Seeking efficiency or price gouging? Evidence from pharmaceutical mergers

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Abstract

We show that pharmaceutical mergers are a response to competitive pressure. Firms whose drugs face more competition tend to become acquirers and these acquirers pursue firms whose drugs hold strong competitive positions in their product spaces. However, we find no evidence of greater post-merger price increases of merging firms' drugs as compared to a control group. Rather, we find robust support for the efficiency perspective of mergers. Firms with a high product overlap are more likely to merge and mergers are followed by a decline in prices of drugs that are similar across the acquirer and target portfolios.

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1. Introduction

The last few years have seen significant consolidation in the pharmaceuticals industry. In 2019 alone, megadeals such as AbbVie's $63 billion bid for Allergan and Bristol-Myers' $74 billion bid for Celgene placed the 2019 M&A deal value at over $400 billion globally. There is growing concern in the media and among lawmakers that such consolidation leads to higher drug prices and stifles innovation. In September 2019, several senators requested that the Federal Trades Commission investigate pharmaceutical mergers for anti-competitive practices and take steps to protect consumers.[1]

Drug prices are the fastest growing component of total health-care costs (Berman et al., 2017). Popular media and academic research have documented an increase over time in the list prices of drugs. In light of the rapid increase in drug prices, M&A activity is being flagged as a possible driver of higher drug prices.[2] Mergers between firms whose drugs treat similar illnesses may give the combined firm a monopoly over a therapeutic area. Mergers that bring multiple blockbuster drugs under one firm can provide that firm with greater negotiating power when setting prices. Moreover, recent evidence suggests that pharmaceutical mergers thwart future competition by discontinuing development of the target firm's innovation projects (Cunningham, Ederer and Ma, 2019)

On the other hand, pharmaceutical firms cite efficiency gains as the primary reason for merging.[3] Product overlap between merging firms can facilitate the sharing of technological knowledge, increase in scale of R&D, reduction in time from drug discovery to FDA approval, as well as elimination of redundancies in the research and production processes. These expected cost savings may be passed on to customers in the form of lower drug prices. Prior evidence based on inter-industry samples finds that product or human capital overlap increases the likelihood of acquisitions due to expected efficiency gains (Bena and Li, 2014, and Hoberg-Philps,2010; Lee, Mauer, and Xu, 2018).

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[1] "Harris, Colleagues Warn That Pharmaceutical Mergers May Threaten Drug Competition, Increase Prices and Reduce Patient Access to Essential Medications." *U.S. Senator Kamala Harris of California*, 17 Sept. 2019.

[2] See Kakani et. al (2020) and Hernandez et. al (2019). Also see Picchi, Aimee. "Drug Prices in 2019 Are Surging, with Hikes at 5 Times Inflation." *CBS News*, 2 July 2019, www.cbsnews.com/news/drug-prices-in-2019-are-surging-with-hikes-at-5-times-inflation/. For examples of price increases in acquired drugs see: "Drug goes from $13.50 a tablet to $750 overnight" *The New York Times*, Sept 20, 2015 at https://www.nytimes.com/2015/09/21/business/a-huge-overnight-increase-in-a-drugs-price-raises-protests.html

[3] For example, in their acquisition offer to Elan, Perrigo states that "the combination is expected to result in more than $150 million" in savings due, in part, to "the elimination of redundant public company costs while optimizing back-office support and the global R&D functions." Also, in its recommended offer to Warner Chilcot, Actavis anticipates "more than $400 million in after-tax operational synergies and related cost reductions, and tax savings."

In this paper, we present the first large sample analysis of these two contrasting views of pharmaceutical mergers. We ask the following questions. First, are pharmaceutical mergers motivated by a desire to reduce competition as often argued by popular media? Second, are pharmaceutical mergers driven by opportunities to exploit synergies, such as those arising from an overlap in the drug portfolios of two firms? Thirdly, and most importantly, we examine the impact of mergers on drug prices. Here we focus on two contrasting, but not mutually exclusive questions. Are cost efficiencies passed on to customers in the form of lower prices if the acquirer and target's drug portfolios are similar? Are pharma mergers followed by an increase in drug prices, especially for drugs that face little or no competition?

To answer these questions, we develop novel drug-level competition measures by web scraping text descriptions of 79,462 drugs products covered by Medicaid between 2007and 2018. We then use the 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. This enables us to calculate the level of competition faced by each drug in its product space based on the number of competing drugs and sales of competing drugs. While other pharmaceutical studies have used therapeutic areas and mechanisms of action to identify substitute products (see Krieger, 2017; Krieger et al, 2018; Cunningham et al, 2018), ours is the first to use granular, drug-level competition measures to examine merger likelihood and post-merger drug prices.

Due to the endogeneity of the merger decision, it is difficult to establish a causal link between acquisitions and change in product prices. The competitive environment of a firm can trigger acquisitions and also independently affect product prices. We are able to mitigate this endogeneity problem due to a unique feature of our data – it contains within-merger variation in both the outcome variable, namely drug prices, and the main explanatory variables, namely competition and drug-similarity. Another advantage of our data relative to prior research is that the quality of the product, i.e. the drug, is likely to be the same before and after the merger.[4] This helps address concerns that post-merger price changes could be due to improvements in product quality or improvements in service (Sheen, 2014).

[4] Some drugs might undergo Phase 4 clinical trials during the acquisition period. However, these are unlikely to have a significant impact on our drug price analysis. Phase 4 trials are post-marketing efforts to further evaluate safety, efficacy and new indications. If harmful effects are discovered, the drug is likely to be withdrawn. New information about efficacy is more likely to lead to changes in precision of the dose rather than formulation of the drug. Finally, some Phase 4 trials are not surveillance studies but are attempts to find new markets for the drug. See Bourin and Chagraoui, 2016; Grudzinskas, 2007; Suvarna, 2010.

Our sample includes about 700 pharmaceutical firms that appear in the Medicaid State Drug Utilization database. Of these, 275 firms are involved in 161 majority stake acquisitions between 2008 and 2017. In conditional logit models that control for factors known to affect pharmaceutical mergers, we find that competitive pressure is a significant determinant of acquisitions. Firms whose drugs face more ex-ante competition are more likely to become acquirers. In contrast, firms whose drugs face less ex-ante competition are more likely to become targets. These findings are robust to different measures of competition such as Herfindahl Index of a product space, number of drugs in that space, and market share of the firm in that space. The findings are also robust to different minimum similarity thresholds used to identify the competing drugs.

These results extend the findings of Hoberg and Phillips (2010). Using product descriptions in 10-K statements to capture firm-level similarity, they find lower merger incidence for firms that are more similar to their local rivals. This is interpreted as a 'competitive effect' in which firms with very near rivals must compete with each other for restructuring opportunities. Our more granular measure of product-level pairwise similarity uncovers new evidence of a differential impact of product-level competition on the likelihood of a firm becoming an acquirer or being acquired.

We also find robust evidence of a synergistic motive for pharmaceutical mergers. A higher ex-ante similarity between the acquirer and target's drug portfolios has a significant positive effect on the probability of a merger pair formation. This finding is consistent with Hoberg and Phillips (2010) as well as with Bena and Li (2014) who find that greater technological overlap between firm pairs increases the likelihood that the firms will merge.

Next, we move to drug-level price analysis. As expected, drug prices are on average higher for drugs with patents and market exclusivity, for drugs approved as part of an expedited approval program, for brand-name drugs, and for biologics. We also find that drugs facing low competition in their product space are on average priced higher. Moving on to the change in drug prices after a merger, we find that, on average, prices of merging firms' drugs are not significantly different after the merger than before. However, several interesting results emerge if we focus on similarity, competition, and drug type.

We first examine whether potential synergistic gains from overlapping drug portfolios are passed on to customers in the form of lower drug prices. Exploiting within-merger variation in

drug prices and drug similarity, we show that drugs that are similar across the acquirer and target's portfolios experience significant price declines after the merger in the magnitude of about 5%-6%, relative to drugs that are not similar. This result holds for both the acquiring firm's drugs and the target's drugs. It is robust to different similarity thresholds and holds after controlling for several factors known to affect drug prices, such as the drug type (e.g. generic, biologic, etc.), the existence of patents and exclusivity, and expedited approval programs.

To address reverse causality, we look at a sample of mergers that were announced but not completed and find no evidence of a decline in the price of similar drugs belonging to the bidders and targets of the withdrawn mergers. Further, an analysis of pre-merger trends in the sample of completed mergers shows that the decline in the price of similar drugs begins at the time of the merger announcement and is not a pre-merger trend. We also examine pre-merger trends of rival drugs that operate in the same product space as the treatment similar drugs and find no evidence of pre-merger negative price pressure in the product spaces of similar drugs. Taken together, these results provide evidence of a post-merger decline in drug prices due to possible efficiency gains from combining similar drug portfolios.

High similarity between the drugs of the merging parties also creates opportunities for anti-competitive behavior. If competition in a product space is low, firms can buy rivals who manufacture similar drugs and raise prices after the merger. We look at subsamples of drugs with high and low levels of competition in their respective product spaces and find that similar drugs experience a decline in price relative to non-similar drugs regardless of the level of competition in the product space. Thus, we do not find evidence that firms, on average, buy directly competing drugs with the intention of raising prices.

Looking within drug type, we find that prices of brand name drugs of the acquirer and target increase after the merger. This increase is not observed in other drug types. Brand name drug prices go up after the merger regardless of the degree of competition in the drug's product space. That is, brand name drugs that face competition from generic or other brand name drugs also increase in price after the merger. This points to possible price inelasticity of demand for brand-name drugs. Prior research in the health sciences field finds evidence of brand loyalty among patients as well as lingering distrust of generic drugs among certain sections of the population (Iosifescu et al., 2008; Kesselheim et al. 2016). The post-merger increase in prices of brand name drugs indicates that merging firms take advantage of brand loyalty.

However, a key question of interest is whether merging firms raise prices more than non-merging firms after the acquisition. We employ a difference-in-differences approach comparing prices of treatment drugs (i.e. drugs manufactured by the acquirer or target) with a set of control drugs of the same drug type that are not affected by a merger of their own manufacturers or by other mergers in their product space. We find that price changes after the merger are, on average, the same for treatment drugs and control drugs. Specifically, brand name control drugs experience similar post-merger price increases as brand name treatment drugs. To further explore whether merging firms raise prices more than non-merging firms when competition is low, we compare price changes in the treatment and control drugs conditional on the level of competition. We find no significant differences. These findings are robust to different similarity thresholds used to define a product space, different measures of competition, and to drug-fixed effects, deal-fixed effects, and quarter-fixed effects.

One limitation of our drug price analysis is that it relies on pre-rebate best prices, which do not accurately capture the net cost for payers such as Medicaid and Medicare. To address this, we show that our results hold in an alternative survey dataset called NADAC that captures the actual price paid for drugs by retail pharmacies. We also conduct a variety of robustness tests to address possible weaknesses in our data and classification of similar drugs. First, we show that our results hold in subsamples of brand name drugs only. Second, we use the well-known Anatomical-Therapeutic-Chemical Classes (ATC) at the five-digit level to identify substitute products and show that our main results hold for this classification. Third, by lowering the minimum similarity threshold upon which a product space is defined, we allow drugs with similar but not exactly the same words to belong in the same product space and find that our results are robust.

Our evidence provides large-sample support for prior suggestive evidence in Richman et al (2017), who argue that pharmaceutical mergers have not led to industry-wide price increases, and that individual drug price increases are due to specific market structures and opportunities. They conclude that "market power is better measured not in industry-wide measures, but instead along functional equivalents", i.e. along submarkets or "pharmacological space." Our study implements this granular approach and provides the first comprehensive analysis of the impact of pharmaceutical mergers on drug prices using drug-level data on competition and drug similarity.

In a contemporaneous paper focused primarily on brand name drugs, Bonaime and Wang (2019) find that the price of drugs owned by merging firms increases after the merger relative to

non-merging firms' drugs. Our paper provides several elements not explored in Bonaime and Wang. First, we examine the role of expected efficiency gains as captured by product overlap on the likelihood of merger pair formation. Second, we provide evidence that ex-ante product overlap is associated with a subsequent decline in the price of similar drugs. Third, we show that the degree of competition faced by a drug is a significant determinant of whether it seeks to buy another firm or itself becomes the target of an acquisition. Fourth, while Bonaime and Wang rely on static firm-level or deal-level measures to capture market power, we use within-merger variation in similarity and competition to mitigate the endogeneity of the merger decision. Finally, although we confirm Bonaime and Wang's finding that the price of brand name drugs owned by merging firms increases after a merger, we show that branded control drugs experience similar increases in price after the merger.

Our research is related to the growing literature on mergers in the pharmaceutical industry. Cunningham et al (2018) show that firms pre-emptively thwart competition by acquiring competing products and discontinuing their development. Higgins and Rodriguez (2006) find that product pipelines affect the pharmaceutical firms' merger decisions. Krieger et al (2018a) show that firms receiving a public health advisory are more likely to acquire drug projects from other firms than initiate internal projects. We add to this literature by providing the first comprehensive evidence of the role of competition and drug overlap on a pharmaceutical firm's decision to merge and its subsequent product market pricing decisions. Our paper is also related to the well-established 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, Mauer, and Xu, 2018. We add to this literature by providing new evidence from the pharmaceutical industry that efficiency gains from ex-ante product overlap are passed on to customers in the form of lower post-merger product prices. One note of caution regarding our evidence is that, like in any industry-specific study, the findings may not be representative of pricing behavior in other industries.

The rest of the paper is organized as follows. Section 2 describes related literature. Section 3 describes the data. Section 4 provides analysis of the likelihood of merger incidence. Section 5 presents analysis of changes in drug prices. Section 6 provides some additional results and Section 7 concludes.

2. Related Literature

Prior evidence suggests that firms experience improvements in operating performance after mergers (e.g. Healy, Palepu and Ruback, 1992; Heron and Lie, 2002). A large literature explores whether these improvements are synergistic or attributable to an increase in market power of the merging firms. Several studies attempt to disentangle efficiency gains from market power by examining stock market reactions to merger announcements (see Eckbo,1983; Stillman, 1983; Fee and Thomas, 2004; Shahrur, 2005). Focusing on announcement returns of rivals, customers and suppliers of the merging parties, these papers conclude that horizontal merges are primarily motivated by improvements in productive efficiencies. In contrast, studies that look directly at product prices after horizontal acquisitions find evidence in support of an increase in selling power (e.g. Borenstein, 1990; Kim and Singal, 1993; Prager and Hannan, 1998; McCabe, 2002; Kwoka and Shumilkina, 2010).

One possible reason why evidence from announcement returns is not consistent with the evidence from product market studies is that synergistic gains and market power effects often coexist in mergers. It is possible that while some products experience an increase in price due to reduced competition, other products that overlap across acquirer and target portfolios experience a price decline due to efficiency gains. Stock market reactions of merging firms, rivals, and customers would reflect the net effect of these contrasting forces. Existing studies are not able to explore the co-existence of these factors due to the lack of within-firm data on product-level similarity and competition.

There is mounting evidence on possible sources of synergistic gains in mergers from studies that look at firm-level measures of similarity. For example, Hoberg and Phillips (2010) find that mergers are more likely between firms that use similar product market language in their 10-K statements. Moreover, announcement returns and post-merger cash flows are higher for firms with similar product market language. Bena and Li (2014) find that technological overlap between firm pairs increases the likelihood that the firms will merge. Acquirers with technological linkage to the target firm produce more patents after the merger. Lee, Mauer and Xu (2018) find that mergers are more likely to occur between firms that have related human capital and measures of human-capital relatedness are positively associated with post-merger performance.

The pharmaceuticals industry provides an ideal setting to build on this research due to the availability of product-level price and sales data, product-level descriptions, and the high

likelihood of unchanged product quality after a merger. While there is scant large-sample evidence on drug prices, there exists an active literature on pharmaceuticals mergers. For example, Krieger et al (2018a) find that firms that receive a public health advisory are more likely to acquire drug projects than internally initiate new projects. Higgins and Rodriguez (2006) and Danzon et al (2007) find that pharmaceutical manufacturers with weaker product piplelines, and with more products facing expiring patent protection, are more likely to undertake acquisitions. Cunningham, Song, and Ederer (2019) show that firms pre-emptively thwart competition by acquiring competing products early on during the development stages and discontinuing their development. This points to the possibility that expectation of competition leads firms to seek acquisitions. However, there is no existing evidence on how competition at the product level affects a firm's decision to become an acquirer or a firm's likelihood of being the target of an acquisition.

3. Prescription drug sample and data sources

In this section, we describe our data sources and sample. We also provide a summary on the construction of product spaces. Section 3.1 describes our data sources and sample of drugs. Section 3.2 describes the construction of product spaces for each drug. Section 3.3 describes the construction of competition measures for the product spaces at different similarity thresholds. In some cases, details about data and variable construction are relegated to Appendix A through Appendix C provided at the end of the paper. Further details on data matching, data validation, 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.[5] The SDUD was established after congress created the Medicaid drug rebate program in 1990 and reports drug utilization data, including total spending and prescriptions dispensed, on a quarterly basis starting from 1991 for all states as well as national totals. SDUD reports a ten-character product name as well as the National Drug Code (NDC), an 11-digit, 3-segment code that uniquely identifies a drug product, including its manufacturer,

[5] For an overview of the Medicaid SDUD database, see Appendix B at the end of this paper. For more details on SDUD and the Medicaid drug reimbursement program, refer to Internet Appendix A.

strength of medication, dosage form, and package size.[6] We obtain a sample of 79,462 unique drug products from the SDUD database and, using the product name, we collect information on therapeutic area and mechanism of action for each product from IBM's Micromedex database. Our drug-level competition measures and similarity measures, described later in section 3.2, are based on the words in the therapeutic area and mechanism of action descriptions for this full sample of almost 80,000 drug products.

To determine whether a drug is a generic or brand-name drug or whether it has patents and exclusivity protection, we match drugs in the SDUD database to the U.S. Food and Drug Administration's (FDA) Orange Book using FDA-provided cross-over between the NDC code and FDA application number. The Orange Book identifies products approved by the FDA, dates of the approval, USPTO patent coverage and expiration dates, and FDA market exclusivity and expiration dates.[7] The Orange Book became electronically available in 2005. We ignore 2006 due to known overreporting of Medicaid sales in 2006 and begin our sample in the first quarter of 2007.[8] Using WaybackMachine, we retrieve electronic Orange Book issues for each year from 2007 to 2018. We match over 80% of the drugs in the SDUD database to an FDA application number using a matching strategy explained in Internet Appendix B. About 57% of the drugs in our sample are generic drugs. Just under 2% are biologics.[9] About 12% of the drugs in our sample have patent or exclusivity protection for at least one quarter during our sample period. Drugs that do not match to the Orange Book are assumed to not have patents or exclusivity coverage. Details regarding the matching of patent and exclusivity data to our sample of drugs is provided in Internet Appendix B.

Next, we identify the manufacturer of each drug and determine if the manufacturer engaged in an acquisition during our sample period. The first segment of the NDC code identifies the labeler

[6] The NDC code uniquely identifies a drug product. The first segment of the code identifies the labeler code, i.e. the manufacturer or distributor of the drug product. The second segment is the product code, which identifies the strength, dosage form, and formulation for a labeler. And the third segment is the package code, which identifies the package sizes and types. For example, Merck's high-cholesterol drug, Zocor, has several strengths. Each strength is given a different product code, e.g. a 9,000 unit of 20 mg Zocor tablets are assigned the NDC 6-740-54, whereas the 9,000 unit package with 10 mg Zocor tablets are assigned the NDC 6-735-54. In both cases, the labeler code for Merck and the package code for 9,000 units per package stay the same, however, the product code changes to reflect the different strengths of the two products.

[7] USPTO patent and FDA market exclusivity are two types of protection that effectively serve the same purpose – protecting the sales of a drug by preventing the entry of competition. Firms usually issue patents in the earlier stages of development, before the drug is approved for US markets. Patents are regulated by the USPTO and currently have a 20-year coverage period before expiration. FDA market exclusivity is issued upon drug approval, and usually lasts 5 years for new chemical entities.

[8] We don't include 2006 because of concerns that the SDUD data may have overstated prescription drug use and spending due to change in reporting following the launch of the Medicare part D prescription drug benefits program (see Breun et al, 2008).

[9] Biologics are produced from living organisms or contain components of living organisms. Biologics are expensive, often representing the cutting-edge of biomedical research.

of the drug, i.e. the manufacturer or distributor. We match each labeler code to a labeler name using the U.S. Food and Drug Administration's (FDA) NDC files and identify the manufacturer of each drug. We identify 690 unique manufacturers of which 413 are private firms. Moreover, 554 of the 690 are US firms and 144 are foreign.[10] Panel A of Table 1 provides descriptive statistics of drugs manufactured by private and public firms, both US-based and foreign. Although there are more private firms selling products to Medicaid, they account for only 7% of total Medicaid spending between 2007 and 2018. Foreign firms account for about 55% of the total 522 billion dollars of Medicaid spending from 2007 to 2018. This is not surprising since 5 of the world's 10 largest pharmaceutical companies are foreign firms. Foreign firms offer many specialty drugs that are expensive. For example, Valeant, a Canadian company, offers lead poisoning drug, Calcium Disodium EDTA, at $40,000 per unit, and Roche, a Swiss company, offers cancer drug Lucentis at a about $30,000 per unit. Private firms have experienced significantly higher sales growth than public firms. This is partly attributable to Medicaid's efforts to replace off-patent products with generics (MACPAC 2017). Private US-based manufacturers offered about 8 times more generic products than brand name products. In contrast, public US-based firms offered about twice as many generics as brand names.

