Mergers that Matter: The Impact of M&A Activity in Prescription Drug Markets*

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Abstract

Which acquisitions lead to higher prescription drug prices? Using a novel dataset of acquisitions, prices, and coverage of branded drugs, we uncover two patterns. First, net-of-rebates prices of drugs with similar indications involved in deals undisclosed to regulators increase by over 88 percent, while their coverage declines. Acquisitions disclosed to regulators are followed by much smaller effects. Second, acquisitions that consolidate drugs with different indications leave markets unaffected on average, but are occasionally followed by prices increases when they significantly expand a company's portfolio. We provide suggestive evidence that these differences stem from specific features of the industry's bargaining structure.

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Pharmaceutical mergers and acquisitions (M&A) have come under increasing scrutiny, with some policymakers conjecturing that these transactions have contributed to high prescription drug prices.[1] The Federal Trade Commission (FTC) has placed particular emphasis on the price effects of "cross-market" acquisitions, which consolidate ownership across drugs in different therapeutic markets and have historically avoided antitrust scrutiny (Federal Trade Commission and Department of Justice, 2023).[2] Whereas traditional economic theory predict that cross-market acquisitions do not affect market outcomes, more recent theories suggest that multi-product sellers may be able to bundle products across markets to extract higher prices from buyers (Dafny et al., 2019). In spite of policy interest however, the empirical evidence on the impact of different types of M&A activity on pharmaceutical market outcomes remains limited.

In this article, we provide novel empirical evidence on the impact of pharmaceutical M&A on market outcomes. Using a novel dataset of U.S. marketing rights and market outcomes of branded prescription drugs, we find that the price of drugs involved in horizontal acquisitions increases by about 21 percent, on average, but that almost half of the effect is driven by acquisitions that avoid regulatory review—which are a small minority of transactions. In contrast, acquisitions across therapeutic areas have almost no effect on prices, although we find that a small subset of especially large acquisitions generate upward pricing pressure consistent with the existence of occasional bundling agreements across classes.

Although prescription drug markets present features that complicate predictions of the effect of consolidation, the intuition from standard models of consolidation still applies to this setting. Rather than simply set prices, drug manufacturers set market-wide "list" prices and then negotiate rebates and insurance coverage with intermediaries known as pharmacy benefit managers (PBMs). Rebates can be conditional on the coverage conditions of both the focal drug and those of its competitors—something that is rarely observed in other settings. Despite these complexities, a manufacturer that owns two substi-

[1] See, for example, a 2019 letter to Federal Trade Commission (FTC) Chairman Joseph Simons from Senators Tammy Baldwin, Richard Blumenthal, Cory Booker, Mazie Hirono, Kamala Harris, Tina Smith, and Bernie Sanders (https://www.baldwin.senate.gov/news/press-releases/pharma-mergers-may-increase-drug-prices-reduce-patient-access-to-medications, retrieved July 18, 2023), and remarks made in March 2021 by FTC Acting Chair Rebecca Kelly Slaughter when announcing the creation of a working group studying pharmaceutical mergers (https://www.ftc.gov/news-events/news/press-releases/2021/03/ftc-announces-multilateral-working-group-build-new-approach-pharmaceutical-mergers, retrieved July 18, 2023).

[2] The FTC recently challenged the acquisition of Horizon Pharmaceuticals by Amgen based on worries about cross-market effects, providing additional motivation for our analysis. See FTC press release at https://www.ftc.gov/news-events/news/press-releases/2023/05/ftc-sues-block-biopharmaceutical-giant-amgen-acquisition-would-entrench-monopoly-drugs-used-treat, retrieved July 13, 2023.

tute drugs will still be disincentivized from offering larger rebates for favorable coverage—just like in standard models of horizontal consolidation—because some patients will substitute to another product they own.

These markets also satisfy some conditions that recent works by Dafny et al. (2019) and Kleiner et al. (2022) argue can lead to higher prices after cross-market mergers. In particular, drug manufacturers typically own large portfolios of drugs that treat different conditions, and must negotiate terms for all drugs with the same intermediaries. Importantly, however, cross-market effects only arise if sellers are able to bundle products across markets, and only if certain conditions on payer payoffs are satisfied. These conditions cannot be easily empirically verified, which makes theoretical predictions for cross-market effects in the drug market ambiguous, and ultimately calls for an empirical analysis of these mergers.

The foundation of our empirical analysis is an extensive M&A database covering 2007 through 2019, which we construct by combining licensed and hand-collected data. Our initial source of information is the SSR Health database, which tracks the pharmaceutical company that records sales for a specific drug in 10-K filings to the Securities and Exchanges Commission (SEC). By identifying instances when the company reporting sales changes, we arrive at an initial list of potential acquisitions. We then supplement this list using SDC Platinum, a database of acquisitions involving U.S. companies.[3] Finally, we verify each deal's details by manually collecting and classifying press releases and publicly available announcements. Our approach has several advantages, including the ability to identify deals where only marketing rights are traded.[4]

Our final database contains 151 deals involving 262 unique products, for a total of 314 drug-deal combinations. These numbers imply that the marketing rights of branded on-patent drugs are traded very frequently. Over one-fourth of all drugs in our sample switched marketing companies at least once during our period of analysis. We also find that horizontal acquisitions, which consolidate the marketing rights of two products in the same therapeutic area, represent a minority (about 25 percent) of all deals in our dataset. Instead, most acquisitions combine products from *different* therapeutic areas, the type of transaction that falls under the FTC's expanded focus.

We combine data on these deals with a panel of drug-level outcomes including average estimated net-of-rebate prices (henceforth, "net prices") and insurance coverage. We then estimate the impact of acquisitions using a stacked difference-in-difference ap-

[3]This database is the predominant source for M&A deals in other papers studying the pharmaceutical industry (see, e.g., Cunningham et al., 2021; Schutz, 2023; Bonaime and Wang, 2024).

[4]Our approach helps identify 49 U.S. marketing rights licensing deals that do not appear in SDC Platinum.

proach with matched control groups. Following horizontal acquisitions, we find net prices increase on average by 21 percent. We find much larger effects when focusing on a small subset of deals whose value falls below the mandatory reporting thresholds established by the Hart-Scott-Rodino Act (HSR Act), which we refer to as "stealth" acquisitions, following Wollmann (2019). The average stealth acquisition leads to an 88 percent increase in net price. These drugs also experience a large drop in health insurance coverage. In contrast, horizontal acquisitions whose value is above the HSR threshold are followed by a smaller increase in net price (13 percent on average). We provide some suggestive evidence that these differences arise because stealth acquisitions occur in markets with more inelastic demand.

We also study acquisitions that consolidate ownership of drugs in different therapeutic areas, which could lead to higher prices through portfolio-level bargaining effects (Dafny et al., 2019; Kleiner et al., 2022). Focusing on deals where acquired drugs became part of a larger portfolio, we find that the average effect of these deals on net price is small and not statistically significant (3.2% on average over the first three years after the acquisition). We find similarly small and insignificant effects in both volume and coverage. However, we find that the price of drugs owned by acquirers that engaged in a small subset of particularly large deals (defined as acquisitions of top-selling drugs or acquisitions that significantly expanded the total net sales of a firm's portfolio), increases by about 20 percent following these deals.

We provide suggestive evidence that the structure of manufacturer-PBM negotiations might be responsible for the lack of widespread cross-market effects. Using our formulary coverage data, we first show that full portfolio exclusions are extremely rare, even though exclusions themselves are not. We then test for the presence of smaller bundles by running a linear probability regression estimating whether being part of a portfolio that contains an excluded product increases the chance of being excluded. We find that the answer is yes, but that the effect is much stronger (a 11pp increase vs. a 1.5pp increase) when the excluded product is in the same therapeutic area. We interpret this as strong suggestive evidence that, unlike what happens in hospital markets, manufacturers and PBMs negotiate at the class level, and that cross-market bundling occurs infrequently.

Taken together, our results suggest that the current scrutiny applied by regulators to pharmaceutical M&A is broadly successful at screening out the most anticompetitive deals and that the negotiation structure of the market limits the impact of the majority of cross-market deals (with possible exceptions for particularly large deals).

This article contributes to three strands of literature. First, it adds to the small but growing literature studying the effect of consolidation in the pharmaceutical industry.

Existing work has focused on the impact of mergers on generic drugs (Hammoudeh and Nain, 2019; Chen et al., 2022), list prices (Bonaime and Wang, 2024), R&D decisions (Higgins and Rodriguez, 2006; Cunningham et al., 2021; Schutz, 2023) and advertising (Dubois and Majewska, 2022). Schutz (2023), also provides some estimates on aggregate net price effects that are broadly consistent with ours. Our contribution is to focus on branded drugs, compile a more expansive database of acquisitions, unpack heterogeneous effects across different types of acquisitions, and use insurance coverage outcomes to provide additional insights into mechanisms.

Second, we contribute to the broader literature on antitrust policy. In particular, our results add to mounting evidence that stealth acquisitions generate particularly strong anticompetitive effects (Cunningham et al., 2021; Wollmann, 2021; Morzenti, 2022), and complements previous work highlighting the role of the HSR Act and how firms can strategically react to the disclosure threshold by engaging in deals that can avoid regulatory scrutiny (Wollmann, 2019; Kepler et al., 2023).[5] We also contribute to the ongoing debate over the effects of cross-market acquisitions by providing evidence on their effects in a market where some of the theoretical conditions may not hold. Contrary to recent evidence from hospital markets (Dafny et al., 2019; Brand et al., 2023), we do not find that acquisitions across therapeutic areas affect prices on average. However, we do identify smaller groups of acquisitions whose effect appear consistent with the theoretical models in these papers. Our results are important because they highlight that cross-market effects depend on specific market structure conditions that can vary across market. As a result, our interpretation is that we should be cautious extending these results to different markets.

Finally, our results speak to equilibrium models of drug pricing. Recent models (e.g., Olssen and Demirer, 2020; Feng and Maini, 2023; Ho and Lee, 2024) have typically assumed market-level competition and some form of negotiation over rebates and formulary position between manufacturers and PBMs. The evidence on the joint response in net price and formulary coverage to unreviewed horizontal mergers is consistent with the structure of these models. Our results on cross-market mergers point to market-by-market negotiations as the predominant structure in the industry, but with potentially important exceptions.

