Seeking efficiency or price gouging? Evidence from pharmaceutical mergers

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Abstract

We examine the impact of mergers on drug prices and document significant differences between the post-merger pricing strategies of highly innovative pharmaceutical firms and other firms. While the former raise prices of overlapping drugs, especially brand name drugs that tend to be first-in-class and patented, we find pervasive evidence of price reductions by generic manufacturers. Our evidence suggests that the price reductions are due to cost cuts realized by less innovative firms in overlapping product spaces. We also show that less innovative acquirers cut R&D and shift product development from high-novelty products to cheaper, less-risky products.

1. Introduction

Significant consolidation in the pharmaceuticals industry in recent years has led to growing concern in the media and among lawmakers that such consolidation leads to higher drug prices. Due to a few incidents of price gouging, such as the 5400% price increase of the toxoplasmosis drug Daraprim, numerous media articles and policy papers propose that mergers are a leading cause of rising drug prices in the United States.[1] In addition, recent academic findings suggest that mergers result in higher drug prices (Bonaime and Wang, 2023) and lower innovation and competition (Cunningham, Ederer and Ma, 2021).

In this paper, we show that while price increases are observed for drugs owned by highly innovative firms, there is also evidence of widespread post-merger reductions in the price of drugs owned by less innovative firms. A central theme of our paper is the distinction between the business models of innovative pharmaceutical firms such as Pfizer which derive most of their revenue from novel first-in-class (FIC) drugs and those of less innovative firms such as Teva Pharmaceuticals that derive significant revenue from generic drugs and 'me-too' brand name drugs. This distinction is important because me-too drugs and generic drugs rely on competitive pricing: me too drugs compete on price with FIC drugs, while generic drugs traditionally generate profit through high-volume sales at low profit margins.

Prior studies show that mergers create opportunities to improve efficiency by eliminating operational redundancies and achieving scale economies. Generic pharmaceutical firms commonly cite cost reductions as the primary reason for merging. For example, Watson expected $300 million in annual cost synergy savings within three years from its acquisition of Actavis in 2012. These synergies included savings in SG&A, R&D, corporate, purchasing, and raw material supply. The

[1]See for example Collins and McCaskill (2017)'s proposal to improve generic competition and Fortune Media's article on high drug prices.

merged firm, which adopted the name Actavis, subsequently acquired Warner Chilcot in 2013 quoting "more than $400 million in after-tax operational synergies and related cost reductions, and tax savings". Yet, we know little about whether cost synergies exist in pharmaceutical mergers and, if they do, whether customers benefit from the same.[2] The only study we know that touches upon efficiency gains in the pharmaceuticals sector is the exploratory review of Richman, Mitchel, Vidal and Schulman (2017).

While the debate about market power and synergies in mergers and acquisitions is not new, we believe it is necessary to address this question in the pharmaceuticals industry for the following reasons. First, the issue is important from both a social and economic perspective because drug prices are the fastest growing component of total health-care costs in the United States (Berman, Lee, Pan, Rizvi and Thomas, 2017). In 2020, the United States spent $535 billion on prescription drugs, which was more than 30% of global prescription drug spending (Tichy et al, 2021). Second, despite numerous media articles and case studies on a handful of infamous price increases, large-sample rigorous analysis of the impact of mergers on drug prices is scarce. Third, the pharmaceuticals industry provides an ideal setting to study mergers due to the availability of product-level price data, established product market classification systems, and a high likelihood of unchanged product quality after a merger. The last point helps address concerns that post-merger price changes could be due to changes in product quality or in service (Sheen, 2014).

Using product-level data on drugs covered by Medicaid between 2007 and 2020, we examine the change in price of drugs after 125 pharmaceutical mergers between 168 unique pharmaceutical firms, both public and privately held. Looking at the subset of drugs that overlap across the acquirer and target portfolios (i.e., products that create opportunities for market power or synergistic gains),

[2] While large-sample evidence on drug prices is scant, there exists an active literature on the drivers of pharmaceuticals mergers (see Krieger, Li and Thakor (2021), Higgins and Rodriguez (2006), Danzon, Epstein, Nicholson, Vernon and Manning (2007)).

we show that highly innovative firms raise prices by 6.3% after the merger relative to control drugs belonging to non-merging firms. In contrast, the price of overlapping drugs belonging to less innovative firms is 5.8% lower after the merger relative to control drugs. According to the Medical Expenditure Panel Survey, adults pay almost half (48%) of prescription drug expenses out-of-pocket on average, with persons aged 65 to 79 paying 56% and those aged 80 and older paying 67% of their total drug expenditures out-of-pocket.[3] Since drugs owned by less innovative firms account for about 75% of all prescriptions dispensed to Medicaid enrollees, the post-merger price reductions by less innovative firms may significantly reduce out-of-pocket expenses for a significant portion of enrollees, and US patients in general (see section 3.1 for a discussion on the representativeness of drugs in Medicaid for the US market).

Exogenous factors can affect both product prices and firms' incentive to merge. Therefore, empirical methods that compare merging firms' drugs to those of non-merging firms suffer from endogeneity due to omitted variables. To address this concern, we exploit within-merger, within-drug variation in prices and focus on the difference between the price change of drugs that overlap across the acquirer and target portfolios and drugs that do not overlap. Overall, the price of overlapping drugs of merging firms is 5.6% lower after a merger than that of non-overlapping drugs of merging firms. We continue to find differences in the post-merger pricing behavior of highly innovative and less innovative firms. In the subsample of highly innovative firms, the price of overlapping drugs increases after the merger relative to non-overlapping drugs. In the subsample of less innovative firms, the price of overlapping drugs, both generic and brand name, declines relative to that of non-overlapping drugs. To account for the fact that drugs owned by innovative

[3] See the summary at Health Policy Institute, Georgetown University at https://hpi.georgetown.edu/rxdrugs/

firms tend to be more expensive FIC drugs, we conduct a revenue weighted analysis and find that our key results continue to hold.

The post-merger price increase of overlapping drugs owned by innovative firms is consistent with the findings of Bonaime and Wang (2023). Their sample is restricted to public firms that are listed on U.S. exchanges, which tend to be highly innovative firms. Our study contains more heterogeneity in firm innovativeness because we include both private firms as well as public firms listed on an overseas exchange but sell their products in the U.S. market. The starkly different post-merger pricing behavior of less innovative firms warrants further investigation because generic drugs and me-too brand name drugs account for a significant share of the U.S. market. The popularity of me-too drugs has increased significantly in the past decade. Over 60% of the drugs listed in the World Health Organization's essential list are me-too drugs (Aronson and Green, 2020). If we divide our sample into me-too and FIC drugs, we find that less innovative firms lower the price of me-too drugs after mergers while highly innovative firms increase FIC prices after mergers. We also note that over 70% of prescriptions filled in the United States are for generic drugs, and these drugs experience a significant post-merger price decline.[4] Although generic drugs account for only 20% of total drug spending in the United States, our findings indicate that payers can shield themselves from post-merger price hikes implemented by innovative pharmaceutical firms by switching their formularies toward generic drug products.

The rest of the paper is devoted to understanding why drug products owned by less innovative firms experience post-merger price declines. We show that less innovative acquirers that have greater product overlap with the target firm experience a post-merger decline in selling, general and administrative expenses (SG&A) relative to control firms. In contrast, highly

[4] "Trends in prescription drug spending, 2016-2021", ASPE, Department of Health and Human Services.

innovative firms do not experience a post-merger reduction in SG&A. These findings suggest that less innovative acquirers extract merger-related cost synergies and reduce prices to keep their generic drugs and me-too drugs' competitively priced.

We also find that less innovative acquirers that have greater product overlap with the target firm reduce research and development expense (R&D) after mergers while innovative acquirers do not. To understand the implications of these R&D savings, we draw on Allergan's acquisition by Actavis in 2014, where Actavis announced R&D reductions of $400 million to be achieved by dropping programs that were not "high probability of success".[5] We examine whether, after a merger, less innovative firms tilt their product pipelines toward less risky products. Using product pipeline data provided by Cortellis Life Sciences data, we show that less innovative firms reduce the development of high-novelty, early-stage drugs products that carry high clinical risk and step-up the development of low-novelty, late-stage products. These findings are consistent with recent evidence on the growing popularity of me-too drugs that are cheaper to develop, carry lower development risk, and are well-positioned to compete on price with FIC drugs (Aronson and Green, 2020).

Our findings contribute to the literature on asset complementarity in mergers and acquisitions, such as Rhodes-Kropf and Robinson (2008), Hoberg and Phillips (2010), Bena and Li (2014), and Lee et al. (2018). Our paper is also related to recent studies by Cunningham et al. (2021) and Bonaime and Wang (2023) which suggest that pharmaceutical mergers are anticompetitive. While we confirm prior evidence of market power being exercised by innovative pharmaceutical firms, we also document pervasive evidence of post-merger price reductions by

[5] See "Actavis rescues Allergan with $66 billion deal", Chemistry World, Nov 23, 2014.

less innovative firms.[6] We show that generic-focused firms, whose business model rests on competitive pricing and bringing products to market quickly, achieve merger-related cost cuts in overhead and R&D to keep their products competitive.

The rest of the papers is organized as follows. Section 2 discusses different business models in the pharmaceuticals industry and implications for post-merger pricing. Section 3 presents the description of our data and variables. Section 4 compares the change in price of merging firms' drugs to that of control drugs. Section 5 compares overlapping and non-overlapping drugs within the same merger. Section 6 explores explanations for the price reductions. Section 7 concludes.

2. The differing business models of branded and generic firms

The pharmaceuticals industry comprises of two markedly different business models. Branded companies such as Eli Lilly and Novo Nordisk invest significant resources into the development of innovative first-in-class (FIC) therapies and rely on patent protection to generate high profit margins in temporary monopolistic product spaces. For these firms, mergers are a means of acquiring product pipelines and maintaining a strong portfolio of patented drugs (Higgins and Rodrigues, 2006). Less innovative firms depend more on the high-volume sales of generic drugs, me-too drugs and off-patent drugs that have low profit margins. For example, Teva derives 55% of its revenue from generic drugs, and the rest from less innovative follow-on branded drugs.

Since consumers are highly sensitive to the price of generic drugs, competitive pricing is a key decision factor for generic companies. In addition, less innovative pharmaceutical firms favor the development of me-too drugs over high-risk R&D programs.[7] Existing evidence shows that

[6] Studies that document synergy gains in mergers are Eckbo, 1983; Stillman, 1983; Healy, Palepu and Ruback, 1992; Heron and Lie, 2002; Fee and Thomas, 2004; Shahrur, 2005, Bena and Li, 2014; Hoberg and Phillips, 2010; Lee, Mauer, and Xu, 2018. Studies that find evidence supportive of the market power effect of mergers in other industries are Borenstein, 1990; Kim and Singal, 1993; Prager and Hannan, 1998; McCabe, 2002; Kwoka and Shumilkina, 2010.

[7] While some me-too drugs may perform worse than an FIC drug (see Zhao et al, 2022), the incremental benefit for most me-too drugs relative to the FIC drug is unknown. This is because the FDA requires firms to demonstrate the safety and efficacy of a drug

me-too drugs are cheaper to develop and are often priced lower than FIC drugs, thus putting price pressure on FIC drugs (DiMasi, 2000; Lee, 2004 Régnier 2013). Given the importance of competitive pricing for generic and me-too drugs, acquisitions by less innovative firms are often motivated by cost synergies. For example, the 2012 acquisition of generic manufacturer Actavis by Watson Pharmaceuticals (the merged firm was renamed Actavis) was justified on the basis of significant R&D and SG&A reductions, and savings in corporate purchases and raw materials. Valeant Pharmaceuticals, a generic company, has undertaken a series of acquisitions that were followed by significant cuts in R&D.[8] Several other pharmaceutical mergers refer to expected improvements in operating efficiency through elimination of redundant jobs.[9]

The examples cited above refer to reductions in SG&A more frequently than reductions in production costs. This difference is likely due to the fact that in the pharmaceuticals industry variable production costs are relatively low compared to SG&A. In our sample, SG&A is, on average, 42% of sales while cost of goods sold (COGS) is 28%. In the subsample of less innovative firms, the difference is starker, with SG&A accounting for 48% of sales and COGS only 22%. If pharmaceutical firms cut overhead costs after acquisitions, the question arises whether these cuts should affect prices. Although economic theory prescribes that pricing decisions be based on marginal (or variable) cost, there is considerable evidence that firms consider fixed costs in their pricing decisions. The surveys by Govindarajan and Anthony (1983) and Shim and Sudit (1995) on American manufacturing companies indicate that more than 60 percent of them use full-cost pricing. This divergence between theoretical recommendations and business practices is well known and discussed in Lere (1986), Hilton, Swieringa, and Turner (1988), Kamphorst et al

relative to a placebo and not relative to existing approved drugs. In the few exceptions where a me-too drug outperformed the FIC, the me-too was considered the best-in-class.