To determine if a manufacturer was involved in acquisition during our sample period, we obtain data from SDC Platinum on completed, global, majority-stake acquisitions of targets that operated in pharmaceutical industry (i.e. target SIC codes between 2830 and 2839) between 2008 and 2017. We select 2008 and 2017 as the starting and ending years for the sample of acquisitions because we require drugs to have at least one year of data before and after an acquisition. We include acquisitions of pharmaceutical firms by non-pharmaceutical firms such as financial buyers due to the possibility that financial buyers recognize the strong competitive position of a target and adjust drug prices to take advantage of it.[11] The sample excludes acquisitions by pharmaceutical firms of targets that are not in the pharmaceuticals industry. Implicitly, we assume that purchases

[10] Since some companies are acquired during our sample period, we start by matching our sample of drugs to the FDA NDC files using a time-sensitive-match by NDC1-year. In most cases, the FDA data identifies when the ownership of a product was transferred from one labeler to another. Next, for labelers that aren't matched, we conduct a second round of matching on NDC1 alone using the FDA's NDC and the NDC/NHRIC databases and Medicaid's product data. We conduct a manual search to verify each labeler in our sample using the Bloomberg terminal, popular business media, and Google searches. Refer to Internet Appendix B for examples on how the FDA identifies when a drug is acquired.

[11] Roumeliotis, Greg. "Private Equity Takes on Big Pharma's Carve-out Challenge." *Reuters*, Thomson Reuters, 11 July 2014, www.reuters.com/article/us-privateequity-pharmaceuticals-portfol/private-equity-takes-on-big-pharmas-carve-out-challenge-idUSKBN0FG21G20140711.

of firms outside the pharmaceutical industry do not affect drug prices. We manually search this M&A sample for each of the 690 unique drug manufacturers. Drug manufacturers in our sample engaged in 161 mergers from 2008 to 2017.

Table 1 panel B presents descriptive statistics for acquirers and targets. The column titled Public in this table includes mergers in which either the target or the acquirer was a publicly traded firm (129 deals with average deal value of $5 billion). The Private column includes deals in which both the acquirer and the target are privately held (32 deals with average deal value of $166 million). In 150 deals, either the target or the acquirer was a US-based firm (with $7 billion in average deal value), and in 11 deals both acquirer and target were foreign manufacturers (with $4 billion in average deal value). Of the 161 targets in our sample, 81 were private firms, and the majority of these firms were based in the US. Target firms tend to be smaller – on average, targets have about one-tenth the average annual sales of acquirers. These finding are consistent with Danzon et al. (2007)'s results who find that target firms are usually smaller in size and are less likely to be based outside the US. In addition, acquirer and target firms have a similar brand name to generics ratios. Finally, targets have substantially higher recent sales growth compared to acquirers.

3.2 Description of drug-level product spaces

To determine the product overlap between an acquirer and target and the competition each firm faces in its product space, we use two drug characteristics that define precisely where a drug falls in the product space. The first characteristic is a drug's therapeutic area, which can be thought of as the drug's market and defines the diseases or conditions that the drug targets (e.g. Schizophrenia). The second characteristic is a drug's mechanism of action which can be thought of as the drug's technology, and defines how the drug works in the body (e.g. selective serotonin reuptake inhibitor (SSRI)). Several papers in the literature have used variations of these two characteristics as proxies for the extent of overlap between products and firms in the pharmaceutical industry. Our overlap measure is closest in spirit to that of Cunningham et al. (2018), who require that competing (substitute) products have exactly the same therapeutic areas and mechanism of action. In addition to this exact matching approach, we relax the stringent constraint and allow competing products to have highly similar, but not exact, words in their

therapeutic area and mechanism of action text descriptions.[12]. Other papers in the literature use more broad definitions for product overlap. For example, Higgins and Rodriguez (2006) use the Uniform Standard of Classification – a broad therapeutic category – to identify firms that have similar products. Krieger et al. (2018a) use the Center for Medicare and Medicaid Service's ICD-10 assessment classification to identify competitor drug products that fall within the same general category. Our method builds on this literature by creating a product space at both the drug and firm levels using a novel data and methodology. To the best of our knowledge, we are the first to create a dynamic and granular measure of competition at the drug-level using comprehensive data on drug utilization, sales and prices.[13]

We use the 79,462 drug products obtained from the Medicaid SDUD data from 2007 to 2018 to create our product spaces.[14] We use a web-scraping algorithm to search IBM's Micromedex database using the product name and collect information on the therapeutic areas and mechanism of action for each drug product. Micromedex provides nearly universal coverage of drugs that were approved by the FDA for US markets. Our sample of 79,462 products matches to 1,556 unique drug profiles in the Micromedex data. When multiple drug products match to the same Micromedex profile, it means the products compete directly with each other.[15] However, drug products with different Micromedex drug profiles may also compete with each other due to partial overlap in therapeutic areas, or mechanism of action or both. That is, the product space of a drug product can extend beyond its unique drug profile. By matching each of the 79,462 products to all of their respective therapy areas and mechanisms of action, we make it possible to determine the pairwise similarity between each drug product, including products that do not share the same drug profile.

[12] Table C.2 in Internet Appendix C provides an example from our drug sample that highlights the impact of changing the similarity threshold on the products that fall in the same competition space.

[13] Cunningham et al (2018), Krieger (2017) and Krieger et al (2018a) replicate their main results in subsamples based on the number of competing products.

[14] We believe that the Medicaid population of drugs is a good representative of the true drug population for the following reasons. First, most of the Medicaid state programs cover drugs that are dispensed as part of a treatment plan for Medicaid enrollees. In 2015, Medicaid spent around $55 billion (or about 15% of total prescription drug spending in the US, pre-rebate.) on prescription drugs, and had about 70 million enrollees of all age groups (Martin et al. 2016). Second, Medicaid is required to cover most of a manufacturer's drugs that are approved for US markets, if that manufacturer conforms to the requirements of the Medicaid Drug Rebate Program. Furthermore, our sample includes all large pharmaceuticals manufacturers.

[15] One reason why multiple drug products can match to the same Micromedex profile is that different strengths (e.g. 10 mg vs 20 mg) and package sizes (20 pills vs 50 pills) of the same drug are assigned different NDC codes. The fact that different strengths and package sizes of the same drug have different NDC codes may lead to an overstatement of the actual number of competing products. However, our sales-based competition measures are not subject to this concern.

We use the cosine similarity method described in Hoberg and Phillips (2016) to find the pairwise similarity between the products in our sample. Our method is based on the intuition that drugs that are substitutes will contain the same, or highly similar, words in the description of their FDA approved therapy areas and mechanism of action. Hoberg and Phillips (2016) find the pairwise similarity between firms on one dimension, i.e. the firm's 10-k business description. In contrast, we find the pairwise similarity between each drug products on two dimensions – the therapy area and the mechanism of action. We clean and standardize the therapeutic area and drug class variables for each drug in our sample by retaining only unique words that add incremental value to the description of a drug product. The purpose of this last exercise is to improve the accuracy of the pairwise similarity. This procedure is explained in detail in Internet Appendix C.

Figure 1 displays the distribution of the number of processed and standardized words in the product description variables for all drugs in our sample. Figure 1A displays the distribution of the number of unique words in the therapeutic area description variable. Most drugs in our sample have less than 20 unique words in their therapeutic area description. Relatively few drugs have more than 40 words. Figure 1B displays the distribution of the number of words in the mechanism of action descriptions for each drug in our sample.

We find the cosine similarity between drug *i* and drug *j*'s therapeutic area words and the cosine similarity between the words in their drug classes. Details are as described in Internet Appendix C. Since we have exactly 79,462 products in our sample, we construct two matrices, both with dimensions equal to 79,462 x 79,462, that contain the pairwise similarity between all products in our sample, on the therapeutic area dimension (we call this matrix *Q_TA*), and the mechanism of action dimension (we call this *Q_MoA*). In Q_TA, the cell corresponding to column *i* and row *j* displays the cosine similarity score between the standardized therapeutic area vectors of drugs *i* and *j*. Note that the pairwise similarity between our drug products is static.

Figure 2A displays the distribution of the non-zero similarity of the therapeutic area descriptions between the unique 1,556 Micromedex drug profiles. Figure 2A indicates that the majority of non-zero similarities between words in the therapeutic area descriptions fall below the 20% threshold. Figure 2B displays the non-zero similarity between mechanism of action descriptions of the unique 1,556 MM drug profiles. The majority of non-zero similarities between words in the drug class descriptions fall just above the 20% threshold.

3.3. Competition measures

We create three fluid measures of competition faced by a firm's drugs in each quarter – a simple drug count measure, a market share measure, and a Herfindahl index. All measures are based on the presence of rival products (i.e. drug products manufactured by rival firms) within a product space defined by a minimum similarity threshold. For our primary analysis, we define product spaces based on the minimum similarity thresholds of 99% and 75%. Competition measures based on the 99% (75%) threshold are given the prefix g99 (g75). Thus, *g99Number* (*g75Number*) is the number of rival drug products in the product space identified using the 99% (75%) threshold. The market share measures *g99Mkt_Share* and *g75Mkt_Share* captures the market share of a firms' drugs within each product space the firm's drugs compete in. The variables *g99HHI* and *g75HHI* capture the level of market concentration within each product space that a firm's drugs compete in. The construction of these variables, which generates within-firm variation in competition, is described in Section A2 of Appendix A. In Internet Appendix C we provide support for the validity for our competition measures by conducting external validation.

Our choice of the 99% threshold is based on Cunningham et al (2018) who argue this to be the correct threshold for capturing drug products that are potential substitutes. In addition, we use the 75% threshold to assess robustness to reasonable adjustments in the similarity threshold. In some graphs, we set the minimum similarity threshold at 50% or 20% to present a contrast. These lower thresholds are more likely to classify drugs that are not very similar as competitors, and are therefore, noisier measures of competition.

Figure 3 displays the distribution of the number of rival products that fall within a product space that is based on a given minimum similarity threshold. In this figure, we provide a contrast by also including the number of competitors if lower similarity thresholds such as 20% and 50% are used. Figure 3 shows that at the 99% minimum similarity threshold, which effectively requires a perfect overlap in therapeutic area and mechanism of action, about 25% of drug products have less than 20 competitors. Only about 3% have more than 500 competing products. The average (median) number of competing rival products using a 99% similarity threshold is 119 (77). In contrast, when we define the competition space loosely at the 20% minimum similarity threshold, the number of competing drugs is quite evenly distributed and more than 50% of drugs have more than 500 competing drugs with an average of about 800. Thus, the 20% minimum threshold is a

noticeably more coarse definition of competition. In Section 6.3, we demonstrate that our main results get progressively weaker as we lower the minimum similarity threshold.

Figure 4 illustrates the distribution of the HHI index across product spaces in our sample. We present the HHI based on our main 99% and 75% similarity thresholds and also, for comparison, using the 50% and 20% thresholds. The higher the similarity threshold, lower the likelihood of finding a similar drug and, the more the density assigned to absolute monopolies. For example, using the g99 specification, about 6% of the products have no competition. This number drops to about 1.5% when we use the 50% threshold. Furthermore, using the 20% specification, less than one percent of the products in our sample fall in an absolute monopoly, and about 25% fall in a highly competitive product space.

4. Merger likelihood analysis

In this section, we examine whether the likelihood of pharmaceutical firms engaging in an acquisition depends on the degree of competition the firms' drugs face and the product overlap between the acquirer and target. In Section 4.1, we describe our method for assessing the probability of becoming an acquirer, the probability of becoming a target, and the probability of two firms pairing up in a merger transaction. In Section 4.2 we describe how competition measures are aggregated at the firm-year level. In Section 4.3, we describe our measures of product overlap between any two firms. Section 4.4 describes control variables and Section 4.5 presents the results.

4.1 Method

To assess the likelihood of a firm becoming an acquirer or a target, we match each acquirer (target) to up to 3 pharmaceutical firms that are the nearest in terms of total drug sales in year *t-1*, provided sales are not less than 50% or greater than 150% of the sales of the acquirer (target). Thus, in each deal, we have one observation for the acquirer (target) and multiple observations for the control acquirers (control targets). Given the matched case-control nature of the study, we run conditional logit regressions following Bena and Li (2014).[16]

$$Event\ Firm_{kd,t} = \alpha + \beta_1\ Competition_{t-1} + \beta_2\ Event\ Firm\ Characteristics_{\ kd,t-1} + Deal\ FE_d + \varepsilon_{kd,t} \quad (1)$$

[16] In addition to size and industry, Bena and Li (2014) also match on book-to-market ratio when selecting control acquirers and control targets. Since majority of targets in our sample are private firms we do not match on the book-to-market ratio.

In the acquirer (target) analysis, the dummy variable *Event Firm*$_{kd,t}$ is equal to one if firm *k* is the acquirer (target) in deal *d* occurring in year t. *Competition*$_{kd,t-1}$ is one of three firm-level competition variables that are constructed from the drug-level competition measures described previously in Section 3.3, namely, HHI, market share, and number of competing rival products. The procedure used to aggregate drug-level measures of competition into firm-level measures is described below in section 4.2. Event Firm Characteristics are control variables that we describe below in Section 4.3. Deal FE_m is the fixed effect for each acquirer (target) and its control acquirers (control targets).

To assess the likelihood of any two firms *k* and *l* pairing up in a merger, we run a conditional logit regression with one observation for each deal and multiple observations for control deals. The sample of control deals or potential deals is constructed by pairing the actual target with each of the control acquirers, and by pairing the actual acquirer with each of the control targets. Since there are up to three control acquirers and three control targets per deal, each deal can have up to 6 control deals. The following equation is estimated using samples of actual merger deals and potential merger deals.

$$Acq\_Tar_{kld,t} = \beta_1\, Overlap_{kld,t-1} + \beta_2\, Acq\ Competition_{kd,t-1} + \beta_3\, Tar\ Competition_{ld,t-1} + \beta_4\, Acq\ Characteristics_{kd,t-1} + \beta_5\, Tar\ Characteristics_{ld,t-1} + Deal\ FE_d + \varepsilon_{kld,t} \quad (2)$$

The dependent variable *Acq_Tar*$_{kld,t}$ is a dummy variable equal to one if the firm pair *kl* is the actual acquirer-target firm pair in deal *d* and zero otherwise. *Overlap*$_{kl}$ is the overlap between the drug portfolios of firm *k* and firm *l*. Construction of the overlap measure between each firm pair is described below in section 4.3. The variable *Acq Competition*$_{kd,t-1}$ (*Tar Competition*$_{ld,t-1}$) is one of three firm-level variables capturing the degree of competition each acquirer (target) faces.

Using the conditional logit models in equations 1 and 2, we are able to examine whether product overlap and product-market competition are significant drivers of merger incidence and merger pairing in the pharmaceutical industry. Our set of control mergers account for possible clustering of pharmaceutical mergers in time as well as any size effects. Finally, we note that all regressions report heteroskedasticity-consistent robust standard errors. Results are similar if standard errors are clustered by merger deal *d*.

4.2 Firm-level competition measures

Our main explanatory variables are firm-level measures of competition and similarity, which are created using the drug-level competition measures described in Section 3.3. The three firm-year measures of competition at the 99% minimum similarity threshold are calculated directly from the three drug-level competition variables, g99Number, g99Mkt_Share and g99HHI described in Section 3.3. Specifically, the variable *g99FirmMkt_Share* for a firm *k* in year *t* is the sales-weighted average of g99Mkt_Share across all product spaces *p* that the firm *k*'s drugs operate in during all quarters *q* of the given year. The variable *g99FirmHHI* for a firm *k* in year *t* is the sales-weighted average of g99HHI across all product spaces *p* that the firm *k*'s drugs operate in during all quarters *q* of the given year. Finally, the variable *g99FirmNumber* for a firm *k* in year *t* is the sales-weighted average of g99Number across all drugs that the firm *k* sells during all quarters *q* of the given year. In a similar fashion, we calculate three firm-year measures of competition at the 75% similarity threshold, namely *g75FirmMkt_Share*, *g75FirmHHI*, and *g75FirmNumber*. Panels A and B of Table 2 summarize these firm-level competition measures for acquirers and their matching control firms as well as targets and their matching control firms. We see in Panel A that acquirers have an average market share of 0.48 while control acquirers have an average market share of 0.49. Average HHI in acquirers' product spaces is 0.50 while control acquirers have an average HHI of 0.53. Acquirers' drugs on average face 108 competing drugs, while control acquirers have an average of 90 competing drugs. A similar comparison for actual targets and control targets is provided in Panel B.

4.3 Firm-level product overlap measures

Prior evidence suggests that the potential synergistic value from shared sales experience, knowledge, or technology can lead to a greater incidence of mergers (see Bena and Li,2014; Higgins and Rodriguez, 2006). To capture this, we create a measure of product overlap using the product spaces described in Section 4.2. This measure is calculated as the number of common or shared product spaces for a pair of firms divided by the total number of product spaces both the firms compete in. This measure can also be equivalently created using the Hoberg and Phillips (2016) cosine similarity method by calculating the similarity between the competition spaces of a firm pair. This measure is bounded between zero and one. Thus, the competition space overlap between firms *k* and *l* in year *t* is calculated as:

$$Overlap_{k,l,t} = Cosine\ similarity\ between\ the\ competition\ spaces\ of\ firm\ k\ and\ firm\ l\ in\ year\ t$$

We define this overlap measure at both the 99% and 75% minimum similarity thresholds. In untabulated results we observe that the more stringently we define the underlying product spaces, the less similar any two firms' products will be. Therefore, there is a greater clustering around zero for the 99% similarity threshold than for the 75% similarity threshold, similar to the patterns observed in figures 3 and 4 for drug-level competition measures. Table 2 Panel C summarizes this product overlap measure for actual target-acquirer pairs and matching pairs. We see that overlap between actual merger pairs is significantly greater than the overlap between control pairs.

4.4 Control Variables

Following Higgins and Rodriquez (2006), we control for patent or exclusivity protection of a firm's total product offering (*Protected Sales*) in all our regressions. We also control for firm size using the natural log of the firm's sales, *Ln(Sales)*, the average annual growth in sales over the 3 years preceding the merger, and the firm's public or private status, *Public*. When referring to the acquiring (target) firm, we add the suffix Acq (Tar) to the variable names.

Correlations between the competition measures and control variables are presented in Table 3. Panel A presents the measures for individual firms. We see that market share and HHI are highly correlated with each other, with correlation coefficients above 0.8. As expected, competition based on the number of competing products is negatively correlated with HHI and market share with correlation coefficients mostly near -0.8 or higher.

4.5. Results

Table 4 Panel A presents coefficient estimates obtained from estimating the conditional logit regression in equation (1) to predict acquirers. The main right-hand side variable of interest is the degree of competition faced by a firm's drug portfolio. In columns 1 through 3, the competition measures are based on the 75% minimum similarity threshold. In columns 4 through 6, the competition measures are based on the 99% minimum similarity threshold. At both thresholds, the coefficient on market share is negative and significant at the 95% confidence interval indicating that firms with a more dominant position in their product markets are less likely to undertake acquisitions. At both similarity thresholds, the coefficient on HHI is negative and statistically significant at the 99% percent confidence interval. Thus, we find that firms operating

in concentrated product markets are less likely to become acquirers. Finally, at both similarity thresholds, the coefficient on the number of competing products is positive and statistically significant at the 99% confidence level. In summary, the three measures of competitive position lead to the same conclusion. The greater the competition a pharmaceutical firm faces, the more likely it is to undertake an acquisition. One explanation for these findings is that the possibility of anti-trust investigations in concentrated markets discourages acquisitiveness. We note that the coefficients on control variables are consistent with prior evidence. Larger firms and publicly traded firms are more likely to become acquirers (Danzon et al (2007)).[17] We find no link between acquisitiveness and sales covered by patent and exclusivity, which we label Protected Sales. The coefficient on sales growth is also statistically insignificant.

Panel B of Table 4 presents coefficient estimates obtained from estimating the conditional logit regression in equation (1) to predict targets. The coefficients on the competition variables are the opposite for the target regressions as compared with the acquirer regressions above. At both similarity thresholds, the coefficients on market share and HHI are positive and statistically significant and the coefficient on the number of competing products is negative and statistically significant. Thus, firms whose drugs enjoy a dominant market position or face less competition are more likely to become targets of an acquisition. Looking at control variables, we find that firms experiencing a higher 3-year average sales growth are more likely to become targets of an acquisition. We also find a positive relation between firm size as measured by sales and the likelihood of becoming a target. Coefficients on both these control variables are consistent with the prior evidence in Bena and Li (2014).

Finally, in Panel C of Table 4, we present coefficient estimates from the conditional logit regression in equation (2), which predicts the formation of merger pairs. We find that the coefficient on Overlap is positive and statistically significant regardless of the similarity threshold and competition measure used in the regression. In this regression, measures of acquirer competition are largely insignificant. However, there remains strong evidence that merger pairs include targets that face less competition in their product spaces.