[5]Another conceptually related paper is Bhattacharya et al. (2023), which employs a similar empirical methodology, but focuses on the impact of enforcement actions by the Department of Justice and Federal Trade Commission in the retail sector. In contrast, we focus on the effects of stealth acquisitions that bypass regulatory scrutiny entirely and on acquisitions across therapeutic areas.

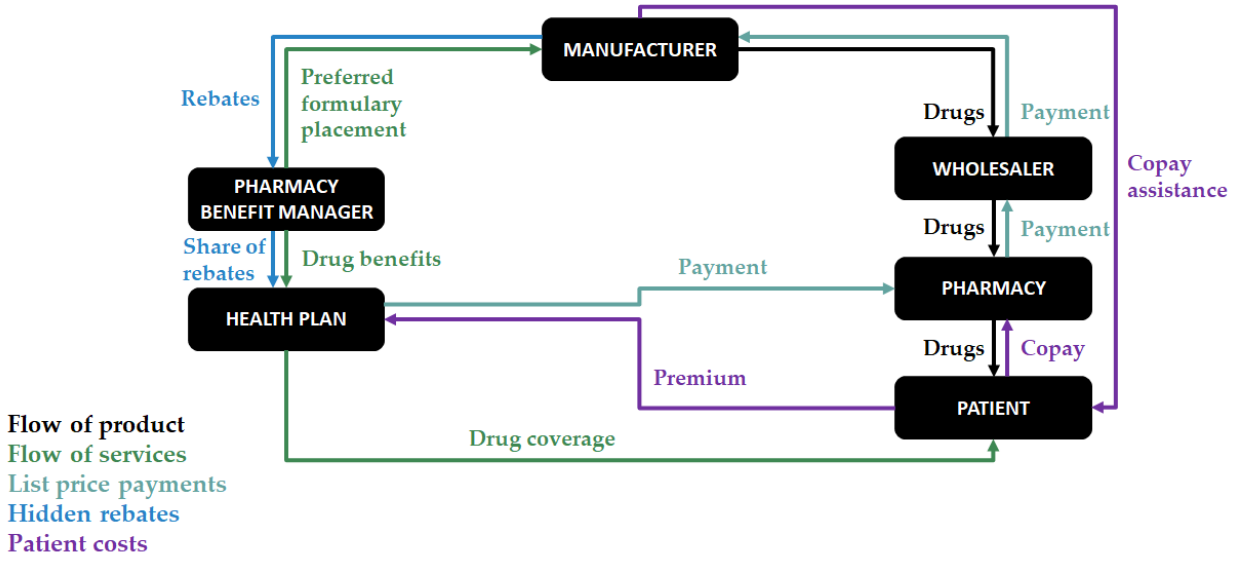


Figure 1: Stylized diagram of drug market relationships

1 Prescription Drug Markets: Institutional Details and Conceptual Framework

1.1 Price-Setting in Prescription Drug Markets

The drug procurement process depends on whether a product is sold to patients through retail channels (e.g., pharmacies) or administered by a physician in an inpatient or outpatient setting. Figure 1 provides a stylized description of the procurement structure of retail prescription drugs. [6]

Effective prices of branded drugs depend on posted list prices and negotiated rebates. List prices are set by manufacturers for the entire U.S. market and determine the transaction costs along the distribution chain, which is depicted on the right-hand side of Figure 1. Wholesalers acquire drugs from manufacturers and distribute them to pharmacies. Pharmacies, in turn, dispense drugs to consumers and receive reimbursement from health plans for all dispensed prescriptions. Both wholesalers and pharmacies earn a margin for each transaction that is usually expressed as a fraction of the list price (Dusetzina and Bach, 2019).

Despite being the most commonly referred-to prices in popular media and policy debates, however, list prices rarely determine the revenues captured by drug manufactur-

[6] For physician administered drugs, the hospital would replace the pharmacy in the distribution chain, and group purchasing organizations would replace PBMs. (Dean et al., 2023) provides a more thorough description of the procurement mechanism of healthcare facilities.

ers or the actual cost of branded drugs to health plans. Instead, effective net prices are determined by hidden rebates that manufacturers negotiate with intermediaries called Pharmacy Benefit Managers (PBMs). PBMs operate as intermediaries between manufacturers and health plans, as shown on the left-hand side of the diagram in Figure 1. The PBM industry is highly concentrated, with the top three PBMs processing 80 percent of prescription drug claims in 2024 (Fein, 2025).

We note three important aspects of price negotiations in the industry. First, PBMs leverage placement on prescription drug formularies to extract higher rebates from manufacturers. Drug formularies are tiered menus of drugs that determine the generosity of insurance coverage for a given health plan. A typical formulary has at least three tiers: a low-cost-sharing tier for generic drugs, a middle tier for preferred branded drugs, and a high tier for non-preferred branded drugs. Formularies can also exclude drugs from coverage, in which case plan enrollees would need to pay list price.

Second, rebates depend on the tier placement of a drug and its competitors. As noted in the Insulin Report of the Senate Finance Committee (United States Senate Finance Committee, 2021), manufacturers offer higher "contingent" rebates for placement in the preferred tier and to place competing drug on non-preferred tiers or exclude them altogether.

Finally, these negotiations often involve firms with broad portfolios of drugs, which past work has argue can create upward pricing pressure even when products are not in direct competition with one another (Dafny et al., 2019; Brand et al., 2023). Manufacturers typically own several drugs across many therapeutic areas, and could leverage their portfolio to extract higher prices or better coverage, as shown in hospital markets by Dafny et al. (2019). However, the scale and complexity of rebate agreements could also incentivize agents to simplify contracts. PBMs must negotiate rebates for over one thousand branded drugs, sold by hundreds of different manufacturers. In this environment, widespread arrangements linking rebates across drugs and therapeutic areas would create an incredibly complex network of interconnected contracts that may be hard to manage even for large, sophisticated firms.

1.2 Conceptual Framework

Despite the complexity of the pharmaceutical industry's market structure, we argue that the intuition from standard models of horizontal mergers still applies, albeit with some small caveats.

Horizontal Consolidation

The standard horizontal merger model predicts that when competing firms merge, they will have an incentive to increase prices, because they now internalize some consumer product substitution. This logic can be applied to our setting with only slight modifications. When drug manufacturers that own competing drugs merge, the combined entity is less incentivized to offer large rebates for favorable formulary placement, because some consumers will again switch between drugs owned by the same firm. This will result in smaller rebates and, likely, worse coverage for drugs involved in the merger.[7]

However, the presence of contingent rebates does cloud quantitative predictions. The size of the impact of a horizontal merger will depend on whether contingent rebates are pro-competitive or anti-competitive in the pre-merger world. On this issue, the closest theoretical result comes from Marvel and Yang (2008), which shows that flexible volume discounts (which are conceptually analogous to rebates contingent on formulary placement because tiering determines patient demand) lead to more competitive prices in a duopoly with horizontal differentiation.[8] However, the main intuition behind their result is that lower prices arise because direct pricing generates "local" competition (i.e., competition over the marginal consumer) whereas volume discounts generate "global" competition (i.e., competition over groups of consumers). In the pharmaceutical market, intermediaries negotiate on behalf of large groups of consumers even without contingent rebates, which means global competition is always present, thereby precluding a clear theoretical prediction.[9]

Although a full study of the role of contingent rebates is beyond the scope of this study, we derive some predictions under a partial equilibrium bargaining model with contingent rebates in Appendix A. We find that, as in Marvel and Yang (2008), contingent rebates are pro-competitive, which in turn means that horizontal mergers have a larger effect on prices relative to a world without contingent rebates. Intuitively, if a firm's competitor is offering additional discounts conditional on excluding the focal firm's drug, the disagreement payoff of the PBM improves, leading to the PBM capturing more value in

[7] Because insurance is not part of standard horizontal merger models, the prediction of worse coverage is not as strong. For example, if formulary design required a set number of drugs in each tier, we might not expect worse coverage for drugs involved in a merger, and might even see better coverage in some cases.

[8] Some recent papers (see, e.g., Olssen and Demirer, 2020; Ho and Lee, 2024) have incorporated contingent rebates but have not assessed their competitive impact.

[9] Another way to view this ambiguity is through the lens of a Stackelberg-Nash model of drug rebates (Conti et al., 2021; Feng and Maini, 2023). The average price for a drug will be the dot product of its net-of-rebate prices under each arrangement times the probability each formulary arrangement is chosen by the PBM. Whether this product is lower when manufacturers can set arrangement-specific rebates will depend on the intermediary's choice function and the underlying demand system.

negotiations with the focal firm. However, we caution that our partial equilibrium analysis simply illustrates a set of incentives that contingent contracts can generate, and is not meant to provide a full description of the general equilibrium effects of these contracts.

Cross-market consolidation

Although most economic models imply that consolidation of two firms without competing products does not generate upward pricing pressure, Dafny et al. (2019) and Kleiner et al. (2022) show that an upstream firm (in our case, the drug manufacturer) that negotiates prices with a downstream payer (an insurance company or pharmacy benefit manager) can extract higher prices by adding another product to its portfolio if three conditions are satisfied. First, the products have common customers. Second, the acquired product is part of a bundle that includes other drugs in the portfolio. Third, the payer's objective function is concave in the number of available products.

In prescription drug markets, the first condition is satisfied for all drugs because health plans enroll patients who take medications from multiple therapeutic areas. However, the second and third condition are ambiguous and not easily testable with available data. Hence, whether portfolio effects exist remains a fundamentally empirical question.[10]

2 Data on Outcomes and M&A Activity in the Pharmaceutical Market

2.1 Data on Pharmaceutical Market Outcomes

To analyze the effect of M&A activity on market outcomes, we assemble a drug-year level panel dataset containing information on prices, sales, and formulary coverage of branded drugs that do not face generic competition. Our data comes from two sources. Data on sales and prices comes from SSR Health, a consulting company specializing in the analysis of the pharmaceutical market. Data on formulary coverage comes from MMIT Analytics, a company that collects information on drug tiering and restrictions from health plan formularies.