[8] For the acquisition of Actavis by Watson, see https://www.fiercepharma.com/pharma/watson-completes-actavis-acquisition. For Valeant's acquisitions, see https://www.fiercebiotech.com/biotech/valeant-turns-to-acquisitions-as-it-cuts-diy-development.

[9] Takeda announced job cuts after its 2015 acquisition of Nycomed and its 2017 merger with Ariad Pharmaceuticals.

(2020), Thépot and Netzer (2008), and Fekrat (1972). Whether pharmaceutical firms engage in full-cost pricing and pass through post-merger overhead cost cuts to prices is ultimately an empirical question. To shed light on these issues, we study both the change in drug prices and change in SG&A after pharmaceutical mergers.

Since generic pharmaceutical firms frequently refer to reductions in R&D after mergers, we also examine post-merger change in R&D. Reduction in R&D is unlikely to matter for the price of existing drug products (by virtue of being a sunk cost), but it has implications for new product development and can shed light on the overall pricing strategy of pharmaceutical firms. R&D cuts announced by Actavis during its acquisition of Allergan (discussed in the introduction above) suggests that generic pharmaceutical firms shift their post-merger product pipeline toward low-novelty products such as me-too drugs which cost less to develop and compete on price with FIC drugs.[10] Therefore, we also examine post-merger changes in firms' product pipelines to better understand whether this example is indicative of a general research and development strategy.

3. Prescription drug sample and data sources

In this section, we describe our data sources and sample. In some cases, details of the data or robustness of results are provided separately in the internet appendix.

3.1 Data sources and sample description

Our sample of drugs is obtained from the Medicaid State Drug Utilization Data (hereafter SDUD), a publicly available resource that provides comprehensive coverage for outpatient drugs paid for by state Medicaid Agencies (see Section IA.1 and IA.2 of the internet appendix for more details). The SDUD reports drug utilization data on a quarterly basis, including total spending and prescriptions dispensed for each state as well as national totals.

[10] See "Actavis rescues Allergan with $66 billion deal", Chemistry World, Nov 23, 2014.

Drugs in Medicaid adequately represent those in the US in two regards. First, Medicaid covers the cost of virtually any drug prescribed to an enrollee as part of a medically necessary treatment plan.[11] Moreover, Medicaid currently covers over 80 million enrollees with a wide range of demographics. Although Medicaid accounts for about 15% of national drug spending, it is legally required to cover *all* drugs offered by a manufacturer if that manufacturer enters into the rebate agreement outlined by the Medicaid Drug Rebate. During our sample period, Medicaid covered outpatient drugs of about 600 manufacturers, suggesting that nearly all approved-for-sale outpatient drugs were covered by Medicaid.

Are Medicaid prices comparable to those paid by private buyers? To answer this question, we first need to understand how Medicaid prices are determined. The Medicaid Best Price rule requires manufacturers to provide Medicaid with the lowest price offered to any other buyer, namely the "best price." Medicaid first pays pharmacy providers that dispense drugs the "actual acquisition cost," which is estimated using an average of the prices paid by wholesalers that buy directly from the manufacturer. Manufacturers then provide Medicaid with rebates to ensure that it gets the best price. Rebates are kept confidential and are difficult to obtain (see, for example, Lakdawalla and Li, 2021). The drug price data in Medicaid's SDUD is reported on a pre-rebate basis. These pre-rebate prices are representative of the average prices paid directly to the manufacturer by pharmacy providers to acquire a drug. SDUD is also a commonly used database. For example, it is used by states to monitor prescription drug expenditures (Young, Rudowitz, Garfield and Musumeci, 2016), and by pharmaceutical manufacturers to benchmark their list prices (MACPAC, 2017). To account for possible weakness in the SDUD database, we cross-validate the SDUD drug prices with those in an alternative drug price survey (namely, Medicaid's

[11] When possible, Medicaid prioritizes cheaper generic, but will cover the brand name if medically required by a patient.

NADAC data) that includes the actual prices paid by retail pharmacies (see Internet Appendix IF for details on matching and comparing our sample to the NADAC data). Our findings are robust using this dataset (see Section ID.3 and Table ID.7 of the Internet Appendix).

We obtain a sample of 70,946 unique drug products, identified by the National Drug Code (NDC), that were sold to Medicaid between the first quarter of 2007 and the third quarter of 2020. Next, we identify the manufacturing firms and use merger data from SDC Platinum to determine whether a drug manufacturer was involved in an acquisition between the third quarter of 2007 and the first quarter of 2020.[12] Acquisitions by pharmaceutical firms of targets that are not in the pharmaceuticals industry are excluded. Table ID.8 of the Internet Appendix lists the SIC codes for deals in our sample. Our sample consists of 125 mergers with 19,357 affected drugs offered by 168 firms. For each drug, we obtain information on drug type (such as generic or brand name drug), patent and exclusivity protection from the Medicaid Drug Rebate Program Data and the FDA's Orange Book and NDC Directory. Drugs that do not match to the Orange Book are assumed to not have patents or exclusivity coverage. Details regarding the matching of drug characteristics is provided in Internet Appendix IA.4.

Table 1 presents statistics for acquirers and targets. Acquiring firms have average quarterly Medicaid sales of $100 million while targets have average quarterly Medicaid sales of $23 million. Table 1 also provides a breakdown by drug type of the average quarterly number of products sold by the acquirer and target. The drug-type categories are not mutually exclusive. For example, both brand name and generic drugs can be prescription drugs. Thus, the number of drugs in each sub-category will not add up to the total number of drugs sold by the acquirer or target.

[12] To match SDUD firms to merger data obtained from SDC. We first use the FDA's NDC directory files and the Medicaid Drug Rebate Program Data files to identify the drug manufacturer's name using the labeler code (i.e., the first segment of the NDC code). Second, we standardize firm names and conduct a fuzzy match between firm names in SDUD and those in either SDC or Compustat historical files. See Section IA.3 in the Internet Appendix for details.

3.2 Product space

In our primary analysis, we define product spaces using the well-accepted Anatomical-Therapeutic-Chemical Classes at the 4th level (hereafter ATC-4).[13] ATC codes are a drug classification system managed by the World Health Organization that classifies the active substances of a drug based on the organ or system on which the drug acts and the drug's therapeutic, pharmacological, and chemical properties. To match each drug in the Medicaid data with an ATC code, we use the ATC to NDC crosswalk provided by Kury and Bodenreider (2017). For the full SDUD sample from 2007q1 to 2020q3, we are able to match about 60% to an ATC code. We increase the match rate to 75% by filling the missing ATC codes of unmatched drugs with the codes of matched drugs with identical active ingredients.[14] More information on ATC classifications and our matching procedure is provided in Internet Appendix IB.

We assume that drugs with the same ATC-4 code are similar. This means that drugs are considered to overlap across the acquiring and target firm's portfolios if they target the same anatomical group, have the same pharmacological therapeutic properties, and the same chemical subgroup. Across all our quarterly drug-price observations, 16% relate to overlapping drugs. A drug-quarter may have multiple observations if its owner was involved in more than one deal.

3.3 Drug price data

We obtain quarterly *Price Per Unit* (PPU) for each drug product from SDUD. SDUD reports quarterly sales and units dispensed for each drug. We winsorize both these variables at the 1% and 99% levels and calculate price per unit (PPU) for each drug-quarter as total sales divided

[13] We present robustness to defining product spaces at different ATC levels in Internet Appendix Section ID.2 and show consistent results in Table ID.6. We also examine the robustness of our findings to a different classification system where we employ the text-based cosine similarity method of Hoberg and Phillips (2016) to find the pairwise similarity between all drugs in our sample along two dimensions - the therapeutic area and the mechanism of action of each drug. Details of the construction of these product spaces are provided in Internet Appendix IC and robustness of our main findings are shown in Table ID.3.

[14] We find that results are similar if we do not fill in the missing ATC codes (i.e., if we use the 60% matched sample).

by total units sold. We use the Consumer Price Index to adjust PPU to 2015 dollars. We examine the change in PPU of drugs, including both the acquiring firm's drugs and the target firm's drugs, during the eight quarters before and eight quarters after the announcement of a merger. To be included in this sample, we require a drug to have at least two quarters of observations before the merger announcement and at least two after. Figure 1 presents the distribution of the percentage change in PPU, calculated as the average drug price after merger announcement less average drug price before announcement divided by the average drug price before.

Looking first at extreme price increases among all drugs (Figure 1 Panel A), about 3% (1%) of drugs experience price increases greater than 500% (1000%). While instances of exorbitant price increases do exist, the median change for all drugs is -10%. However, there is noticeable heterogeneity across groups. Brand name drugs experience a median change of 10% (Panel B). Generic drugs experience a median price change of -15% (Panel C). Finally, drugs that overlap across acquirer and target portfolios have a median price change of -10% (Panel D).

In our first set of tests shown in Section 4 below, we compare the change in price of merging firms' drugs (i.e., treated drugs) to a sample of control drugs. We match each treated drug to a control drug in the same ATC4 market but owned by a pharmaceutical firm that did not experience a merger in the past 16 quarters. The control drug is matched along several dimensions: brand name/generic, presence of drug records during the same quarters, patent status, and innovativeness of the manufacturer. Patented drugs are drugs with patents expiring in five years or later. Unpatented drugs are drugs that have no patent protection or have patents that are expiring within five years.[15] A firm is classified as highly innovative if the percentage of its products that are patented as of merger announcement quarter is in the top quartile of the sample (henceforth, for

[15] We follow Cunningham et al (2021) in choosing 5 years of remaining patent protection as the cutoff for distant patent expiration. Our results are similar if we instead use a 3-year cutoff.

brevity, referred to as INV firms).[16] The remaining firms are referred to as less innovative firms (LINV firms, for brevity). For merging firms, innovativeness is defined using the acquirer's patent portfolio.[17] In Panel A of Table 2, we summarize PPU, and various characteristics of drugs owned by the acquirer or target (treatment sample) as well as control drugs. Since the sample of control drugs is matched on drug type, patent status, and firm innovativeness the differences in means between the treated and control group in the bottom row of Table 2 Panel A are negligible.

In Panel B of Table 2, we present average PPU of treated and control drugs within various sub-groups such as brand name drugs, generic drugs, biologic drugs, patented drugs, and unpatented drugs. We also compare the price level of drugs that overlap across the acquirer and target portfolios to the price level of control drugs. Finally, we look at price levels within subsamples of drugs owned by INV firms and LINV firms. In most subsamples presented in Panel B of Table 2, we see statistically significant differences in the price levels of treatment and control drugs. As in Bonaime and Wang (2023), we do not explicitly match on price levels as doing so reduces the pool of control drugs and potentially biases the difference-in-difference estimates.

4. Comparing drugs of merging firms with those of non-merging firms

In this sub-section, we compare treatment drugs to a sample of control drugs belonging to firms that did not engage in a merger in the 16 quarters centered around the merger. Since mergers are staggered over time, we use the following "stacked" difference-in-differences (DID) model:

$$\ln(PPU)_{dmt} = \delta_1(Post_{mt} \times Treated_{dm}) + \theta_{md} + \omega_{mt} + \varphi_{aq} + \varepsilon_{dmt} \qquad (1)$$

[16] Patents are known to be associated with innovation (see for example, Acs, Anselin and Varga, 2002). To alleviate any measurement error concerns related to our measure of innovativeness, we rerun our tests using above-median and the top tercile to define innovativeness and find qualitatively similar results.

[17] Table ID.2 of Internet Appendix ID provides summary statistics on deal innovativeness.

The dependent variable is the natural log of the PPU of a treated or control drug *d* associated with merger *m* occurring during event quarter *t*. *Post* is an indicator variable that takes the value of 1 for all quarters (up to 8) following merger *m* and 0 for all quarters (up to 8) prior to the merger. *Treated* is an indicator equal to 1 for drugs owned by merging firms and 0 for drugs owned by non-merging firms. Following the recommendations of Gormley and Matsa (2011) and Baker, Larcker, and Wang (2022), we saturate drug- and time-fixed effects with deal indicators: θ_{md} are drug-deal fixed effects, which control for time-invariant differences in prices across drugs and ω_{mt} are event-quarter fixed effects. To control for the evolution of prices in each product category regardless of merger occurrence we include ATC4-product-category times calendar-quarter fixed effects φ_{aq}. We present robust standard errors clustered at the drug level.

