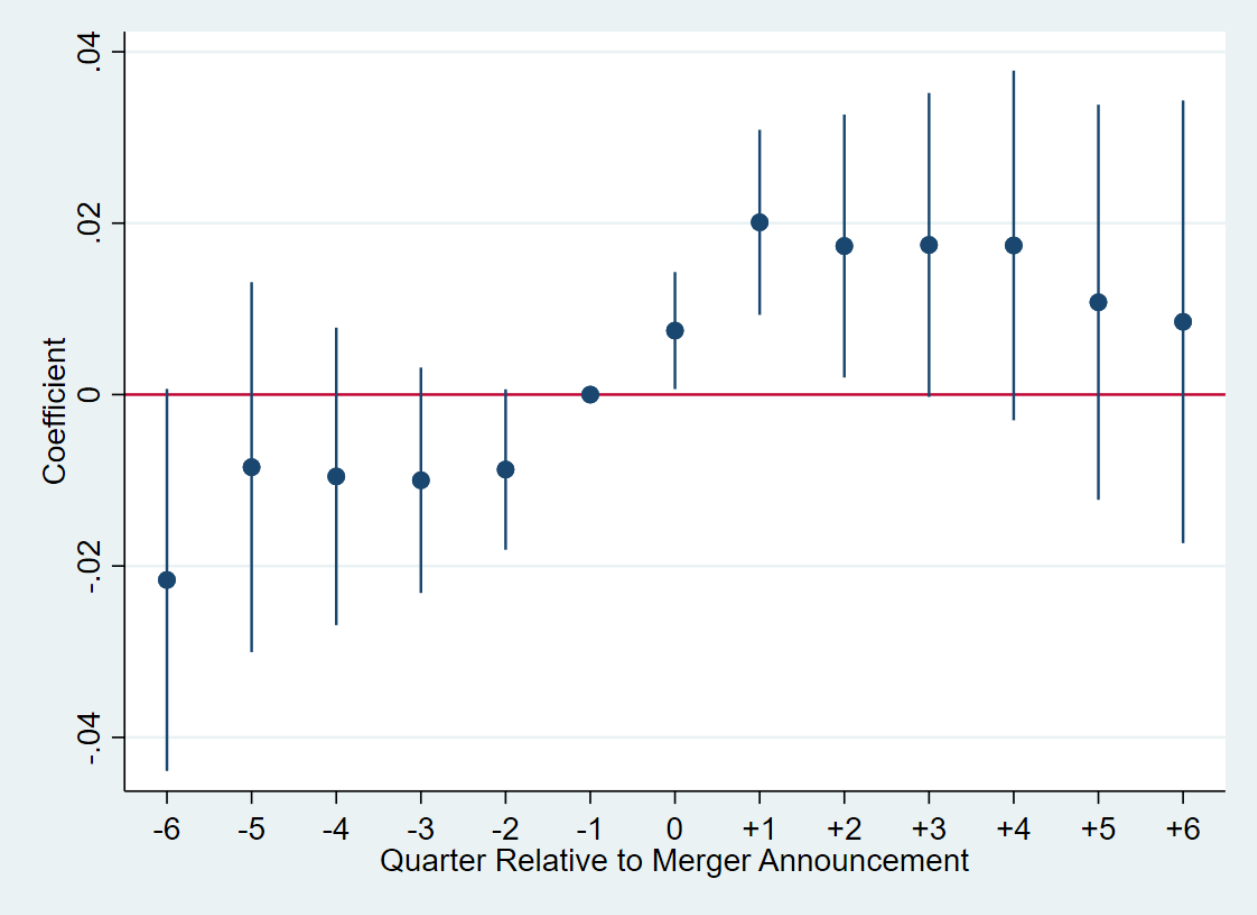


Figure 6
Drug Price Trends Around Merger Announcements
This figure plots price dynamics of sample drugs whose product markets consolidate around the merger event, relative to control drugs. The plot depicts coefficient estimates of θ_t and their 95% confidence intervals from the following difference-in-differences regression:

$$Ln(Price_{i,k,t}) = \sum_{\substack{t=-6 \\ t\neq -1}}^{+6} \theta_t Qtr_t * Consolidate_{i,k} + \delta_{i,k} + \eta_{k,t} + \epsilon_{i,k,t}.$$

The dependent variable is the natural logarithm of the inflation-adjusted price of pharmaceutical product i, associated with deal k, averaged over quarter t. *Consolidate* is an indicator that equals one for acquirer drugs whose product market overlaps with a target firm product market. We match each sample drug with a similar control drug produced by the same firm, as detailed in Section 3. Qtr_t is an indicator that equals one if the observation corresponds to event quarter t. $\delta_{i,k}$ and $\eta_{k,t}$ represent product (NDC)-deal and deal-event-time fixed effects.