SSR Health provides quarterly data on list prices, net sales, and estimated average net-of-rebates prices of branded prescription drugs for the U.S. market. The database

[10] While anecdotal cases of drug bundles have been documented (see, e.g., the Regeneron v. Amgen case at https://storage.courtlistener.com/recap/gov.uscourts.ded.79058/gov.uscourts.ded.79058.1.0.pdf, retrieved September 25, 2025), it is unclear whether bundling agreements are common.

contains information for over 1,000 branded drugs from 2007–2019 and covers almost all of U.S. branded drug spending.[11] For each drug and year, SSR Health records a list price, an average net-of-rebates price (henceforth, net price) based on SEC filings, and net sales. We use this information to also back out an estimate of units sold as net sales divided by net price. SSR net prices are estimated by comparing two different data sources (net sales from company SEC filings and invoice sales and volume sold from a third-party vendor) they can be subject to significant measurement error and year-to-year fluctuations. To reduce the effect of this error on our analysis, we apply a winsorizing procedure that screens for large outliers.[12]

Our formulary coverage data comes from MMIT Analytics. The MMIT database covers almost exactly the same set of drugs covered by the SSR Health data, but only from 2011–2019.[13] The data contain monthly snapshots of coverage at the drug and health insurance plan level. For each plan, we observe enrollment numbers. Comparisons of MMIT plan enrollment data with the American Community Survey, suggest that MMIT covers around 90% of all health insurance enrollees across commercial insurance, Medicare, Medicaid, and the ACA health exchanges (Kakani et al., 2024).

We construct several measures of formulary coverage at the drug-year level. For each drug and health plan, MMIT reports the formulary tier of the drug and any administrative restrictions placed by the formulary, such as prior authorization (PA) and step therapy (ST).[14] We also observe the structure of each formulary (e.g., the number of tiers and their name), which helps us understand the relative standings of drugs within the formulary and make comparisons across formularies. Our primary metric of interest is a summary "coverage generosity" variable that we create (following Geruso et al., 2019) by generating a harmonized tier structure and mapping each drug to a tier within that structure. Doing so allows us to make comparisons across plans and years. We then average this variable at the drug-year level using plan enrollment as weight.[15]

[11] As we previously reported in Feng et al. (2023), a comparison of SSR total revenue figures to IQVIA reports suggests that, in 2018, SSR Health covered ~90 percent of U.S. invoice sales, and ~80 percent of U.S. net sales (IQVIA Institute for Human Data Science, 2019). The missing portion comes mainly from drugs marketed by privately-owned companies, which are not required to disclose information to the SEC.

[12] We describe this procedure in detail in Appendix B.2, and include evidence that it does not significantly affect our results.

[13] The discrepancies in terms of drugs covered come from two sources: drugs whose patent expired before 2011, and minor missing data issues across the two datasets, which affect only a handful of drugs.

[14] Prior authorization means that physicians are required to submit a form to the insurer and gain approval before prescribing a drug. Step therapy requires that other drugs be tried first before a physician is allowed to prescribe the focal drug.

[15] See Appendix B.3 for more details. Appendix E.1 also reports additional analyses looking at specific types of restrictions, including: (i) whether a drug is covered on a formulary; (ii) whether the formulary places PA or ST restrictions on prescriptions; and (iii) whether a drug is unrestricted and covered on a

2.2 Data on M&A activity

To analyze the impact of M&A activity on the pharmaceutical market, we construct a novel dataset tracking the marketing company of each prescription drug in our panel. We rely on two primary data sources, supplemented with hand-collected data.

Our first source is SSR Health. When recording net sales data from SEC filings, SSR notes changes in the company reporting sales of a drug. In most cases, this indicates that the company marketing the drug has changed. Using SSR Health data, we compile an initial list of potential deals by treating the firm reporting net sales in period $t-1$ as the target company and the company reporting net sales in period t as the acquiring company.

We then supplement this list using SDC Platinum, a database that reports deals between firms. We select a subsample of the SDC database restricted to deals that involve at least one company or drug for which we have price and coverage data.

We then manually merge the two lists and confirm the details of each deal by searching press releases and other publicly available documents online. Through this process, we occasionally fill in additional details, such as the deal's financial terms.[16]

Finally, to select the sample of deals included in the analysis, we implement three sets of restrictions. First, we exclude purely financial deals (such as cash payments or royalty streams) that do not involve the transfer of any drug's marketing rights. Second, we exclude deals that only involve drugs whose patents have already expired. Third, we exclude all acquisitions by Bausch Health (formerly Valeant Pharmaceuticals), a company that was investigated by the SEC for improper revenue recognition and misleading disclosures, and whose price data is likely to be inaccurate. [17]

After finalizing a list of deals, we classify them along three dimensions. First, we identify drug acquisitions that qualify as horizontal—that is, combine substitute products. To make this determination, we check whether any drugs acquired in the deal could be considered a direct competitor of a drug in the acquiring company's portfolio. We define competitors as drugs sharing the same 3-digit Anatomical Therapeutic Chemical code (ATC-3), a standard classification commonly used in the economics literature.[18] Some drugs have

preferred formulary tier, with favorable cost-sharing.

[16] A version of our dataset, which does not include proprietary information from SSR Health or SDC Platinum, and is entirely based on hand-collected data from press releases, is available at https://www.lucamaini.com/data.

[17] We provide more background details on Valeant and additional suggestive evidence in support of the SEC's findings in Appendix C.

[18] The ATC is a hierarchical classification of drugs developed by the World Health Organization that consists of a 5-level alphanumeric code, where the first level refers to the anatomical group, the second level refers to the therapeutic subgroup, the third level refers to the pharmacological subgroup, the fourth level

multiple ATC codes, and we consider all of them when defining substitutability. As a result, our definition of substitute products is much more likely to include products that are not particularly close substitutes (type I error) than to exclude instances of actual substitute products (type II error).

Second, we used the dollar value of the deal to determine whether it meets the disclosure requirements of the Hart-Scott-Rodino Act (hereafter, HSR Act). Initially passed in 1976, the HSR Act establishes a pre-merger notification program that requires companies to notify antitrust enforcement agencies before a planned acquisition. In 2000, an amendment to the Act introduced an exemption for any acquisition valued below $50 million and any acquisitions valued below $200 million subject to additional constraints on the size of the companies involved.[19] Both thresholds are adjusted annually for inflation. Because we do not have access to Federal Trade Commission data, we cannot observe directly whether the agency received a merger notification or not. We also do not have sufficient information in our data to test whether the companies involved satisfy the size requirement for the higher threshold. Instead, we classify all deals with a reported acquisition value below the higher threshold as "stealth" acquisitions.[20]

Finally, we identify deals that resulted in the acquired products becoming part of a larger portfolio. The goal of this classification is to find the subset of mergers most likely to generate cross-market effects. We include two acquisitions in this group: (i) deals where the acquiring company has higher net sales than the target company in the four quarters before the acquisition; and (ii) deals where the acquiring company acquires the entire target company.

2.3 Characteristics of M&A Activity in the Pharmaceutical Market

Our final dataset includes 151 deals involving the marketing rights of 262 distinct patent-protected branded drugs, representing over one-quarter of all drugs in our sample. 42 drugs are acquired more than once.

refers to the chemical subgroup, and the last level indicates the exact chemical substance. Drugs that share the same ATC-3 code share the same broad indication (e.g. diabetes, corresponding to ATC-2 code A10), and broad mechanism of action (e.g., insulins, corresponding to ATC-3 code A10A, vs. other glucose-lowering drugs, corresponding to ATC-3 code A10B).

[19] The effects of the amendment were first described in Wollmann (2019).

[20] We refine our classification using data on acquisitions granted early termination by the FTC (we thank Tom Wollman for generously providing this data). Early termination can be requested by the parties involved to close the deal before the regularly required 30-day waiting period (starting from the notification date) and is granted if the agency finds that the deal is unlikely to have anticompetitive effects. Only one of our "stealth" acquisitions appears on the early termination list. Our main analysis excludes this deal from the "stealth" acquisition group, but the results are robust to switching its classification.

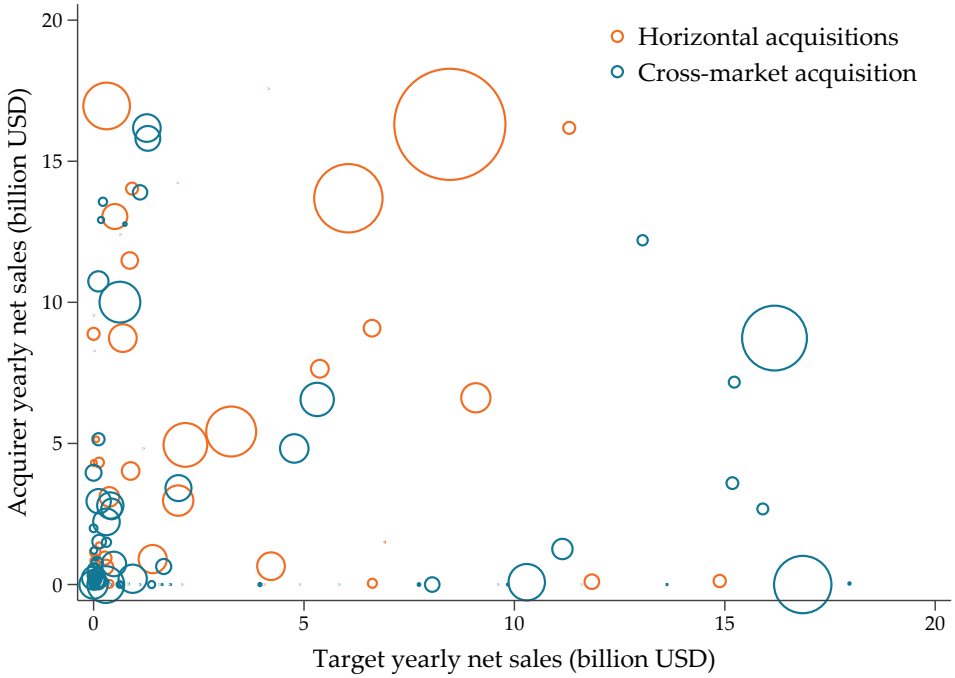


Figure 2: M&A Activity in the Pharmaceutical Market

Notes: *this figure shows heterogeneity across M&A activity along several dimensions. First, deals are placed on the plane according to the size of the target company, on the x-axis, and the size of the acquiring company on the y-axis. Both are measured as total net sales in the four quarters preceding the acquisition. Second, deals are color-coded in categories. Deals in orange are horizontal acquisitions that involve drugs in the same therapeutic area. Deals in blue are acquisitions across therapeutic areas. Finally, the size of each marker is proportional to the total net sales of all drugs acquired in the years following the acquisition.*

Figure 2 provides an overview of these deals, including their size (measured by the future net sales stream of acquired assets) and the size of the companies involved (measured by net sales in the four quarters before the acquisition). We also mark horizontal acquisitions separately. About 25 percent of drug acquisitions in the sample are classified as horizontal.