Combined these results support prior evidence that product overlap is a significant determinant of merger pairing. We also provide new evidence that pharmaceutical firms are more

[17] Although our control firms are matched on size as measured by sales, we still include sales as an independent variable. We do so because control firms can have sales between 50% and 150% of the acquirer's (target's) sales, leading to sufficient variation in size.

likely to become targets of an acquisition if their drug products enjoy a strong competitive position. The fact that transaction incidence depends on product market competition makes it imperative that an analysis of change in drug prices around acquisitions account for the endogeneity of acquisitions.

5. Change in drug prices around mergers

In this section, we examine the change in drug prices after mergers in the pharmaceuticals industry. We wish to understand how drug prices are affected by the product overlap between the acquirer and target and the degree of competition in the drug's market. Since competition is also a significant determinant of the merger itself, we focus on within-drug and within-deal variation. Our data permit this because we have within-drug variation in prices, within-drug variation in the measures of competition, and within-deal variation in the measures of drug similarity. We obtain Price per Unit (PPU) for each drug product in the Medicaid SDUD database. PPU is equal to the total spending on the drug divided by the number of units dispensed in a given quarter. A unit is a drug product in the smallest denomination as offered by the pharmaceutical company. One drawback of using PPU is that these are pre-rebate prices and may not reflect the actual price paid by Medicaid. Insofar as post-rebate prices are correlated with pre-rebate best prices, changes in the pre-rebate best prices are likely to affect post-rebate prices.[18] This leads to a sample of about 1,600,000 unique drug-quarters, across 50 quarters, and about 80,000 unique drug products identified by the NDC code. We use the Consumer Price Index to adjust PPU to 2015 dollars. Table B1 in Appendix B displays summary statics for this sample of drug price over the period from 2007Q1 to 2018Q2.

In Section 5.1 below we examine whether the change in drug price after a merger is related to the similarity between the acquiring firm's and target firm's drugs portfolios. In Section 5.2, we compare price changes in treatment drugs to a set of randomly matched control drugs.

[18] See Appendix B for a discussion on the validity of the Medicaid pricing data for our research question. An alternative survey-based data called NADAC data provides the actual prices paid by retail pharmacies for a drug. In Table B.2 of Appendix B we show that the distribution between NADAC and SDUD is very similar and also show that the difference in average prices between the two databases is statistically insignificant. Appendix B also lists advantages of the SDUD database over NADAC. Furthermore, we replicate our main results in Table B.3 of Appendix B using the NADAC data and find qualitatively similar results.

5.1 Similarity and the change in drug prices

In this section, we examine whether synergistic gains from product overlap between the acquirer and target are passed on to customers in the form of lower product prices. We use a panel of drug products that are affected by an acquisition and examine the change in the price of a drug after the merger conditional on the similarity of the target and acquirer portfolios in that drug's market. We examine the change in prices of treatment drugs, including both the acquiring firm's drugs and the acquired firm's drugs during the 8 quarters before and 8 quarters after the merger announcement. To be included in this sample, we require a treatment drug to have at least 2 quarters of observations before the merger and at least 2 after. If an acquirer engages in more than one acquisition in less than 8 quarters, we allow the same acquirer products to appear more than once in our data.[19]

5.1.1 Model specification

We use the following model to estimate the change in drug prices after a merger

$$\Delta Ln(PPU)_{id,q} = \alpha + \beta_1 Post_{dq} + \beta_2 Post_{dq} * Similar_{id} + \beta_3 Similar_{id} + \beta_4 Post_{dq} * Competition_{id,q} + \beta_5 Competition_{id,q} + \beta_6 Drug\ Controls_{i,q} + Drug\ or\ Deal\ Fixed\ Effects + \varepsilon_{i,q} \quad (3)$$

where $\Delta Ln(PPU)_{id,q}$ is the change in natural logarithm of the price of drug *i* in deal *d*, calculated as the natural log of the drug's price in quarter *q* less the natural log of price in the first available quarter before the merger. Defined as such, the left-hand side captures the percentage change in the drug's price relative to the price in the first available quarter. In Appendix C, we demonstrate robustness of our results if the left hand side variable is simply the natural log of drug price. In regression (3) above, $Post_{dq}$ is a dummy variable equal to 1 if the quarter q falls after the announcement of merger *d* and zero if it falls before the announcement. In an alternative specification presented in Appendix C, we show that our main result holds if we compare price before merger announcement with price after merger completion. Our main independent variable, $Similar_{id}$, is a dummy variable defined at the drug-level that is equal to one if the drug is similar to a product sold by the merger counterparty over the four quarters preceding the merger. Thus, for an acquirer's (target's) drug, the variable Similar is equal to 1 if the drug shares a competition space with at least one of the target (acquiring) firm's drugs and zero otherwise. This similarity

[19] However, in this situation, we require that products must have been owned by the repeat acquirer at least 8 quarters prior to the merger. Thus, newly acquired products are not included in the subsequent merger's observations if that merger happens less than 8 quarters after the first acquisition.

dummy variable varies within a merger because each drug owned by an acquirer or target falls in a different product space. The variable $Competition_{id,q}$ in equation (3) is either market share of the drug in its competition space or HHI of the drug's competition space using either the 99% or the 75% similarity threshold. Both measures are described in Section 3.3. In the interest of space, we do not present results using the number of rival drugs as a measure of competition. However, our results are robust for that measure as well. We note that the level of competition a drug faces is likely to change after the merger. Our measures of drug-level competition are dynamic, meaning the measures are updated every quarter and therefore account for any change in competition faced by a drug after the merger. All drug-level control variables included in equation (3) are defined in Appendix A. The first three columns of Table 5 Panel A summarize our drug-level competition, overlap and control variables for the sample of treated drugs, i.e. drugs whose manufacturers were engaged in an acquisition.[20] Columns 4 through 6 summarize the variables for a set of control drugs, which is described later in Section 5.2. Correlations between the variables are presented in Panels B and C of Table 5.

5.1.2 Baseline results

We begin by providing a univariate comparison of $\Delta Ln(Drug\ Price)$ before and after an acquisition. Focusing only on columns 1 through 3 of Table 6 Panel A, we see that the change in drug prices of the treatment sample is lower after the merger than before for all drugs and also within subsets of drugs such as brand name drugs, generics and biologics. In Panel B of Table 6, we present a univariate difference-in-difference comparison of the change in the price of a drug before and after the acquisition conditional on the merger counterparty having a similar drug. We see that change in price of both similar drugs and non-similar drugs is more negative after the merger than before. However, the change is significantly more negative for similar drugs than for non-similar drugs. For example, the difference in difference is 8% at the 99% similarity threshold and 6.8% at the 75% similarity threshold.

In Table 7, we move to the multivariate analysis and present estimates of equation (3). In the first four columns of Table 7, we use deal-fixed effects exploiting within-merger variation in the dummy variable Similar as well as in control variables such as competition. All regressions also include time fixed effects and standard errors are clustered at the merger deal level. All

[20] Note that we do not calculate the variable Similar for control drugs since they do not undergo a merger.

variables that appear as interaction terms are also included separately though not tabulated in the interest of space.

In columns 1 and 2, the measure of competition used as a control variable is market share, while in columns 3 and 4, competition is measured with HHI. In this table and all subsequent tables, the top row of the table indicates which measure of competition is employed in the regression. The key variable of interest is the interaction of Similar and Post which has negative and statistically significant coefficient. Thus, after the merger, the change in price is significantly more negative for drugs that share at least one competition space with the merger counterparty as compared with drugs that do not share any. This result holds for both the 99% and 75% similarity thresholds. We note that the coefficient on Similar itself is positive, which indicates that drugs that are similar across the target and acquirer portfolios experienced more positive price changes prior to the merger than non-similar drugs. However, the post-merger decline in price of similar drugs more than offsets this effect. The coefficient on Post*Similar in column 1 indicates that prices are on average 6% lower after the merger relative to the first quarter before the merger.

To account for unobserved drug characteristics, columns 5 through 8 of Table 7 present the same regressions using drug-fixed effects instead of deal-fixed effects. Since the variable Similar does not have sufficient within-drug variation, it is excluded in these regressions. The coefficient on the interaction of Post and Similar remains negative and statistically significant. Thus, we find robust evidence that the prices after the merger are lower for drugs that are similar to products offered by the merger counterparty. In Table 8, we present the same analysis but separately for sub-samples of drugs manufactured by the acquirer and target. The specifications shown in Table 8 and all subsequent tables employ drug-fixed effects. However, results are robust if deal-fixed effects are used instead. Panel A (B) presents results at the 99% (75%) similarity threshold. We see that the interaction of Similar and Post has a negative and statistically significant coefficient in all specifications in Panel A, and in 5 of the 6 specifications in Panel B. Thus, the link between drug similarity and post-merger decline in price is quite robust.

5.1.3 Possibility of anticompetitive pricing of similar drugs

Similarity across drug portfolios of acquirer and target firms also creates opportunities for anti-competitive behavior. If the product space of the similar drugs is not highly competitive, merging firms may raise prices after the similar drugs come under common ownership. In

untabulated tests, we split the sample into subsets of drugs facing high and low competition in their product spaces based on the median value of competition. We find that the coefficient on the interaction of Post and Similar is negative and statistically significant in both subsamples. That is, similar drugs experience a decline in price even when competition in the product space of similar drugs is low. To check whether the decline in price of similar drugs is significantly affected by the degree of competition in the shared product space, we use triple interactions of Post, Similar, and our measures of competition. If merging firms take advantage of low competition in a shared product space by raising prices of the similar drugs, the coefficient on the triple interaction Post x Similar x Competition should positive. In Panel C of Table 8, the coefficient on this interaction term for both our HHI measure and market share measure of competition is seen to be either insignificant or negative. Therefore, we do not find evidence for the anti-competitive motive for mergers. The regression in Panel C includes the same set of control variables shown in Panels A and B but the coefficients are not reported in the interest of space.

5.1.4 Brand name drugs

In Tables 7 and 8, we find robust evidence that the price of brand name drugs increases after the merger. However, other drug types show no change in price or even a decrease in price. For example, generic drugs and patent protected drugs display a decline in prices after mergers. Our finding that brand-name prices rise after the merger is consistent with Bonaime and Wang (2019). Since many brand-name drugs face competition from generics, we explore this result further by looking within subsamples of high and low levels of competition in the product space. In untabulated tests, we find that brand-name prices go up in both subsamples. In Panel D of Table 8, we check for possibly different price changes of brand-name drugs conditional on competition. The triple interaction of Post x Brand Name x Competition is mostly statistically insignificant. That is, brand-name prices increase after the merger regardless of the degree of competition the drug faces and points to the possible price inelasticity of demand for brand-name drugs. The regression in Panel D includes the same set of control variables shown in Panels A and B but the coefficients are not reported in the interest of space.

5.1.5 Withdrawn deals and pre-merger trends

One explanation for the negative and statistically significant coefficient on the interaction of Post and Similar is that merger-induced efficiency gains in the overlapping products lead to lower prices. However, the negative coefficient may be due to reverse causality. It could be argued that mergers in overlapping product spaces occur in anticipation of expected price declines in those product spaces, possibly as an attempt to mitigate the future price declines. Under this scenario, price declines in the similar drugs would be observed even in the absence of a merger. We test this alternate explanation by looking at withdrawn pharmaceutical mergers. We use the same merger selection criteria described in Section 3.1 but focus on pharmaceutical mergers that were announced but not completed. After the matching process we are left with only 10 withdrawn deals. While the number of withdrawn mergers is small, the 18 parties involved in the failed mergers tend to be large pharmaceutical firms that manufacture just over 8000 unique drug products in our sample. This gives us sufficient drug-level variation in the dummy variable Similar. Table 9 presents estimates of our baseline regression in equation (3) for drugs affected by withdrawn deals at the 99% similarity threshold. We see that the coefficients on the interaction of Post and Similar are now either positive and significant or statistically indistinguishable from zero. These results are qualitatively unchanged if we use the 75% similarity threshold instead. Thus, in the sample of withdrawn mergers, we see no evidence of a decline in the price of similar drugs after the merger announcement.

We also conduct a price-trend analysis to strengthen the causal link between mergers and the post-merger decline in the price of similar drugs. We create dummy variables for each of the 16 quarters surrounding the announcement of the merger, up to eight quarters before the merger announcement and up to eight quarters after. We estimate equation (3) again but, instead of interacting the dummy variable Similar with Post, we interact it with dummy variables for each of the quarters surrounding merger announcement. The observed post-merger price declines of similar drugs can be attributed to potential merger synergies if there is no difference between similar and non-similar drugs in the several quarters leading up to the merger. Panel A of Figure 5 plots the coefficient of the interaction between the quarter dummy variables and Similar along with 95% confidence intervals. We see that the coefficients on the interaction of Similar with the quarter dummies are mostly insignificant in the quarters prior to the merger. In contrast, the interaction of Similar with several quarters after the merger announcement is negative and

statistically significant. We note that although the coefficient on the interaction in the quarter immediately following merger announcement is insignificant at the 95% confidence interval, it is significant at the 90% confidence interval. Thus, significant price declines in similar drugs are not a pre-merger phenomenon and occur mostly after the merger. One exception is the interaction of Similar with the one quarter preceding the merger announcement, which is negative and significant.

There are two possible explanations for the negative and significant coefficient in the quarter immediately preceding merger announcement. One explanation is that the merging firms start to implement price reductions in similar drugs in anticipation of synergies from the soon-to-be-announced merger. The other explanation is that an exogenous price decline in a given product space causes firms operating in that product space to quickly engage in mergers. There are three reasons why we believe this reverse causality explanation is unlikely. First, as already shown above, mergers that are announced but withdrawn are not followed by a decline in the price of similar drugs. Second, in untabulated tests we find that drugs owned by the target firm operating in the same product space do not experience a significant price decline in the quarter preceding merger announcement. For target firm's similar drugs, price declines are observed only a few quarters after merger announcement. Third, we find that rival drugs in the same product space also do not experience a pre-merger decline in price. Panel B of Figure 5 shows a price trends analysis for rival drugs that fall in the same product space as the similar treatment drugs but are not affected by a merger. Rival drugs are required to be the same drug type and have the same patent and exclusivity status as the similar drug. Panel B shows that rivals in the same product space do not experience a decline in price in the quarters preceding the merger.[21] Together these findings point to a causal impact of the merger on price decline of similar drugs.

We note that in Panel B of Figure 5, there is some indication of a post-merger downward trend in the price of rival drugs. Although the coefficients are statistically insignificant at the 95% confidence, a few are significant at the 90% confidence level (the latter is not evident from the graph). The weak decline in rival drug products could be indicative of price matching by competitors in a bid to avoid losing market share to the merged firm's cheaper products. We find

[21] In Panel B of Figure 5, coefficients on the interaction of Similar with the 7th and 8th quarter after a merger are dropped due to collinearity with quarterly time-fixed effects. If we run the analysis without time-fixed effects, we still see no evidence of a pre-merger decline in the price of rival drug products.

that the weakly downward pattern in post-merger prices of rival drug prices is observed only if a merger is completed. In untabulated tests, we look at price patterns of drugs operating in the same product space as similar drugs (i.e. rivals of similar drugs) in the sample of *withdrawn* mergers. In that sample, rivals of similar drugs demonstrate significant post-announcement price increases. Recall from Table 9 that similar drugs of the bidder and target in the sample of withdrawn mergers also experience price increases. Together our findings suggest that completed mergers not only lead to significantly lower prices for the acquirer's and target's similar drugs but also put downward price pressure on products competing with the similar drugs.

5.2 Change in drug prices relative to control drugs: the role of competition

In Table 7 and 8, the coefficient on the interaction of Post and the two competition variables market share and HHI are generally positive and statistically significant. That is, drugs facing less competition in their respective product spaces experience relatively greater price increases after the merger. In this section, we focus not on similar drugs but on all drugs affected by a merger and explore the role of competition in the product space. To understand pricing behavior in the absence of a merger, we compare prices changes in treatment drugs with prices changes observed in a randomly selected group of control drugs.

We randomly match each treatment drug product to a control drug – a drug produced by a firm that did not engage in a merger in the eight quarters before or eight after the announcement of the treatment drug's acquisition deal. We require the randomly selected drug to be the same drug type as the treatment drug (e.g. biologic, brand name, generic etc.), the same patent or market exclusivity status, and to have as many quarterly price observations available as the treatment drug. Additionally, we require the matched control drug to not fall in the same product space as the treatment drug (i.e. the control drug is not a rival drug) since changes in the concentration of that competition space around the merger may impact the pricing of control drugs and consequently contaminate our estimation results. We allow a drug to serve as a control drug for more than one treatment drug. The mean (maximum) number of times a drug is used as a control is 2.6 (13). We use a difference-in-difference approach and compare the change in price between treatment drugs and control drugs before and after a merger.

We estimate the following model with up to eight quarters of price data before and up to eight quarters after the announcement of a merger:

$$\Delta Ln(Drug\ Price)_{id,q} = \alpha + \beta_1\ Post_{dq} + \beta_2\ Post_{dq} * Treatment_{id} + \beta_3 Treatment_{id} + \beta_4 Post * Competition_{id,q} + \beta_5\ Post_{dq} *\ Competition_{id,q} * Treatment + \beta_6\ Competition_{id,q} + \beta_6\ Drug\ Controls_{\ i,q} + Drug\ FE_i + \varepsilon_{i,q} \quad (4)$$

In equation (4), the only new addition is a dummy variable called *Treatment* which is equal to one for treatment drugs, that is, drugs belonging to either the acquirer or the target firm and zero otherwise. We include the same drug characteristics as control variables as in equation (3), such as brand name drug, generic, biologic, patent protected and expedited approval. For each control variable, we include an interaction with Post to understand whether prices of specific drug types are affected more than others. We also include triple interactions of each control variable with Post and Treatment to examine whether prices of treatment drugs behave differently than control drugs around the merger.

Results are presented in Table 10. Panel A (Panel B) presents results using the 99% (75%) minimum similarity threshold. In each panel, columns (1) through (3) use market share as the competition measure and columns (4) through (6) use HHI. Results are presented separately for acquirer's drugs, target's drugs, and all drugs. In both Panels A and B, the interaction of Post and Competition is positive and significant in 5 of the 6 specifications indicating that drugs facing less competition experience larger increases in price after the merger. Thus, in the sample including treatment and control drugs, we continue to find a strong link between low competition and high drug prices.

However, in light of accusations that pharmaceutical mergers cause drug prices to rise, we focus on the difference between treatment drugs and control drugs. In both panels of Table 10, the coefficient on the interaction of Treatment and Post is statistically insignificant implying that after the merger the change in price is on average similar for treatment drugs and control drugs. We also note that the triple interaction of Post,Treatment, and Brand Name is statistically insignificant indicating that brand name drugs in the control sample experience similar increases in price after the merger as compared with treatment brand name drugs. Finally, we point to the triple interaction of Competition, Treatment and Post, which is statistically insignificant in all regression specification, indicating that prices of treatment drugs and control drugs respond similarly to changes in the competition measures around the merger.

We also look at triple interactions of Treatment and Post with other drug types such as biologic, patented, generic etc. Most of these triple interactions are also statistically insignificant.

Overall, looking within drug type, we do not find a consistent pattern of greater price increases for treatment drugs relative to control drugs.

6. Additional tests

In this section, we present a quick summary of additional tests in support of the evidence in Sections 4 and 5.

6.1. Robustness within subsamples of drug type and controlling for sales share in the similar product space

In Table 11, we repeat the baseline analysis from Table 7 in subsamples based on drug type. Specifically, we look within subsamples of brand name drugs, generic drugs, and biologics. For brevity, we only show results for the 99% similarity threshold and do not tabulate coefficients on all the control variables. In columns 1 through 4, we use market share to control for competition in the product space while in columns 5 through 8 we use HHI to control for competition (coefficients on competition not shown). In this table, we also include the size of the firm's revenues arising from the similar space as a control variable. The variable Similar Sales is calculated as the firm's sales in the product space that is similar to that of the merger counter party divided by the firm's total sales. For comparison with Table 7, analysis for the full sample of drugs is also shown. We see that the interaction term of Post and Similar is negative and significant in all specifications except for the subsample of biologic drugs. Biologics account for just over 10% of Medicaid expenditures. Thus, our results are robust for a large majority of drugs in the Medicaid database and hold even after we control for the share of a firm's sales arising from the similar product space.

6.2 Brand name drugs, alternate price measure, and alternate product space classification

The largest, most innovative pharmaceutical firms focus on brand name drugs and biologics, while numerous small firms manufacture only generic drugs. For this reason, the price dynamics of brand name drugs can be different than those for generics. Although many pharmaceutical research papers focus only on brand name drugs, we have opted to include generic drugs in our sample as they account for more than 20% of Medicaid expenditures. In this subsection, we repeat the baseline price regressions of Table 7 using the subsample of brand name drugs only. We start by using the same Medicaid SDUD drug price data employed in all previous

price regressions in Section 5 and present results in column 1 of Table 12. We see that the interaction of Similar and Post and negative and statistically significant.