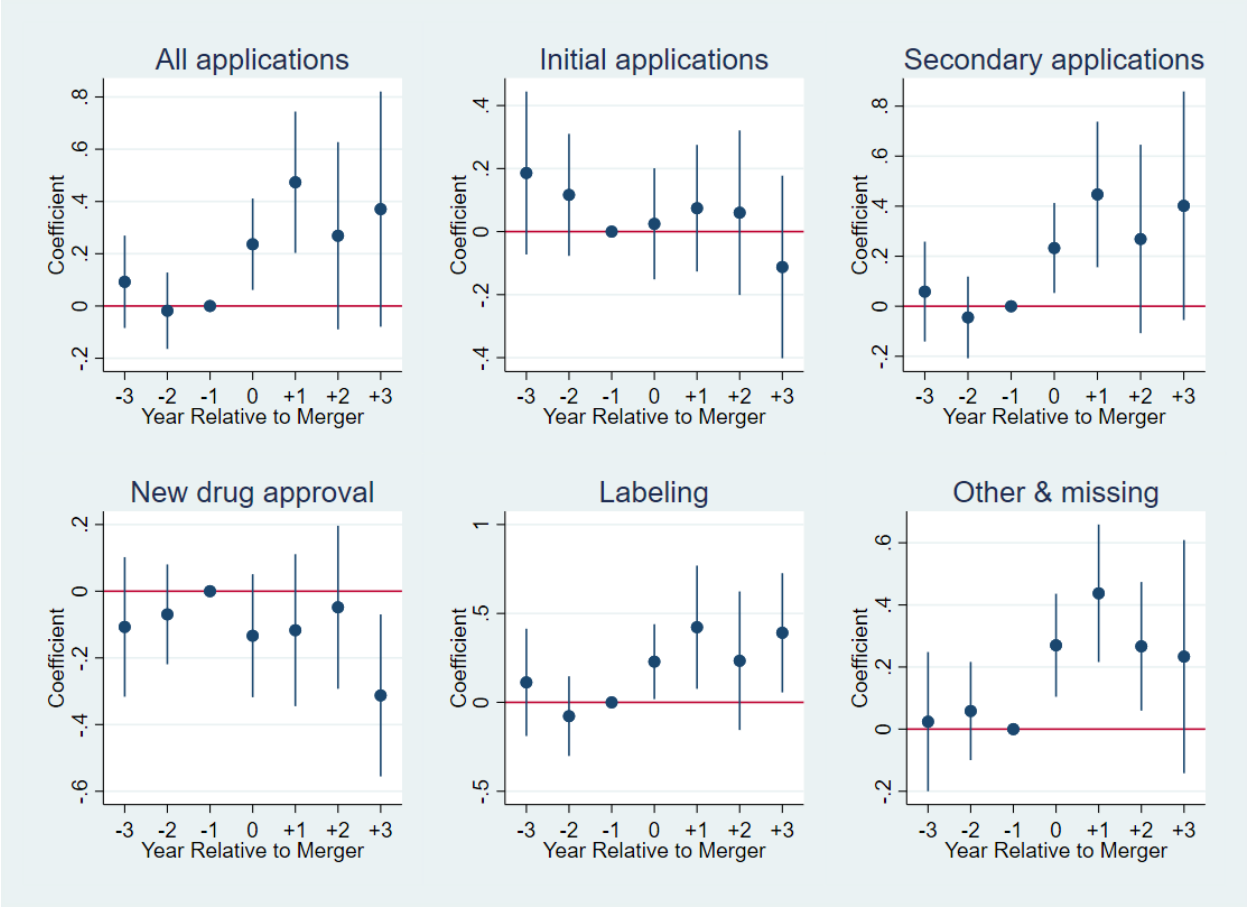


Figure 7
Innovation Trends Around Mergers
This figure tests the parallel trends assumptions and plots innovation differences between acquiring and non-acquiring firms. Plots depict coefficients estimates of θ_t and their 95% confidence intervals from difference-in-differences regressions on innovation metrics as follows:

$$Innovation_{j,k,t} = \sum_{\substack{t=-3 \\ t\neq -1}}^{+3} \theta_t Year_{k,t} * Merger_k + \gamma X_{j,t-1} + \gamma_k + \delta_{k,t} + \epsilon_{j,k,t}$$

The first dependent variable is the natural log of one plus all FDA new drug applications. We then bifurcate drug applications into initial versus secondary applications. Initial (or "original") applications are first-time new drug applications whereas secondary (or "supplemental") applications are changes to an FDA approved application. Finally, we create three groups based on submission classification codes (illustrated in Appendix Table IA8): new drug approvals, labeling changes, and all other codes, including missing values. At the deal level, we match each acquiring firm with the control firm closest in predicted acquisition likelihood from the Harford (1999) model that did not conduct an acquisition the year of the deal. We include the seven years spanning from three years prior to the merger until three years after the merger. $Year_{k,t}$ is an indicator that equals one if the observation corresponds to event year t relative to the merger year. $X_{j,t-1}$ are firm controls the prior year, defined and summarized in the Appendix, and γ_k and $\delta_{k,t}$ represent deal and deal-event-time fixed effects.