Estimates of equation 1 are presented in Table 3. In columns 1 and 2, we include only a limited set of fixed effects, while column 3 presents estimates from the saturated model shown in equation 1. Note that in all columns except column 1, event-quarter fixed effects ω_{mt} absorb the stand-alone $Post_{mt}$ indicator. In columns 1 through 3, which include all drugs in our sample, the interaction of Post and Treated is statistically indistinguishable from zero. Thus, in the full sample, we observe no difference between the post-merger price change of treated drugs relative to control drugs. In columns 4 to 7, we examine prices in different drug sub-groups (not mutually exclusive) such as brand name drugs, generic drugs, patented drugs, and unpatented drugs. The coefficient on the interaction term indicates heterogeneity across subgroups in the post-merger price change. The prices of treated brand name drugs and patented drugs increase after the merger, but those of treated generic drugs and unpatented drugs do not. Since brand name drugs and patented drugs tend to belong to INV firms, we look within subsamples of drugs owned by INV firms (column 9)

and LINV firms (column 8) separately.[18] The interaction term indicates that the price increase of treated drugs is observed only in the sub-sample of drugs owned by INV firms. Drugs owned by LINV firms do not display price increases relative to control drugs. This evidence points towards the possibility that INV firms have different post-merger pricing strategies than LINV firms.

The results presented in Panel A of Table 3 present average changes in drug prices within several samples but do not distinguish between drugs that overlap across the acquirer and target portfolios and those that do not. Product overlap is an important consideration in mergers and acquisitions since opportunities to exercise market power or extract merger synergies arise when the acquirer and target similar products (Bonaime and Wang, 2023). In Panel B of Table 3, we present estimates of equation 1 only for drugs that overlap across the target and acquirer portfolios. All estimates in Panel B employ the saturated model shown in equation 1. In column 1, we see that the interaction of Treated and Post is negative and statistically significant at the 1% level, indicating that overlapping treatment drugs decline in price after the merger relative to control drugs. This post-merger decline in the price of overlapping drugs is driven by generic drugs (column 3) and unpatented drugs (column 4). In contrast, the price of overlapping patented drugs increases after mergers (column 5). Since generic drugs and unpatented drugs tend to be manufactured by LINV firms, we look at overlapping drugs in subsamples of LINV and INV firms respectively. Column 6 (column 7) shows that overlapping drugs belonging to LINV (INV) firms experience post-merger price declines (increases) relative to control drugs.

In Panel C, we check whether this contrast between the post-merger price change of overlapping drugs belonging to INV and LINV firms hold within different drug-type subsamples such as generic, brand name, patented, and unpatented. We find that for the drugs of LINV firms

[18] About 27% (4%) of drugs owned by INV (LINV) are patented, and about 65% (15%) owned by INV (LINV) are brand name.

(columns 1 to 4), the interaction of Treated and Post has a negative sign in all subsamples and is statistically significant for generic drugs and unpatented drugs. In contrast, for innovative firms (columns 5 to 8), the interaction of Treated and Post has a positive sign in all subsamples and is statistically significant for brand name drugs and patented drugs.

An important identifying assumption in the DID results shown in Table 3 is that the treatment and control group have parallel trends. We test for parallel trends using the following equation that allows the effects to vary by quarter

$$\ln(PPU)_{dmt} = \sum_{t=-8}^{t=8} \rho_t \, Treated_{dm} \times Q_{mt} + \theta_{md} + \omega_{mt} + \varphi_{aq} + \varepsilon_{dmt} \quad (2)$$

In this equation, we have replaced the variable Post with multiple indicators Q_{mt} that take the value one for observations corresponding to quarter t relative to merger announcement. If the parallel trends assumption holds, the coefficients on the interaction of Treatment and the event quarter indicators should be insignificantly different from zero prior to the merger. Figure 2 plots estimates of differences in the price trends between treatment and control drugs. Figure 2A is based on the full sample, while Figure 2B is restricted to overlapping drugs only. In both figures 2A and 2B, the pre-merger ρ_t are statistically indistinguishable from zero. In Figures 2C and 2D respectively, we present estimates of equation 2 separately for overlapping drugs of LINV firms and INV firms. Again, the pre-merger ρ_t are statistically indistinguishable from zero.

In both Figures 2B and 2C, it is noticeable that the difference between the price of overlapping treatment drugs and control drugs declines for up to 5 quarters after merger announcement and then rises. In Figure ID.1.A in the Internet Appendix, we show that the reversion toward zero after 5 quarters is due to a decline in the price of control drugs after five quarters. Since control drugs operate in the same ATC4 market, our evidence suggests that non-merging firms' price-match overlapping treatment drugs to keep their products competitive.

We highlight two takeaways from this subsection. First, there is heterogeneity in post-merger price movements across drug types. Second, INV and LINV firms have different post-merger strategies with price decreases (increases) observed for overlapping products of LINV (INV) firms. While these findings shed light on price changes, they are subject to endogeneity concerns. We discuss our identification strategy in the next section.

5. Overlapping versus non-overlapping drugs within the merger sample

Although Table 3 suggests that significant price changes occur at the time of a merger, the merger may not be the cause of the change. The merger decision itself is endogenous because unobserved factors that affect drug prices may create incentives for firms to merge. As in Bonaime and Wang (2023), we address endogeneity of the merger decision by focusing on the sample of merging firms and compare the change in price of overlapping drugs owned by the merging firms with the change in price of non-overlapping drugs owned by the merging firms. The underlying premise is that merging firms' drugs in the same product market (i.e. overlapping drugs) are impacted by the merger while non-overlapping drugs are not. In the internet appendix, we also address selection concerns using a quasi-experiment in which treatment drugs are compared to drugs belonging to firms involved in withdrawn merger bids (see Section ID.1 and Table ID.1 in in the internet appendix).

In Table 4 Panel A, we summarize characteristics of all merging firms' drugs, as well of subsamples of overlapping drugs and non-overlapping drugs of merging firms. This sample includes all drugs owned by the acquirer or target and is referred to as the main sample. We see that overlapping and non-overlapping drugs of merging firms have significantly different characteristics. For example, overlapping drugs are less likely to be patented, and less likely to be brand name. To address this concern, we run all our tests within subsamples based on drug type.

However, for robustness, we also create a smaller sample called the matched sample in which each overlapping drug of the merging firms is matched to a non-overlapping drug within the same merger that has average quarterly sales within 50% to 150% of the overlapping drug and has the same patent coverage status. Panel A of Table 4 shows that in the matched sample, differences between overlapping and non-overlapping drugs are mostly insignificant.

We estimate the stacked DID regression model in equation 3 below using drugs owned by merging firms only.

$$\ln(PPU)_{dmt} = \alpha_1(Post_{mt} \times Overlap_{dm}) + \zeta_a + \theta_{md} + \mu_q + \omega_{mt} + \varepsilon_{dmt} \quad (3)$$

Here PPU is the price of drug *d* produced by the acquirer or target in merger *m* at event quarter t. *Overlap* is an indicator variable equal to one if the drug belongs to a product market that is shared between the merging firms, i.e., a product market that is consolidating due to the merger. *Post* is an indicator variable that takes the value of 1 for all quarters (up to 8) following merger *m* and 0 for all quarters (up to 8) prior to the merger. The coefficient of interest is α_1 which compares the change in price after the merger across overlapping and non-overlapping drugs. As before, θ_{md} are drug-deal fixed effects, ω_{mt} are event-quarter fixed effects, ζ_a are ATC4 product market fixed effects and μ_q are calendar quarter fixed effects.[19] Note that θ_{md} absorb the stand-alone *Overlap* indicator and ω_{mt} absorb the stand-alone *Post* indicator.[20]

Results using the main sample are presented in columns 1 through 5 of Table 5 while results using the matched sample are presented in columns 6 through 10. Panel A of Table 5

[19] Unlike the sample in Table 3, where at least two drug price records are available in each market-quarter (treatment and control drugs), in this sample, a market may have a single drug, i.e. a non-overlapping market. Therefore, we do not include the ATC4-product-category times calendar-quarter fixed effects φ_{aq} in this specification.

[20] We replicate our main tests using an alternative event window in which we compare the 8 quarters before announcement with the 8 quarters after merger *completion* (see Table ID.4 in the Internet Appendix) and using a cross-sectional sample (Table ID.5).

presents findings for all firms (including both INV and LINV firms). Column 1 and column 6 includes all drug types while the remaining columns present findings in subsamples based on drug type. The interaction of Post and Overlap is negative and significant for all drugs, brand name drugs, generic drugs, and unpatented drugs. That is, drug prices in markets that experience consolidation due to the merger (i.e. overlapping markets) experience post-merger price declines relative to non-overlapping markets. The only drug category in which we observe prices increases for overlapping markets is patented drugs (column 5 of Panel A).

Next, we look at LINV and INV firms separately in Panels B and C respectively. In Panel B, the coefficient on the interaction of Post and Overlap is again negative and significant for all subsamples except patented drugs. That is, LINV firms reduce prices of overlapping drugs relative to non-overlapping drugs in all subsamples except for drugs that have distant patent expirations. Note that the latter comprise less than 4% of observations for LINV firms.

In stark contrast, Panel C shows that INV firms increase prices of overlapping drugs relative to non-overlapping drugs. These price increases are observed in nine of the ten specifications shown in Panel C. Panel C captures the findings of Bonaime and Wang (2023) who find a post-merger price increase in overlapping product markets relative to non-overlapping product markets. Their sample is restricted to firms publicly listed on a U.S. exchange, which tend to be highly innovative companies. About 65% of U.S.-listed public firms in our sample are classified as INV. Our study includes both private and public firms. Moreover, the public firms in our sample include firms listed on an overseas exchange (see footnote 21). Only about 25% of private and non-U.S.-listed public firms are classified as highly innovative. The heterogeneity in firm type in our sample allows us to document differences in the post-merger strategies of highly

innovative and less innovative firms.[21] The price increases by INV firms are consistent with the exercise of market power, while the price decreases by LINV firms suggest that merger-related efficiency gains exist and are passed on through to prices. Since our findings are qualitatively similar in the main sample and the matched sample, in the interest of space all remaining tests use the main sample. However, the remaining findings also hold in the matched sample.

A key feature that distinguishes INV firms from LINV firms is the novelty of products developed by the firms. As discussed earlier, INV firms invest significant resources into the development of FIC drugs and depend on patent protections to recoup the investment. In contrast, LINV firms depend relatively more on a price-competition model through the lower-cost development of me-too drugs and generics. To highlight this difference in the business models of INV and LINV firms, we estimate equation 3 for FIC drugs and me-too drugs separately. Using the full Medicaid SDUD database dating back to 1991, we classify a drug as an FIC drug if it is the first drug to target a given ATC-4 therapeutic market. Me-too drugs are defined as those that begin targeting an ATC-4 market after an FIC drug is already present in that market.

Results are presented in Table 6. For this analysis, generic drugs are included in the me-too category when looking at the full sample of drugs (column 1) or when looking at drugs without patents (column 5). However, by definition there are no generic drugs in column 3 (brand name me-too drugs) or in column 7 (patented me-too drugs). We also note that a generic drug is never classified as a FIC drug. Columns 1 and 2 of Table 6 - Panel A show that, after the merger, overlapping FIC drugs increase in price while overlapping me-too drugs decline. In columns 3 and

[21] We believe our decision to include foreign firms is justified because in recent decades drug manufacturing has shifted out of the United States. As of 2019, only 28% of manufacturing facilities making active pharmaceutical ingredients (APIs) were located in the United States. See "Safeguarding Pharmaceutical Supply Chains in a Global Economy", a 2019 congressional testimony by Janet Woodcock of the FDA. Private and foreign-listed firms, which account for 45% of treated drugs in our sample, mostly focus on generic drugs. For example, ranking firms by their share of Medicaid generic drug revenues, 12 of the top 20 firms are either private or listed on overseas stock exchanges. In contrast, ranking firms by their share of Medicaid brand name or biologic drug revenue, 19 of the top 20 firms are US publicly listed firms.

4, we focus on brand name drugs only and again find that overlapping me-too drugs experience post-merger price declines relative to non-overlapping me-too drugs. In contrast, overlapping FIC drugs increase in price relative to non-overlapping FIC drugs. We also look within subsamples of patent status and observe prices increases for patented FIC drugs (column 8), and price declines for unpatented me-too drugs (column 5).