Next we test robustness in alternate settings used by other papers. For example, in a related paper, Bonaime and Wang (2020) use drug price data from the National Average Drug Acquisition Cost (NADAC) developed by Myers and Stauffer LC which contains price actually paid by retail pharmacies. Almost 90% of Bonaime and Wang's sample of drugs are brand name drugs. Therefore, in the first variation, we run the baseline regression using NADAC price data on the subsample of brand name drugs. We note that the NADAC sample is significantly smaller than the SDUD sample for two reasons. First NADAC data begin only in 2012. Second, almost all products in NADAC are also in SDUD, whereas less than 60% of the SDUD products are also in NADAC. Results are presented in columns 2 and 5 of Table 12. The interaction of Similar and Post is negative and statistically significant.[22] Thus, we continue to find evidence of a greater post-merger decline in the price of similar drugs relative to non-similar drugs.

Next, we address possible weaknesses in our classification of drugs into product spaces. In a method similar to that employed by Cunningham et. al (2019), we identify similar drugs based on text descriptions of FDA approved therapeutic areas and mechanism of action of a drug. Inconsistencies in the use of words to describe therapeutic areas and mechanism action can create noise in our measure. Therefore, we use the well-established Anatomical-Therapeutic-Chemical Classes (ATC) at the five-digit level to identify substitute products and check if our main result is robust. In results presented in columns 3 and 6 of Table 12, the dummy variable Similar is based on the ATC classification[23]. The left hand side variable is the same as in our baseline specifications in Table 7, i.e. change in price from the SDUD database. A drawback of using the ATC codes is that we are not able to match them to a large number of drug products in the Medicaid SDUD database. That explains why the sample size in columns 3 and 6 is significantly lower than in column (1). Nonetheless, we find that the interaction of Similar and Post remains negative and statistically significant in columns 3 and 6. That is, our main result is robust if we use an alternate classification system to identify similar drugs.

[22] In Appendix B we present a more detailed discussion of NADAC data and show our results are also robust for the full sample of drugs when using NADAC data.

[23] For more information on the methodology used to match our sample of drugs to the ATC codes, refer to Internet Appendix D.

6.3 Lower similarity thresholds

Here we examine the impact of varying the minimum similarity threshold on both of our main analyses - the likelihood of merger occurrence and the change in drug prices. The lower the minimum similarity threshold used to define a competition space, the more likely we are to pick up products that are not true competitors. Thus, our main findings should weaken as the minimum similarity threshold is lowered.

In Panel C of Table 4, we provided evidence that firms with a higher product overlap are more likely to pair up in mergers. Table 13 presents estimates of the same merger pair analysis in equation (2) using different similarity thresholds. We present the coefficient on Overlap for thresholds 99%, 75%, 50%, and 20%. As usual, we present two sets of results, one with market share as the control variable for competition and another with HHI as the control variable. In Panel A of Table 13, we see the magnitude of the coefficient on Overlap decreases as the similarity threshold is lowered. The regression R-squared and t-statistics also decrease as the threshold is lowered.

We also look at how the effect of changing the similarity threshold on our drug price analysis. Table 13 Panel B repeats the price analysis of Table 7 at different similarity thresholds. For brevity, we present only the coefficient on the interaction of the dummy variable Similar with the dummy variable Post. Again, we see the magnitude of the coefficient on the interaction of Post and Overlap decreases as the similarity threshold is lowered. Taken together, the results in this section indicate that at higher minimum similarity thresholds, our measures of product overlap and drug similarity are good proxies for expected synergistic gains in merger.

Although our main results weaken as we lower the similarity threshold to 20%, we note the coefficients are still statistically significant. The reason is that even the 20% similarity threshold captures a meaningful overlap of drug characteristics. As is evident from Figure 2, about 75% of non-zero drug similarities fall below the 20% similarity threshold.

7. Conclusion

The concurrent increase in drug prices and consolidation in the pharmaceuticals industry has led to speculation that pharmaceutical mergers are anti-competitive and cause drug prices to rise. An alternative argument is that mergers between firms with a product overlap creates opportunities for cost reductions as well as opportunities for growth via shared technological expertise and networks.

We investigate these contrasting viewpoints of pharmaceutical mergers by creating novel product-market competition measures and pairwise overlap measures. We apply the Hoberg and Phillips (2016) cosine similarity method on the product descriptions of a comprehensive sample of drug products on the US market between 2007 and 2018. We vectorize the textual descriptions of each drug's therapeutic area and mechanism of action and identify the drug's product location space based on the similarity of its therapeutic area and mechanism of action description to that of other drugs. This enables us to create a drug-level measure of similarity as well as dynamic measures of drug-level competition. Using these measures, we examine the role of product overlap and competition in pharmaceutical mergers

We find that drug-level competition is a significant determinant of merger likelihood. Firms whose drugs face higher levels of local competition are likely to become acquirers, while firms whose drugs face little competition are likely to be targeted. Although competitive pressures are a significant determinant of merger incidence, we do not find evidence that mergers *cause* an increase in drug prices. We show that after the merger, the change in price of drugs manufactured by the acquirer and target is on average similar to that of control drugs.

Our findings corroborate past evidence on the role of asset complementarities in mergers. We show that firms with overlapping product markets are more likely to pair up in a merger, and that the price of overlapping products declines more after the merger relative to the price of non-overlapping products. These findings are consistent with the notion that firms realize efficiency gains when merging with firms that compete in similar product markets, and some of these gains are passed on to customers as lower prices.

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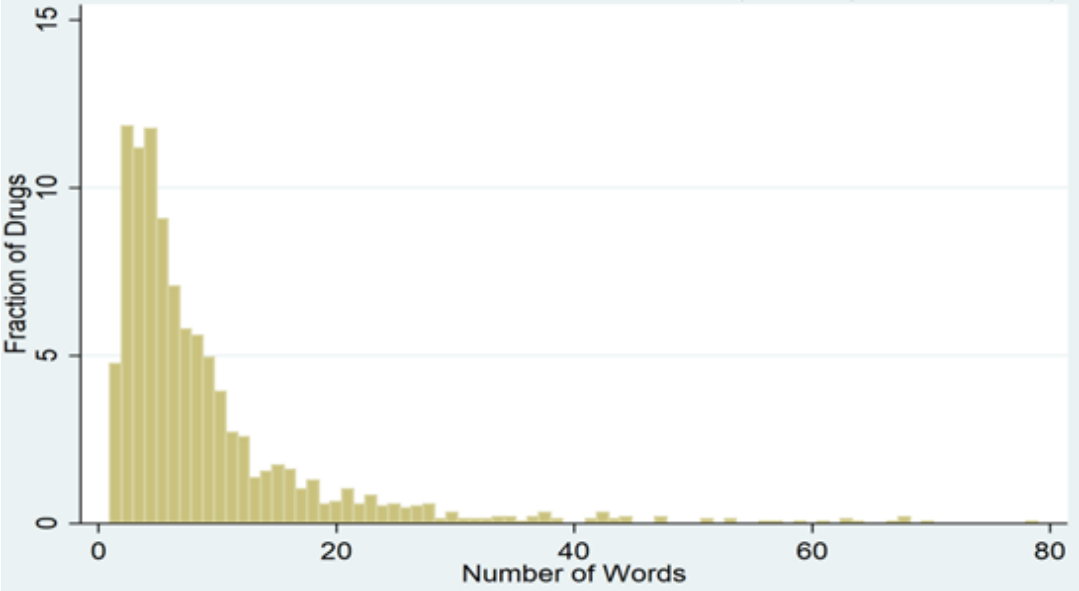
Figure 1: This figure displays the distribution of the number of words in the description for all drug products in our sample. Panel A shows the distribution of the number of words in the therapeutic area descriptions. Panel B shows the distribution of the number of words in the mechanism of action descriptions.

Panel A: Distribution of the Number of Words (Therapeutic Area)



Panel B: Distribution of the Number of Words (Mechanism of Action)

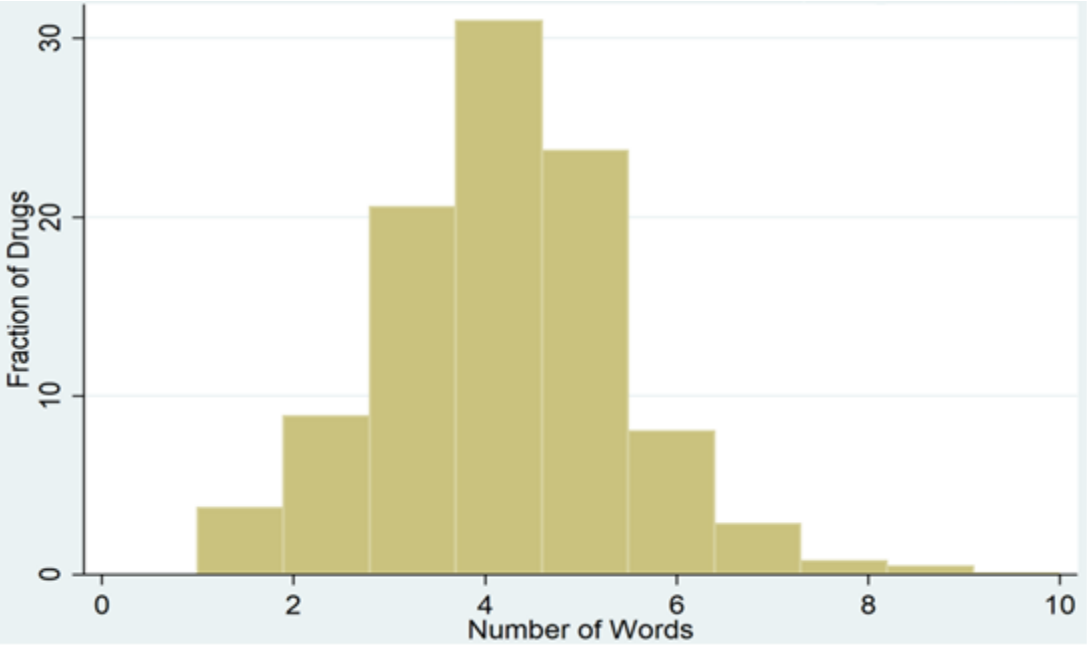
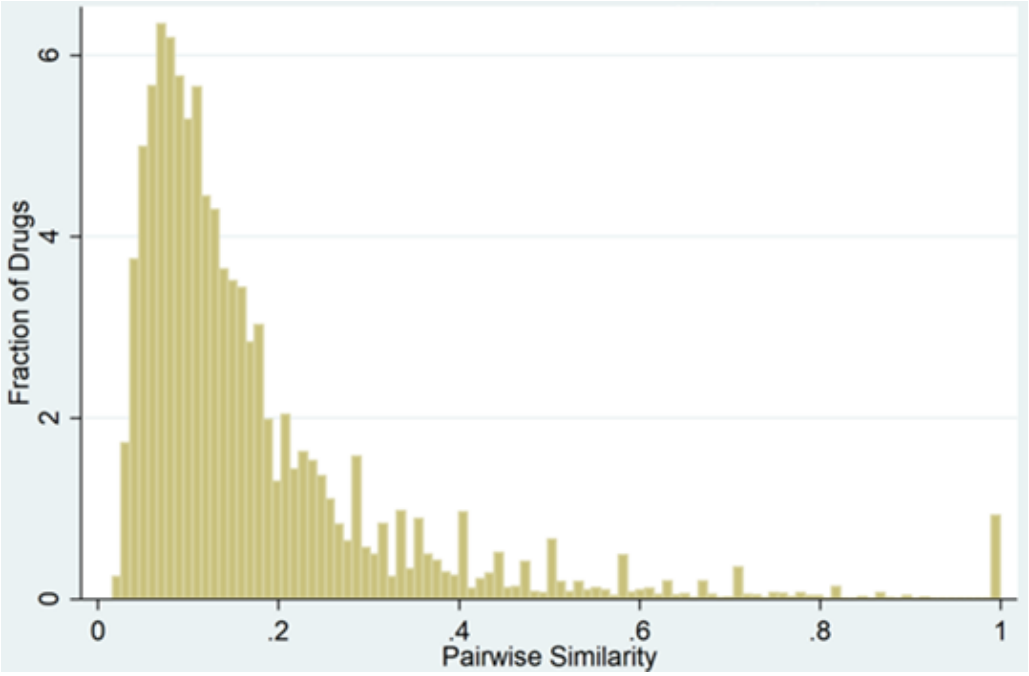


Figure 2: This figure provides the distribution of the non-zero pairwise similarity between the words used in the descriptions of the 1,556 unique MicroMedex drug profiles in our sample. Panel A displays the distribution of the non-zero pairwise similarity between the words used in the therapeutic area descriptions. Panel B displays the distribution of the non-zero pairwise similarity between the words used in the mechanism of action descriptions.

Panel A: Distribution of the Pairwise Similarity (Therapeutic Area)



Panel B: Distribution of the Pairwise Similarity (Mechanism of Action)

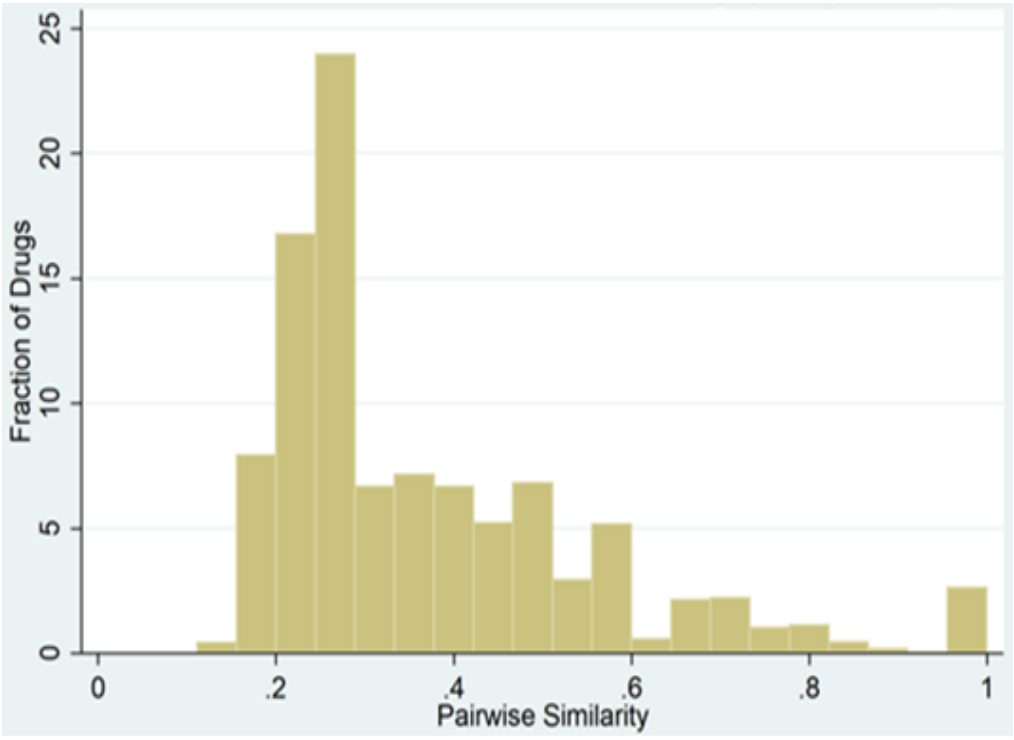


Figure 3: This figure displays the distribution of the number of rival drug products within a product space based on a given minimum similarity threshold. For example, when the label g99 (g75) is used, the number of rival products have over 99% (75%) similarity in the words in their mechanism of action descriptions and the words in their therapeutic area descriptions, with the focal drug.

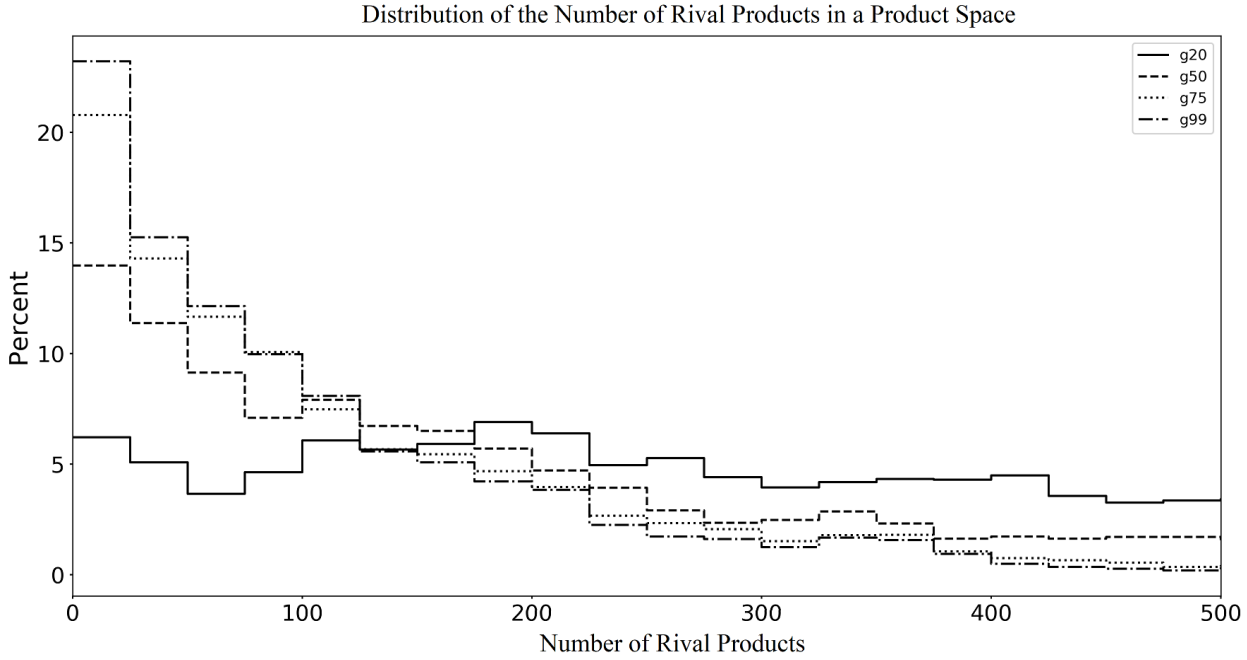


Figure 4: This figure displays the distribution of the Herfindahl-Hirschman Index (HHI) across product spaces based on a given minimum similarity threshold. For example, when the label g99 (g75) is used, HHI of a product is the sum of the squared market shares of all drug products across all firms that fall in that product space using the 99 percent similarity threshold.

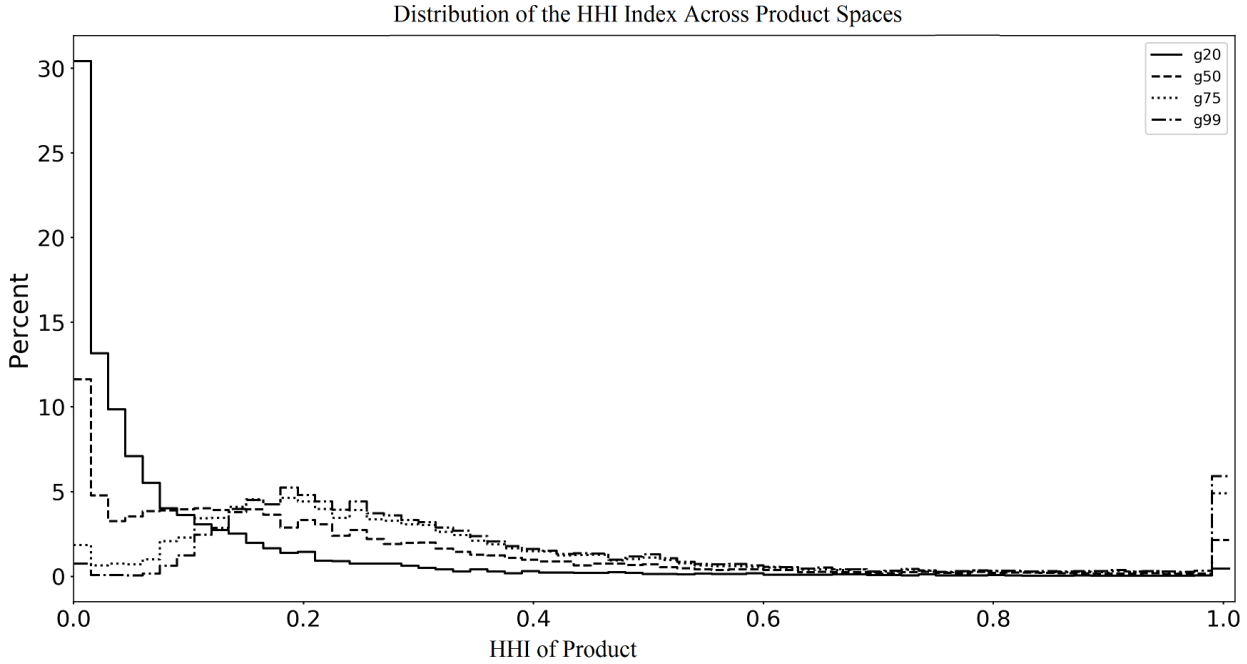


Figure 5: Panel A displays price trends for treatment drugs that are similar to products manufactured by the merger counterparty. The blue dots correspond to coefficient estimates from regressions similar to the one reported in column 5 of Table 7 except the interaction of Similar and Post is replaced with the interactions of Similar with an indicator variable for each of the 16 quarters surrounding merger announcement. The coefficient on each interaction is plotted along with its 95% confidence interval. The quarter in which the merger is announced is omitted. Furthermore, the 8th quarter before the merger announcement is omitted because it serves as the base group.
Panel B displays price trends for rival drugs, i.e. drugs that operate in the same product space as the similar drugs in the treatment sample but are manufactured by firms that have not engaged in a merger in the 16 quarters around the merger. As in Panel A, the graph plots the coefficients of the 16 quarterly indicator variables. The 8th quarter before the acquisition is omitted and serves as the base group. Due to a smaller sample size, the 7th and 8th quarter coefficients after a merger are omitted due to multicollinearity with quarter fixed effects. Both graphs below use the market share as the control for competition variable and define product space at the 99% minimum similarity threshold. All regressions below use drug and quarter fixed effects.