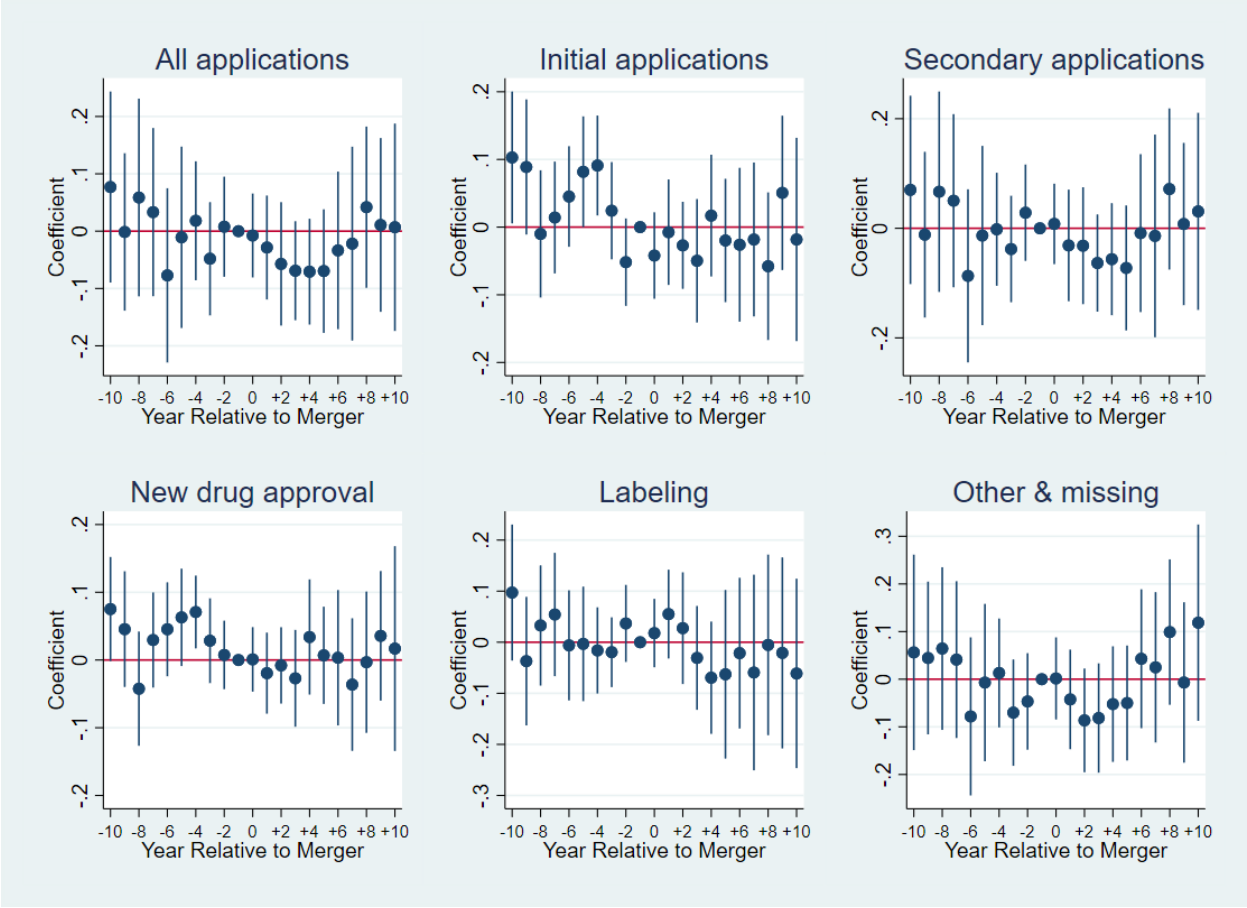


Figure 8

Long-run Innovation Trends Around Mergers

This figure plots innovation differences between acquiring and non-acquiring firms. We extend our sample to include any firm that submits an FDA new drug application between 1990 and 2020 with available Compustat data. We include the 21 years spanning from ten years prior to the merger until ten years after the merger. Otherwise, our methodology and model are identical to those discussed and presented in Figure 7.

Table 1. Summary Statistics

This table presents summary statistics on drugs characteristics, pharmaceutical innovation metrics, and pharmaceutical M&A announcements between 2013 and 2019. Panel A presents statistics at the drug-year level for the full sample of drugs covered in the Centers for Medicare and Medicaid Services (CMS) survey. *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 2019 dollars. Created from the NADAC database, *Brand name*, *Generic*, *Prescription*, and *Over-the-counter* are indicator variables for these drug characteristics. *Patent* (*Exclusivity*) is an indicator equal to one if the drug is under patent (exclusivity protected), as noted in the Food and Drug Administration (FDA) database. *Units reimbursed* are the total units reimbursed, expressed is millions, in the prior year as reported in Medicaid's State Drug Utilization Data (SDUD). Panel B presents innovation metrics derived from the FDA New Drug Approval database. *All applications* represent all FDA new drug applications, aggregated at the firm-year level. First, we segment new drug application into *Initial*, first-time or "original" applications, and *Secondary*, or "supplemental," applications representing changes to an FDA approved application. We then form three groups of applications by submission classification codes, illustrated in Appendix Table IA8: *New drug*, *Labeling*, and *Other & missing*. Panel C presents summary statistics of M&A announcements in the Securities Data Corporation (SDC) database between 2013 and 2019 associated with drug prices reported in the NADAC survey. *Public target*, *Private target*, and *Subsidiary* are indicators denoting with the target firm is publicly traded, privately held, or a subsidiary of the acquiring firm, as reported in SDC.

	Mean	Std. Dev.	P10	Median	P90
Panel A: Drug characteristics					
Price	9.163	179.900	0.027	0.244	6.586
Brand name	0.140	0.347	0	0	1
Generic	0.860	0.347	0	1	1
Prescription	0.855	0.353	0	1	1
Over-the-counter	0.145	0.353	0	0	1
Patent	0.071	0.257	0	0	0
Exclusivity	0.020	0.139	0	0	0
Units reimbursed (millions)	0.302	2.767	0	0.004	0.445
Panel B: Innovation metrics					
All applications	33.454	62.264	0	6	90
Initial	3.646	9.525	0	0	11
Secondary	29.808	56.005	0	5	85
New drug	0.536	1.080	0	0	2
Labeling	19.620	42.375	0	2	56
Other & missing	13.297	23.164	0	3	36
Panel C: Deal characteristics					
Deal value (in $billions)	3.400	9.115	0.095	0.670	8.662
Public target	0.297	0.458	0	0	1
Private target	0.347	0.477	0	0	1
Subsidiary	0.356	0.480	0	0	1

Table 2. Difference-in-differences Sample Summary Statistics

This table presents drug characteristics for our difference-in-differences sample. We first summarize all acquirer drugs the quarter prior to the acquisition. We then summarize the sample of acquirer drugs whose product market consolidates as a result of the merger. We match each sample drug with a control drug produced by the same acquiring firm but without target overlap. We select control drugs with identical characteristics (brand name/generic, prescription/over-the-counter, under patent, under exclusivity) and with the closest total units reimbursed the quarter of the acquisition. *Brand name*, *Generic*, *Prescription*, and *Over-the-counter* are indicator variables for drug characteristics created from the NADAC database. *Patent* (*Exclusivity*) is an indicator equal to one if the drug is under patent (exclusivity protected), as noted in the Food and Drug Administration (FDA) database. *Units (millions)* are the total units reimbursed in the prior year as reported in Medicaid's State Drug Utilization Data (SDUD).