Table 1 presents additional statistics on the deals in our data. The average acquisition has a value of approximately $5.4 billion. However, this masks substantial variation. Our data includes a handful of very large mergers—such as the 2009 Pfizer-Wyeth (67 billion USD) merger or the 2015 Actavis-Allergan merger (68 billion USD)—as well as many small acquisitions of single drugs with values below 100 million USD. Indeed, the median deal involves the trading of marketing rights of a single on-patent branded product.[21]

We also report statistics split across deals in three categories that we focus on in our subsequent analysis: horizontal acquisitions valued above the HSR threshold, horizontal acquisitions valued below the HSR threshold, and cross-market acquisitions by larger

[21] Deals often also involve other assets not captured in our data, such as generic drugs and unapproved drug candidates.

Table 1: Pharmaceutical deal characteristics

		Overall	Horizontal acquisitions above the HSR threshold	Horizontal acquisitions below the HSR threshold	Cross-market acquisitions by a larger company
DEAL-LEVEL					
Count		151	32	7	94
Value of transaction ($ mill.)	mean	5,389	12,202	112	6,442
	median	1,000	5,848	49	1,608
Number of products	mean	2.11	3.97	1.14	2.57
	median	1	1	1	1
DRUG-DEAL-LEVEL					
Count		314	58	8	186
Product age at acquisition	mean	7.74	7.66	5.38	7.85
	median	6	7	4.5	6

Notes: *statistics are reported at the deal or drug-deal level. Data on value of transaction comes from SDC Platinum and media reports, and is only available for 109 out of 151 deals. Product statistics reflect only acquired assets that are included in the SSR Health database. The number of products of horizontal acquisitions refers only to products that share an ATC-3 code with a product owned by the acquiring company.*

companies (note that individual deals can fall under multiple classifications if they involve more than one drug). Horizontal acquisitions above the HSR threshold are the largest in value and number of products involved. In part, this is a mechanical effect: the more drugs are involved in a deal, the higher the chance that a pair of drugs will share the same ATC-3 code.[22] In contrast, acquisitions below the HSR threshold are much smaller: all of them except for one involve a single drug. The drugs involved also tend to be at a slightly earlier stage in their life-cycle, about two fewer years removed from their launch date relative to drugs acquired in horizontal deals above the HSR threshold (5.38 versus 7.66). However, these average ages are well after the period when drugs experience the highest sales growth.[23]

Finally, Table 2 reports some basic summary statistics on the acquired drugs in our sample and compares them to drugs that were never acquired. Acquired drugs experience faster list and net price growth but have lower net sales and comparable formulary coverage to other drugs. The only exception is the set of drugs acquired in horizontal acquisitions below the HSR threshold, which appear to have worse coverage.

[22]The average number of drugs involved in an horizontal acquisition above the HSR threshold is 3.97, as reported in the Table, but only 1.8 classify as horizontal acquisitions.

[23]On average, drug sales grow rapidly over the first two years on the market, and plateau around years four or five after launch on average.

Table 2: Drugs characteristics

	Non-acquired drugs		Acquired drugs							
			Overall		Horizontal acquisitions above the HSR threshold		Horizontal acquisitions below the HSR threshold		Cross-market acquisitions by larger company	
	median	IQR	median	IQR	median	IQR	median	IQR	median	IQR
SALES AND PRICES (2007–2019)										
Net sales (million USD)	197	[46.70; 587.00]	152.3	[40.10; 367.25]	129.83	[47.00; 342.85]	94	[31.09; 209.00]	166.8	[44.78; 393.50]
Annual WAC growth	6.80%	[2.4%; 11.4%]	8.70%	[3.5%; 13.9%]	8.80%	[4.0%; 13.7%]	12.60%	[7.4%; 20.8%]	8.10%	[3.0%; 13.4%]
Annual net price growth	3.20%	[-5.6%; 11.8%]	5.30%	[-4.2%; 16.0%]	6.40%	[-4.0%; 16.1%]	9.40%	[-1.1%; 28.7%]	4.90%	[-4.3%; 15.3%]
COVERAGE (2011–2019)										
Fraction covered	0.86	[0.79; 0.94]	0.85	[0.80; 0.92]	0.86	[0.81; 0.93]	0.82	[0.77; 0.88]	0.85	[0.80; 0.92]
Fraction unrestricted	0.6	[0.40; 0.72]	0.6	[0.46; 0.70]	0.6	[0.47; 0.71]	0.45	[0.39; 0.57]	0.61	[0.47; 0.70]
Fraction preferred	0.12	[0.04; 0.27]	0.12	[0.05; 0.26]	0.13	[0.07; 0.26]	0.19	[0.04; 0.30]	0.11	[0.05; 0.24]
Count	681		245		48		8		156	

Notes: *all statistics reported at the drug-year level. Net sales, wholesale acquisition cost (WAC), and net price data come from SSR Health, which covers 2007-2019. Fraction covered, unrestricted, and preferred come from our own calculations based on the MMIT data, which covers 2011-2019. The count of acquired drugs in this table is lower than the count reported in Table 1 because some drugs are acquired more than once and because we do not have price and coverage data for all drugs involved in acquisitions.*

3 Methodological Approach

Our methodological approach relies on a difference-in-difference estimator with a matched control group. For each acquired drug, we build a control group using Coarsened Exact Matching (Iacus et al., 2012). For each drug j and acquisition k, we attempt to select drugs that: (i) have been on the market for a similar number of years ("age") at the time of acquisition k; (ii) share the same general therapeutic area as drug j but are not close enough in product space that they would be affected by a potential price increase after product j is acquired; iii) are marketed by a similarly sized company; and iv) generate similar revenue in the four quarters before acquisition k. This approach aims to control for general trends in different therapeutic areas, secular lifecycle trends in market outcomes, differences in marketing strategies across small and large drug manufacturers, and differences between high- and low-revenue drugs.

We note some specific measurement details. We measure age as years from launch, company size as average yearly sales between 2007–2019, and revenue using sales net of rebates. To identify drugs with similar, but not too similar, indications, we select drugs that share the same first level of the Anatomical Therapeutic Chemical code, or ATC-1, as the treated product but exclude drugs that share the same ATC-4 code.[24] To match company size, we divide companies into three buckets based on average yearly net sales during our period of analysis. We use $250 million and $2.5 billion as thresholds because they are round numbers that return similarly-sized groups in terms of number of firms. We exclude acquired drugs from any control group.

In several instances, matching on all variables returns empty control cohorts. In those cases, we match on fewer variables. To minimize the chance that results are driven by noise, we require matched control groups to contain at least five drugs and select the cohort that matches the largest number of variables.[25]

Our final sample includes 169 drug-acquisition units, of which 82 are matched based on age and year, 34 are matched based on age, year, and ATC-1, 38 are matched based on age, ATC-1, and firm size, 4 are matched based on age, ATC-1, and net sales, and 11 are matched on all variables. We drop 145 events because of missing data (we require all drugs to have non-missing data in the years immediately before and after the year of acquisition).[26]

[24] In robustness checks, we repeat the analysis excluding drugs that share the same ATC-3 code, and recover nearly identical estimates (see Appendix D.3).

[25] Appendix B.4 provides additional details on the matching procedure, and Appendix D.3 provides several checks that our estimates are robust to the set of variables used in the matching.

[26] Table A1 in Appendix B.1 has additional information on sample selection.

Using these matched treated and control groups, we generate two types of estimates. First, we analyze the effect of groups of acquisitions with certain specific characteristics (e.g., horizontal acquisitions, acquisitions by a larger company, etc.) by running stacked difference-in-difference regressions of the form

$$Y_{jt} = \alpha_j + \delta_t + \sum_{t=-3}^{t=3} \beta_t \times \text{Treated}_j + \varepsilon_{jt} \tag{1}$$

where j indexes drugs, and t is years relative to acquisition k. α_j and δ_t control for drug and time fixed effects, respectively. These regressions provide us with an average effect across groups of acquisitions. They also allow us to assess whether the effects occur immediately after the acquisition occurs or if they change over time.