In Panels B and C, we present the same analysis for LINV and INV firms respectively. As expected, the majority of the me-too drugs belong to LINV firms while the majority of FIC drugs are owned by INV firms. In Panel B, we see that LINV firms reduce the price of overlapping me-too drugs but do not change the price of their overlapping FIC drugs (except for the small fraction of their patented FIC drugs in column 8). In Panel C, the opposite pattern is observed. INV firms increase the price of overlapping FIC drugs but leave the prices of their overlapping me-too drugs unchanged. The results in Tables 5 and 6 provide further support for the differing pricing behavior of INV and LINV firms. We explore explanations for these findings in Section 6.

Next, to test for parallel pre-trends, we replace Post in equation 3 with multiple indicators Q_{mt} that take the value one for each quarter t relative to merger announcement and estimate the following stacked DID model:

$$\ln(PPU)_{dmt} = \sum_{t=-8}^{t=8} \delta_t \, Overlap_{dm} \times Q_{mt} + \zeta_a + \theta_{md} + \omega_{mt} + \mu_q + \varepsilon_{dmt} \quad (4)$$

The coefficients δ_t estimated using the main sample are presented in Figure 3. We present trends for all drugs (Figure 3A), drugs of LINV firms (Figure 3B), and drugs of INV firms (Figure 3C). The coefficients δ_t are insignificant for the pre-merger quarters in all three figures, which indicates that pre-trends are not a significant concern. In Figure 3A (all drugs) and Figure 3B (drugs of LINV firms), we see that the post-merger decline in the price of overlapping drugs relative to non-overlapping persists till five quarters after merger announcement and then reverts towards

zero. In Figure ID.1.B of the internet appendix, we show that the price difference gradually dissipates because prices of non-overlapping drugs of merging firms begin to also decline after five quarters. These findings suggest that price cuts are initially implemented in product markets where the synergies are generated, but eventually the price reductions become more widespread within the firm. In Section 6, we explore the existence of synergies in overlapping product spaces.

Next, we address two concerns with the baseline results presented in Tables 5. The first concern relates to the economic significance of our findings. The post-merger price decline is driven by generic drugs, which are cheap compared to brand name drugs and account for about 20% of drug spending in the United States. To address this issue, we run sales-weighted regressions where each observation is weighted by the drug's sales in the quarters before the merger. The second concern relates to the fact that our analysis includes drugs (both overlapping and non-overlapping) that are affected by multiple mergers during our sample period, provided the mergers are more than 16 quarters apart. If the effect of a merger on drug prices lasts longer than 16 quarters, our DID estimates could reflect differences in treatment effects over time between different treatment cohorts (see Baker et al, 2022). To address this concern, we re-run equation 3 after dropping previously treated drugs from our sample (i.e. any drug affected by more than one merger is included for the first merger and dropped for subsequent mergers).

Table 7 presents results for both the weighted regressions and the regressions with the not-previously-treated sample. The sample in Panel A includes all drugs, Panel B is restricted to drugs of LINV firms, while Panel C presents results for drugs owned by INV firms. The findings are qualitatively unchanged in these regressions. When looking at all drugs in Panel A, we see a decline in the price of overlapping drugs relative to non-overlapping drugs. Panel B shows that

this price decline is driven by products owned by LINV firms. Panel C confirms that INV firms increase prices in overlapping product markets.

To summarize, the post-merger price reductions by LINV firms are consistent with the synergistic-gains hypothesis while price increases by INV firms support the market power hypothesis. In the next section, we explore possible explanations for this heterogeneity in the post-acquisition pricing behavior.

6. Understanding the decline in drug prices

Anecdotal evidence presented in Section 2 refers to two types of post-merger cost reductions in the pharmaceuticals industry. First, merging firms reduce overhead costs by laying off workers and eliminating overlap in some non-production operations. Under the full-cost pricing paradigm, reductions in overhead costs after a merger can be a possible explanation for the post-merger decline in prices. Since LINV firms reduce prices while INV firms do not, we study post-merger SGA changes of both INV and LINV firms.

Second, product overlap can lead to cost savings through elimination of redundancies in the R&D process. Anecdotal evidence cited earlier in this article suggests LINV firms reduce R&D after a merger by switching their product pipelines toward low-risk products, i.e., less novel products with a shorter development time and lower clinical risk than first-in-class (FIC) drugs. These less novel products tend to be me-too drugs which, according to prior evidence, compete on price with the FIC drugs (Aronson and Green, 2020, Dimasi (2000), Lee (2003)). To explore if LINV firms indeed change their product pipelines towards less novel, cost-effective products, we examine post-merger changes in R&D as well the change in the composition of firms' product pipelines after a merger.

6.1. Firm-level analysis of R&D and SG&A

We obtain quarterly data from Compustat and calculate two firm-level variables. R&D_TA is research and development expense divided by total assets. SGA_Sales is selling, general and administrative expenses divided by sales. Since integration of facilities is needed to realize operational synergies, we compare these two variables over the 8 quarters before merger announcement and the 8 quarters after completion. The merger announcement and completion quarters and any quarters in between are excluded. Since only a small number of targets in our sample have Compustat data available, we examine the change in these variables for the acquiring firms only. We find the relevant records for 51 acquirers listed on U.S. exchanges that conducted 109 mergers over our sample period.

Next, we identify matching firms for the actual acquirers and targets from the set of manufacturers that sell to Medicaid. For each acquiring (target) firm, we identify control firms that meet the following conditions: (i) Medicaid sales between 50% and 150% of the acquirer's (target's) Medicaid sales, and (ii) the number of drugs offered to Medicaid are between 50% and 150% of the number of drugs offered by the acquirer (target). If this procedure identifies multiple control firms for the acquirer or the target, we randomly select one. The acquirer's matched firm and target's matched firm form a hypothetical merger pair. The final panel has an observation level of firm-deal-quarter and includes 66 actual deals conducted by 37 actual acquirers matched to 34 hypothetical acquirers.

We calculate the sales overlap percentage between each pair (actual and hypothetical) as the acquirer's sales in ATC4 markets in which the target firm also sells products, divided by the total sales of the acquirer in the 8 quarters before the merger completion. Next, we define an indicator called *Sales Overlap Dummy (SPD)*, to capture a high degree of sales overlap between the two firms. This variable takes a value of 1 for deals with a sales overlap percentage greater

than the median value and takes a value of zero otherwise. Summary statistics of quarterly R&D_TA, SGA_Sales, and overlap for the treatment sample (i.e., actual acquirers), and the sample of hypothetical acquirers are shown in Internet Appendix IE.

We estimate the following regression separately for actual acquirers and their matching firms using OLS with firm-fixed effects, deal-fixed effects, and quarter-fixed effects.

$$Y_{fmt} = \gamma_0 + \gamma_1 Post_{mt} + \gamma_2\, SPD_m + \gamma_3 Post_{mt} \times SPD_m + \mathcal{F}_f + \emptyset_m + \mu_q + \varepsilon_{fmt} \qquad (5)$$

The dependent variable, *Y*, is quarterly R&D_TA or SGA_Sales during event quarter *t* for firm *f* participating in deal *m*. *Post* is a dummy variable that takes the value 1 for the eight quarters after merger completion and 0 for the eight quarters before merger announcement. $\mathcal{F}_f$, $\emptyset_m$, μ_q are firm, deal, and calendar quarter fixed effects respectively. The coefficient of interest is γ_3, which captures whether the post-merger change in *Y* depends on the degree of product overlap between the acquirer and target. We run this analysis for all acquirers in our sample in Panel A of Table 8, and separately for INV and LINV acquirers in Panel B.

In columns 1 through 3 of Panel A, the dependent variable is R&D_TA. Column 1 shows that γ_3, the interaction of Post and Sales Overlap Dummy, is negative and significant at the 5% level for actual acquirers, which suggests that R&D is lower after the merger for acquirers that have greater overlap with target firms. In contrast, column 2 shows that for the sample of matching firms, γ_3 is positive and significant at the 1% level. To test if the change in R&D conditional on overlap is significantly different across acquirers and matching firms, we pool the two samples together and include a triple interaction of Post, Sales Overlap Dummy (SPD), and an indicator variable called *Actual* that takes the value 1 if a firm *f* in merger deal *m* is an actual acquirer and zero if it is a matching firm. All variables and their double interactions are also included in the regression but not tabulated for brevity. Column 3 shows the results of this difference-in-

differences test for R&D. The coefficient on the triple interaction is negative and statistically significant at the 1% level, which implies that acquirers with greater product overlap with the target experience a drop in R&D expense relative to the sample of matched firms.

Columns 4 and 5 of Table 8 show estimates of equation 5 with SGA_Sales as the dependent variable. Column 6 presents estimates of the triple interaction in a pooled regression with SGA_Sales as the dependent variable. The triple interaction in column 6, which captures the difference between actual and matching acquirers is negative and statistically significant at the 5% level. That is, acquirers in deals with high product overlap experience a drop in SGA expense relative to the sample of control firms.

We recognize that unlike the drug-level analysis, these firm-level findings do not establish causality and present correlations at best. Nonetheless, the decline in SG&A offers a possible explanation for the post-merger decline in prices. Next, we present this analysis separately for INV firms and LINV firms in Panel B of Table 8. Of the 66 total deals in the firm-level sample, we classify 31 as involving LINV acquirers and 35 as INV. In the interest of space, only the pooled regression results are presented in Panel B. We see that for LINV acquirers (columns 1 and 2 of Panel B), the triple interaction of SPD, Post, and Actual is negative and significant in both the R&D_TA and SGA_Sales regressions. For INV acquirers (columns 3 and 4), the triple interaction is insignificant. That is, LINV acquirers experience a post-merger decline in R&D and SG&A relative to control firms, while INV acquirers do not.

An argument can be made for why LINV firms might put more emphasis on post-merger SG&A cuts than innovative firms. LINV firms derive majority of their revenue from generic drugs, which face competition from substitute products. The existence of substitute products implies a higher price elasticity of demand. That is, small changes in price can have a large impact on the

quantity demanded. For this reason, LINV merging firms have an incentive to cut costs and pass through some of the cost savings to customers.[22] Post-merger R&D cuts by LINV firms merit further investigation. While R&D is a sunk cost for pricing decisions of existing products, it has implications for new product development. Next, we examine how the product pipeline of LINV firms changes after a merger relative to that of INV firms.

6.2 Changes in the product pipeline

To better understand the implications of R&D cuts by LINV, we compare the post-merger product pipeline of LINV with that of INV in overlapping markets. Prior research shows that acquired overlapping drug projects are less likely to be developed (Cunningham et al, 2021). However, we are interested in learning whether the product development strategies of INV and LINV firms differ in overlapping markets, conditional on product novelty.

We obtain product development data from Cortellis Life Sciences. Cortellis is a repository of pharmaceutical product innovation that is used in both industry and academia.[23] It provides information on drug development milestones and ownership for over 30,000 drugs developed by over 7,000 firms. We hand match our sample of merging firms to Cortellis using firm name. For a deal to be included in our analysis, both acquirer and target must have product development data before and after the merger announcement and there must be overlap between the two firms. Of the 125 mergers in our study, 45 mergers (25 INV and 20 LINV) satisfy this requirement with a total of 3,936 projects. Here, we use ICD10 codes provided by Cortellis to identify overlapping product spaces.[24] An acquirer and target are classified as having overlap if both have products in

[22] In unreported tests, we find that the number of units dispensed of overlapping drugs owned by LINV firms is higher after the merger relative to those of INV firms. This increase in units sold is in line with our finding that LINV firms reduce prices of overlapping drugs while INV firms raise prices.
[23] See Krieger (2021), and Garfinkel and Hammoudeh (2020).
[24] We switch from using ATC4 codes to ICD10 codes because it is more easily matched to the medical condition descriptions in Cortellis. Matching ATC4 to these descriptions (or to ICD10 codes) is challenging because ATC4

the same ICD10. ICD10 is an established medical classification system published by the WHO and is commonly used in health organizations in the US to classify medical conditions.

Next, we identify the quarters in which a development event was reported (e.g., graduation from phase-II to phase-III). We define development to preclinical trials or phase-I as an early-stage development event and to phase-II, phase-III, or FDA approval as late-stage development events. We have 719 development events of which 404 are early-stage and 315 are late-stage. For each event, we measure the novelty of the product under development based on how many other products under development use the same technology (i.e., target action). For each drug-quarter, we calculate the number of other drug products that use the same technology and define the novelty of the drug as high (low) if this number is below (above) the sample median. For robustness, we use an alternative measure in which we define the novelty of the drug as high (low) if the number of other *FDA approved* drugs that use the same target action is below (above) the sample median.