		Difference-in-differences sample			
	All acquirer drugs	Sample	Controls	Sample - Control	
	(1)	(2)	(3)	Difference	t-stat
Price	14.191	10.874	8.072	2.802	2.489
Brand name	0.270	0.215	0.215	0	N/A
Generic	0.730	0.785	0.785	0	N/A
Prescription	0.847	0.895	0.895	0	N/A
Over-the-counter	0.153	0.105	0.105	0	N/A
Patent	0.135	0.098	0.098	0	N/A
Exclusivity	0.038	0.025	0.025	0	N/A
Total units reimbursed (millions)	0.334	0.426	0.359	0.067	1.846

Table 3. Mergers and Drug Prices

This table presents difference-in-differences regressions of acquirer drug prices on merger activity. We exploit within-deal variation in product market consolidation around mergers to compare prices of sample drugs and matched control drugs. The dependent variable is *Ln(Price)*, which equals the natural log of the National Average Drug Acquisition Cost (NADAC) per unit, averaged over the quarter and expressed in 2019 dollars. *Consolidate* is an indicator that equals one for acquirer drugs with target-firm overlap and zero for matched control drugs. Overlap implies the target firm produces a drug sharing the same ATC3 code or has similar drugs in the production pipeline. Each sample drug is matched with a control drug produced by the same manufacturer, with identical characteristics (brand name/generic, prescription/over-the-counter, under patent, under exclusivity), closest in total units reimbursed the quarter of the acquisition. If multiple control drugs have the same total units reimbursed, then we match with the drug closest in unit price. *Post* is an indicator that equals one the quarters of and after the merger. We vary the number of quarters around the merger, as noted. We include product (NDC)-deal and deal-event-time fixed effects. In parentheses we present t-statistics based on robust standard errors clustered at the product-level.

	± 1 qtr	± 2 qtr	± 3 qtr	± 4 qtr	± 5 qtr	± 6 qtr
	(1)	(2)	(3)	(4)	(5)	(6)
Consolidate*Post	0.013***	0.018***	0.020***	0.022***	0.022**	0.022**
	(3.144)	(3.239)	(3.070)	(2.863)	(2.499)	(2.275)
Fixed effects	Product (NDC)-Deal, Deal-Event Time					
Observations	41,609	68,514	93,857	118,159	141,683	163,787
Adjusted R^2	0.002	0.002	0.001	0.001	0.001	0.001

Table 4. Alternative Classifications of Acquirer/Target Overlap

This table examines the robustness of the Table 3 difference-in-differences regressions of drug prices on merger activity to alternative classifications of acquirer/target product market overlap. Our original overlap classification conditions on at least one 2nd (3-digit) level ATC code of the acquirer drug matching at least one 2nd (3-digit) level ATC code of a target drug. 3-digit ATC codes correspond to therapeutic subgroup. We first show robustness to the 3rd (4-digit), 4th (5-digit), and 5th (7-digit) levels of classifications, which correspond to the pharmacological subgroup, chemical subgroup, and chemical substance, respectively. We provides examples of ATC code hierarchy and overlap definitions in Internet Appendix Table IA1. We then show robustness to matching on mechanism of action (MoA) or established pharmacologic class (EPC).

	4-digit ATC code		5-digit ATC code		7-digit ATC code		MoA or EPC	
	± 4 qtr	± 6 qtr	± 4 qtr	± 6 qtr	± 4 qtr	± 6 qtr	± 4 qtr	± 6 qtr
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consolidate*Post	0.025***	0.027***	0.035***	0.040***	0.037***	0.041***	0.030***	0.031**
	(3.632)	(2.947)	(4.915)	(4.229)	(4.125)	(3.539)	(2.998)	(2.307)
Fixed effects	Product (NDC)-Deal, Deal-Event Time							
Observations	94,160	130,885	71,373	99,443	45,125	62,870	53,216	74,504
Adjusted R^2	0.002	0.001	0.003	0.003	0.003	0.003	0.002	0.001

Table 5. Robustness of Mergers and Drug Prices to Alternative Samples and Controls

This table examines the robustness of the Table 3 difference-in-differences regressions of drug prices on merger activity. Models (1) and (2) exclude acquirer drugs with product market overlap with target firms in more than one merger. Models (3) and (4) restrict potential control drugs to drugs with no target product market overlap during our sample period. Models (5) and (6) combine the above two robustness tests.