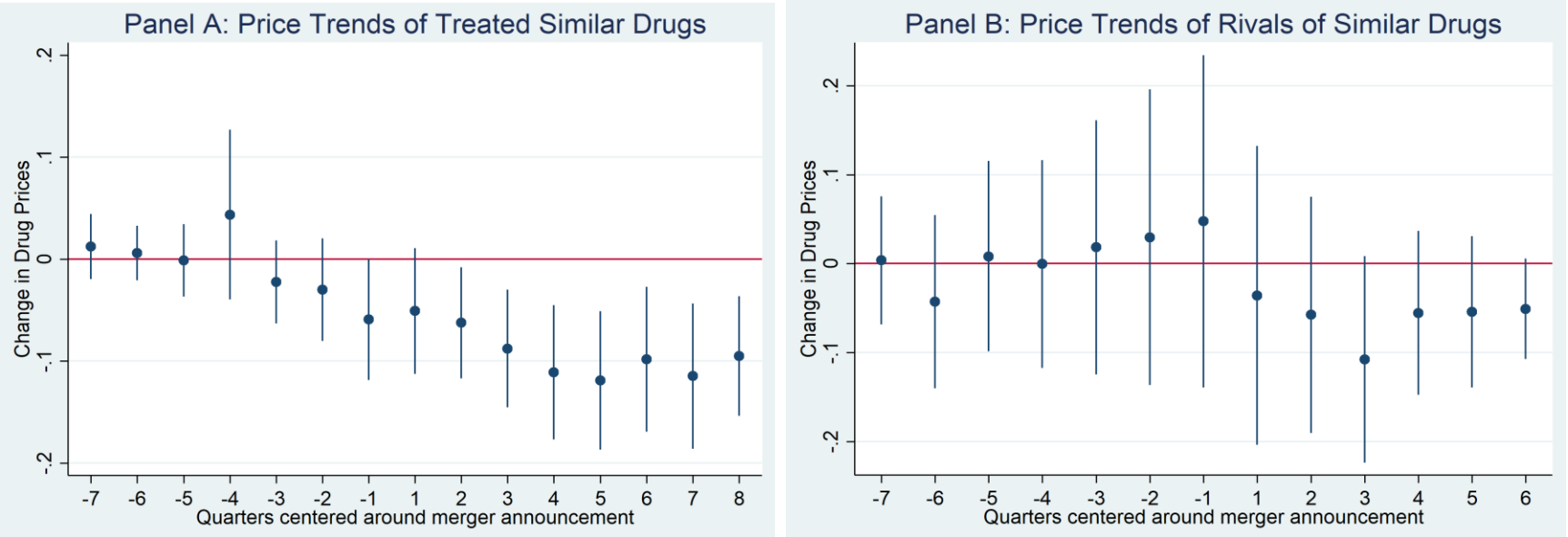


Table 1: Descriptive statistics of all manufacturers, acquirers, and targets

This table provides descriptive statistics for 690 drug manufacturers in our sample period of 2007 through 2018. We provide statistics separately for firms headquartered in the US and foreign firms and also separately for public and private firms. Panel A displays statistics on product offerings and sales. *Unique Brand*, *Unique Generic*, and *Unique Biologic* represent respectively the annual average number of brand name drugs, generic drugs, biologics. *Unique Drugs (All)* represents all drug products offered. *Average Sales* is the average annual sales. *Sales growth* is the average annual growth of the firm's sales in the 3 years preceding merger announcement. *Total Sales All* is the sum of sales of all firms in the corresponding subsample over the entire sample period. *Protected Sales* is calculated as the total sales of a firm's products that are covered by either patents or exclusivity, and this coverage expires in 5 or more years, divided by the total sales of a firm in the year before the merger is announced.

Panel B displays descriptive statistics on firms that engage in a mergers and acquisitions (M&A) during the 2007 to 2018 sample period. *Tar* is short for target, and *Acq* for acquirer. Number Tar (Acq) Firms represent the number of unique targets (acquirers). In the "Number of M&A" item, 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. An acquisition is counted as US-based if either the target *or* the acquirer was based in the US and foreign if both the target *and* acquirer were headquartered outside the US.

Panel A: Descriptive Statistics on Drug Manufacturers

	All Firms			***US Based***			***Foreign***		
	Public	Private	All	Public	Private	All	Public	Private	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of Firms	277	413	690	180	375	554	106	38	144
Unique Brand	37	4	19	36	2	13	39	17	34
Unique Generic	105	22	59	82	17	39	135	63	118
Unique Biologic	4	0	2	3	0	1	4	2	3
Unique Drugs (All)	179	43	104	159	37	78	205	93	179
Average Sales ($Million)	244	15	117	196	9	72	304	59	247
Sales Growth	2	9	5	2	9	6	1	11	3
Total Sales All ($Billion)	486	36	522	219	20	239	267	16	283
Protected Sales	0.41	0.11	0.25	0.48	0.10	0.23	0.32	0.21	0.29

Panel B: Descriptive Statistics on Merger and Acquisitions

	All Firms			***US Based***			***Foreign***		
	Public	Private	All	Public	Private	All	Public	Private	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of M&A	129	32	161	118	32	150	11	0	11
Average M&A Value($Mil)	5455	166	5176	7265	137	6898	4112	187	3901
Number of Tar Firms	80	81	161	63	73	136	17	8	25
Unique Tar Brand	23	5	14	23	4	13	21	18	20
Unique Tar Generic	47	43	45	49	45	47	39	27	35
Unique Tar Biologic	2	0	1	2	0	1	1	2	1
Unique Tar Drugs (All)	91	95	93	91	99	95	92	56	80
Tar Average Sales($Mil.)	65	21	43	61	16	37	80	64	75
Tar Sales Growth	2.93	3.84	3.37	3.44	4.08	3.77	0.95	0.59	0.86
Tar Protected Sales	0.49	0.12	0.31	0.53	0.10	0.30	0.35	0.27	0.32
Number of Acq Firms	114	47	161	53	45	98	61	2	63
Unique Acq Brand	105	12	97	139	12	126	79	13	74
Unique Acq Generic	269	33	250	301	38	276	244	27	230
Unique Acq Biologic	7	0	6	9	1	8	5	0	5
Unique Acq Drugs (All)	447	64	416	537	79	492	380	46	358
Acq Average Sales ($Mil.)	580	29	535	677	33	61	506	24	474
Acq Sales Growth	0.51	2.57	0.66	0.70	4.42	1.02	0.36	0.62	0.38
Acq Protected Sales	0.39	0.14	0.37	0.39	0.10	0.36	0.38	0.19	0.37

Table 2: Summary statistics of firm-level variables used in the merger likelihood analyses

This table provides summary statistics of annual firm-level variables. Panel A reports descriptive statistics for acquirers and their matched control firms. Panel B reports descriptive statistics for targets and their matched control firms. Panel C displays descriptive statistics for the product overlap between actual acquirer-target pairs and hypothetical pairs formed using control firms. The variables *g99FirmMkt_Share, g99FirmHHI,* and *g99FirmNumber* are firm-level competition measures at the 99% similarity threshold. *g75FirmMkt_Share, g75FirmHHI,* and *g75FirmNumber* are firm-level competition measures at the 75% similarity threshold. *Protected Sales* is calculated as the total sales of a firm's products that are covered by either patents or exclusivity, and this coverage expires in 5 or more years, divided by the total sales of a firm in the year before the merger is announced. *Ln(Sales)* is the natural log of the sales in the year preceding merger announcement. *Sales growth* is the average annual growth of the firm's sales in the 3 years preceding merger announcement. Public is a dummy variable equal to one if the firm is publicly listed, and zero if private. *g99Overlap* (*g75Overlap*) measures the extent of overlap between the drug portfolios of the pair of firms at the 99% (75%) similarity threshold. All firm-level variables are defined in Table A1 in Appendix A. The difference between the control and treatment group is significant if an asterisk is reported on the treatment variables. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: Summary Statistics on the Variables in the Likelihood of Becoming an Acquirer Analysis

	Acquirer			***Matched Control Firm***		
	Mean (1)	Median (2)	SD (3)	Mean (4)	Median (5)	SD (6)
g99FirmMkt_Share	0.48	0.45	0.28	0.49	0.45	0.32
g99FirmHHI	0.50	0.43	0.25	0.53	0.45	0.26
g99FirmNumber	108.24*	82.04**	99.19	90.4	54.00	93.26
g75FirmMkt_Share	0.45	0.42	0.28	0.46	0.44	0.32
g75FirmHHI	0.46	0.41	0.26	0.49	0.44	0.27
g75FirmNumber	154.1	87.73*	164.78	122.89	72.99	142.11
Protected Sales	0.39	0.31*	0.35	0.36	0.16	0.39
Ln(Sales)	18.76	18.89	1.99	18.63	18.84	1.99
Sales Growth	0.61	0.18	1.70	2.26	0.19	20.99
Public	0.94***	1.00***	0.24	0.68	1.00	0.47

Panel B: Summary Statistics on the Variables in the Likelihood of Becoming a Target Analysis

	Target			***Matched Control Firm***		
	Mean (1)	Median (2)	SD (3)	Mean (4)	Median (5)	SD (6)
g99FirmMkt_Share	0.47***	0.34***	0.39	0.32	0.17	0.35
g99FirmHHI	0.56***	0.41***	0.31	0.45	0.33	0.28
g99FirmNumber	75.19***	38.05***	93.6	110.86	80.32	116.15
g75FirmMkt_Share	0.44***	0.31***	0.39	0.30	0.15	0.34
g75FirmHHI	0.52***	0.39***	0.32	0.42	0.29	0.28
g75FirmNumber	97.85**	46.84**	129.2	132.29	92.55	138.87
Protected Sales	0.34***	0.03***	0.43	0.23	0.00	0.38
Ln(Sales)	15.7	16.03	2.74	15.26	15.62	2.73
Sales Growth	3.71	0.24	21.04	11.7	0.23	132.72
Public	0.52**	1.00***	0.50	0.42	0.00	0.49

Panel C: Summary Statistics on the Drug Portfolio Overlap Variables in the Merger Pair Formation Analysis

	Acquirer-Target Pair			***Hypothetical Control Pair***		
	Mean (1)	P50 (2)	SD (3)	Mean (4)	P50 (5)	SD (6)
g99Overlap	0.08***	0.04***	0.11	0.05	0.00	0.08
g75Overlap	0.09***	0.05**	0.12	0.06	0.00	0.09

Table 3: Correlation between the firm-level variables

This table reports the correlation matrix between the variables used in the merger likelihood analyses. Panel A provides the correlation matrix for the sample of individual firms. Panel B provides the correlation matrix for the sample of firm pairs. *Tar* is short for target, and *Acq* for acquirer. *g99FirmMkt_Share, g99FirmHHI,* and *g99FirmNumber* are firm-level competition measures at the 99% similarity thresholds. Likewise, *g75FirmMkt_Share, g75FirmHHI,* and *g75FirmNumber* are firm-level competition measures at the 75% similarity thresholds. *g99Overlap* and *g75Overlap* measure the extent of overlap between the drug portfolios of the firm pair at the 99% similarity and 75% similarity levels respectively. All firm-level variables are defined in Table A1 of Appendix A.

Panel A: Correlation Matrix for Individual Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)g99FirmMkt_Share	1.00									
(2)g99FirmHHI	0.86	1.00								
(3)g99FirmNumber	-0.80	-0.85	1.00							
(4)g75FirmMkt_Share	0.98	0.84	-0.79	1.00						
(5)g75FirmHHI	0.81	0.94	-0.82	0.86	1.00					
(6)g75FirmNumber	-0.77	-0.81	0.98	-0.79	-0.84	1.00				
(7)Protected Sales	0.49	0.45	-0.41	0.48	0.43	-0.39	1.00			
(8)Ln(Sales)	0.40	0.16	-0.04	0.38	0.14	-0.01	0.28	1.00		
(9)Sales Growth	-0.06	-0.05	0.05	-0.06	-0.04	0.04	-0.04	-0.02	1.00	
(10)Public	0.41	0.32	-0.28	0.40	0.30	-0.26	0.38	0.47	-0.07	1.00

Panel B: Correlation Matrix for Firm Pairs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)g99Overlap	1.00												
(2)g75Overlap	0.95	1.00											
(3)Acq g99FirmMkt_Share	-0.17	-0.17	1.00										
(4)Acq g99FirmHHI	-0.19	-0.20	0.93	1.00									
(5)Acq g99FirmNumber	0.21	0.21	-0.58	-0.63	1.00								
(6)Acq g75FirmMkt_Share	-0.20	-0.21	0.96	0.90	-0.59	1.00							
(7)Acq g75FirmHHI	-0.23	-0.24	0.86	0.93	-0.61	0.93	1.00						
(8)Acq g75FirmNumber	0.24	0.27	-0.45	-0.49	0.78	-0.56	-0.64	1.00					
(9)Tar g99FirmMkt_Share	-0.27	-0.25	0.08	0.06	-0.02	0.11	0.09	-0.07	1.00				
(10)Tar g99FirmHHI	-0.30	-0.30	0.05	0.04	0.01	0.08	0.07	-0.04	0.91	1.00			
(11)Tar g99FirmNumber	0.29	0.26	0.02	0.01	0.01	0.00	-0.02	0.05	-0.61	-0.61	1.00		
(12)Tar g75FirmMkt_Share	-0.27	-0.27	0.09	0.06	-0.03	0.11	0.10	-0.07	0.96	0.88	-0.60	1.00	
(13)Tar g75FirmHHI	-0.28	-0.30	0.07	0.06	-0.01	0.10	0.09	-0.05	0.85	0.91	-0.57	0.92	1.00
(14)Tar g75FirmNumber	0.28	0.30	0.04	0.03	0.00	0.02	0.00	0.05	-0.52	-0.54	0.84	-0.58	-0.59

Table 4: Merger Likelihood

This table displays results of conditional logit regression used to estimate the likelihood that a pharmaceutical firm engages in an acquisition during the sample period 2008 to 2017. In panel A (panel B), the dependent variable is a dummy variable equal to one if the firm becomes an acquirer (target), and zero otherwise. For each acquirer (target) we match up to three control firms based on total annual sales as explained in Section 4. In Panel C, the dependent variable is equal to one if a firm pair is the actual acquirer and target in the acquisition, and zero if the pair is hypothetical. The formation of hypothetical merger pairs is explained in Section 4 of the paper. The variable *Competition* is one of three firm-level continuous variables, namely FirmMkt_Share, HHI, or FirmNumber. The title of each column indicates which of the three competition variables is used in the regressions. The first (last) three columns use the 75% (99%) similarity threshold as indicated by the g75 (g99) prefix on the competition variables. In Panel C, the dependent variable takes the value 1 if the firm-pair is the actual acquirer and target of the merger and 0 for hypothetical firm pairs. The variable *Overlap* measures the extent of similarity between the drug portfolios of a firm-pair in the year before the merger occurs. *Acq* is short for acquirer, and *Tar* for target. The variables *Ln(Sales)*, *Sales Growth*, *Protected sales* and *Public* are described in the legend for Table 2 and in Table A1 of Appendix A. All regressions use deal fixed-effects. Robust standard errors are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: Probability of Becoming an Acquirer

	75% Similarity Threshold			***99% Similarity Threshold***		
Competition Variable is:	*g75FirmMkt_Share*	*g75HHI*	*g75FirmNumber*	*g99FirmMkt_Share*	*g99HHI*	*g99FirmNumber*
	(1)	(2)	(3)	(4)	(5)	(6)
Competition	-1.032**	-1.333***	0.003***	-0.927**	-1.308***	0.004***
	(-2.419)	(-2.728)	(3.478)	(-2.150)	(-2.616)	(3.042)
Protected Sales	0.165	0.187	0.177	0.139	0.176	0.230
	(0.509)	(0.568)	(0.590)	(0.430)	(0.538)	(0.729)
Ln(Sales)	0.916***	0.879***	0.803***	0.925***	0.906***	0.909***
	(3.454)	(3.242)	(3.020)	(3.494)	(3.313)	(3.421)
Sales Growth	-0.001	0.001	-0.002	-0.001	0.001	-0.003
	(-0.032)	(0.094)	(-0.466)	(-0.048)	(0.033)	(-0.773)
Public	2.508***	2.519***	2.697***	2.490***	2.498***	2.587***
	(5.107)	(5.141)	(4.885)	(5.022)	(5.030)	(4.943)
Observations	488	488	488	488	488	488
Pseudo R-squared	0.17	0.18	0.19	0.17	0.18	0.19

Panel B: Probability of Becoming a Target

	75% Similarity Threshold			***99% Similarity Threshold***		
Competition Variable is:	*g75FirmMkt_Share*	*g75HHI*	*g75FirmNumber*	*g99FirmMkt_Share*	*g99HHI*	*g99FirmNumber*
	(1)	(2)	(3)	(4)	(5)	(6)
Competition	0.973**	1.130**	-0.002*	1.094***	1.286***	-0.003**
	(2.565)	(2.428)	(-1.657)	(2.965)	(2.818)	(-2.316)
Protected Sales	0.133	0.141	0.360	0.0751	0.088	0.286
	(0.456)	(0.477)	(1.290)	(0.257)	(0.297)	(0.989)
Ln(Sales)	0.835***	0.858***	0.833***	0.835***	0.862***	0.850***
	(3.931)	(4.053)	(3.964)	(3.927)	(4.037)	(3.953)
Sales Growth	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(3.576)	(3.659)	(3.600)	(3.602)	(3.655)	(3.858)
Public	0.304	0.285	0.344	0.297	0.288	0.322
	(1.118)	(1.043)	(1.269)	(1.091)	(1.062)	(1.204)
Observations	510	510	510	510	510	510
Pseudo R-squared	0.14	0.14	0.13	0.15	0.14	0.14

Panel C: Probability of Forming a Merger Pair

	75% Similarity Threshold			***99% Similarity Threshold***		
Competition Variable is:	*g75FirmMkt_Share*	*g75HHI*	*g75FirmNumber*	*g99FirmMkt_Share*	*g99HHI*	*g99FirmNumber*
	(1)	(2)	(3)	(4)	(5)	(6)
Overlap	6.273***	5.998***	5.853***	7.945***	7.465***	7.875***
	(5.003)	(4.946)	(4.960)	(5.373)	(5.318)	(5.089)
Acq Competition	-0.242	-0.379	0.002*	-0.130	-0.297	0.002
	(-0.512)	(-0.782)	(1.784)	(-0.280)	(-0.603)	(1.237)
Tar Competition	1.254***	1.454***	-0.003**	1.577***	1.746***	-0.006**
	(3.020)	(2.750)	(-2.178)	(3.772)	(3.350)	(-2.309)
Acq Protected Sales	0.406	0.426	0.457	0.386	0.423	0.471
	(1.285)	(1.367)	(1.581)	(1.155)	(1.262)	(1.425)
Tar Protected Sales	0.401	0.383	0.627**	0.327	0.316	0.509
	(1.313)	(1.251)	(1.997)	(1.072)	(1.046)	(1.486)
Ln(Acq Sales)	0.714***	0.691**	0.704***	0.743***	0.744***	0.763***
	(2.674)	(2.562)	(2.584)	(2.727)	(2.704)	(2.591)
Ln(Tar Sales)	0.591**	0.638***	0.567**	0.601***	0.656***	0.586***
	(2.403)	(2.806)	(2.510)	(2.684)	(3.132)	(2.825)
Acq Sales Growth	-0.003	-0.003	-0.005	-0.003	-0.003	-0.005
	(-0.788)	(-0.844)	(-1.322)	(-0.728)	(-0.847)	(-1.474)
Tar Sales Growth	0.002***	0.002***	0.003***	0.002***	0.002***	0.003***
	(2.698)	(3.044)	(3.159)	(2.637)	(2.946)	(3.195)
Acq Public	1.979***	1.996***	2.157***	1.948***	1.966***	2.062***
	(4.622)	(4.737)	(4.308)	(4.658)	(4.774)	(4.483)
Tar Public	0.341	0.339	0.404	0.363	0.405	0.428
	(1.231)	(1.199)	(1.475)	(1.276)	(1.415)	(1.567)
Observations	667	667	667	667	667	667
Psuedo R-squared	0.16	0.16	0.16	0.18	0.17	0.18