Anecdotal evidence suggests that generic manufacturers cut R&D with the intention of switching toward less novel, less risky products that have higher probability of achieving FDA approval. To explore this possibility, we define a dependent variable called *NumEvent_Novelty*, that counts the number of development events for merger m in event quarter t in one of the following six specifications (i) any low-novelty product (ii) any high-novelty product (iii) early-stage, low-novelty product (iv) early-stage, high-novelty product, (v) late-stage, low-novelty product, and (vi) late-stage, high-novelty product. We run the following regression:

$$NumEvent\_Novelty_{mt} = \xi_1 LINV_m * Post_{mt} + \emptyset_m + \mu_q + \epsilon_{mt} \qquad (6)$$

In this equation, $LINV_m$ is an indicator variable equal to one if the acquirer is classified as a LINV and zero if it is classified as INV. Post is an indicator variable equal to one for the 12 quarters

includes information on both medical condition and chemical composition, whereas ICD10 (and Cortellis descriptions) only includes the former.

following the announcement of merger m and 0 for the 12 quarters before announcement. Here, we opt for a longer pre- and post-event window than in previous sections to account for the longer drug development cycle.[25] $\emptyset_m$ and μ_q represent deal and calendar-quarter fixed effects respectively. We run this model for each of the six drug development events described above.

Results are presented in Table 9. In the first row of Table 9, novelty is defined using all drugs (FDA approved products). We see that the coefficient $\xi_1$is negative and significant at the 10% (5%) level in column 4. This finding indicates that LINV firms reduce the development of high novelty early-stage products relative to INV firms. We also see that the coefficient $\xi_1$is positive and significant at the 5% level in column 5 for both measures of novelty, indicating that LINV firms step up the development of low-novelty, late-stage products relative to INV firms.

Overall, the findings in Table 9 support the anecdotal evidence that generic LINV firms cut R&D by shifting away from projects with high risk in favor of projects that have a higher likelihood of FDA approval due to the lower novelty or due to already being in the later stages of development.[26]

7. Conclusion

Recent increases in drug prices and consolidation in the pharmaceuticals industry has led to speculation that mergers are anti-competitive. An alternative argument is that mergers between firms with product overlap create opportunities for cost reductions that can be passed on to customers. We investigate these contrasting viewpoints of pharmaceutical mergers using price data on drug products covered by Medicaid and find evidence of both phenomena in overlapping product spaces. Highly innovative firms increase prices of overlapping first-in-class drugs, while

[25] The average time that a project spends under development before FDA approval is 8 years, and between 1-3 years in each development stage (Hay et al. (2014).
[26] Hay et al. (2014) report that only 10% (16%, 50%) of phase-I (phase-II, phase-III) are eventually approved.

less innovative firms reduce prices of follow-on drugs (often called me-too drugs) and generic drugs in overlapping product spaces. Price trends in overlapping product spaces indicate that these price declines begin after the merger, not before.

We find that less innovative firms experience post-merger reductions in SG&A relative to a sample of control firms while highly innovative firms do not. Our findings suggest that the price reductions implemented by less innovative pharmaceutical firms are likely attributable to cost savings in non-production operations. We also find that less innovative firms reduce R&D after mergers. An analysis of product pipeline data indicates that the reductions in R&D are due to switch in the product pipeline toward less novel, late-stage products.

Our product-level data permit us to identify which product spaces benefit from price reductions due to possible efficiency gains and which are vulnerable to the abuse of market power. Our findings should help guide antitrust authorities on how to balance the efficiency and market power effects of mergers when making the decision to challenge a pharmaceutical merger.

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Figure 1: Distribution of the Change in Drug Prices Around Mergers

This figure displays the distribution of the percentage change in drug prices around mergers. The sample is summarized in Table 4 and includes drugs owned by 168 firms that engaged in 125 mergers in our sample. The percentage change in price is calculated as the average drug price over the eight quarters after merger announcement less average drug price over the eight quarters before merger announcement divided by the average price before. The price of a drug is price per unit (PPU), calculated for each drug as its quarterly Medicaid spending divided by the number of units dispensed. Figure 1.A shows the distribution for all drugs, 1.B for brand name drugs, 1.C for generic drugs, and 1.D for overlapping drugs.

Figure 1.A: All Drugs

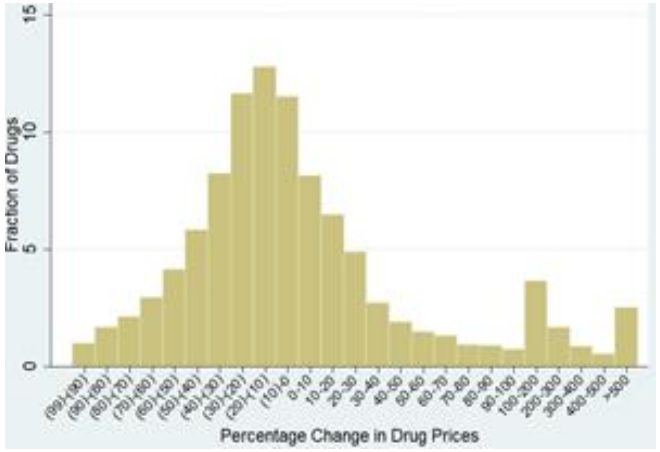

Figure 1.B: Brand Name Drugs

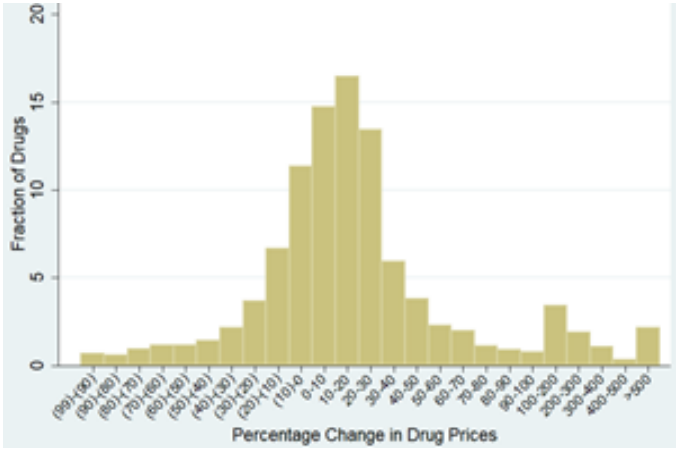

Figure 1.C: Generic Drugs

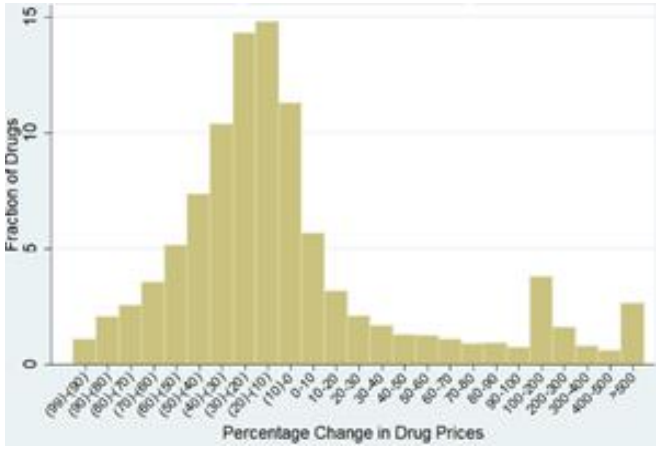

Figure 1.D: Overlap Drugs

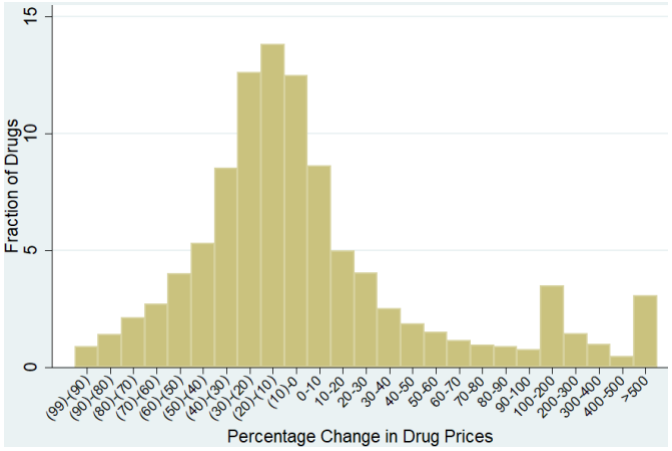

Figure 2: Drug Price Trends Around Mergers: Merging and Non-Merging Firms

This figure displays the price trends of merging firms' drugs around merger announcements, relative to those of non-merging firms. The sample is described and summarized in Table 2 and has an observation level of drug-deal-quarter. The graphs plot ρ_t from equation 2, i.e., the coefficients on the interaction of *Treated* and event quarter indicators Q_{mt} for each of the 16 quarters centered around announcement. *Treated* is an indicator variable equal to one for drugs owned by merging firms and zero for control drugs owned by non-merging firms. The dependent variable, $Ln(PPU)$, is the natural log of a drug's quarterly price per unit. All graphs below are based on tests that cluster standard errors by drug and include drug times deal fixed effects (θ_{md}), market time calendar quarter fixed effects (φ_{aq}) and event quarter fixed effects (ω_{mt}). The caps represent the 95% confidence interval of the corresponding estimates. In Figure 2.A, the sample includes all drugs. Figure 2.B is based on the subsample of drugs that are overlapping across the merging firms' drug portfolios, and their matched controls. In Figure 2.C and Figure 2.D, the tests are based on the subsample of overlapping drugs owned by less innovative (LINV) and innovative (INV) firms respectively.

Figure 2.A: All Drugs

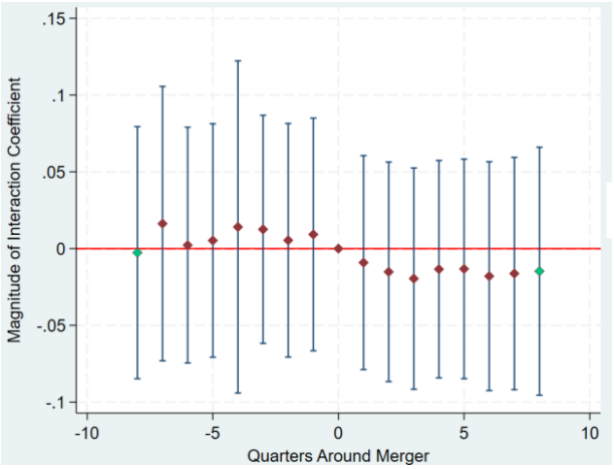

Figure 2.B: Overlapping Drugs

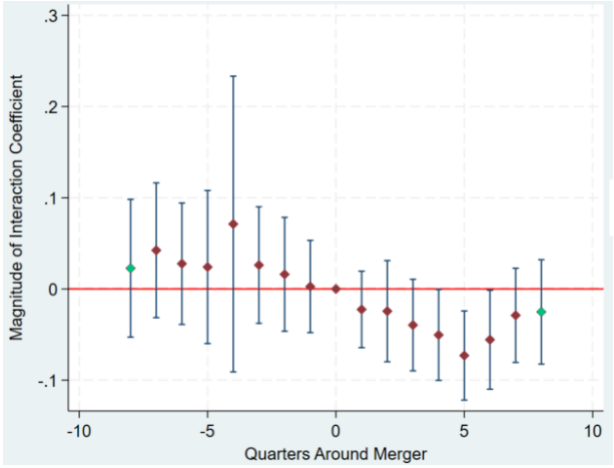

Figure 2.C: Overlapping Drugs of Less Innovative Firms.