	Remove multiple treatments		Select controls with no overlap		Remove multiple treatments and select controls with no overlap	
	± 4 qtr	± 6 qtr	± 4 qtr	± 6 qtr	± 4 qtr	± 6 qtr
	(1)	(2)	(3)	(4)	(5)	(6)
Consolidate*Post	0.034***	0.033***	0.016	0.016	0.035***	0.034***
	(3.658)	(2.737)	(1.570)	(1.369)	(3.711)	(2.743)
Fixed effects	Product (NDC)-Deal, Deal-Event Time					
Observations	74,864	105,460	116,119	139,210	75,130	105,837
Adjusted R^2	0.002	0.001	0.001	0.000	0.003	0.002

Table 6. Cross-sectional Variation in Mergers' Impact on Prices

This table presents triple difference-in-differences regressions of drug prices on merger activity, based on Table 3 baseline models with drug-level interactions. *Concentrated* is an indicator equal to one for concentrated product markets, i.e., if the number of labelers in the product market the year before the merger falls below the median. If a drug is associated with multiple ATC3 codes, we assign it to the code with the fewest labelers. *No generic* equals one if the drug faces no generic competition in the same ATC7 code space. *Pipeline* equals one if the overlap between the drug and the target firm's drug portfolio stems from a drug in the pipeline rather than a drug that has already entered the market.

	Concentrated product market		No generic competition		Overlap from drug pipeline	
	± 4 qtr	± 6 qtr	± 4 qtr	± 6 qtr	± 4 qtr	± 6 qtr
	(1)	(2)	(3)	(4)	(5)	(6)
Concentrated*Consolidate*Post	0.049***	0.051***				
	(3.418)	(2.780)				
No generic*Consolidate*Post			0.057***	0.104***		
			(3.272)	(4.472)		
Pipeline*Consolidate*Post					-0.014	-0.011
					(-0.974)	(-0.642)
Concentrated*Post	-0.025*	-0.026				
	(-1.951)	(-1.571)				
No generic*Post			0.016	0.012		
			(1.147)	(0.701)		
Consolidate*Post	0.005	0.004	0.026***	0.023**	0.024***	0.023**
	(0.447)	(0.301)	(3.277)	(2.168)	(2.804)	(2.189)
Fixed effects	Product (NDC)-Deal, Deal-Event Time					
Observations	118,159	163,787	118,159	163,787	118,159	163,787
Adjusted R^2	0.003	0.002	0.003	0.002	0.001	0.001

Table 7. Acquirer Returns around Merger Announcements

This table presents five-day cumulative abnormal returns (CARs) to acquirers around M&A announcements. Panel A examines the full sample pharmaceutical mergers with available drug price and stock price data. *Horizontal* (*Diversifying*) deals involve an acquirer and a target with the same (different) 4-digit SIC codes. *Some overlap* (*No overlap*) denotes deals for which the acquiring and target firms share at least one product market (no product markets). Panel B conditions on the subsample of deals with at least some product market overlap between the acquirer and target. *High overlap* (*Low overlap*) indicates deals with above-average or above-median (below-average or below-median) acquirer/target product market overlap, measured as the total reimbursement amount of acquirer overlapping drugs, scaled by acquirer size (total assets). *Pipeline overlap* indicates the overlap between the acquirer and target firm's drug portfolio stems from a drug in the target's pipeline rather than a drug that has already entered the market. t-statistics are presented below.

Panel A: Full sample of pharmaceutical mergers

All Deals	Horizontal	Diversifying	Horizontal - Diversifying	Some overlap	No overlap	Some - No overlap
0.015***	0.029***	0.002	0.027***	0.016***	0.015*	0.001
(3.11)	(3.41)	(0.38)	(2.79)	(2.97)	(1.93)	(0.13)

Panel B: Subsample

High overlap (> mean)	Low overlap (< mean)	High - Low	High overlap (> median)	Low overlap (< median)	High - Low	Other overlap	Pipeline overlap	Other - Pipeline
0.050***	0.009*	0.041***	0.028***	0.005	0.022**	0.025**	0.010**	0.015
(2.59)	(1.91)	(3.04)	(2.81)	(1.21)	(2.11)	(2.26)	(2.08)	(1.37)

Table 8. Firm-level Matching and Common Support

This table confirms that our propensity score matching achieves well balanced control firms and satisfies the common support condition. At the deal level, we match each acquiring firm with the control non-acquiring firm closest in predicted acquisition likelihood based on the Harford (1999) model the year of the deal. This table presents means and differences in propensity score and the covariates from the acquisition likelihood model. Table IA9 presents the acquisition likelihood model. Table A1 defines our variables.

	Acquirer	Control	Difference	t-stat
Sales growth	1.363	0.254	1.110	0.964
Noncash working capital	-0.001	-0.019	0.018	1.676
Leverage	0.310	0.323	-0.013	-0.651
Market-to-book	4.438	3.931	0.506	0.221
Price-to-earnings	12.196	5.893	6.303	1.006
Size	9.623	9.627	-0.004	-0.012
Cash deviation	0.000	0.001	-0.001	-0.901
Avg. abnormal returns	0.085	0.119	-0.034	-1.005
Propensity score	0.366	0.363	-0.005	0.147

Table 9. Pharmaceutical Mergers and Innovation

This table presents difference-in-differences regressions of firm-level innovation on merger activity. At the deal level, we match each acquiring firm with the control firm closest in predicted acquisition likelihood that did not conduct an acquisition the year of the deal. Acquisition likelihood is estimated using the Harford (1999) model presented in Table IA9. We include seven years around the merger. *Post* corresponds to the year of and three years after the merger. The dependent variable in models is the natural log of one plus FDA new drug applications. Model (1) includes all FDA new drug applications. Models (2) and (3) segment on submission type: "Original" applications are first-time new drug applications whereas "supplemental" applications are changes to an FDA approved application. Models (4)–(6) segment on submission classification codes, illustrated in Appendix Table IA8. Model (4) presents new drug approvals, Model (5) presents new FDA applications related to labeling changes, and Model (6) includes the remaining classification codes (including missing codes). Control variables, which are lagged, are defined in Table A1. We include deal and deal-event-time fixed effects in all models and present t-statistics based on robust standard errors clustered at the firm level.