Table 5: Summary Statistics of Drug-Level Variables

Panel A provides summary statistics on the drug-level variables measured quarterly. The first three columns provide descriptive statistics for 379,598 drug-quarters relating to 20,246 unique treatment drugs. The next three columns provide descriptive statistics for 250,256 control drugs quarters relating to 13,350 unique control drugs. Treatment drugs are drugs that were either acquired or owned by an active acquirer during the period from 2008 to 2017 and have at least 2 quarters of data (and up to 8 quarters) before the deal announcement and at least 2 (up to 8) after deal announcement. The selection of control drugs is described in Section 5.2. Panel B (Panel C) reports the correlation coefficients between the drug-level variables for the sample of treatment (control) drugs.
$\Delta LnPPU$ is calculated for each drug-quarter as natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the merger. *g99Similar* (*g75Similar*) is an indicator variable equal to one if the acquirer (target) sells a drug that is highly similar to that of the target (acquirer) at the 99% (75%) similarity threshold, and zero otherwise. The variables *g99Mkt_Share, g99HHI,* and *g99Number* are drug-level competition measures at the 99% similarity threshold. The variables *g75Mkt_Share, g75HHI,* and *g75Number* are drug-level competition measures at the 75% similarity threshold. All other drug-level variables are defined in Table A2 of Appendix A. The difference between the control and treatment group is significant if an asterisk is reported on the treatment variables. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: Descriptive Statistics for Treatment and Control Drug-Level Variables

	Treatment			***Control***		
	Mean	Median	S.D.	Mean	Median	S.D.
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLnPPU	-0.048***	-0.025***	0.705	-0.069	-0.044	0.746
g99Mkt_Share	0.245***	0.127***	0.295	0.189	0.057	0.281
g75Mkt_Share	0.224***	0.112***	0.280	0.175	0.049	0.270
g99HHI	0.363***	0.279***	0.247	0.346	0.269	0.235
g75HHI	0.328***	0.257***	0.244	0.316	0.248	0.234
g99Number	116.105***	72.000***	137.977	130.000	89.000	143.000
g75Number	141.744***	84.000***	169.047	156.000	105.000	168.000
Brand Name	0.224	0.000	0.417	0.222	0.000	0.415
Biologic	0.013	0.000	0.114	0.010	0.000	0.101
Generic	0.643	1.000	0.479	0.661	1.000	0.473
Patent	0.146***	0.000***	0.353	0.136	0.000	0.343
Expedited Approval	0.025***	0.000***	0.155	0.021	0.000	0.144
Public	0.908***	1.000***	0.289	0.655	1.000	0.475
Ln(Sales)	20.019***	20.486***	1.590	18.310	18.683	1.968
Target	0.282	0.000	0.450	-	-	-
g99Similar	0.120	0.000	0.325	-	-	-
g75Similar	0.133	0.000	0.339	-	-	-
g99Similar Sales	0.004	0.000	0.040	-	-	-
g75Similar Sales	0.005	0.000	0.042	-	-	-

Panel B: Correlation Matrix for the Treatment Drug Sample

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. g99Mkt_Share	1.00																
2. g75Mkt_Share	0.94	1.00															
3. g99HHI	0.71	0.66	1.00														
4. g75HHI	0.60	0.70	0.86	1.00													
5. g99Number	-0.35	-0.33	-0.37	-0.31	1.00												
6. g75Number	-0.30	-0.33	-0.33	-0.38	0.85	1.00											
7. Brand Name	0.38	0.34	0.34	0.28	-0.14	-0.12	1.00										
8. Biologic	0.18	0.20	0.19	0.20	-0.08	-0.08	-0.06	1.00									
9. Generic	-0.31	-0.29	-0.34	-0.31	0.10	0.11	-0.73	-0.14	1.00								
10. Patent	0.38	0.36	0.33	0.29	-0.08	-0.07	0.60	0.11	-0.45	1.00							
11. Exp	0.23	0.24	0.22	0.22	-0.07	-0.05	0.25	0.08	-0.20	0.32	1.00						
12. Public	0.08	0.08	0.03	0.03	-0.01	0.00	0.09	0.02	0.04	0.08	0.04	1.00					
13. Ln(Sales)	0.16	0.16	0.06	0.04	-0.01	-0.01	0.13	0.02	0.04	0.12	0.05	0.46	1.00				
14. Target	-0.04	-0.05	0.00	0.01	-0.03	-0.03	-0.05	0.03	-0.05	-0.06	-0.02	-0.44	-0.45	1.00			
15. g99Similar	-0.09	-0.10	-0.11	-0.13	0.14	0.19	-0.07	-0.03	0.00	-0.08	-0.03	-0.10	-0.10	0.24	1.00		
16. g75Similar	-0.10	-0.10	-0.12	-0.10	0.16	0.16	-0.09	-0.03	0.01	-0.08	-0.03	-0.11	-0.10	0.24	0.94	1.00	
17. g99Sim Sales	-0.02	-0.02	-0.03	-0.03	0.07	0.09	0.01	-0.01	0.00	0.01	0.00	0.02	-0.02	-0.02	0.24	0.26	1.00
18. g75Sim Sales	-0.02	-0.03	-0.03	-0.05	0.07	0.12	0.01	-0.01	0.00	0.01	0.00	0.01	-0.02	-0.02	0.28	0.26	0.96

Panel C: Correlation Matrix for the Control Drug Sample

	1	2	3	4	5	6	7	8	9	10	11	12
1. g99Mkt_Share	1.00											
2. g75Mkt_Share	0.96	1.00										
3. g99HHI	0.67	0.64	1.00									
4. g75HHI	0.60	0.67	0.88	1.00								
5. g99Number	-0.36	-0.34	-0.36	-0.31	1.00							
6. g75Number	-0.32	-0.34	-0.32	-0.39	0.86	1.00						
7. Brand Name	0.48	0.47	0.36	0.33	-0.18	-0.15	1.00					
8. Biologic	0.18	0.19	0.15	0.16	-0.09	-0.09	-0.06	1.00				
9. Generic	-0.35	-0.35	-0.32	-0.32	0.11	0.13	-0.69	-0.16	1.00			
10. Patent	0.46	0N44	0.37	0.33	-0.15	-0.11	0.61	0.13	-0.44	1.00		
11. Exp	0.31	0.30	0.27	0.25	-0.11	-0.08	0.23	0.11	-0.18	0.33	1.00	
12. Public	0.16	0.15	0.11	0.09	-0.08	-0.09	0.15	0.05	-0.02	0.11	0.04	1.00
13. Ln(Sales)	0.30	0.28	0.12	0.08	-0.11	-0.07	0.25	0.06	0.03	0.24	0.10	0.33

Table 6: Univariate Comparison of Change in Drug Price

This table provides univariate statistics for the change in drug prices surrounding merger announcement. Panel A provides the change in price of treatment and control drugs. Treatment drugs are drugs that were either acquired or owned by an active acquirer during the period from 2008 to 2017 and have at least 2 quarters of data (and up to 8) before the deal is announcement and at least 2 (and up to 8) after. The selection of control drugs is described in Section 5.2. The variables *Brand Name*, *Generic*, and *Biologic* are defined in Table A2 of Appendix A.

Panel B provides the change in price for treatment drugs only. *g99Similar* (*g75Similar*) is an indicator variable equal to one if the acquirer (target) sells a drug that is highly similar to that of the target (acquirer) at the 99% (75%) similarity threshold, and zero otherwise. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: Price Changes Around Mergers ($\Delta LnPPU$)

	Treatment Drugs			***Control Drugs***			
	Before	*After*	*Difference*	*Before*	*After*	*Difference*	*Diff in diff (3)-(6)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All Drugs	-0.017	-0.078	0.061***	-0.026	-0.111	0.085***	-0.021***
Brand Name	0.028	0.142	-0.115***	0.035	0.122	-0.087***	-0.026***
Generic	-0.034	-0.161	0.130***	-0.049	-0.197	0.149***	-0.018***
Biologic	-0.001	0.024	-0.023	0.022	0.072	-0.049**	0.025

Panel B: Price Changes Around Mergers ($\Delta LnPPU$) of Treatment Drugs Conditional on Similarity

	Before	*After*	*Difference*
	(1)	(2)	(3)
g99Similar=1	-0.003	-0.134	0.131***
g99Similar=0	-0.018	-0.070	0.051***
Difference	0.014***	-0.064***	0.080***
g75Similar=1	-0.004	-0.124	0.120***
g75Simialr=0	-0.018	-0.071	0.052***
Difference	0.014***	-0.053***	0.068***

Table 7: Price Changes Around Mergers and Similarity: Treatment Sample Only

This table displays the results from a regression of the change in drug price around merger announcement on the similarity between the merging firms' drugs. The sample includes drugs that were either acquired or owned by an acquirer during the period from 2008 to 2017 and have at least 2 quarters of data (and up to 8) before the deal is announcement and at least 2 (and up to 8) after. The dependent variable, ΔLnPPU is calculated for each drug-quarter as the natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the merger. Post is a dummy equal to one if the observation occurs in one of the 8 quarters after the merger announcement, and zero if the observation is from one of the 8 quarters before. *Similar* represents *g99Similarity* (*g75Similarity*) in the columns labeled 99% (75%) similarity threshold. The control variable Competition is either *g99Mkt_Share* or *g99HHI* when the 99% similarity threshold is used. When the 75% similarity threshold is used, the variable Competition is either *g75Mkt_Share* or *g75HHI*. All variables are defined in Table A2 of Appendix A. All variables in the interaction terms are also included separately but not tabulated. Standard errors are clustered at the deal level. t-stats are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Competition Variable	Market Share		HHI		Market Share		HHI	
Similarity Threshold	*99%*	*75%*	*99%*	*75%*	*99%*	*75%*	*99%*	*75%*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.009	0.011	-0.007	0.006	0.013	0.014	-0.001	0.008
	(0.277)	(0.343)	(-0.224)	(0.180)	(0.360)	(0.385)	(-0.024)	(0.225)
Similar	0.052***	0.051***	0.048***	0.046***	-	-	-	-
	(3.597)	(3.589)	(3.106)	(3.039)	-	-	-	-
Similar*Post	-0.060***	-0.049**	-0.049**	-0.042*	-0.081***	-0.070***	-0.057***	-0.050**
	(-2.738)	(-2.036)	(-2.276)	(-1.798)	(-4.110)	(-3.281)	(-2.931)	(-2.368)
Competition	0.135***	0.131***	0.067***	0.061***	0.361***	0.393***	0.030	0.050
	(6.519)	(5.874)	(3.620)	(3.485)	(7.420)	(7.375)	(0.841)	(1.617)
Competition*Post	0.177***	0.159***	0.126***	0.093***	0.148***	0.136***	0.115***	0.090***
	(5.899)	(5.178)	(5.055)	(3.245)	(5.008)	(4.449)	(4.946)	(3.729)
Brand Name*Post	0.118***	0.131***	0.141***	0.151***	0.133***	0.145***	0.146***	0.156***
	(3.136)	(3.448)	(3.739)	(4.019)	(3.469)	(3.754)	(3.868)	(4.108)
Biologic*Post	-0.072	-0.058	-0.026	-0.009	-0.045	-0.032	-0.002	0.011
	(-1.047)	(-0.832)	(-0.402)	(-0.141)	(-0.695)	(-0.497)	(-0.039)	(0.179)
Generic*Post	-0.112***	-0.109***	-0.102***	-0.102***	-0.112***	-0.109***	-0.104***	-0.103***
	(-2.970)	(-2.875)	(-2.852)	(-2.848)	(-2.875)	(-2.772)	(-2.821)	(-2.778)
Patent*Post	-0.041**	-0.040**	-0.032*	-0.031*	-0.044**	-0.044**	-0.045**	-0.044**
	(-2.254)	(-2.259)	(-1.860)	(-1.825)	(-2.361)	(-2.453)	(-2.520)	(-2.457)
Exp*Post	-0.036*	-0.034*	-0.026	-0.022	-0.027	-0.027	-0.025	-0.022
	(-1.800)	(-1.693)	(-1.244)	(-1.022)	(-1.282)	(-1.287)	(-1.193)	(-1.064)
Public	0.001	0.000	-0.002	-0.003	-0.037	-0.039	-0.044	-0.045
	(0.062)	(0.005)	(-0.080)	(-0.116)	(-1.169)	(-1.244)	(-1.467)	(-1.506)
Ln(sales)	0.006	0.006	0.008	0.008	0.030***	0.030***	0.036***	0.036***
	(0.586)	(0.640)	(0.861)	(0.873)	(3.319)	(3.329)	(4.026)	(4.021)
Fixed Effects	Deal and Quarter	Deal and Quarter	Deal and Quarter	Deal and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	525,915	525,915	525,915	525,915	525,915	525,915	525,915	525,915
R-squared	0.060	0.058	0.054	0.054	0.586	0.586	0.583	0.583

Table 8: Price Changes Around Mergers and Similarity: Acquirer and Target Subsamples

This table displays the results from a regression of the change in drug price around merger announcement on the similarity between the merging firms' drugs. Results are presented separately for drugs that were acquired (Target sample) or drugs that were owned by an acquirer (Acquirer sample) and also for the combined sample (All) during the period from 2008 to 2017. The dependent variable, $\Delta LnPPU$ is calculated for each drug-quarter as the natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the merger. *Post* is a dummy equal to one if the observation occurs in one of the 8 quarters after the merger announcement, and zero if the observation is from one of the 8 quarters before. Panel A presents results at the 99% similarity threshold; *Similar* is *g99Similarity*, and the control variable for Competition is either *g99Mkt_Share* or *g99HHI*. Panel B presents results at the 75% similarity threshold; *Similar* is g75Similarity, and the control variables for Competition is either *g75Mkt_Share* or *g75HHI*. Panel C (Panel D) uses the same regression model as in Panel A and adds the triple interaction term *Similar*Competition (Brand name*Competition* Post*). All variables are defined in Table A2 of Appendix A. Variables in the interaction terms are also included separately but not tabulated. Standard errors are clustered at the deal level. t-stats are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: 99% Minimum Similarity Threshold

Competition Variable	Market Share			HHI		
	Target	*Acquirer*	*All*	*Target*	*Acquirer*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.043	0.007	0.013	0.004	-0.005	-0.001
	(0.909)	(0.159)	(0.360)	(0.072)	(-0.120)	(-0.024)
Similar*Post	-0.102***	-0.064***	-0.081***	-0.066**	-0.043**	-0.057***
	(-2.846)	(-3.063)	(-4.110)	(-1.988)	(-2.047)	(-2.931)
Competition	0.497***	0.321***	0.361***	-0.054	0.048	0.030
	(4.838)	(6.643)	(7.420)	(-0.659)	(1.110)	(0.841)
Competition*Post	0.059	0.172***	0.148***	0.148**	0.111***	0.115***
	(0.941)	(5.988)	(5.008)	(2.563)	(4.542)	(4.946)
Brand Name*Post	0.129**	0.134***	0.133***	0.123**	0.156***	0.146***
	(2.384)	(2.803)	(3.469)	(2.286)	(3.212)	(3.868)
Biologic*Post	0.017	-0.072	-0.045	0.027	-0.017	-0.002
	(0.234)	(-0.881)	(-0.695)	(0.436)	(-0.229)	(-0.039)
Generic*Post	-0.116***	-0.114**	-0.112***	-0.111***	-0.103**	-0.104***
	(-2.734)	(-2.451)	(-2.875)	(-2.619)	(-2.253)	(-2.821)
Patent*Post	0.025	-0.060***	-0.044**	0.000	-0.055**	-0.045**
	(0.635)	(-2.655)	(-2.361)	(0.011)	(-2.464)	(-2.520)
Exp*Post	-0.118	-0.014	-0.027	-0.136	-0.006	-0.025
	(-1.413)	(-0.812)	(-1.282)	(-1.600)	(-0.323)	(-1.193)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	107,889	418,026	525,915	107,889	418,026	525,915
R-squared	0.565	0.593	0.586	0.563	0.591	0.583

Panel B: 75% Minimum Similarity Threshold						
Competition Variable	Market Share			HHI		
	Target	*Acquirer*	*All*	*Target*	*Acquirer*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.041	0.009	0.014	0.002	0.006	0.008
	(0.870)	(0.199)	(0.385)	(0.046)	(0.141)	(0.225)
Similar*Post	-0.084**	-0.057***	-0.070***	-0.049	-0.041**	-0.050**
	(-2.368)	(-2.718)	(-3.281)	(-1.395)	(-1.996)	(-2.368)
Competition	0.477***	0.368***	0.393***	-0.064	0.074*	0.050
	(4.199)	(6.546)	(7.375)	(-0.897)	(1.765)	(1.617)
Competition*Post	0.063	0.156***	0.136***	0.145***	0.081***	0.090***
	(1.072)	(5.073)	(4.449)	(3.249)	(2.753)	(3.729)
Brandname*Post	0.140**	0.146***	0.145***	0.135**	0.164***	0.156***
	(2.600)	(3.022)	(3.754)	(2.472)	(3.374)	(4.108)
Biologic*Post	0.023	-0.057	-0.032	0.035	-0.002	0.011
	(0.317)	(-0.682)	(-0.497)	(0.547)	(-0.027)	(0.179)
Generic*Post	-0.115***	-0.111**	-0.109***	-0.107**	-0.103**	-0.103***
	(-2.646)	(-2.375)	(-2.772)	(-2.540)	(-2.256)	(-2.778)
Patent*Post	0.012	-0.058***	-0.044**	0.001	-0.053**	-0.044**
	(0.305)	(-2.651)	(-2.453)	(0.017)	(-2.382)	(-2.457)
Exp*Post	-0.120	-0.014	-0.027	-0.141	-0.003	-0.022
	(-1.402)	(-0.756)	(-1.287)	(-1.644)	(-0.146)	(-1.064)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	107,889	418,026	525,915	107,889	418,026	525,915
R-squared	0.558	0.582	0.578	0.559	0.584	0.580
Panel C: The Interaction of Similarity with Competition (99% Similarity Threshold)						
Competition Variable	Market Share			HHI		
	Target	*Acquirer*	*All*	*Target*	*Acquirer*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)
Similar*Competition*Post	-0.252**	-0.081	-0.202**	-0.187	0.022	-0.067
	(-2.180)	(-0.401)	(-2.043)	(-1.532)	(0.088)	(-0.721)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	107,889	418,026	525,915	107,889	418,026	525,915
R-squared	0.566	0.592	0.587	0.563	0.590	0.582
Panel D: The Interaction of Brand Name with Competition (99% Similarity Threshold)						
Competition Variable	Market Share			HHI		
	Target	*Acquirer*	*All*	*Target*	*Acquirer*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)
Brand Name*Competition*Post	0.085	-0.130***	-0.076	0.021	-0.022	-0.016
	(1.059)	(-2.633)	(-1.380)	(0.281)	(-0.528)	(-0.240)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	107,889	418,026	525,915	107,889	418,026	525,915
R-squared	0.565	0.594	0.585	0.563	0.592	0.583

Table 9: Price Changes Around Mergers and Similarity: Withdrawn Deals

This table displays the results from a regression of the change in drug price around mergers that were announced during the period from 2008 to 2017 but not completed. The sample includes drugs that were either owned by the bidder or by the target of the bid and have at least 2 quarters of data (and up to 8) before the deal is announcement and at least 2 (and up to 8) after. The main right-hand-side variable is the similarity between the bidder and target's drugs. The dependent variable, $\Delta LnPPU$ is calculated for each drug-quarter as the natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the announcement of the merger. *Post* is a dummy equal to one if the observation occurs in one of the 8 quarters after the merger announcement, and zero if the observation is from one of the 8 quarters before. The variable *Similar* represents *g99Similarity*. The control variable Competition is either *g99Mkt*_Share or *g99HHI*. All variables are defined in Table A2 of Appendix A. All variables in the interaction terms are also included separately but not tabulated. Standard errors are clustered at the deal level. t-stats are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Competition Variable	Market Share			HHI		
	Target	*Acquirer*	*All*	*Target*	*Acquirer*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.093***	-0.170***	-0.130***	-0.073**	-0.240***	-0.165***
	(-3.249)	(-4.448)	(-6.260)	(-2.466)	(-5.977)	(-7.521)
Similar*Post	0.051***	0.02	0.038***	0.040***	0.015	0.028***
	(4.400)	(1.322)	(3.894)	(3.379)	(0.967)	(2.787)
Competition	0.390***	0.487***	0.451***	0.104*	0.157***	0.166***
	(7.328)	(10.565)	(12.614)	(1.875)	(3.425)	(4.500)
Competition*Post	0.115***	0.314***	0.291***	0.026	0.283***	0.232***
	(5.692)	(16.357)	(20.286)	(1.053)	(12.403)	(13.273)
Brand Name*Post	0.060**	0.181***	0.129***	0.073***	0.246***	0.174***
	(2.330)	(4.746)	(6.103)	(2.847)	(6.572)	(8.351)
Biologic*Post	-0.027	0.026	-0.031	-0.012	0.069	-0.002
	(-0.359)	(0.439)	(-0.697)	(-0.158)	(1.154)	(-0.045)
Generic*Post	0.005	0.055	0.013	0.005	0.106***	0.039**
	(0.214)	(1.511)	(0.685)	(0.241)	(2.909)	(2.073)
Patent*Post	0.026	-0.082***	-0.065***	0.036*	-0.094***	-0.071***
	(1.408)	(-5.543)	(-5.520)	(1.952)	(-6.278)	(-6.060)
Exp*Post	-0.073***	-0.020	-0.030*	-0.061***	0.024	0.009
	(-3.939)	(-0.821)	(-1.853)	(-3.259)	(1.011)	(0.539)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	26,894	65,935	92,829	26,894	65,935	92,829
R-squared	0.523	0.540	0.535	0.519	0.537	0.532