Second, we estimate the following regression equation for each drug acquisition event:

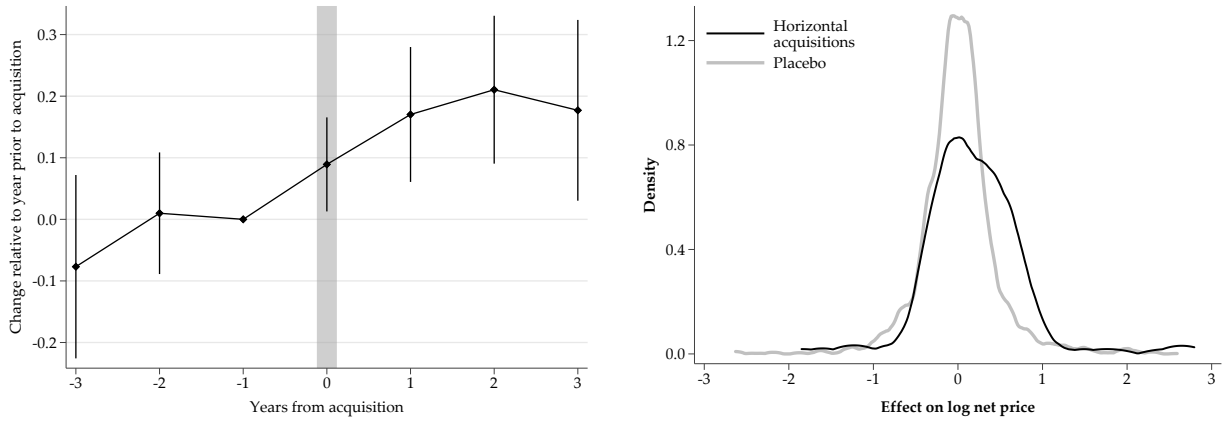
$$Y_{jt} = \alpha_j + \beta_{0,k} \times \text{Post}_t + \beta_{1,k} \times \text{Post}_t \times \text{Treated}_j + \varepsilon_{jt} \tag{2}$$

In this second set of regressions, we only include a single treatment coefficient. As in the previous regression, we include up to three years before and after the acquisition, but exclude the acquisition year. Acquisitions happen at different times during the year, and we do not know when prices will respond to any change in incentives or market structure. In all regressions, we cluster standard errors at the drug level.

The $\beta_{1,k}$ estimates from this second set of regressions helps us illustrate the variation in response size across deals, which we visualize as distributions of coefficients. To help distinguish between noise and signal in these distributions, we also create a placebo distribution of coefficients, which we create by randomly assigning a placebo treatment to drugs that were never acquired, and then estimating the difference in price before and after the placebo "event" using the same methodology described above.

The primary outcomes we study in these two sets of regressions are net price, volume sold, and population-weighted coverage generosity (i.e., the average formulary tier measure defined in Section 2.1). We apply a log transformation to the first two variables. We report results on log list price, log net sales, and other formulary coverage variables (fraction covered, fraction unrestricted, and fraction preferred) in Appendix E.1.

Our approach yields causal estimates under two assumptions. The first is the parallel trends assumption—i.e., that the average change in the outcome of interest of the acquired drug would have been the same as in the matched control group had the drug not been acquired. The main concern with this assumption is that acquisitions are not random, and acquiring companies may be targeting drugs with unobservably better long-



(a) Stacked DiD

(b) Distribution of Effects

Figure 3: Change in net price after horizontal acquisitions

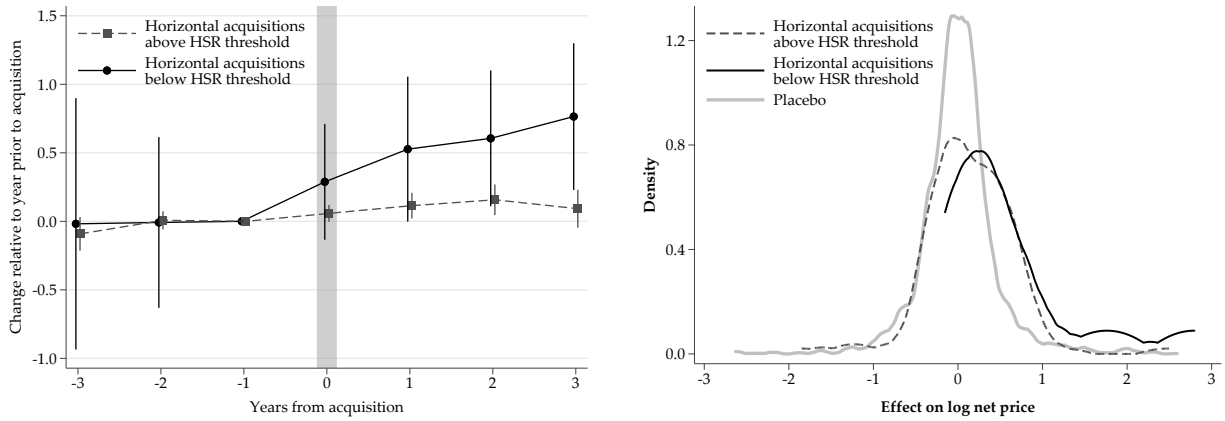
Notes: Panel A reports estimates of $\beta_t$in Equation 1, focusing on the log net price response of acquired drugs that overlap with an acquirer's drug. We also report 95 percent confidence intervals for each estimate, with standard errors clustered at the drug level. Panel B reports the distribution of $\beta_{1,k}$ estimates from Equation 2 for the same set of drug-events, and also displays the distribution of estimates from a placebo study.

term prospects. To assess the robustness of our estimates to this assumption, we estimate a specification where we allow for differential linear trends for the treated drug and the matched control group. This robustness check, discussed in more detail in Appendix D.2, returns estimates similar to those found in our main specification.

The second assumption is that the drugs included in the control group are unaffected by the acquisition. This rules out any spillover effects arising from competition between substitute drugs (some of which may be included in the control group). If such a spillover existed, it would most likely attenuate our estimates. However, we believe this to be a second-order concern for two reasons. First, our results are robust to excluding from the control group drugs with the same ATC-3 as the treated drug. Second, we do not find any evidence of spillover effects in our analysis (see Appendix E.2).

4 The Effect of Horizontal Acquisitions

We begin by presenting evidence on the effect of horizontal acquisitions, which include the sample of all acquired and owned-by-acquirer drugs that share at least one ATC-3 code.



(a) Stacked DiD

(b) Distribution of Effects

Figure 4: Change in net price after horizontal acquisitions

Notes: *Panel A reports estimates of β_t in Equation 1, focusing on the log net price response of drugs involved in horizontal acquisitions. Each figure breaks out acquired drugs by whether the value of their associated deal is above or below the higher HSR threshold. We also report 95 percent confidence intervals for each estimate, with standard errors clustered at the drug level. Panel B reports the distribution of $\beta_{1,k}$ estimates from Equation 2 for the same drug-event groupings, and also displays the distribution of estimates from a placebo study.*

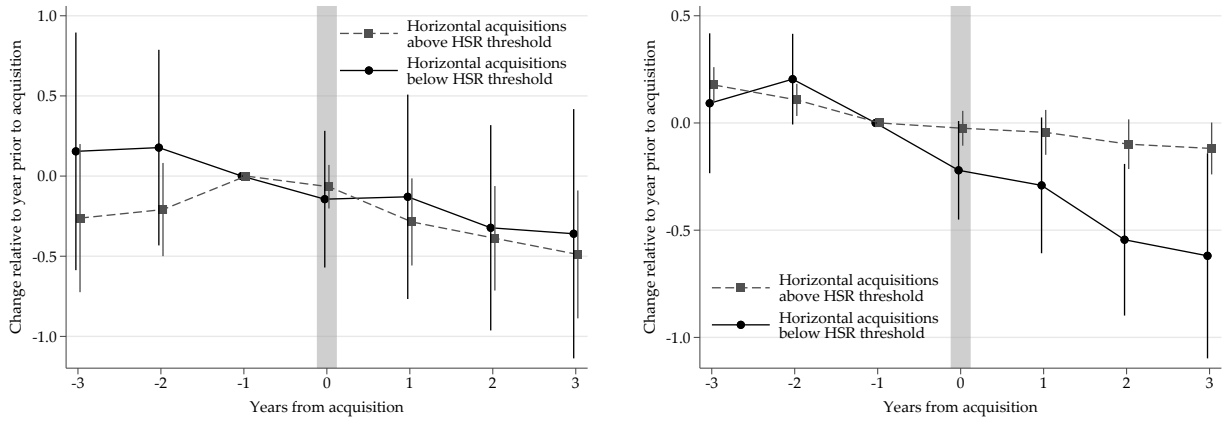
4.1 Effect on Net Price

Figure 3 plots the effect of horizontal acquisitions based on a sample size of 107 drug-year events. Prices increase by 21% relative to the last year before the acquisition, with a relatively flat pre-trend before the deal takes place (Figure 3, Panel A). However, the distribution of responses shows excess mass on the right tail relative to the placebo distribution, rather than a uniform shift, suggesting that only a subset of all events resulted in a real price increase (Figure 3, Panel B).

To further unpack this observed heterogeneity and understand the role played by the regulatory review process, we look at stealth acquisitions separately. Most deals in the distribution shown in Figure 3 had a value above the Hart-Scott-Rodino Act threshold for mandatory review by the Federal Trade Commission. Because the FTC screens these deals to prevent anti-competitive ones from being completed, most of the deals in the sample are likely selected to have a smaller effect.

To eliminate the role of this selection, we focus on deals that fall below the HSR threshold (fourteen drug-year events in total) and plot their distribution separately in Figure 4.[27] The results suggest that selection plays an important role. The products involved in stealth horizontal acquisitions experience on average an 88 percent increase in net price. The ef-

[27] We do not know the value of every deal. We treat missing values as if their value were above the HSR threshold. Only two horizontal acquisition have missing values. Including them in either sample does not affect the results.



(a) Stacked DiD (Volume)

(b) Stacked DiD (Coverage Generosity)

Figure 5: Changes in volume and coverage after after horizontal acquisitions, split

Notes: *The figures report estimates of β_t in Equation 1, focusing respectively on the log units and coverage generosity of drugs involved in horizontal acquisitions. Each figure breaks out drugs by whether the value of their associated deal is above or below the higher HSR threshold. We also report 95 percent confidence intervals for each estimate, with standard errors clustered at the drug level.*

fect is statistically significant albeit imprecisely estimated, suggesting substantial heterogeneity across the effect of individual deals. Conversely, deals above the HSR threshold experience on average a 13 percent increase in net price, which is only significant in years 1 and 2 after the acquisition. Panel B of Figure 4 suggests that the main difference in the distribution of the effects of individual deals between the two groups is in the tails. Virtually no stealth deals result in lower prices (left tail), and a much larger fraction is followed by very large price increases (right tail).