		Initial vs. secondary		Submission classification		
	All applications	Initial	Secondary	New drug	Labeling	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Merger*Post	0.310**	-0.054	0.322***	-0.090	0.305***	0.285***
	(2.657)	(-0.724)	(2.726)	(-1.462)	(2.724)	(3.162)
Controls	Ln(Assets), Cash, ROA, Leverage, Z-score, M/B					
Fixed effects	Deal, Deal-Event Time					
Observations	990	990	990	990	990	990
Adjusted R^2	0.102	0.034	0.098	0.014	0.072	0.075

Table 10. Pharmaceutical Mergers and Long-run Innovation

This table presents difference-in-differences regressions of firm-level innovation on merger activity analogous to those in Table 9 except that we extend our sample to include any Compustat firm that submits an FDA new drug application between 1990 and 2020 and we include the 21 years spanning from ten years prior to the merger until ten years after the merger.

		Initial vs. secondary		Submission classification		
	All applications	Initial	Secondary	New drug	Labeling	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Merger*Post	-0.033	-0.052*	-0.023	-0.032	-0.020	-0.011
	(-0.619)	(-1.816)	(-0.434)	(-1.097)	(-0.353)	(-0.218)
Controls	Ln(Assets), Cash, ROA, Leverage, Z-score, M/B					
Fixed effects	Deal, Deal-Event Time					
Observations	15,044	15,044	15,044	15,044	15,044	15,044
Adjusted R^2	0.013	0.003	0.014	0.002	0.007	0.010

Appendix

Table A1. Control Variable Definitions
This table present variable definitions of our firm-level control variables and variables used in the Harford (1999) acquisition likelihood model. Variables are constructed from CRSP and Compustat data and are winsorized at the 1st and 99th percentiles.

Control variables	
Ln(Assets)	The natural log of total assets.
Cash	Cash and cash equivalents, scaled by total assets.
ROA	Operating income before depreciation (EBITDA) divided by the book value of total assets.
Leverage	The sum of long-term debt and debt in current liabilities divided by the book value of total assets.
Z-score	The modified Altman's (1968) Z-score, defined as (1.2*Working capital + 1.4*Retained earnings + 3.3*EBIT + 0.999*Sales)/Total assets.
Market-to-book (M/B)	Market value of equity (price times number of shares) divided by book value of equity.
Harford (1999) variables	
Sales growth	Percentage growth in sales, averaged from year t - 4 to t - 1.
Noncash working capital	Current assets minus current liabilities and cash and cash equivalents, divided by total assets, averaged from year t - 4 to t - 1.
Leverage	Book value of debt divided by the market value of equity, averaged from year t - 4 to t - 1.
Market-to-book	The market value of equity divided by the book value of equity, averaged from year t - 4 to t - 1.
Price-to-earnings	Stock price divided by earning per share, averaged from year t - 4 to t - 1.
Size	The natural log of total assets at the beginning of year t.
Cash deviation	The difference between the firm's cash and cash equivalents as a percentage of total assets and the predicted industry average cash ratio at the beginning of year t
Avg. abnormal returns	The average daily abnormal percentage returns estimated from a market model using daily returns over the prior year.

Table A2. Firm-level Summary Statistics

This table presents summary statistics of the intersection of companies with M&A announcements reported in the Securities Data Corporation (SDC) database and 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 2019. Firm characteristics are based on Compustat data and are defined in Table A1.

	Mean	Std. Dev.	P10	Median	P90
Ln(Assets)	9.366	2.020	6.232	9.923	11.706
Cash	0.333	0.283	0.066	0.238	0.693
ROA	0.029	0.186	-0.108	0.054	0.157
Leverage	0.356	0.190	0.109	0.331	0.609
Z-score	1.273	1.780	-0.240	1.396	3.208
Market-to-book (M/B)	2.451	56.295	1.506	3.919	12.328

Internet Appendix

Table IA1. Anatomical Therapeutic Chemical (ATC) Codes
Panel A of this table presents an example on the ATC classification system from the World Health Organization (https://www.whocc.no/atc/structure_and_principles/). Panel B shows all 1-digit Anatomical Therapeutic Chemical codes.

Panel A: ATC hierarchy example

Level	Level description	Code	Name
1st (1-digit)	Anatomical main group	A	Alimentary tract and metabolism
2nd (3-digit)	Therapeutic subgroup	A10	Drugs used in diabetes
3rd (4-digit)	Pharmacological subgroup	A10B	Blood glucose lowering drugs, excl. insulins
4th (5-digit)	Chemical subgroup	A10BA	Biguanides
5th (7-digit)	Chemical substance	A10BA02	Metformin

Panel B: 1-digit ATC codes

Code	Name	Short Name
A	Alimentary tract and metabolism	Dietary
B	Blood and blood forming organs	Blood
C	Cardiovascular system	Cardiovascular
D	Dermatologicals	Dermatologics
G	Genito urinary system and sex hormones	Urinary & Sex
H	Systemic hormonal preparations, excl. sex hormones and insulins	Hormonal
J	Antiinfectives for systemic use	Antiinfectives
L	Antineoplastic and immunomodulating agents	Immune
M	Musculo-skeletal system	Musculo-Skeletal
N	Nervous system	Nervous
P	Antiparasitic products, insecticides and repellents	Antiparasitic
R	Respiratory system	Respiratory
S	Sensory organs	Sensory
V	Various	Various

Table IA2. 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 2019 and with drug prices reported in the National Average Drug Acquisition Cost (NADAC) survey conducted for the Centers for Medicare and Medicaid Services (CMS).