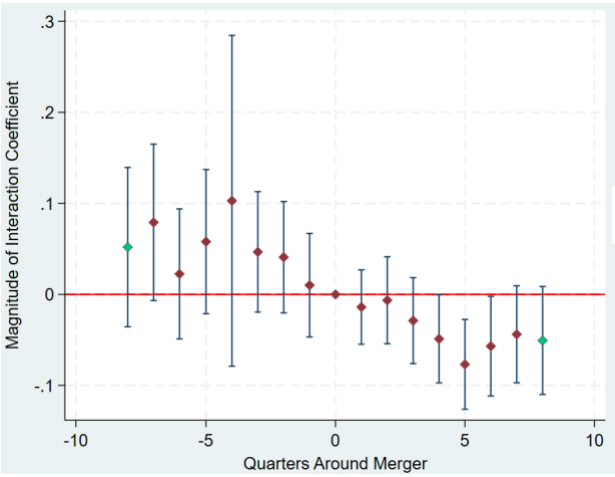

Figure 2.D: Overlapping Drugs of Innovative Firms

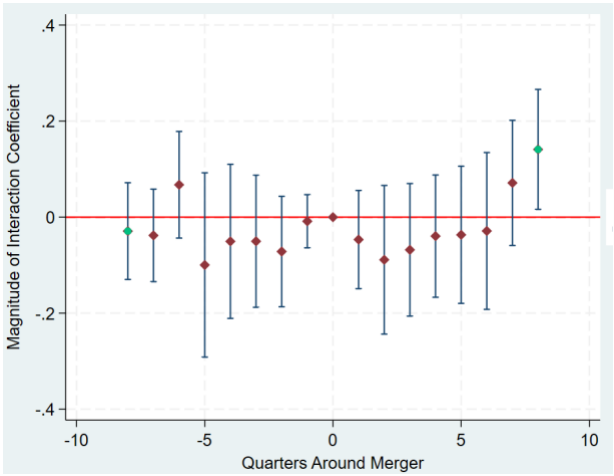

Figure 3: Drug Price Trends Around Mergers: Treated Drugs Only

This figure displays the price trends of overlapping drugs relative to those of non-overlapping drugs around merger announcements. The sample (summarized in Table 4) includes drugs owned by merging firms and has an observation level of drug-deal-quarter. The graphs plot δ_t from equation 4, i.e., the coefficients on the interaction of *Overlap* with event quarter indicators for each of the 16 quarters centered around announcement. *Overlap* is an indicator equal to one for drugs in markets where both merging firms operate, and zero for markets where only one of the merging firms operates. The dependent variable, $Ln(PPU)$, is the natural log of a drug's quarterly price per unit. All regressions cluster standard errors by drug and include calendar quarter (μ_q), event quarter (ω_{mt}), deal times drug (θ_{md}), and market fixed effects (ζ_a). The caps represent the 95% confidence interval of the corresponding estimates. In Figure 3.A, the sample includes all drugs of merging firms. The sample in Figure 3.B (Figure 3.C) includes drugs owned by less innovative (LINV) and innovative (INV) firms.

Figure 3.A: All Drugs

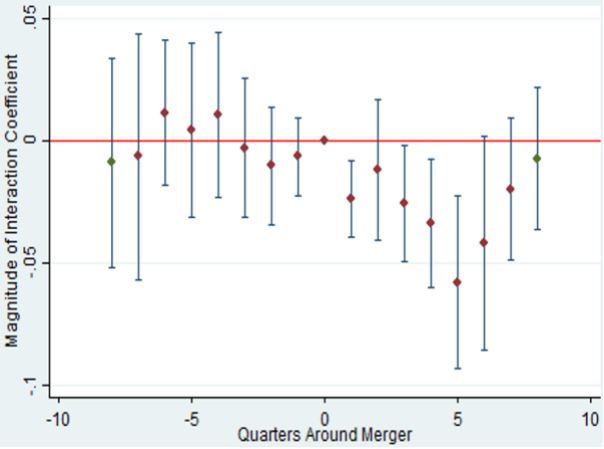

Figure 3.B: Drugs of Less-Innovative Firms (LINV)

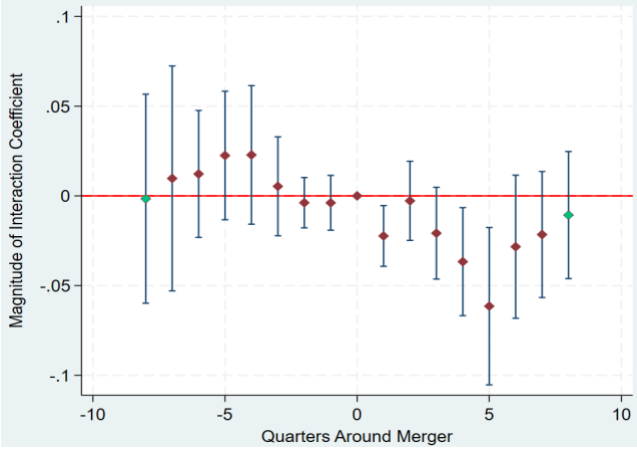

Figure 3.C: Drugs of Innovative Firms (INV)

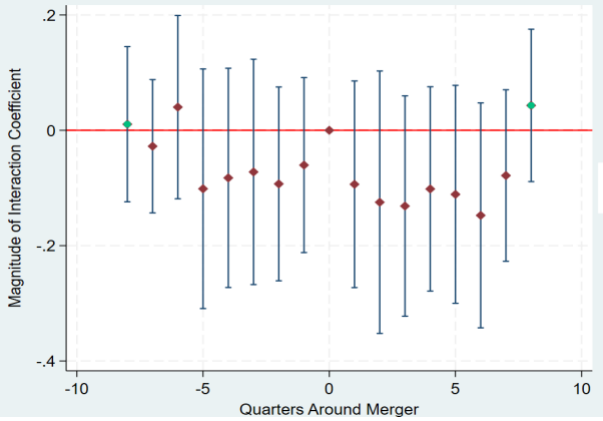

Table 1: Descriptive Statistics of Acquirers and Targets

This table provides descriptive statistics for 168 drug manufacturers that were involved in 125 mergers from 2007q3 through 2019q4 (inclusive). Statistics are displayed for both targets and acquirers and are based on the 8 quarters preceding merger announcement. In the row titled *Number of M&A*, an acquisition is counted as public if either the target *or* acquirer was public and counted as private if both the target *and* acquirer were private firms. *Transaction Value* is the average transaction value of the merger deal in $ millions. *Number of target (acquirer) firms* represent the number of unique targets (acquirers). *Avg. sales per quarter* is the firm's average quarterly Medicaid drug sales. *Avg. sales per quarter from patented drugs* is the average quarterly sales of a firm's drug products with 5 or more years remaining on patent coverage. *Sales growth* is the average quarterly growth of the firm's drug sales. *Avg. number of drug products* is the quarterly average of the number of drugs offered by a firm. The average number of patented drugs, prescription drugs, brand name drugs, generic and biologic drugs offered per quarter is also provided.

	US Public	Private or Foreign Public	All
	(1)	(2)	(3)
Number of M&A	110	15	125
Transaction value ($ millions):	8,424	1,169	7,813
Number of firms:			
Acquirers	42	20	62
Targets	72	53	125
Avg. sales per quarter ($ millions):			
Acquirer	122	23	100
Target	30	14	23
Avg. sales per quarter from patented drugs ($ millions):			
Acquirer	71	8	56
Target	18	5	12
Sales Growth (%):			
Acquirer	40	52	43
Target	23	64	41
Avg. number of drugs offered per quarter:			
Acquirer	381	152	328
Target	85	71	79
Avg. number of patented drugs offered per quarter:			
Acquirer	74	12	60
Target	19	5	13
Avg. number of prescription drugs offered per quarter:			
Acquirer	288	109	246
Target	65	59	62
Avg. number of brand name drugs offered per quarter:			
Acquirer	127	16	101
Target	32	9	22
Avg. number of generic drugs offered per quarter:			
Acquirer	250	135	223
Target	50	62	55
Avg. number of biologic drugs offered per quarter			
Acquirer	4	0	3
Target	3	0	2

Table 2: Summary Statistics: Merging and Non-Merging Firms

This table displays summary statistics and univariate differences for the drug- and firm-level variables used in the tests of Table 3. The sample consists of treated and control drugs and the observation level is drug-deal-quarter. A treated (control) drug is one that is sold by a firm that engaged (did not engage) in a merger. We match each treated drug to a control drug with the same drug type (i.e., brand, generic or biologic), patent status, therapeutic market, and firm innovativeness. Furthermore, a treated drug and its matched control are required to have at least 2 (and up to 8) quarters of price data before *and* after the focal merger's announcement. We randomly select one control drug if more than one is matched to a treated drug. The resulting sample consists of the prices of 18,864 treated drugs matched with 11,344 control drugs from 2007q1 through 2020q3 for a total of 1,177,375 drug-deal-quarter observations.
PPU is the quarterly price-per-unit of a drug. *Brand* (*Generic*, *Biologic*) is an indicator variable equal to one if the drug is classified as a brand name (generic, biologic, respectively) drug. *Overlap* is an indicator variable equal to one if a treated drug targets a therapeutic market in which the merger counterparty also sells. Control drugs matched to overlapping treated drugs are also assigned a value of one for the *Overlap* indicator since they must target the same market. *Patent* is an indicator variable equal to one if a drug is covered by either a patent or FDA marketing exclusivity, *and* the protection expires in more than 5 years. *Innovative* is an indicator equal to one if the firm is classified as innovative (INV), and equal to zero if classified as less innovative (LINV). Firms are classified as innovative if their percentage of patented products is in the top quartile of the sample and as less innovative otherwise. Note that firm innovativeness for merging firms is defined using the acquirer's drugs and is defined for each control firm separately.
Panel A displays the average value of each variable in the full sample (first row), the sample of drugs owned by merging firms (second row), the sample of control drugs (third row), and the difference in means of the variable between the treated and control drugs. Panel B displays the average PPU in each subsample for the treated drugs (first row), control drugs (second row), and the difference in means of the PPU between treated and control drugs. Statistically significant differences in means are marked by asterisks as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: Variable Average Values

	PPU	Brand	Generic	Biologic	Overlap	Patent	Innovative (INV)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Full Sample	24.56	0.27	0.68	0.01	0.16	0.09	0.27
Treated	23.88	0.27	0.68	0.01	0.16	0.09	0.27
Control	25.25	0.27	0.68	0.01	0.16	0.09	0.27
Difference	*-1.36***	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*

Panel B: Average PPU Values by Subsample

	All	Brand	Generic	Biologic	Overlap	Non-Overlap	Patent	No Patent	Less-Innovative (LINV)	Innovative (INV)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment	23.88	56.36	4.52	24.48	16.90	25.27	120.43	14.08	13.06	53.27
Control	25.25	62.59	4.32	23.04	15.49	27.16	153.01	12.11	9.44	67.87
Difference	*-1.36***	*-6.23****	*0.20*	*1.44*	*1.41**	*-1.91***	*-32.58****	*1.96****	*3.62****	*-14.60****

Table 3: Drug Price Changes Around Mergers: Merging and Non-Merging Firms

The tests in this table examine the change in prices for merging firms' (Treated) drugs relative to those of non-merging (Control) firms' drugs. The table displays results from the difference-in-differences estimation in equation (1). The sample and the variables used in these tests are described and summarized in Table 2. The dependent variable, $Ln(PPU)$, is calculated for each drug-quarter as the natural log of a drug's price per unit. *Post* is a dummy equal to one for the quarters after the merger announcement, and zero for the quarters before. *Treated* is an indicator equal to one for drugs owned by merging firms and zero for those owned by control firms.
In all the panels, the column heading "All" indicates the full corresponding sample, "Brand" ("Generic") indicates the subsample of brand name (generic) drugs, "No Patent" indicates the subsample of drugs with no patents or with patents expiring within 5 years. "Patent" indicates the subsample of drugs with more than 5 years remaining on patent coverage. "LINV" ("INV") indicates the subsample of drugs owned by less innovative (innovative) firms. In Panel A, the full sample of treated and control drugs is used. The tests in Panel B are based on the subsample of overlapping treated drugs and their matched controls. The tests in Panel C include use the same subsample of overlapping drugs but are further partitioned by less innovative (columns 1-4) and innovative (columns 5-8) firms. The fixed effects used in each test are indicated at the bottom of each panel. Standard errors are clustered by drug. t-statistics are reported in parentheses. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1.