4.2 Effect on Access: Volume and Coverage Generosity

Figure 5 plots the effect of horizontal acquisitions below and above the HSR threshold on volume (Panel A) and coverage (Panel B). Both types of acquisitions are followed by a slight decline in volume sold, although the difference is not statistically significant. We do not find noticeable differences across the two groups. However, we find that deals below the HSR threshold are followed by significantly lower coverage. Coverage generosity also worsens over time, possibly due to lags in the contracting process. The decline of -0.5 in our coverage generosity metric is interpretable as equivalent to shifting coverage of the drug from the preferred to the non-preferred tier for half of the U.S. population.

4.3 Additional Results and Robustness checks

We confirm these results by conducting a variety of robustness checks, which we report in Appendix D. In particular, we confirm that our results are robust to defining overlap using ATC-4 instead of ATC-3 (Appendix D.1), including differential pre- and post-acquisition trends for treatment and control groups (Appendix D.2), and excluding drugs with the same ATC-3 code from the control group or making other changes to the matching algorithm (Appendix D.3).

We also report the effect of horizontal acquisitions on list prices, net sales and different types of formulary coverage restrictions (i.e., exclusion, administrative restrictions, and placement on a preferred tier) in Appendix E.1, and the spillover effects of stealth acquisitions affect products that are not directly involved in the deal, but share an ATC code with the products involved. We only find a small, delayed increase in price for drugs sharing the same ATC-4 as drugs involved in a stealth acquisition, thus further validating our choice to exclude those drugs from matched control groups..

4.4 Discussion: why do stealth acquisitions have a different effect on market outcomes?

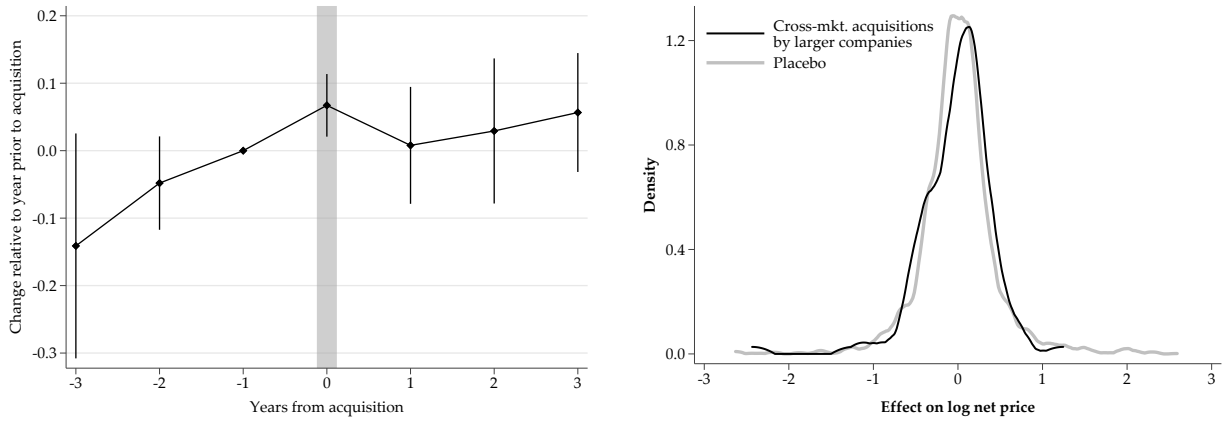
Overall, the evidence suggests that, relative to other horizontal acquisitions, stealth acquisitions can: (i) raise prices significantly more; and (ii) lose coverage without losing too much volume. This discrepancy suggests that drug manufacturers are less likely to engage in an anticompetitive acquisition when they have to disclose the acquisition to regulators—presumably because they expect regulators to either block the deal or require divestments.

We provide some suggestive evidence that the ex-ante characteristics of stealth acquisitions indicate a higher potential for anticompetitive effects by showing that they happen in less elastic markets.[28] We use drug-level estimates of own-price elasticity from Einav et al. (2018) to calculate the average elasticity for each ATC-3 and then compare elasticities in ATC-3s where stealth horizontal acquisitions happen to ATC-3s where other horizontal acquisitions happen.[29] For context, the estimates in Einav et al. (2018) predominantly reflect extensive margin substitution rather than therapeutic substitution.[30]

[28] We also test whether markets in which stealth acquisitions occur have fewer products, but do not find any significant differences.

[29] Einav et al. (2018) estimate elasticities for the 100 highest selling drug products in Medicare Part D. This does not cover any of the drugs involved in stealth mergers, so we chose to use their estimates to construct ATC-3 level elasticities,

[30] Although not definitive, the authors present two pieces of evidence related to this: i) class-level elas-



(a) Stacked DiD (Net Price)

(b) Distribution of Effects (Net Price)

Figure 6: Effect of cross-market acquisitions by larger companies on net price

Notes: *Panel A reports estimates of β_t in Equation 1, focusing on the response in log net price for drugs acquired by larger companies. We also report 95 percent confidence intervals for each estimate, with standard errors clustered at the drug level. Panel B reports the distribution of $\beta_{1,k}$ estimates from Equation 2 for the same drug-events and corresponding outcome, and also display the distribution of estimates from a placebo study.*

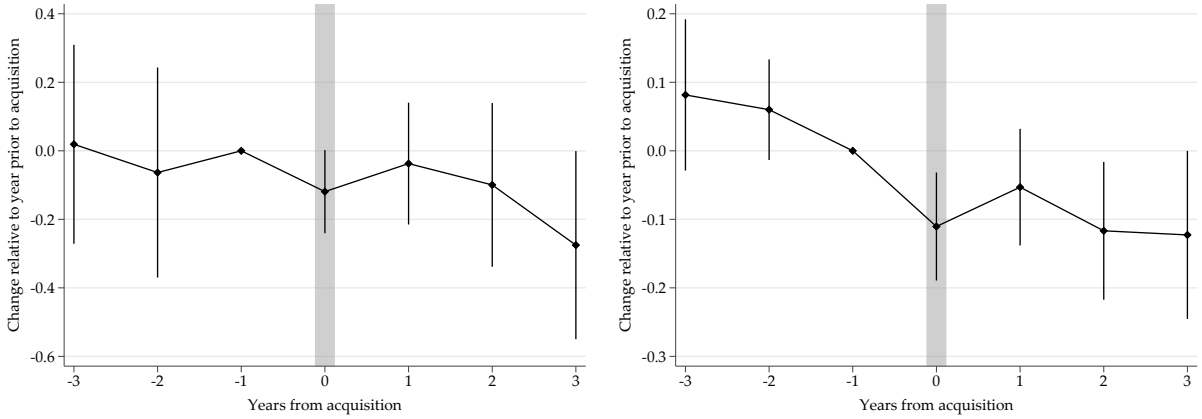
In other words, these are likely markets for "necessity" treatments. We find that drugs in markets where stealth acquisitions take place have an average elasticity of -0.12, whereas drugs in other markets with horizontal acquisitions have an average elasticity of -0.27, a statistically significant difference. This suggestive relationship is consistent with stealth mergers occurring in classes with limited extensive margin substitution, which allows for the manufacturer to raise prices, lose favorable coverage, but still maintain volume.

5 The Effect of Cross-Market Acquisitions

In our second set of analyses, we study acquisitions of drugs across therapeutic classes, which represent the vast majority of the acquisitions in our sample. As noted earlier, these deals have recently come under additional scrutiny from regulators (Federal Trade Commission and Department of Justice, 2023).

Our primary test for cross-market effects focuses on acquisitions where the acquirer is larger than the target company. This will exclude deals where large companies divest drug assets to smaller companies, which decrease the size of the portfolio associated with the

ticities are similar to drug-level elasticities; and ii) elasticity estimates are similar when focusing on drugs without therapeutic substitutes. This distinction matters, because if their estimates were reflective of the elasticity of substitution across drugs in the same class, then we would actually expect higher gains to mergers in markets with higher elasticity (lower initial price due to strong competition).



(a) Stacked DiD (Volume)

(b) Stacked DiD (Coverage Generosity)

Figure 7: Effect of cross-market acquisitions by larger companies on volume and coverage

Notes: *The figures report estimates of β_t in Equation 1, focusing respectively on the log units and coverage generosity for drugs acquired by larger companies. We also report 95 percent confidence intervals for each estimate, with standard errors clustered at the drug level.*

drugs in question and therefore do not satisfy the conditions in the theoretical literature.[31] We also exclude horizontal acquisitions, and focus on acquired drugs, which experience the biggest change in portfolio.