	Acquiror SIC											
Target SIC	Med Chem (2833)	Pharma Prep (2834)	Bio Products (2836)	Soap (2841)	Chemicals (2899)	Surgical (3841)	Orthopedic (3842)	Electro Med (3845)	Opthalmic (3851)	Med, Dent, & Hosp (5047)	Wholesale Drugs (5122)	Bio Research (8731)
Med Chem (2833)	0	1	0	0	0	0	0	0	0	0	0	0
Pharma Prep (2834)	1	98	3	1	2	3	0	0	0	1	0	1
Bio Products (2836)	1	39	5	0	0	1	1	0	0	0	0	0
Cosmetics (2844)	0	1	0	0	0	0	0	0	0	0	0	0
Ag Chem (2879)	0	0	0	0	1	0	0	0	0	0	0	0
Electro Components (3679)	0	1	0	0	0	0	0	0	0	0	0	0
Surgical (3841)	0	4	0	0	0	0	1	0	0	2	0	0
Electro Med (3845)	0	3	0	0	0	0	0	0	0	1	0	0
Opthalmic (3851)	0	1	0	0	0	0	0	0	0	0	0	0
Med, Dent, & Hosp (5047)	0	0	0	0	0	0	1	0	0	1	1	0
Wholesale Drugs (5122)	0	3	1	0	0	0	0	0	0	1	3	0
Drug Stores (5912)	0	0	0	0	0	0	0	0	0	0	2	0
Software (7372)	0	0	0	0	0	0	0	0	0	0	1	0
Comp Sys Design (7373)	0	0	0	0	0	1	0	0	0	0	0	0
Med & Surgical (8062)	0	0	0	0	0	0	0	1	0	0	0	0
Med Lab (8071)	0	1	0	0	0	0	0	0	0	0	0	0
Health Services (8099)	0	1	0	0	0	0	0	0	0	0	1	0
Bio Research (8731)	0	9	1	0	0	0	0	0	0	0	0	0

Table IA3. ATC Code Overlap and Sample Construction
This table provides a hypothetical example of how we sample drugs with product market consolidation. For each deal, we match each acquirer drug with all drugs produced by the target. In our baseline regressions, a drug is sampled if at least one of its ATC3 codes corresponds to at least one of the target drug's ATC3 code. The majority of drugs in our sample (65%) are associated with only one ATC3 code and 20% correspond to two ATC3 codes. The mean number of ATC3 codes is 1.88.

Acquirer Drug	Acquirer Drug ATC code(s)	Target Drug	Target Drug ATC code(s)	Product Market Consolidation
A1	R05	T1	J01	
A1	R05	T2	B01	
A1	R05	T3	M01	0
A1	R05	T4	L01; M01	
A1	R05	T5	N05	
A2	B01	T1	J01	
A2	B01	T2	B01	
A2	B01	T3	M01	1
A2	B01	T4	L01; M01	
A2	B01	T5	N05	
A3	L01	T1	J01	
A3	L01	T2	B01	
A3	L01	T3	M01	1
A3	L01	T4	L01; M01	
A3	L01	T5	N05	
A4	L01; M01	T1	J01	
A4	L01; M01	T2	B01	
A4	L01; M01	T3	M01	1
A4	L01; M01	T4	L01; M01	
A4	L01; M01	T5	N05	
A5	L01; R01	T1	J01	
A5	L01; R01	T2	B01	
A5	L01; R01	T3	M01	1
A5	L01; R01	T4	L01; M01	
A5	L01; R01	T5	N05	

Table IA4. Alternative Matching Procedure: Drug-level Propensity Score Matching
This table verifies the robustness of our main results to selecting control drugs based on propensity score matching. Panel A illustrates our drug-level propensity score model estimating product market overlap likelihood. *Patent* (*Exclusivity*) is an indicator equal to one if the drug is under patent (exclusivity protected), as noted in the FDA database. *Generic* is an indicator variable equal to one for generic drugs and zero for brand name drugs. *Over-the-counter* is an indicator variable equal to one for over-the-counter drugs and zero for prescription drugs. *Total units (millions)* are the total units reimbursed in the prior year as reported in Medicaid's State Drug Utilization Data (SDUD). Panel B confirms that our propensity score matching process satisfies the common support condition. We present means and differences in the covariates from our matching model and in propensity score across sample and control drugs. We match each sample drug (with overlap) with the control drug (without overlap) produced by the same drug manufacturer closest in predicted overlap likelihood the quarter of the acquisition based on the propensity score model in Panel A. Overlap implies the target firm produces a drug sharing the same ATC3 code or has similar drugs in the pipeline. Panel C verifies the robustness of our baseline results presented in Table 3 to this alternative matching procedure.