Table 10: Price Changes Around Mergers: Treatment and Control Drugs

This table compares the change in drug price around merger announcement of treatment drugs and control drugs. Treatment drugs are drugs that were either acquired or owned by an acquirer during the period from 2008 to 2017 and have at least 2 quarters of data (and up to 8) before the deal is announcement and at least 2 (and up to 8) after. The selection of control drugs is described in Section 5.2. The dependent variable, $\Delta LnPPU$ is calculated for each drug-quarter as the natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the merger. *Treatment* is a dummy variable equal to one if the drug is a treatment drug, and zero if it is a control drug. *Post* is a dummy equal to one if the observation occurs in one of the 8 quarters after the deal announcement, and zero if one of the 8 quarters before. In Panel A, Competition is either *g99Mkt_Share* or *g99HHI*. In Panel B, Competition is either *g75Mkt_Share* or *g75HHI*. Both Panel A and Panel B display results for three subsamples: drugs owned by the target, drugs owned by the acquirer, and all drugs. All drug-level variables are defined in Table A2 of Appendix A. Variables in the interaction terms are also included separately but not tabulated. Standard errors are clustered at the deal level. t-stats are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: 99% as the Minimum Similarity Threshold

Competition Variable	Market Share			HHI		
	Target	*Acquirer*	*All*	*Target*	*Acquirer*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.019	0.019	0.008	-0.038	0.001	-0.010
	(-0.614)	(0.955)	(0.388)	(-1.071)	(0.076)	(-0.494)
Competition	0.108***	0.130***	0.125***	0.013	0.010	0.012
	(3.114)	(5.899)	(6.820)	(0.353)	(0.554)	(0.718)
Competition*Post	0.093*	0.163***	0.151***	0.077	0.091***	0.088***
	(1.881)	(6.461)	(5.901)	(1.508)	(3.643)	(3.591)
Treatment	0.007	0.035	0.030*	-0.002	0.016	0.017
	(0.337)	(1.382)	(1.902)	(-0.054)	(0.580)	(0.926)
Treatment*Post	0.011	0.003	-0.004	-0.006	0.008	-0.002
	(0.258)	(0.087)	(-0.120)	(-0.150)	(0.187)	(-0.066)
Treatment* Competition*Post	0.003	0.018	0.013	0.078	0.031	0.040
	(0.030)	(0.602)	(0.384)	(1.058)	(0.847)	(1.135)
Brand name*Post	0.130***	0.063**	0.079***	0.147***	0.097***	0.110***
	(3.581)	(2.527)	(3.468)	(3.848)	(3.797)	(4.531)
Treatment*Brand name* Post	0.026	0.043	0.048	0.009	0.030	0.033
	(0.454)	(0.927)	(1.281)	(0.181)	(0.624)	(0.905)
Generic*Post	-0.097***	-0.128***	-0.116***	-0.088**	-0.118***	-0.106***
	(-2.868)	(-6.534)	(-5.736)	(-2.446)	(-5.891)	(-4.944)
Treatment*Generic* Post	0.007	0.010	0.017	0.005	0.009	0.014
	(0.132)	(0.251)	(0.509)	(0.100)	(0.221)	(0.444)
Biologic*Post	0.121	-0.031	0.016	0.146*	0.016	0.061
	(1.440)	(-0.864)	(0.373)	(1.774)	(0.434)	(1.399)
Treatment*Biologic* Post	-0.089	-0.044	-0.044	-0.113	-0.047	-0.054
	(-1.013)	(-0.733)	(-0.872)	(-1.350)	(-0.816)	(-1.122)
Patent*Post	0.002	0.009	0.008	0.005	0.016	0.015
	(0.040)	(0.581)	(0.496)	(0.093)	(1.039)	(0.906)
Treatment*Patent* Post	0.034	-0.063**	-0.047**	0.023	-0.061**	-0.047**
	(0.612)	(-2.485)	(-2.008)	(0.451)	(-2.354)	(-1.993)
Exp *Post	-0.040	-0.060***	-0.056***	-0.031	-0.034**	-0.033**
	(-1.313)	(-4.166)	(-4.159)	(-0.965)	(-2.198)	(-2.231)
Treatment*Exp* Post	-0.051	0.043**	0.029	-0.079	0.031	0.013
	(-0.503)	(2.161)	(1.214)	(-0.766)	(1.498)	(0.523)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	187,382	745,139	932,521	187,382	745,139	932,521
R-squared	0.312	0.315	0.314	0.311	0.312	0.312

Panel B: 75% as the Minimum Similarity Threshold						
Competition Variable	Market Share			HHI		
	Target	*Acquirer*	*All*	*Target*	*Acquirer*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.019	0.020	0.009	-0.033	0.011	-0.001
	(-0.626)	(1.034)	(0.442)	(-0.908)	(0.579)	(-0.051)
Competition	0.097**	0.130***	0.123***	0.013	0.022	0.022
	(2.581)	(5.903)	(6.725)	(0.363)	(1.179)	(1.270)
Competition*Post	0.105**	0.152***	0.144***	0.064	0.063***	0.063***
	(2.018)	(6.014)	(5.637)	(1.435)	(2.841)	(2.982)
Treatment	0.008	0.033	0.030*	0.000	0.020	0.021
	(0.371)	(1.342)	(1.873)	(0.005)	(0.743)	(1.148)
Treatment*Post	0.013	0.006	-0.001	-0.006	0.012	0.001
	(0.321)	(0.141)	(-0.032)	(-0.154)	(0.265)	(0.025)
Treatment* Competition*Post	-0.007	0.009	0.005	0.082	0.024	0.035
	(-0.073)	(0.290)	(0.131)	(1.180)	(0.612)	(1.004)
Brandname*Post	0.128***	0.068***	0.083***	0.149***	0.102***	0.114***
	(3.565)	(2.757)	(3.688)	(3.919)	(3.976)	(4.728)
Treatment*Brandname* Post	0.033	0.047	0.052	0.016	0.034	0.037
	(0.575)	(1.025)	(1.402)	(0.311)	(0.703)	(1.017)
Generic*Post	-0.096***	-0.127***	-0.115***	-0.088**	-0.117***	-0.106***
	(-2.866)	(-6.457)	(-5.674)	(-2.385)	(-5.900)	(-4.922)
Treatment*Generic* Post	0.006	0.011	0.016	0.005	0.008	0.013
	(0.119)	(0.267)	(0.505)	(0.108)	(0.197)	(0.417)
Biologic*Post	0.115	-0.025	0.019	0.149*	0.022	0.066
	(1.368)	(-0.715)	(0.442)	(1.824)	(0.591)	(1.535)
Treatment*Biologic* Post	-0.083	-0.035	-0.037	-0.110	-0.037	-0.046
	(-0.909)	(-0.578)	(-0.725)	(-1.277)	(-0.628)	(-0.945)
Patent*Post	0.002	0.012	0.011	0.008	0.020	0.019
	(0.049)	(0.756)	(0.645)	(0.166)	(1.319)	(1.168)
Treatment*Patent* Post	0.030	-0.063**	-0.048**	0.021	-0.064**	-0.050**
	(0.541)	(-2.493)	(-2.007)	(0.400)	(-2.458)	(-2.101)
Exp* Post	-0.043	-0.053***	-0.051***	-0.028	-0.026*	-0.025*
	(-1.318)	(-3.626)	(-3.691)	(-0.847)	(-1.706)	(-1.753)
Treatment* Exp* Post	-0.054	0.039*	0.025	-0.085	0.027	0.008
	(-0.523)	(1.893)	(1.007)	(-0.809)	(1.249)	(0.330)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	187,382	745,139	932,521	187,382	745,139	932,521
R-squared	0.312	0.315	0.314	0.311	0.312	0.312

Table 11: Price Changes Around Mergers and Similarity: By Drug Type

This table displays the results from a regression of the change in drug price around merger announcement on the similarity between the merging firms' drugs in subsamples of brand name drugs, generic drugs, and biologic drugs. The sample includes drugs that were either acquired or owned by an acquirer during the period 2008 to 2017 and have at least 2 quarters of data (and up to 8) before the deal is announcement and at least 2 (and up to 8) after. The dependent variable, $\Delta LnPPU$ is calculated for each drug-quarter as the natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the merger. *Post* is a dummy equal to one if the observation occurs in one of the 8 quarters after the merger announcement, and zero if the observation is from one of the 8 quarters before. *Similar* is *g99Similarity*, which is a dummy variable equal to 1 if the acquirer's (target's) drug is similar to the target's (acquirer's) drug based on the 99% similarity threshold. The control variable Competition is either market share (*g99Mkt_Share*) or HHI (*g99HHI*) as indicated in the top row of the table. The regression specification is the same as in Table 7 with one additional variable, *Similar Sales*, which is calculated as the firm's sales in a product space that is similar to that of the merger counter party divided by the firm's total sales. See Table 7 for the other variables included in the regression but not reported here. Standard errors are clustered at the deal level. t-stats are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Competition Variable	Market Share				HHI			
	Brand Name	*Generic*	*Biologic*	*All*	*Brand Name*	*Generic*	*Biologic*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	-0.032*	-0.044***	-0.023	0.013	-0.036*	-0.049***	-0.053	-0.001
	(-1.968)	(-3.215)	(-0.269)	(0.367)	(-1.945)	(-2.950)	(-0.435)	(-0.016)
Similar*Post	-0.115***	-0.067***	-0.010	-0.084***	-0.100***	-0.044*	0.007	-0.062***
	(-3.087)	(-2.955)	(-0.144)	(-4.138)	(-2.656)	(-1.814)	(0.084)	(-3.079)
Similar Sales*Post	0.025	0.154	0.507	0.103	0.047	0.250	7.119	0.161*
	(0.329)	(1.142)	(0.051)	(1.212)	(0.619)	(1.641)	(0.742)	(1.782)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	116,598	344,220	5,727	525,915	116,598	344,220	5,727	525,915
R-squared	0.605	0.596	0.517	0.586	0.603	0.593	0.516	0.583

Table 12: Price Changes for Brand Name Drugs: Alternative Specifications

This table displays the results from a regression of the change in drug price around merger announcement on the similarity between the merging firms' drugs using the subsamples of brand name drugs only. The dependent variable, $\Delta LnPPU$ is calculated for each drug-quarter as the natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the announcement of the merger. *Post* is a dummy equal to one if the observation occurs in one of the 8 quarters after the merger announcement, and zero if the observation is from one of the 8 quarters before. In the columns titled SDUD, we use drugs list price data from Medicaid's SDUD database. In columns titled NADAC, we use drug price data from an alternative survey database called NADAC that reports retail pharmaceuticals prices. In columns titled *Product Space Classification: g99*, the variable *Similar* is the dummy variable *g99Similarity*, which is equal to 1 if the textual description of the acquirer's (target's) drug is similar to the target's (acquirer's) drug along the therapeutic area and mechanism of action dimensions based on the 99% similarity threshold. In the columns titled *Product Space Classification: ATC*, *Similar* is a dummy variable equal to 1 if the acquirer's (target's) drug has the same 5-digit Anatomical-Therapeutic-Chemical Classes (ATC) code as a drug manufactured by the target (acquirer). The regression specification is the same as in Table 7. See legend of Table 7 for the other variables included in the regression but not reported here. Standard errors are clustered at the deal level and are reported in parenthesis. Standard errors are clustered at the deal level. t-stats are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Competition Variable		Market Share			HHI	
Price Data Source	*SDUD*	*NADAC*	*SDUD*	*SDUD*	*NADAC*	*SDUD*
Product Space Classification	*g99*	*g99*	*ATC*	*g99*	*g99*	*ATC*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.032*	-0.070***	-0.012	-0.036*	-0.062***	-0.022**
	(-1.972)	(-6.218)	(-1.384)	(-1.953)	(-5.215)	(-2.223)
Similar*Post	-0.113***	-0.160***	-0.038***	-0.097***	-0.164***	-0.025**
	(-3.296)	(-12.814)	(-3.969)	(-2.810)	(-13.337)	(-2.536)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	116,598	14,127	74,694	116,598	14,127	74,694
R-squared	0.605	0.725	0.578	0.603	0.723	0.577

Table 13: Using Different Minimum Similarity Thresholds

Panel A displays the results from conditional logit regressions used to predict the likelihood of merger pair formation. The regression specifications are the same as in Panel C of Table 4 but additional similarity thresholds of 50% and 20% are shown. The dependent variable takes the value 1 if the firm-pair is the actual acquirer and target of the merger and 0 for hypothetical firm pairs. *Overlap* measures the extent of similarity between the drug portfolios of a firm pair in the year before the merger occurs. See the legend of Table 4 for control variables included but not reported in this table. All regressions in Panel A use deal fixed-effects. Robust standard errors are reported in parenthesis.
Panel B displays the results of regressions of the change in drug price around merger announcement on the similarity between the merging firm's drugs. The dependent variable $\Delta LnPPU$ is calculated for each drug-quarter as the natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the merger. *Post* is a dummy equal to one if the observation occurs in one of the 8 quarters after the merger announcement, and zero if the observation is from one of the 8 quarters before. *Similar* is the dummy variable *g99Similarity* if 99% similarity, the dummy variable *g50Similarity* if the 50% similarity threshold is used and so on. At each threshold the dummy variable is equal to 1 if the acquirer's (target's) drug is similar to the target's (acquirer's) drug at that threshold and zero otherwise. Regression specifications are the same as in Table 7. See legend of Table 7 for the other variables included in the regression but not reported here. Standard errors are clustered at the deal level. t-stats are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: Likelihood of a Merger Pair Formation: Decreasing Minimum Similarity Thresholds

Competition Variable	Market Share				HHI			
Similarity Threshold	*99%*	*75%*	*50%*	*20%*	*99%*	*75%*	*50%*	*20%*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overlap	7.945***	6.273***	3.936***	2.068***	7.465***	5.998***	3.794***	2.068***
t-stat	(5.373)	(5.003)	(4.459)	(3.748)	(5.318)	(4.946)	(4.418)	(3.792)
Observations	667	667	667	667	667	667	667	667
R-Squared	0.176	0.16	0.145	0.124	0.173	0.158	0.136	0.123

Panel B: Price changes and Similarity: Decreasing Minimum Similarity Thresholds

Competition Variable	Market Share				HHI			
Similarity Threshold	*99%*	*75%*	*50%*	*20%*	*99%*	*75%*	*50%*	*20%*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Similar*Post	-0.081***	-0.070***	-0.049**	-0.041**	-0.057***	-0.050**	-0.032	-0.032*
t-stat	(-4.110)	(-3.281)	(-2.260)	(-2.403)	(-2.931)	(-2.368)	(-1.537)	(-1.943)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Deal and Quarter	Deal and Quarter	Deal and Quarter	Deal and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	525,915	525,915	525,915	525,915	525,915	525,915	525,915	525,915
R-Squared	0.585	0.585	0.585	0.583	0.583	0.583	0.583	0.583

Appendix A: Definition of variables and construction of competition measures

Section A1: Definition of variables

Table A.1 below presents definitions of the firm-level variables used in the merger likelihood analysis. In Table A.1 all variables except sales growth are measured as of the year preceding merger announcement. Table A.2 below presents definitions of drug-level variables used in the drug price analysis.

Table A.1: Firm-level variables

g99FirmMkt_Share (g75FirmMkt_Share)	the sales-weighted average of g99Mkt_Share (g75Mkt_Share) across all product spaces that a firm's drugs operate in during all quarters of the given year. See section 4.2, or table A.2 for definition of g99Mkt_Share (g75Mkt_Share)
g99FirmHHI (g75FirmHHI)	the sales-weighted average of g99HHI (g75HHI) across all product spaces that a firm's drugs operate in during all quarters of the given year. See section 4.2, or table A.2 for definition of g99HHI (g75HHI).
g99FirmNumber (g75FirmNumber)	the sales-weighted average of g99Number (g75Number) across all product spaces that a firm's drugs operate in during all quarters of the given year. See section 4.2, or table A.2 for definition of g99Number and g75Number.
Ln(Sales)	the natural log of a firm's average annual sales.
Overlap	the number of common or shared product spaces for a pair of firms divided by the total number of product spaces both the firms compete in. This measure can also be equivalently created using the Hoberg and Phillips (2016) cosine similarity method by calculating the similarity between the product spaces of a firm pair.
Public	a dummy equal to one if the firm is public, and zero if private.
Protected Sales	the total sales of a firm’s products in a year that are covered by patents or exclusivity for at least 5 more years, divided by the total sales of a firm in that year.
Sales Growth	the average annual growth of the firm sales in the 3 years before the merger announcement.

Table A.2: Drug-level variables

Variable	*Definition*
ΔLnPPU	calculated for each drug-quarter as the natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the merger
Brand Name	dummy variable equal to one if the drug is a brand name drug as identified in the FDA product data file and FDA Orange Book.
Biologic	dummy variable equal to one if the drug is a biologic as identified by the FDA product file and FDA Purple Book
Exp	dummy variable equal to one if the drug was approved as part of an Expedited Approval program, i.e. if the drug matched to a record in one of the 4 following FDA databases: Accelerated Approval Program, Fast Track Approval Programs, Breakthrough Designation Programs, and Priority Review Programs. See Internet Appendix B for more information and summary statistics about drugs approved as part of an expedited approval program.
Generic	dummy variable equal to one if the drug is a brand name drug as identified in the FDA product data file and FDA Orange Book.
g99HHI (g75HHI)	the sum of squared market shares, measured quarterly, of drug products that fall within a product space constructed using the minimum similarity threshold of 99% (75%).
g99Mkt_Share (g75Mkt_Share)	the sales, measured quarterly, from all of a firm's products that fall in a product space divided by the total sales of that product space in quarter q. Product space are constructed using the minimum similarity threshold of 99% (75%).
g99Number (g75Number)	the number of drugs, measured quarterly, manufactured by rival firms that fall above the minimum similarity threshold of 99% (75%), with the focal drug on both their normalized therapeutic area and normalized mechanism of action word descriptions.
g99Similar (g75Similar)	dummy variable equal to one if the acquirer (target) sells a drug that is highly similar to that of the target (acquirer) at the 99% (75%) minimum similarity threshold and zero otherwise. Measured using data from the four quarters preceding merger announcement.
g99Similar Sales (g75Similar Sales)	ratio between zero and one calculated by dividing a firm's sales in a product space that overlaps with that of the merger counter-party, by the firm's total sales using the 99% (75%) minimum similarity threshold. Measured in the quarter preceding merger announcement,
Patent	dummy variable equal to one if the drug was either covered by patent protection or FDA market exclusivity, or both, in quarter q, and zero otherwise.
Post	dummy variable equal to one if the observation occurs in one of the 8 quarters after the deal announcement, and zero if one of the 8 quarters before.
Target	dummy variable equal to one for drugs that were acquired during the period from 2008 to 2017, and have at least 2 quarters of data (up to 8) before the deal announcement and at least 2 after (up to 8).
Treatment	dummy variable equal to one for drugs that were either acquired or owned by an active acquirer during the period from 2008 to 2017, and have at least 2 quarters of data (up to 8) before the deal announcement and at least 2 after (up to 8).

Section A2: Description of the competition variables

In this section, we describe the construction of our competition variables at both the 99% and 75% minimum similarity thresholds.

g99Number* and *g75Number

This is our simplest measure of competition, namely the number of rival products for a given drug product *i*. We identify a fluid product space $Prod\_Space_{i,g99,q}$ for drug product *i* in quarter *q* as all drug products that fall above the 99% minimum similarity threshold with drug *i* on both their normalized therapeutic area variables *and* their normalized mechanism of action variables. More specifically, the count measure of competition for drug *i* is defined as

$$g99Number_{i,q} = Number\ of\ rival\ drug\ products\ in\ Prod\_Space_{i,g99,q} \qquad \text{(A1)}$$

This measure of competition is simply the number of drugs manufactured by rival firms (i.e. not drug *i*'s manufacturer) in $Prod\_space_{i,g99,q}$. Details on how $Prod\_space_{i,g99,q}$ is constructed is provided in Internet Appendix C2. We note that the 99% minimum similarity threshold results in a product space that includes only drugs with a perfect overlap in therapeutic area and mechanism of action. We create another count measure called $g75Number_{i,q}$, which is defined in the same manner using the 75% similar threshold instead of 99%. The 75% minimum threshold is a broader measure as it permits drugs with somewhat different therapeutic areas or mechanism of design to belong to the same product space.

g99Mkt_Share and g75Mkt_Share

The second competition measure is market share and captures the dominance of a firm's drugs within the product space the drug falls in. In this measure, we calculate the sales market share of all drugs produced by a firm that fall in the same product space using a given similarity threshold. For a firm *k* with one or more drugs operating in product space *p* in quarter *q*, the market share at the 99% threshold is

$$g99Mkt\_Share_{k,p,q} = \frac{Sales\ of\ all\ firm\ k's\ drug\ product\ in\ Prod\_Space_{p,g99,q}}{Sales\ of\ all\ drug\ products\ in\ Prod\_Space_{p,g99,q}} \qquad \text{(A2)}$$

This measure generates within-firm variation in market share since drugs manufactured by the same firm can fall in different product spaces. Drugs produced by the same firm that operate in different product

spaces will have different values of market share. We similarly define $g75Mkt\_Share_{k,p,q}$ as firm *k*'s market share in the product space *p* in quarter *q* based on the 75% minimum similarity threshold.

g99HHI and g75HHI

For our third measure, we calculate a Herfindahl Index (HHI) which determines how concentrated a product space is by finding the sum of squared market shares of drug products that fall within that space. The HHI index of the product space *p* in quarter *q* is the sum of the squared market shares of all drug products across all firms that fall in product space *p* in quarter *q*. For example, if at minimum similarity threshold of 99%, K firms produce drugs that fall in product space *p* in quarter *q*, the HHI for product space *p* is defined as

$$g99HHI_{p,q} = \sum_{k=1}^{K} \left(g99Mkt\_Share_{k,p,q}\right)^2 \quad \text{(A3)}$$

This measure also generates within-firm variation in HHI since drugs manufactured by the same firm can fall in different product spaces. Drugs produced by the same firm that operate in different product spaces will have different values of HHI. Similarly, we calculate the HHI of each product space using the 75% minimum similarity threshold and call it $g75HHI_{p,q}$. We note again that at the 99% minimum similarity threshold, the market share and HHI measures are based on product space in which rival drugs have perfect overlap in therapeutic area and mechanism of action. In contrast, when the 75% minimum threshold is used, market share and HHI are based on product space which may include drugs with a partial overlap in therapeutic area and mechanism of action.