5.1 Core evidence on cross-market effects

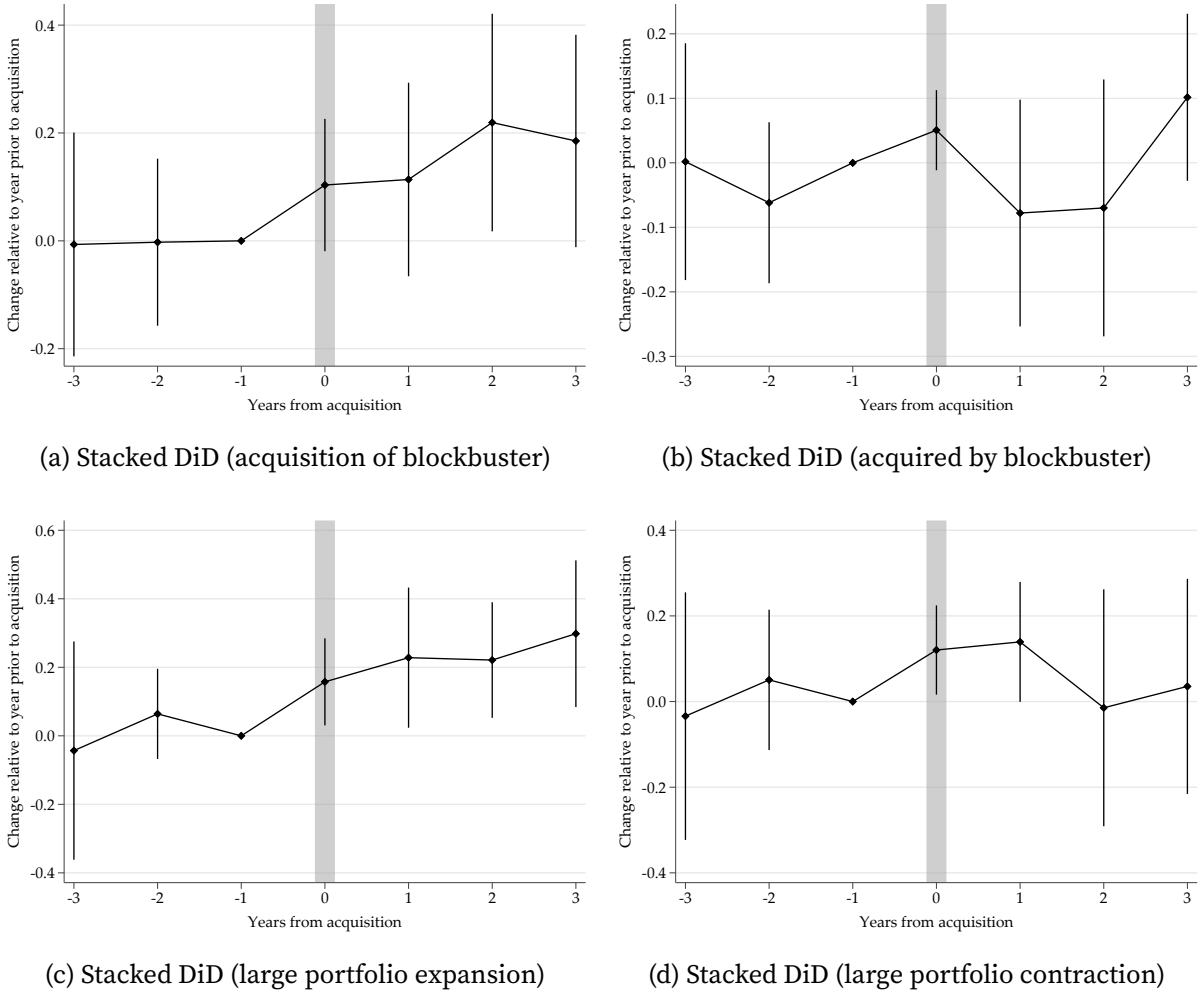
Panel A of Figure 6 plots the effect of cross-market acquisitions by larger companies. Although we do find that these acquisitions are followed by higher prices, the effect is small, not statistically significant, and preceded by significant pre-trends. The distribution of the effect of these deals (Panel B) is also nearly identical to to the placebo distribution.

Figure 7 shows responses in volume and coverage. We find that cross-market acquisitions by larger companies are followed by a slight decline in volume and coverage, with the coverage estimate appearing borderline significant, though of opposite sign relative to the expected effect. Overall, these results suggest that acquisitions across therapeutic areas do not impact the competitive equilibrium of the market on average.

5.2 Additional tests of cross-market effects

Because our findings differ from those of hospital markets (see, e.g., Brand et al., 2023; Dafny et al., 2019), we run additional analyses to check whether cross-market acquisitions lead to higher prices.

[31] For completeness, we report results associated with these transactions in Appendix E.4.



(a) Stacked DiD (acquisition of blockbuster)

(b) Stacked DiD (acquired by blockbuster)

(c) Stacked DiD (large portfolio expansion)

(d) Stacked DiD (large portfolio contraction)

Figure 8: Net price effects of large cross-market deals

Notes: *Each panel reports estimates of β_t in Equation 1, focusing on the log net price response of (i) drugs owned by a firm that acquires a blockbuster drug (Panel A), (ii) drugs acquired by firms that already own a blockbuster drug (Panel B), (iii) drugs that become part of a much larger portfolio (Panel C), and (iv) drugs that become part of a much smaller portfolio (Panel D). We also report 95 percent confidence intervals for each estimate.*

Our additional tests are motivated by the theoretical model in Dafny et al. (2019), which implies that cross-market effects appear only when the payoff function is concave in the number of products included as a threat point. Because payers are negotiating over hundreds of branded drugs, losing a few additional drugs might not be enough to push the payer to a very concave part of its payoff function.

To identify deals that are more likely to satisfy the concavity condition, we consider two options. First, we study "blockbuster" drugs. If a drug is highly valued by potential enrollees, it may be more likely to trigger the concavity condition for the payer. We define drugs in the top 5% of yearly sales in any given year during their lifecycle as blockbuster

drugs.[32] Given this definition, we look at: (i) the effect of being acquired by a company that owns a blockbuster drug (on acquired drugs whose previous company did not own a blockbuster drug); and (ii) the effect of acquiring a blockbuster product (on drugs owned by a company without a blockbuster drug).

Second, we look at deals that resulted in broader expansion (or contraction) of a company's portfolio. To identify these deals, we examine the change in net sales of every acquiring company after they make an acquisition and focus on the set of acquisitions in the upper decile of subsequent sales growth. We also look at the difference in net sales for target companies that sell assets and select those with the lowest decile of sales growth to look at the effect of portfolio contractions.

Figure 8 reports our results. Being acquired by a company who owns a blockbuster drug (Panel A, 39 drug-year events) does not affect price. However, we find that the price of drugs owned by a company that acquires a blockbuster drug (Panel B, 19 drug-year events) increases by approximately 19 percent. Drugs owned by a company that makes a large portfolio expansion (Panel C, 16 drug year events) increase in price by approximately 28 percent, but do not find that portfolio contractions (Panel D, 19 drug-year events) lead to lower prices.

While these results are consistent with the existence of cross-market effect in a small subset of pharmaceutical deals, we interpret them cautiously. A plausible alternative explanation is that companies making a large acquisition (of many drugs or a single blockbuster product) have large and stable revenue streams, which, in turn, is likely correlated with having an unobservably high-performing drug portfolio.

5.3 Why do cross-market acquisitions have small effects?

The lack of widespread cross-market effects raises the question of how to reconcile these results with the evidence from hospital markets.

One possible explanation is that drug companies may not systematically negotiate over their entire portfolio of drugs but instead conduct class-by-class negotiations and only occasionally engage in cross-market bundling.[33] We provide suggestive evidence con-

[32] The definition is at the drug level, so it applies to all years in which we see a drug, regardless of sales in that specific year. The threshold needed to achieve blockbuster status varies from year to year but ranges from $1.2 to $1.8 billion. In popular media, drugs are considered "blockbusters" when they achieve $1 billion in yearly sales. We prefer using a year-specific threshold to account for inflation and pharmaceutical market expansion.

[33] This hypothesis is supported by qualitative evidence collected through discussions with former PBM and pharmaceutical executives—all of whom noted that negotiations are typically conducted separately by disease area.

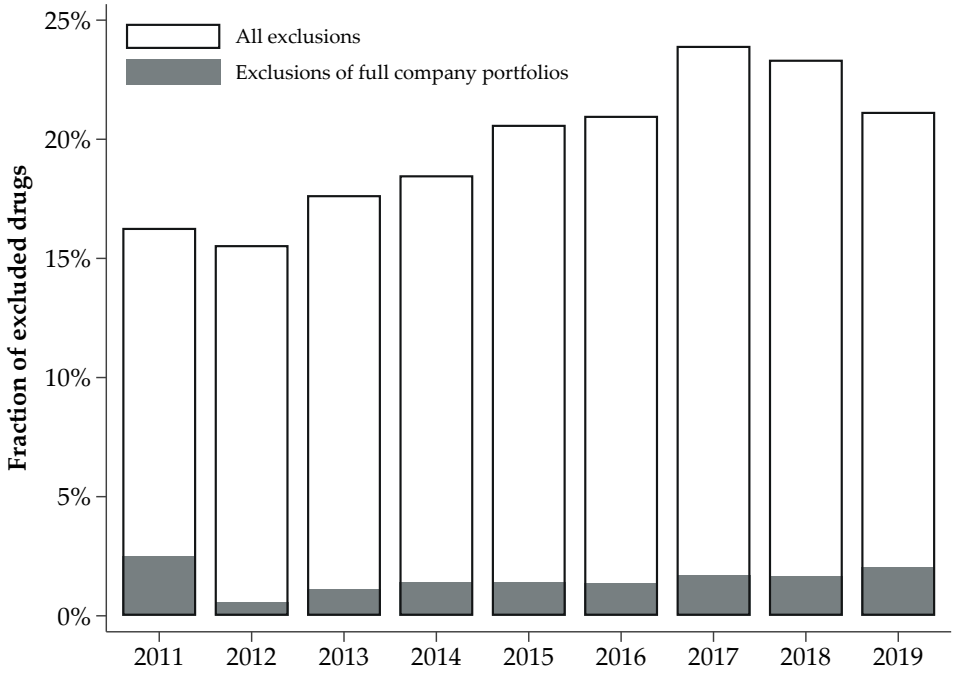


Figure 9: Exclusion rate of drugs across formularies

Notes: *This figure displays the average exclusion rate across formularies of commercial plans and highlights the fraction of exclusions that arise from exclusions of the entire portfolio of companies.*

sistent with this hypothesis by calculating the likelihood of total portfolio exclusions in commercial formularies using the MMIT data.[34] In the set of drugs marketed by multi-product companies, we first compute the fraction of drugs excluded from each formulary. We then only count exclusions when the company's entire portfolio is excluded.

Figure 9 shows that, even though exclusions are frequent (between 15% and 20% on the average commercial formulary), only a tiny fraction comes from exclusions of entire company portfolios.

Even if total portfolio exclusions are rare, partial cross-market tie-ins may still occur. To test for partial tie-ins, we look for evidence of joint exclusions within a firm's portfolio. We estimate a linear probability model where we regress an indicator for exclusion against an indicator for whether another drug marketed by the same manufacturer is also

[34] We limit our analysis to commercial formularies because Medicaid and Medicare plans have restrictions that limit the ability to exclude drugs. Medicaid has to cover all drugs, while Medicare plans cannot exclude drugs in six protected classes (anticonvulsants, antidepressants, antineoplastics, antipsychotics, antiretrovirals, and immunosuppressants to prevent organ transplant failure).

excluded:

$$Excluded_{jkft} = I_{jkft}\{\text{Another company } k \text{ exclusion in formulary } f \text{ and year } t\} + \\ + \alpha_{jt} + \delta_{tf} + \varepsilon_{jkft} \quad (3)$$

where j indexes the drug, k the manufacturer, f the formulary, and t the year. As controls, we include drug-year and formulary-year fixed effects. Intuitively, for a focal drug and year, the coefficient is estimated from variation in coverage rates across formularies where one group excludes another drug marketed by the drug's manufacturer and the other does not, adjusting for each formulary's average generosity in that year.