Panel A: Propensity to Overlap Model

Dependent variable: *Consolidate*	
Patent	-0.124***
	(-4.701)
Exclusivity	-0.052
	(-1.124)
Generic	-0.006
	(-0.253)
Over-the-counter	0.325***
	(17.037)
Total units (millions)	0.005*
	(1.734)
Constant	-0.952***
	(-52.434)
Observations	39,354
Pseudo R^2	0.0126

Panel B: Matching and Common Support

	Sample	Control	Difference	t-stat
Patent	0.085	0.082	0.003	-1.287
Exclusivity	0.021	0.019	0.001	-1.808
Over-the-counter	0.089	0.090	-0.001	1.421
Generic	0.821	0.822	-0.001	1.036
Total units (millions)	0.371	0.300	0.071	-1.779
Propensity score	0.246	0.246	0.000	0.761

Panel C: Baseline DID

	± 4 qtr	± 6 qtr
	(1)	(2)
Consolidate*Post	0.018**	0.018*
	(2.236)	(1.898)
Fixed effects	Product (NDC)-Deal, Deal-Event Time	
Observations	165,737	119,599
Adjusted R^2	0.001	0.001

Table IA5. Robustness of Baseline Results to Winsorizing Drug Prices
This table examines the robustness of the Table 3 difference-in-differences regressions of drug prices on merger activity to winsorizing the dependent drug price variable.

	± 1 qtr (1)	± 2 qtr (2)	± 3 qtr (3)	± 4 qtr (4)	± 5 qtr (5)	± 6 qtr (6)
Consolidate*Post	0.013***	0.016***	0.018***	0.019***	0.019**	0.019**
	(3.071)	(2.983)	(2.783)	(2.578)	(2.212)	(2.020)
Fixed effects	Product (NDC)-Deal, Deal-Event Time					
Observations	41,609	68,514	93,857	118,159	141,683	163,787
Adjusted R^2	0.002	0.001	0.001	0.001	0.001	0.001

Table IA6. Robustness to Excluding Pipeline Drugs from Overlap
This table presents the robustness of our Table 3 difference-in-differences regressions of drug prices on merger activity to excluding pipeline overlap from the product market overlap definition. Pipeline overlap between the drug and the target firm's drug portfolio stems from a drug in the pipeline rather than a drug that has already entered the market. In the regressions below, pipeline overlap is not considered overlap.

	± 1 qtr	± 2 qtr	± 3 qtr	± 4 qtr	± 5 qtr	± 6 qtr
	(1)	(2)	(3)	(4)	(5)	(6)
Consolidate*Post	0.015***	0.020***	0.022***	0.024***	0.023**	0.023**
	(3.199)	(3.240)	(3.040)	(2.835)	(2.451)	(2.212)
Fixed effects	Product (NDC)-Deal, Deal-Event Time					
Observations	36,539	60,164	82,364	103,565	124,174	143,676
Adjusted R^2	0.002	0.002	0.002	0.001	0.001	0.001

Table IA7. Robustness of Baseline Results to Re-normalizing Pre/Post Cutoff
This table examines the robustness of the Table 3 difference-in-differences regressions of drug prices on merger activity to re-normalizing the cutoff between the pre-merger and post-merger period. To account for anticipatory effects, we include quarter -1 in the post-merger period. We must exclude our first model from one quarter before the merger to one quarter after since all observations would now occur in the post-merger period.

	± 2 qtr	± 3 qtr	± 4 qtr	± 5 qtr	± 6 qtr
	(1)	(2)	(3)	(4)	(5)
Consolidate*Post	0.018***	0.020***	0.021***	0.021**	0.021**
	(3.035)	(2.939)	(2.755)	(2.415)	(2.228)
Fixed effects	Product (NDC)-Deal, Deal-Event Time				
Observations	68,514	93,857	118,159	141,683	163,787
Adjusted R^2	0.001	0.001	0.001	0.001	0.001

Table IA8. New Drug Approval by Submission Classification Code

This table provides summary statistics on the distribution of US Food and Drug Administration (FDA) New Drug Approval (NDA) classifications by type.

Submission Classification	All new drug applications?	New labeling?	New drug approval?	% Total Applications
Labeling	Yes	Yes	No	66.7%
Type 1 - New Molecular Entity	Yes	No	Yes	0.7%
Type 2 - New Active Ingredient	Yes	No	Yes	0.1%
Type 3 - New Dosage Form	Yes	No	Yes	0.6%
Type 4 - New Combination	Yes	No	Yes	0.2%
Type 5 - New Formulation or New Manufacturer	Yes	No	Yes	0.8%
Type 7 - Drug Already Marketed without Approved NDA	Yes	No	Yes	0.1%
Type 8 - Partial Rx to OTC Switch	Yes	No	Yes	0.0%
Type 9 - New Indication Submitted as Distinct NDA, Consolidated with Original	Yes	No	Yes	0.0%
Type 10 - New Indication Submitted as Distinct NDA - Not Consolidated	Yes	No	Yes	0.0%
Type 1 - New Molecular Entity and Type 4 - New Combination	Yes	No	Yes	0.1%
Type 2 - New Active Ingredient and Type 3 - New Dosage Form	Yes	No	Yes	0.0%
Type 2 - New Active Ingredient and Type 4 - New Combination	Yes	No	Yes	0.0%
Type 3 - New Dosage Form and Type 4 - New Combination	Yes	No	Yes	0.0%
Other	Yes	No	No	30.7%

Table IA9. Firm-level Propensity Score Matching

This table illustrates our propensity score model for our innovation analyses. We estimate acquisition likelihood using the Harford (1999) acquisition likelihood model. Variables are defined in Table A1.

Dependent variable: Acquisition Indicator	
Sales growth	0.025*
	(1.93)
Noncash working capital	1.076
	(1.22)
Leverage	-0.409
	(-0.83)
M/B	0.002
	(0.51)
P/E	0.001
	(0.39)
Ln(Assets)	0.283**
	(6.70)
Cash deviation	5.249
	(0.41)
Abnormal return	1.273
	(3.08)
Constant	-3.141***
	(-7.78)
Observations	401
Pseudo R^2	0.1553