Panel A: All Drugs

			All	Brand	Generic	No Patent	Patent	Less innovative (LINV)	Innovative (INV)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	0.016	-0.025	0.015	0.093**	-0.016	0.018	-0.017	-0.031**	0.136***
	(0.728)	(-0.557)	(1.038)	(2.415)	(-1.178)	(1.289)	(-0.228)	(-2.286)	(4.545)
Post	-0.101***								
	(-11.071)								
Treated*Post	0.006	0.007	0.007	0.033**	0.007	0.003	0.048*	-0.000	0.035***
	(0.706)	(1.027)	(1.020)	(2.160)	(0.894)	(0.431)	(1.897)	(-0.063)	(2.673)
Constant	0.052**	0.024	0.004	1.426***	-0.448***	-0.213***	2.125***	-0.272***	0.751***
	(2.553)	(0.976)	(0.301)	(40.866)	(-38.455)	(-17.831)	(31.205)	(-24.298)	(27.513)
Drug FE	Yes	Yes							
Calendar Qtr FE	Yes	Yes							
Deal FE	No	Yes							
Market FE	No	Yes							
Event Qtr FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drug*Deal FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market*Cal Qtr FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,177,375	1,177,374	1,177,363	313,705	800,145	1,068,251	109,096	859,590	317,738
R-squared	0.471	0.603	0.700	0.618	0.559	0.658	0.694	0.652	0.730

Panel B: Overlap Drugs

	All	Brand	Generic	No Patent	Patent	Less Innovative (LINV)	Innovative (INV)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treated	-0.105***	-0.243***	-0.061**	-0.083***	-0.482***	-0.177***	0.169**
	(-4.529)	(-3.374)	(-2.488)	(-3.694)	(-2.895)	(-7.719)	(2.489)
Treated*Post	-0.047***	0.046	-0.080***	-0.060***	0.153**	-0.058***	0.063*
	(-3.535)	(1.243)	(-5.313)	(-4.450)	(2.458)	(-4.216)	(1.750)
Constant	-0.168***	1.533***	-0.349***	-0.312***	2.273***	-0.417***	0.870***
	(-9.160)	(25.768)	(-18.251)	(-17.667)	(16.275)	(-23.093)	(15.564)
Event Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drug*Deal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mkt*Cal Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	193,885	35,921	137,345	183,107	10,763	156,483	37,381
R-squared	0.701	0.568	0.563	0.679	0.632	0.671	0.683

Panel C: Overlapping Drugs Partitioned by Firm Innovative Status

	Less innovative Firms (LINV)				Innovative Firms (INV)			
	Brand	Generic	No Patent	Patent	Brand	Generic	No Patent	Patent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated	-0.164**	-0.167***	-0.185***	0.052	-0.300***	0.766***	0.364***	-0.914***
	(-2.011)	(-6.697)	(-7.934)	(0.376)	(-2.849)	(9.366)	(6.028)	(-3.462)
Treated*Post	-0.034	-0.071***	-0.057***	-0.086	0.107**	0.077	0.027	0.286***
	(-0.758)	(-4.587)	(-4.096)	(-1.393)	(2.046)	(1.468)	(0.703)	(3.010)
Constant	1.612***	-0.387***	-0.494***	1.860***	1.476***	-0.020	0.550***	2.645***
	(25.558)	(-19.679)	(-26.934)	(17.809)	(16.754)	(-0.352)	(11.680)	(11.364)
Event Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drug*Deal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mkt*Cal Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,137	123,237	151,368	5,107	20,774	14,098	31,716	5,656
R-squared	0.510	0.557	0.652	0.546	0.594	0.577	0.675	0.672

Table 4: Summary Statistics: Merging Firms' Drugs

This table displays summary statistics and univariate differences for the drug-level variables in the treated sample. The sample consists only of drugs owned by merging firms and the observation level is drug-deal-quarter. Each drug in the sample is required to have at least 2 (and up to 8) quarters of price data before *and* after the focal merger's announcement. The resulting sample consists of the prices of 19,357 drugs produced by 168 firms that engaged in 125 merger deals from 2007q1 and until 2020q3, or 614,010 drug-deal-quarter observations. *PPU* is the quarterly price-per-unit of a drug. *Brand* (*Generic, Biologic*) is an indicator variable equal to one if the drug is classified as a brand name (generic, biologic, respectively) drug. *Overlap* is an indicator equal to one if the acquirer's (target's) drug has the same ATC4 code (i.e., operates in the same therapeutic market) as any of the target's (acquirer's) drugs, and zero otherwise. *Patent* is an indicator variable equal to one if a drug is covered by either a patent or FDA marketing exclusivity, *and* the protection expires in more than 5 years. *INV* is an indicator equal to one if the firm is classified as innovative, and zero otherwise. Firms are classified as innovative if their percentage of patented products is in the top quartile of the sample and as less innovative otherwise. Note that firm innovativeness is defined using the acquirer's drugs. Panel A displays the average value of each variable in the full sample (first row), the sample of drugs in non-overlapping markets (second row), the sample of drugs in overlapping markets (third row), and the difference in means of the variable between the two groups (fourth row). Panel B displays the average PPU for each group and the difference in means of the PPU between the two groups. Statistically significant differences in means are marked by asterisks as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: Characteristics of Overlapping and Non-Overlapping drugs

	Overlap	PPU	Brand	Generic	Biologic	Patent	INV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Full *(n= 614796)*	0.16	25.30	0.29	0.65	0.01	0.14	0.28
Non-Overlap		26.72	0.31	0.64	0.01	0.15	0.29
Overlap		17.94	0.20	0.69	0.01	0.08	0.20
Difference		8.78***	0.11***	-0.05***	0.00***	0.07***	0.09***
Full *(n= 195084)*	0.50	17.01	0.19	0.70	0.01	0.07	0.20
Non-Overlap		17.75	0.20	0.71	0.01	0.07	0.20
Overlap		18.25	0.19	0.70	0.01	0.07	0.20
Difference		-0.50*	0.01*	0.01	0.00	0.00	0.00

Panel B: PPU Average Values Partitioned by Subsamples

	All	Brand	Generic	Biologic	Patent	No Patent	Less Innovative	Innovative
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Main Sample				
Non-Overlap	26.72	55.46	4.58	736.22	116.16	15.27	15.91	52.54
Overlap	17.94	56.54	4.39	712.32	94.83	12.98	4.53	72.13
Difference	8.78***	-1.08	0.19	23.91	21.32**	2.31***	11.37***	-19.59***
				Matched Sample				
Non-Overlap	17.75	55.83	4.45	716.95	93.34	10.92	12.25	31.63
Overlap	18.25	57.13	4.41	728.03	100.99	12.91	4.41	71.14
Difference	-0.50*	-1.31**	0.04*	-11.09***	-7.65***	-1.98***	7.82***	-39.50***

Table 5: Product Similarity and the Change in Drug Prices: Merging Firms' Drugs

This table presents the change in price of merging firms' drugs conditional on therapeutic market overlap. The table displays results from the DID estimation shown in equation 3. The sample and the variables used in these tests are described and summarized in Table 4. The dependent variable, $Ln(PPU)$, is calculated for each drug-quarter as the natural log of a drug's price per unit (PPU). *Post* is a dummy equal to one for the quarters after the merger announcement, and zero for the quarters before. *Overlap* is an indicator equal to one if the acquirer's (target's) drug has the same ATC4 code (i.e., operates in the same therapeutic market) as any of the target's (acquirer's) drugs, and zero otherwise. The tests in Panel A are based on drugs of all merging firms. In Panel B (Panel C), the tests are based on the sample of drugs owned by less innovative (innovative) merging firms. In each panel, columns 1 to 5 use the main sample which includes all treated drugs, while columns 6 through 10 use the matched sample in which each overlapping treated drug is matched to a non-overlapping treated drug with same patent coverage status and similar sales. Columns 1 and 6 in each panel includes all drugs in the corresponding sample, columns 2 and 7 are restricted to brand name drugs, 3 and 8 to generic drugs, 4 and 9 to drugs with no patents or patents expiring within five years, and column 5 and 10 to drugs with patents expiring after five years. All regressions include the following fixed effects: event-quarter fixed effects (ω_{mt}), calendar-quarter fixed effects (μ_q), deal times drug fixed effects (θ_{md}), and ATC market or product category fixed effects (ζ_a). Standard errors are clustered by drug. t-statistics are reported in parentheses. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

	Main Sample					**Matched Sample**				
	All	Brand	Generic	No-Patent	Patent	All	Brand	Generic	No-Patent	Patent
	Panel A: All Drugs									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overlap*Post	-0.056***	-0.071***	-0.043***	-0.035***	0.054***	-0.038***	-0.027**	-0.042***	-0.044***	0.081***
	(-8.633)	(-5.225)	(-5.322)	(-5.345)	(4.437)	(-3.156)	(-2.255)	(-2.778)	(-3.515)	(3.124)
N	614,010	173,953	404,973	549,610	64,400	194,722	38,658	138,142	184,162	10,560
R-squared	0.956	0.958	0.912	0.938	0.985	0.940	0.940	0.909	0.933	0.971
	Panel B: Drugs of Less Innovative Firms (LINV)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overlap*Post	-0.063***	-0.118***	-0.024***	-0.044***	0.089***	-0.043***	-0.036***	-0.052***	-0.047***	0.066**
	(-8.785)	(-7.112)	(-5.431)	(-5.941)	(3.508)	(-3.122)	(-2.928)	(-3.272)	(-3.306)	(2.477)
N	442,225	63,441	357,502	425,755	16,470	156,258	15,144	126,052	151,496	4,762
R-squared	0.921	0.941	0.948	0.970	0.969	0.934	0.934	0.912	0.929	0.968
	Panel C: Drugs of Innovative Firms (INV)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Overlap*Post	0.040***	0.019**	0.159***	0.039**	0.043***	0.040*	0.015*	0.211**	-0.031	0.096***
	(4.131)	(2.236)	(4.477)	(2.267)	(2.941)	(1.759)	(1.663)	(2.208)	(-1.184)	(2.821)
N	171,785	110,512	47,471	123,855	47,930	38,464	23,514	12,090	32,666	5,798
R-squared	0.960	0.956	0.921	0.958	0.980	0.937	0.942	0.874	0.928	0.973

Table 6: Product Similarity and the Change in Drug Prices: First-in-Class and Me-Too Drugs

This table examines the change in merging firms' drug prices conditional on whether the drug is a first-in-class (FIC) drug or not. The sample is the same as that used in Table 5 and is summarized in Table 4. The table displays results from the DID estimation shown in equation 3. The dependent variable, $Ln(PPU)$, is calculated for each drug-quarter as the natural log of a drug's price per unit. *Post* is a dummy equal to one for the quarters after merger announcement, and zero for the quarters before. *Overlap* is an indicator equal to one if the acquirer's (target's) drug has the same ATC4 code (i.e., operates in the same therapeutic market) as any of the target's (acquirer's) drugs, and zero otherwise. Panel A is based on drugs of all merging firms. In Panel B (Panel C), the tests are based on the sample of drugs owned by less innovative (innovative) merging firms. The columns labeled "Me-Too" ("FIC") displays estimates of equation 3 using the sample of drugs classified as "me-too" (first-in-class). To define FIC and me-too drugs, we use the full Medicaid SDUD sample dating back to 1991 and define a drug as FIC if it is the first drug to target a given ATC4 therapeutic market. Me-too drugs are defined as those that begin targeting an ATC4 market after an FIC drug. All regressions include the following fixed effects: event-quarter fixed effects (ω_{mt}), calendar-quarter fixed effects (μ_q), deal times drug fixed effects (θ_{md}), and ATC market or product category fixed effects (ζ_a). Standard errors are clustered by drug. t-statistics are reported in parentheses. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: All Drugs

	All Drugs		Brand		No-Patent		Patent	
	Me-Too	FIC	Me-Too	FIC	Me-Too	FIC	Me-Too	FIC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overlap*Post	-0.068***	0.051***	-0.090***	0.045**	-0.052***	0.095	0.029	0.076**
	(-3.144)	(2.984)	(-3.781)	(1.981)	(-5.682)	(1.359)	(1.115)	(2.595)
Observations	515,256	98,754	79,343	94,610	484,865	64,745	30,391	34,009
R-squared	0.941	0.954	0.956	0.949	0.930	0.944	0.979	0.975

Panel B: Drugs of Less Innovative Firms (LINV)

	All Drugs		Brand		No-Patent		Patent	
	Me-Too	FIC	Me-Too	FIC	Me-Too	FIC	Me-Too	FIC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overlap*Post	-0.061***	0.047	-0.153***	0.034	-0.056***	0.076	0.048	0.162***
	(-5.406)	(1.481)	(-3.473)	(1.440)	(-5.379)	(0.482)	(1.245)	(3.048)
Observations	414,331	27,894	37,378	26,063	404,205	21,550	10,126	6,344
R-squared	0.929	0.946	0.938	0.935	0.923	0.941	0.975	0.968

Panel C: Drugs of Innovative Firms (INV)