In Internet Appendix C3 we provide support for the validity for our competition measures by conducting external validation.

Appendix B: Medicaid Drug Prices

Section B.2 1 of this appendix provides more information on Medicaid's State Drug Utilization Data (hereafter SDUD). Section B.2 compares SDUD to an alternative survey based data called the National Drug Acquisition Cost data (hereafter NADAC) and demonstrates robustness of our results to the NADAC data.

Section B.1: SDUD Institutional Background

Our sample of drugs is obtained from SDUD, a publicly available resource that provides comprehensive coverage for outpatient drugs paid for by state Medicaid Agencies. The SDUD was established after congress created the Medicaid drug rebate program in 1990 and reports drug utilization and price data on a quarterly basis starting from 1991 for all states as well as national totals. SDUD reports a ten-character product name as well as the National Drug Code (NDC), an 11-digit, 3-segment code that uniquely identifies a drug product, including its manufacturer, strength of medication, dosage form, and package size.

SDUD reports two items for each drug-quarter. First, fee-for-service (FFS) utilization which is the reimbursement for dispensing the drug as a standalone treatment. Second, the managed care organization utilizations (MCO), which reflects the drug's reimbursements as part of a bundled service. MCO's are observed in the SDUD data after 2009 but have become popular in recent years. In our main price analyses, we use an aggregated measure which includes both FFS and MCO data. For robustness, we rerun our price analyses using FFS data alone, since this type of utilization exists throughout our sample, and find qualitatively similar results. Notably, both items report total drug spending on a pre-rebate basis.

Table B.1 provides the distribution of prices for different drug types such as biologics, generic, and brand name from 2007Q1 to 2018Q2. Section B1 in the Internet Appendix B explains how we identify the drug type. We observe that the average price per unit of drugs in our sample is about $70 for brand name

drugs, $7 for generics, $840 for biologics and $3 for OTC. Although not shown here, the average price of a drug is $65 if covered by a patent and $619 if covered by the FDA market exclusivity. For more information on drugs covered by patent and exclusivity, see Table B.1 in Internet Appendix B. Table B.2 in the Internet Appendix shows that drugs approved as part of an expedited approval program are significantly more expensive – the average price is $412 for Fast-Track Designation drugs, $2,321 for Breakthrough Designation drugs, $325 for Accelerated Approval Program drugs and $470 for Priority Review drugs. This is consistent with the findings in Aggarwal (2013).

For drugs that were prescribed less than 11 times, Medicaid is obligated by the Federal Privacy Act and the HIPAA privacy rile to protect the privacy of individual beneficiaries and other persons. In these cases, SDUD suppresses directly identifying information such as the number of prescriptions and total sales. These observations comprise about 25% of the SDUD observations from 2007Q1 till 2018Q2. These drugs cannot be used to calculate the sales-based competition measures market share and HHI. However, we use these drugs to calculate competition measures based on the number of competing products.

Table B.1: Distribution of drug prices across drug types over time

This table presents average price per unit (PPU) for Medicaid SDUD national spending sample from 2006Q1 and until 2018Q2. Average PPU is reported for each type of drug as well as for all drugs combined. The first row ,labeled n, of every period displays the number of unique products for the respective subsample, and the second row displays the average PPU. The column "Not Matched" accounts for the drugs in the SDUD database that were not matched to an FDA application number and, therefore, cannot be classified into a drug type. Column "Unapproved" represents the drugs that were temporarily allowed on the market before FDA approval due to drug shortages. OTC stands for Over-the-Counter.

		All Drugs	Not Matched	OTC	Unapproved	Biologics	Generics	Brand Name	Supplement
All Periods	n	79,462.0	15,475.0	5,287.0	1,238.0	1,349.0	41,361.0	12,008.0	2,744.0
	PPU	32.8	22.3	2.7	10.1	839.1	6.7	69.7	24.8
2006	n	28,007.0	7,667.0	1,947.0	398.0	216.0	12,051.0	4,210.0	1,518.0
	PPU	43.5	36.9	28.8	22.3	559.1	30.6	74.0	46.0
2007	n	33,469.0	9,488.0	2,267.0	450.0	291.0	14,471.0	4,765.0	1,737.0
	PPU	16.4	11.6	0.2	2.6	430.9	5.3	29.7	40.1
2008	n	34,657.0	8,169.0	2,388.0	564.0	356.0	16,025.0	5,421.0	1,734.0
	PPU	16.1	11.4	0.2	5.0	433.5	3.8	33.3	30.0
2009	n	34,942.0	6,721.0	2,391.0	656.0	387.0	17,377.0	5,825.0	1,585.0
	PPU	22.6	32.6	0.3	8.0	543.5	4.6	44.2	32.6
2010	n	37,312.0	6,494.0	2,687.0	738.0	474.0	19,104.0	6,309.0	1,506.0
	PPU	23.3	22.2	0.3	6.0	651.1	4.8	46.7	21.5
2011	n	38,405.0	5,416.0	2,915.0	799.0	521.0	20,546.0	6,919.0	1,289.0
	PPU	23.6	17.5	0.3	6.7	690.1	3.7	48.8	17.9
2012	n	39,358.0	4,616.0	3,200.0	789.0	566.0	21,939.0	7,263.0	985.0
	PPU	28.1	23.8	0.4	6.5	836.3	4.5	54.6	11.2
2013	n	39,939.0	3,721.0	3,233.0	769.0	652.0	23,061.0	7,626.0	877.0
	PPU	31.7	26.4	0.4	8.2	917.2	5.2	61.6	7.9
2014	n	40,221.0	2,935.0	3,264.0	752.0	744.0	24,032.0	7,717.0	777.0
	PPU	33.4	30.1	0.6	11.5	883.6	5.3	67.8	5.0
2015	n	40,651.0	1,917.0	3,171.0	748.0	906.0	25,268.0	7,971.0	670.0
	PPU	41.9	13.3	0.5	12.3	869.7	6.3	104.6	2.9
2016	n	40,795.0	1,408.0	3,015.0	667.0	926.0	26,220.0	7,941.0	618.0
	PPU	43.7	12.9	1.0	17.0	953.4	6.8	103.9	2.6
2017	n	41,615.0	1,238.0	2,989.0	620.0	949.0	27,454.0	7,809.0	556.0
	PPU	51.6	8.3	6.5	16.7	1,184.9	6.8	120.3	8.9
2018	n	35,348.0	719.0	2,434.0	471.0	783.0	23,970.0	6,532.0	439.0
	PPU	49.0	7.2	0.2	20.9	1,128.8	6.9	112.7	2.1

Section B2: How Reliable are drug prices in the Medicaid SDUD? A cross-validation with NADAC

The SDUD pricing data are reported on a pre-rebate basis. As shown in Figure A1 of the Internet Appendix, the SDUD reports drug spending based on the lesser price of several benchmarks. Prior to 2013, the most common benchmark was the estimated acquisition cost (EAC), which is based on the drug's acquisition wholesale price (AWP) plus a dispensing fee. However, the AWP came under scrutiny and litigation due to concerns that AWP prices are inflated. In 2013, Medicaid contracted with Myers and Stauffer LC to conduct surveys of retail community pharmacy prices, and to develop the NADAC pricing benchmark that reports actual acquisition costs (AAC) paid by retail community pharmaceuticals for a drug. This became the new benchmark for state Medicaid programs. The difference between the prices in the SDUD and the NADAC is therefore the dispensing fee.

We cross validate our SDUD drug sample using the NADAC data. Since the two databases report updates at different times, we collapse observations by drug-year and average prices out over each year for both databases. This results in 126 thousand drug-year observations in the NADAC and 203 thousand in the SDUD. SDUD has a few advantages over the NADAC. First, the SDUD data is reported from 1990 to present, whereas the NADAC data begins only in mid-2013. Second, the SDUD data has more comprehensive coverage. Focusing on the period after 2012, 87% of the data available in NADAC is also covered in SDUD. In contrast, less than 60% of SDUD data are covered in NADAC. This confers a significant advantage to the SDUD database for the purposes of our project because to calculate the extent of competition in each product space, we require as comprehensive a coverage as possible of drugs operating in a product space. Moreover, we examine the impact of an acquisition on drug pricing, and NADAC does not report data on many drugs that were acquired. For example, Daraprim, notoriously known for a 5433% increase in list price in the 3rd quarter of 2015 is present in the SDUD database. Medicaid's SDUD shows an increase of about 600% in the cost of Daraprim from 2015 Q2 to 2015 Q3. (The percentage increase in SDUD is lower than that in the list price because Medicaid receives the best actual acquisition

cost of a drug). In contrast NADAC data does not show any price increase for Daraprim from Q2 to Q3 of 2015 and in subsequent quarters the drug is not reported in the NADAC data. Furthermore, many drugs well known for price hikes such as Syprine and Demser are not present in the NADAC data whereas the price increases are reported in the SDUD.

On average, however, NADAC prices do not appear to be significantly different from the SDUD. We run summary statistics on the distribution and test the difference in mean price across the two databases. In Table B.2 we see no statistically significant difference between the two databases. Finally, we construct a quarterly NADAC panel and replicate our baseline results of Table 7. Table B.3 reports these results. The interaction of Post and Similar is negative and statistically significant confirming our main finding that prices of similar drugs decline more after the merger than those of non-similar drugs. Thus, our findings hold in the NADAC price data.

Table B.2: Comparing the SDUD to NADAC

Panel A reports the distribution of the price per unit between the SDUD and NADAC databases. Panel B reports the test of the difference between the average ppu of the SDUD and the NADAC.

Panel A: Distribution of ppu in NADAC and SDUD

Statistic	SDUD PPU	NADAC PPU
mean	9.753259	9.660512
min	0.0001	0.00011
p1	0.0184783	0.009955
p5	0.0569587	0.01979
p10	0.0916747	0.02753
p25	0.1874062	0.074175
p50	0.5072919	0.2578433
p75	2.065625	1.355905
p90	7.802658	6.57475
p95	16.20662	13.25788
p99	98.76089	83.53432
max	18106.43	18401.89

Panel B: Difference between the SDUD and the NADAC drug price per unit

Variable	N	Mean
SDUD PPU	106,541	9.75
NADAC PPU	106,541	9.66
Difference	106,541	0.0927
(t-stat)		(0.44)

Table B.3: Within Deal Change in Drug Prices Using the NADAC data

This table displays the results from replicating the baseline regressions in Table 7 using the drug price data reported in NADAC. The sample includes drugs that were either acquired or owned by an active acquirer during the period from 2013 to 2017 and have at least 2 quarters of data (up to 8) before the deal announcement and at least 2 after (up to 8). Panel A display results for three subsamples: drugs owned by the target, drugs owned by the acquirer and all drugs. Panel B provides results using subsamples of drug type – brand name drugs, generic drugs, and biologic drugs. The dependent variable $\Delta LnPPU$ is calculated for each drug-quarter as the natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the merger. *Post* is a dummy equal to one if the observation. *Similar* is an indicator variable equal to one if the acquirer (target) sells a drug that is highly similar to that of the target (acquirer) at the 99% similarity threshold, and zero otherwise. The control variable for competition is either market share or HHI as indicated in the top row. All drug-level variables are defined in Table A2 of Appendix A. All variables in the interaction terms are also included separately but not tabulated. Standard errors are clustered at the deal level. t-stats are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: Drug Price Changes						
Competition variable		Market Share			HHI	
	Target	*Acquirer*	*All*	*Target*	*Acquirer*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.011	0.006	0.000	-0.045***	0.043***	0.027***
	(-1.054)	-0.636	-0.036	(-4.125)	-4.256	-3.85
Similar*Post	-0.016**	-0.038***	-0.040***	-0.006	-0.030***	-0.034***
	(-2.510)	(-5.649)	(-8.737)	(-0.915)	(-4.613)	(-7.474)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Deal and Quarter	Deal and Quarter	Deal and Quarter	Deal and Quarter	Drug and Quarter	Drug and Quarter
Observations	29,393	125,287	154,680	29,393	125,287	154,680
R-squared	0.74	0.751	0.749	0.741	0.746	0.746
Panel B: Price Changes Across Drug Types						
Competition variable		Market Share			HHI	
	Brand name	*Generic*	*Biologic*	*Brand name*	*Generic*	*Biologic*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.070***	-0.073***	-0.024	-0.062***	-0.062***	0.001
	(-6.218)	(-19.497)	(-0.648)	(-5.215)	(-12.120)	-0.034
Similar*Post	-0.160***	-0.018***	-	-0.164***	-0.016***	-
	(-12.814)	(-3.427)	-	(-13.337)	(-2.997)	-
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Deal and Quarter	Deal and Quarter	Deal and Quarter	Deal and Quarter	Drug and Quarter	Drug and Quarter
Observations	14,127	127,876	192	14,127	127,876	192
R-squared	0.725	0.753	0.908	0.723	0.749	0.903

Appendix C: Price Changes Around Mergers and Similarity: Using Alternative Dependent Variable and Alternative Event Window

Table C.1: Using Log of Price Per Unit as Dependent Variable

This table displays the results from replicating the baseline regressions in Table 7using an alternative measure of drug price as the dependent variable. Here, the dependent variable is the natural log of price per unit, *Ln(PPU*). The lagged value of *Ln(PPU*) is included as an independent variable. The sample includes drugs that were either acquired or owned by an acquirer during the period from 2008 to 2017 and have at least 2 quarters of data (up to 8) before the deal announcement and at least 2 after (up to 8). Panel A display results for three subsamples: drugs owned by the target, drugs owned by the acquirer and all drugs. Panel B provides results using subsamples of drug type – brand name drugs, generic drugs, and biologic drugs. *Post* is a dummy equal to one if the observation. *Similar* is an indicator variable equal to one if the acquirer (target) sells a drug that is highly similar to that of the target (acquirer) at the 99% similarity threshold, and zero otherwise. The control variable for competition is either market share or HHI as indicated in the top row. All drug-level variables are defined in Table A2 of Appendix A. All variables in the interaction terms are also included separately but not tabulated. Standard errors are clustered at the deal level. t-stats are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Panel A: Drug Price Changes						
Competition variable	Market Share			HHI		
	Target	*Acquirer*	*All*	*Target*	*Acquirer*	*All*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.035***	0.011	0.016***	0.011	0.003	0.006
	(2.703)	(1.590)	(2.648)	(0.804)	(0.417)	(1.040)
Similar*Post	-0.078***	-0.043***	-0.057***	-0.045***	-0.023***	-0.034***
	(-9.649)	(-6.890)	(-11.768)	(-5.515)	(-3.655)	(-6.960)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	91,299	349,572	440,871	91,299	349,572	440,871
R-squared	0.954	0.965	0.962	0.953	0.965	0.962
Panel B: Price Changes Across Drug Types						
Control variable	Market Share			HHI		
	Brandname	*Generic*	*Biologic*	*Brandname*	*Generic*	*Biologic*
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.020**	-0.019***	-0.021	-0.021**	-0.026***	-0.016
	(-2.382)	(-4.820)	(-0.599)	(-2.462)	(-5.540)	(-0.392)
Similar*Post	-0.081***	-0.053***	0.013	-0.065***	-0.026***	0.043
	(-5.623)	(-9.291)	(0.115)	(-4.550)	(-4.610)	(0.399)
Firm-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	97,904	288,722	4,867	97,904	288,722	4,867
R-squared	0.963	0.937	0.982	0.963	0.936	0.982

Table C.2: Alternative window for examining the change in drug price

In this table, we replicate our baseline results in Table 7 using an alternative definition for the window in which we examine the change in drug prices. Here we examine change in price before merger announcement with change in price after merger completion. The sample includes drugs that were either acquired or owned by an acquirer during the period from 2008 to 2017 and have at least 2 quarters of data (and up to 8) before the deal is announcement and at least 2 (and up to 8) after the deal is completed. The dependent variable, $\Delta LnPPU$ is calculated for each drug-quarter as the natural log of the price per unit of the drug minus the natural log of the earliest available price per unit in the 8 quarters before the merger. *Post* is a dummy equal to one if the observation occurs in one of the 8 quarters after the merger announcement, and zero if the observation is from one of the 8 quarters before. *Similar* represents *g99Similarity* (*g75Similarity*) in the columns labeled 99% (75%) similarity threshold. The control variable Competition is either *g99Mkt_Share* or *g99HHI* when the 99% similarity threshold is used. When the 75% similarity threshold is used, the variable Competition is either *g75Mkt_Share* or *g75HHI*. All variables are defined in Table A2 of Appendix A. All variables in the interaction terms are also included separately but not tabulated. Standard errors are clustered at the deal level. t-stats are reported in parenthesis. The significance level represented by the asterisks is as follows: *** p<0.01, ** p<0.05, * p<0.1

Competition Variable	Market Share		HHI		Market Share		HHI	
Similarity Threshold	*99%*	*75%*	*99%*	*75%*	*99%*	*75%*	*99%*	*75%*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.002	0.005	-0.019	-0.004	0.008	0.009	-0.009	0.002
	(0.068)	(0.129)	(-0.541)	(-0.123)	(0.185)	(0.216)	(-0.205)	(0.047)
Similar	0.055***	0.053***	0.050***	0.048***	-	-	-	-
	(3.608)	(3.521)	(3.077)	(2.953)	-	-	-	-
Similar*Post	-0.058**	-0.043	-0.043*	-0.033	-0.080***	-0.067***	-0.051**	-0.042
	(-2.368)	(-1.574)	(-1.763)	(-1.225)	(-3.522)	(-2.629)	(-2.175)	(-1.615)
Competition	0.137***	0.131***	0.067***	0.057***	0.346***	0.378***	0.040	0.063**
	(6.272)	(5.606)	(3.532)	(3.295)	(7.417)	(7.392)	(1.065)	(1.991)
Competition*Post	0.215***	0.195***	0.156***	0.118***	0.183***	0.168***	0.138***	0.107***
	(6.503)	(5.789)	(6.036)	(4.066)	(5.588)	(4.983)	(5.383)	(4.118)
Brand Name*Post	0.143***	0.158***	0.171***	0.184***	0.157***	0.171***	0.176***	0.187***
	(3.465)	(3.808)	(4.197)	(4.510)	(3.626)	(3.923)	(4.158)	(4.399)
Biologic*Post	-0.077	-0.060	-0.017	0.003	-0.072	-0.057	-0.022	-0.005
	(-1.175)	(-0.912)	(-0.282)	(0.046)	(-1.092)	(-0.848)	(-0.359)	(-0.083)
Generic*Post	-0.121***	-0.118***	-0.108***	-0.108***	-0.122***	-0.120***	-0.112***	-0.111***
	(-2.968)	(-2.856)	(-2.798)	(-2.783)	(-2.801)	(-2.696)	(-2.694)	(-2.651)
Patent*Post	-0.051***	-0.050***	-0.041**	-0.040**	-0.057***	-0.056***	-0.057***	-0.056***
	(-2.783)	(-2.812)	(-2.383)	(-2.352)	(-2.965)	(-3.056)	(-3.174)	(-3.102)
Exp*Post	-0.048**	-0.047**	-0.037*	-0.032	-0.039*	-0.040*	-0.034	-0.031
	(-2.376)	(-2.269)	(-1.711)	(-1.459)	(-1.735)	(-1.753)	(-1.518)	(-1.367)
Public	0.003	0.002	-0.000	-0.001	-0.027	-0.030	-0.035	-0.036
	(0.164)	(0.078)	(-0.002)	(-0.061)	(-0.727)	(-0.805)	(-0.962)	(-0.999)
Ln(sales)	0.003	0.003	0.005	0.005	0.017	0.017	0.021	0.021
	(0.356)	(0.384)	(0.532)	(0.536)	(1.447)	(1.439)	(1.592)	(1.583)
Fixed Effects	Deal and Quarter	Deal and Quarter	Deal and Quarter	Deal and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter	Drug and Quarter
Observations	516,348	516,348	516,348	516,348	516,348	516,348	516,348	516,348
R-squared	0.066	0.064	0.060	0.059	0.587	0.587	0.585	0.584