	All Drugs		Brand		No-Patent		Patent	
	Me-Too	FIC	Me-Too	FIC	Me-Too	FIC	Me-Too	FIC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overlap*Post	-0.022	0.060**	-0.035	0.058**	-0.023	0.051**	0.003	0.085***
	(-0.903)	(2.626)	(-1.027)	(2.165)	(-0.820)	(2.198)	(0.090)	(2.829)
Observations	100,925	70,860	41,965	68,547	80,660	43,195	20,265	27,665
R-squared	0.965	0.957	0.969	0.954	0.952	0.945	0.982	0.977

Table 7: Sales Weighted Regressions and Excluding Previously Treated Drugs

This table presents robustness of results shown in Table 5. The sample is the same as the one used in Table 5 and is summarized in Table 4. The dependent variable, $Ln(PPU)$, is calculated for each drug-quarter as the natural log of a drug's price per unit. *Post* is an indicator variable equal to one for the quarters after the merger announcement, and zero for the quarters before. *Overlap* is an indicator variable equal to one if the acquirer's (target's) drug has the same ATC4 code (i.e., operates in the same therapeutic market) as any of the target's (acquirer's) drugs, and zero otherwise. Tests in Panel A are based on drugs of all merging firms. In Panel B (Panel C), the tests are based on the sample of drugs owned by less innovative (innovative) merging firms. In each panel, results are reported for two separate tests. The first test, labeled "Sales-Weighted Regression", displays estimates from weighted regressions where each drug is weighted by its sales in the quarters before the merger. In the second test, labeled "Excluding Previously Treated", drugs involved in more than one merger during the sample period (e.g., those owned by repeat acquirers) are only included for the first merger and are dropped for subsequent mergers. All regressions include the following fixed effects: event-quarter fixed effects (ω_{mt}), calendar-quarter fixed effects (μ_q), deal times drug fixed effects (θ_{md}), and ATC market or product category fixed effects (ζ_a). Standard errors are clustered by drug. t-statistics are reported in parentheses. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: All Drugs

		All	Brand name	Generic	No-Patent	Patent
		(1)	(2)	(3)	(4)	(5)
Sales-Weighted Regression	Overlap*Post	-0.041***	-0.074***	-0.018*	-0.069***	0.037**
		(-6.110)	(-2.719)	(-1.946)	(-3.887)	(2.292)
	Observations	614,010	173,953	404,973	549,610	64,400
	R-squared	0.984	0.982	0.955	0.982	0.986
Excluding Previously Treated	Overlap*Post	-0.118***	-0.071**	-0.043*	-0.096***	0.064*
		(-5.833)	(-2.117)	(-1.840)	(-4.628)	(1.902)
	Observations	271,470	78,037	172,662	237,083	34,387
	R-squared	0.949	0.951	0.905	0.935	0.979

Panel B: Drugs of Less Innovative Firms (LINV)

		All	Brand name	Generic	No-Patent	Patent
		(1)	(2)	(3)	(4)	(5)
Sales-Weighted Regression	Overlap*Post	-0.050**	-0.088**	-0.016*	-0.033**	0.017*
		(-2.548)	(-2.059)	(-1.760)	(-2.339)	(1.809)
	Observations	442,225	63,441	357,502	425,755	16,470
	R-squared	0.977	0.978	0.955	0.973	0.985
Excluding Previously Treated	Overlap*Post	-0.054**	-0.052	-0.051*	-0.056**	0.027
		(-2.114)	(-1.131)	(-1.954)	(-2.469)	(1.456)
	Observations	190,954	26,587	151,080	181,680	9,274
	R-squared	0.936	0.937	0.905	0.928	0.979

Panel C: Drugs of Innovative Firms (INV)

		All	Brand name	Generic	No-Patent	Patent
		(1)	(2)	(3)	(4)	(5)
Sales-Weighted Regression	Overlap*Post	0.040**	0.018**	0.048	-0.039	0.042***
		(1.997)	(2.268)	(1.267)	(-1.179)	(3.113)
	Observations	171,785	110,512	47,471	123,855	47,930
	R-squared	0.986	0.984	0.964	0.987	0.986
Excluding Previously Treated	Overlap*Post	0.031**	0.025*	0.031	-0.051	0.034***
		(1.983)	(1.834)	(0.748)	(-1.243)	(2.851)
	Observations	80,516	51,450	21,582	55,403	25,113
	R-squared	0.960	0.958	0.901	0.945	0.980

Table 8: Changes in R&D and SG&A Spending

This table reports results from OLS regressions of an acquiring firm's research and development (R&D) expense and its selling, general and administrative (SG&A) expense on the product overlap with the target firm. The sample is summarized in Table IE.1 of Internet Appendix IE and consists of 66 completed mergers matched to 66 control deals and the observation level is firm-deal-quarter. The matching procedure is described in Section 6.1. The dependent variables R&D_TA and SG&A_Sales are quarterly R&D spending divided by total assets and quarterly SG&A spending divided by total sales, respectively. *Post* is a dummy variable equal to one for the 8 quarters (at least 2) after merger completion and zero for the 8 quarters (at least 2) before merger announcement. The quarters in between announcement and completion are excluded. *Actual* is a dummy variable equal to one for actual deals and zero for control deals. *Sales Overlap Dummy (SPD)* is an indicator equal to one if the sales overlap between the merging parties of a deal is above the sample median. Sales overlap of a deal is calculated as the acquirer's Medicaid revenue from drugs that have the same ATC4 code as any of the target's drugs divided by the total Medicaid sales of the acquirer drugs. Sales overlap is calculated using data from the 8 quarters preceding merger announcement. In Panel A, columns 1 and 4 (columns 2 and 5) focus on the subsample of actual (control) deals. The tests in columns 3 and 6 use a pooled sample that combines actual and control deals. All variables in the interaction terms are also included separately but not tabulated.

In Panel B, all columns use the pooled sample which includes both actual and control deals. Columns 1 and 2 (columns 3 and 4) focus on the subsample of less innovative (innovative) deals. All regressions include firm, deal, and calendar quarter fixed effects with robust standard errors. *t*-statistics are reported in parentheses. Significance levels are represented by asterisks as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: Full Sample

Dependent Variable	R&D_TA			SGA_Sales		
	Actual	*Control*	*All*	*Actual*	*Control*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)
SPD*Post	-0.003**	0.015***	0.014***	-0.087	0.530**	0.538**
	(-2.316)	(2.807)	(3.131)	(-1.036)	(2.045)	(2.117)
SPD*Post*Actual			-0.016***			-0.745**
			(-3.518)			(-2.445)
Observations	956	880	1,836	961	822	1,783
R-squared	0.632	0.568	0.567	0.208	0.411	0.346

Panel B: Sample Partitioned on the Innovativeness of the Acquiring Firm

	Less Innovative Deals (LINV)		Innovative Deals (INV)	
	R&D_TA	SGA_Sales	R&D_TA	SGA_Sales
	(1)	(2)	(3)	(4)
SPD*Post	0.049***	1.840**	0.000	0.049***
	(3.428)	(1.966)	(0.100)	(2.674)
SPD*Post*Actual	-0.064***	-2.414**	-0.003	-0.031
	(-3.399)	(-2.046)	(-0.745)	(-1.437)
Observations	873	854	963	929
R-squared	0.579	0.397	0.592	0.801

Table 9: Changes in Product Pipeline

This table compares post-merger changes in drug development of innovative (INV) firms and less innovative firms (LINV) in overlapping product markets. A market is considered overlapping if any of the acquirer's (target's) drugs has the same ATC-4 code (i.e., operates in the same therapeutic market) as any of the target's (acquirer's) drugs. The observation level is deal quarter and the sample includes 45 mergers with at least 2 quarters before merger and 2 quarters after merger. The dependent variable is the number of product development events for a merger in quarter *t* with six possible definitions of a development. The six columns respectively capture the development of: (1) any low-novelty product (2) any high-novelty product (3) an early-stage, low-novelty product (4) an early-stage, high-novelty product, (5) a late-stage, low-novelty product, and (6) a late-stage, high-novelty product. We define development to the preclinical or phase-I stages as an early-stage development event and development to phase-II, phase-III, or FDA approval stages as late-stage development events. In the first row, a product is defined has high (low) novelty if the number of other drug products that use the same target action is below (above) the sample median. In the second row, a product is defined has high (low) novelty if the number of other *FDA approved* drug products that use the same target action is below (above) the sample median. *Post* is a dummy equal to one for the quarters after the merger announcement, and zero for the quarters before. LINV is an indicator variable equal to one if the acquirer is classified as a less innovative firm and zero if it is classified as an innovative firm. Firms are classified as innovative if their percentage of patented products is in the top quartile of the sample and as less innovative otherwise.
All regressions include deal fixed effects and calendar quarter fixed effects with robust standard errors. *t*-statistics are reported in parentheses. Significance levels are represented by asterisks as follows: *** p<0.01, ** p<0.05, * p<0.1.

		All Drugs		**Early Stage**		**Late Stage**	
		Low Novelty	High Novelty	Low Novelty	High Novelty	Low Novelty	High Novelty
		(1)	(2)	(3)	(4)	(5)	(6)
Novelty based on all projects	Post*LINV (ξ_1)	0.029	-0.056	0.025	-0.106*	0.168**	-0.025
		(0.697)	(-0.375)	(0.688)	(-1.774)	(1.990)	(-0.580)
	Observations	980	980	980	980	980	980
	R-squared	0.185	0.581	0.218	0.520	0.095	0.392
Novelty based on FDA approved projects	Post*LINV (ξ_1)	0.179**	-0.206	0.140*	-0.143**	0.157**	-0.094
		(2.130)	(-1.621)	(1.850)	(-2.132)	(2.327)	(-1.538)
	Observations	980	980	980	980	980	980
	R-squared	0.415	0.498	0.424	0.393	0.149	0.373

Appendix A: Variable and Sample Definitions

Table A.1: Variable and Sample Definitions

The firm-level variables are defined in Panel A and the drug-level variables in Panel B.

Panel A: Firm-Level Variables	
Actual	indicator equal to one for actual mergers and zero for control mergers.
Acquirer (Bidder)	indicator equal to one if the firm was an acquirer (bidder) in the completed (withdrawn) merger.
Deal Innovativeness	defined by first calculating the percentage of an acquirer's total products that are patented (named patent percentage) as of the merger announcement quarter, then by sorting deals into quartiles on acquirer patent percentage. ***Less-Innovative (innovative) deals*** are those in the bottom 3 (top) quartiles of acquirer patent percentage.
INV	indicator equal to one if a firm is classified as an innovative firm
LINV	indicator equal to one if a firm is classified as a less innovative firm
Post	indicator equal to one for the 8 quarters after deal completion and zero for the 8 quarters before announcement.
R&D_TA	the firm's R&D spending in Compustat Fundamentals Quarterly divided by total assets.
Sales Overlap	sales of the acquirer's (or control acquirer's) that are in the same ATC-4 market as any of the target's (or control target's) drugs divided by the total sales of the acquirer's (control acquirer's) in the quarters before the merger.
Sales Overlap Dummy (SPD)	indicator equal to one if the sales overlap between the merging parties of a deal is above the sample median
SG&A_Sales	the firm's SG&A in Compustat Fundamentals Quarterly divided by the total sales.
Panel B: Drug-level variables	
Brand name	indicator equal to one if the drug is a brand name, and equal to zero otherwise.
Biologic	indicator equal to one if the drug is a biologic, and equal to zero otherwise.
Early-Stage Development	an early-stage development event is identified if a project advances to the preclinical trial or to phase-I
FIC	indicator equal to one if a drug was the first to sell in an ATC4 market
Generic	indicator equal to one if the drug is a generic, and equal to zero otherwise
Late-Stage Development	a late-stage development event is identified if a project advances to phase-II, phase-III or is FDA approved
Ln(PPU)	calculated for each drug-quarter as the natural log of the price per unit of the drug
Me-too	indicator equal to one if a drug started selling in an ATC4 market after the FIC
No Patent	drugs with no patent coverage, or with coverage expiring in less than 5 years, as of the deal announcement date.
Novelty (# of approved)	a product is defined has high (low) novelty if the number of other *FDA approved* drug products that use the same target action is below (above) the sample median
Novelty (# of projects)	a product is defined has high (low) novelty if the number of other drug products that use the same target action is below (above) the sample median
Patent	drugs with patent coverage that expires in 5 or more years relative to the merger announcement date
Post	indicator equal to one for the quarters after the merger announcement, and zero for the quarters before.
Overlap	indicator equal to one if the acquirer's (target's) drug is in the same ATC-4 market as any of the target's (acquirer's).
Treatment	indicator equal to one for drugs either acquired or owned by an acquirer and equal to zero for control drugs.