Table 3 presents the results. We find products are approximately 3pp more likely to be excluded if they are owned by a company with at least one other excluded product on the same formulary. However, the effect is largely driven by exclusions of drugs that share the same ATC-3 code. Cross-market exclusions are associated with only a 1.5pp increase in likelihood of exclusion. Conversely, drugs owned by the same manufacturer are 11pp more likely to be excluded if another drug in the portfolio that shares the same manufacturer is excluded. This effect represents an over 50 percent increase relative to the baseline exclusion rate of about 21 percentage points among drugs included in the analysis.

We interpret this as being economically meaningful, although we note that if exclusions were strictly enforced at the portfolio (or portfolio-class) level we would expect a point estimate equal to 1. Instead, our results are consistent with negotiations being more often conducted class-by-class (or even drug-by-drug), with occasional cross-market bundling schemes.

The decentralization of negotiations could result from several factors. Returns to centralized negotiation may be small, given limited concavity in payoff functions because of the large number of drugs. Organizational frictions may also matter. Large drug companies are often split into divisions by therapeutic area, and each division may have its own information and negotiation incentives, making centralization difficult (Hortacsu et al., 2024). Moreover, contracting contingencies, especially across markets, would create complicated rebate structures, which PBMs might prefer to avoid for logistical reasons.

We also note one additional, policy-relevant feature of the market structure that may be suppressing cross market effects. Because the distribution and negotiation channels are typically separate, enrollees of formularies that exclude drugs can still access them through retail pharmacies at list prices, making it difficult for manufacturers to enforce

Table 3: Correlation in exclusion rates within company and formulary

	Drug Excluded			
	(1)	(2)	(3)	(4)
Indicator for other excluded product from the same company	0.032 (0.004)			
Indicator for other excluded product from the same company in the same ATC-3		0.109 (0.006)		0.109 (0.006)
Indicator for other excluded product from the same company in a different ATC-3			0.015 (0.004)	0.015 (0.004)
Observations	2,793,659	2,793,659	2,793,659	2,793,659
R^2	0.516	0.521	0.515	0.521

***Notes**: Estimates from Equation 3 using plan-drug-year level data from MMIT. Standard errors are clustered at the drug-year level.*

full exclusion.[35] A more integrated system, which could result from vertical mergers of PBMs and pharmacies, could potentially lead to larger subsequent cross-market effects.

6 Conclusion

In this article, we conduct a detailed retrospective analysis of acquisitions involving on-patent branded drugs. We identify two key results. First, "stealth" horizontal acquisitions, whose value exempts them from being disclosed in advance to regulatory authorities, result in very large price increases and reduced insurance coverage. Second, we find little evidence of widespread price increases following "cross-market" acquisitions that only involve drugs in different therapeutic areas.

The "stealth" acquisition result supports the hypothesis that antitrust authorities impose effective constraints on anticompetitive deals in the pharmaceutical market. More specifically, given that the FTC did not take enforcement actions related to on-patent branded drugs in the years leading up to and during our sample period, the findings suggest that regulators are deterring larger horizontal mergers that would lead to large price effects. Our large point estimates also suggest that regulators play a particularly important role in markets where consumers are insured and price insensitive or where firms compete on price for favorable positioning. Further work is necessary to unpack the contributions of these features of market structure to the price effect of horizontal mergers.

The "cross-market" result suggests that, even in markets with negotiations between

[35]For the PBM, the only loss from the disagreement would be the lack of rebates, which would be less damaging than having no access at all.

manufacturers and large buyers over many products, mergers that expand a company's portfolio do not necessarily result in large price increases. We suggest two possible explanations why. The first depends on the degree of centralization of negotiations. Our suggestive evidence using formulary coverage data (which is also supported by anecdotal evidence from industry insiders) suggests that negotiations generally happen at the class, or even drug level, with only occasional bundling of products across therapeutic areas. The second depends on concavity conditions on the payer payoff function that must hold in order for cross-market mergers to generate large effects. These conditions are more likely to be satisfied when portfolios expand significantly, and we find some evidence that a small subset of large cross-market acquisitions did in fact lead to higher prices, though we suggest caution in interpreting these results due to the potential presence of confounders. The results speak to the FTC's 2024 challenge of the Amgen-Horizon merger on cross-market grounds and also add to the broader body of evidence on when cross-market effects may be relevant.

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Online Appendix

A A Partial Equilibrium Model of Contingent Rebates

We derive theoretical results under a partial equilibrium model of contingent rebates. As noted in the main text, the goal is to illustrate marginal incentives, rather than derive results under a full equilibrium model.

A.1 Setup

We consider a model with N drug markets, indexed by $j \in \{1, \ldots, N\}$. In each market, a single-product manufacturer competes with a "fringe" multi-product manufacturer that owns N products, one in each market. Products in the same market are (possibly imperfect) substitutes. No substitution is possible across products in different markets. Products owned by the "main" single-product manufacturer are noted by superscript m, while products owned by the fringe manufacturer are noted by the superscript o (for outside option). We also assume that prices of fringe products are exogenously set at $p_j^o(\mathcal{F})$ for all j, and focus on price negotiation between the single-product manufacturers and the PBM.

The goal of negotiations for the single-product manufacturer is to be included on the formulary. A formulary is defined as a set of N couples $\mathcal{F} = \left\{\left(f_j^m, f_j^o\right)\right\}_{j=1}^N$, where f_j^i is a binary indicator for inclusion. For simplicity, we assume that demand for pharmaceutical products $D_j^i(\mathcal{F})$ is determined entirely by the formulary arrangement and does not depend directly on price.[36] This assumption allows us to present the Nash Bargaining problem over prices between the manufacturer and the PBM as a negotiation over a lump sum L_j^m, with equilibrium prices implicitly defined as $p_j^m = \frac{L_j^m}{D_j^m(\mathcal{F})}$.

A.2 Partial equilibrium analysis

We assume that the manufacturer and the PBM negotiate over a single price. Since there is no substitution across markets, each negotiation can be analyzed independently. The negotiation between the PBM and the single-product manufacturer in market j takes the

[36] This assumption broadly reflects the real-world implications of manufacturer-PBM negotiations. Copay payments are tier-specific, but unrelated to price. Coinsurance payments and payments under the deductible depend on list price, which is generally set by manufacturers outside of PBM negotiations (which instead negotiate rebates that are generally not passed through to patients at point of sale).

following form:

$$\max_{L_j^m} \left[\phi\left(\mathcal{F}\right) - L_j^m - p_j^o\left(\mathcal{F}\right) D_j^o\left(\mathcal{F}\right) - \left(\phi\left(\mathcal{F}_j'\right) - p_j^o\left(\mathcal{F}'\right) D_j^o\left(\mathcal{F}_j'\right)\right)\right] \times \left[L_j^m\right] \tag{A1}$$

where $\phi\left(\mathcal{F}\right)$ is the PBM's welfare from securing formulary $\mathcal{F}$, and $\mathcal{F}_j'$ is the "disagreement" formulary (which only includes the fringe product in market j).

The first-order condition of this problem implies that manufacturers earn a split of the gains from trade:

$$L_j^m = \frac{1}{2}\left[\phi\left(\mathcal{F}\right) - \phi\left(\mathcal{F}_j'\right) - \left(p_j^o\left(\mathcal{F}\right) D_j^o\left(\mathcal{F}\right) - p_j^o\left(\mathcal{F}_j'\right) D_j^o\left(\mathcal{F}_j'\right)\right)\right] \tag{A2}$$

These gains from trade are the PBM's marginal benefit of including the product (i.e., $\phi\left(\mathcal{F}\right) - \phi\left(\mathcal{F}_j'\right)$) minus the extra spending on the fringe product if the main product is excluded (i.e., $p_j^o\left(\mathcal{F}_j'\right) D_j^o\left(\mathcal{F}_j'\right) - p_j^o\left(\mathcal{F}\right) D_j^o\left(\mathcal{F}\right)$).

A.3 Effect of price contingencies

We compare the outcome of the negotiations with and without contingent rebates. Without contingencies, $p_j^o\left(\mathcal{F}\right) = p_j^o\left(\mathcal{F}_j'\right) = \bar{p}_j^o$, which implies that the extra spending on the fringe product is proportional to the change in demand:

$$L_j^m = \frac{1}{2}\left[\phi\left(\mathcal{F}\right) - \phi\left(\mathcal{F}_j'\right) - \bar{p}_j^o\left(D_j^o\left(\mathcal{F}\right) - D_j^o\left(\mathcal{F}_j'\right)\right)\right] \tag{A3}$$

Conversely, with contingencies, as long as $p_j^o\left(\mathcal{F}\right) > p_j^o\left(\mathcal{F}_j'\right)$, the extra spending on the fringe product is *less than* proportional to the change in demand. Note that this result does not depend on the fringe product price *level*, but rather on the price *difference* between what is offered for the full formulary vs. the formulary that only includes the fringe. Further, while $p_j^o\left(\mathcal{F}\right) > p_j^o\left(\mathcal{F}_j'\right)$ is an assumption, it likely holds because manufacturers should want to push the PBM towards a formulary that excludes its competitors.[37]

Result 1. Equilibrium prices are lower when firms have to face contingent prices from competing manufacturers that offer favorable conditions for exclusion of competing products.

[37] This is also consistent with the results of the model in Ho and Lee (2024), and the contracts in the Senate Finance Committee investigation of insulins (United States Senate Finance Committee, 2021).

A.4 Effect of horizontal consolidation with and without price contingencies

To mimic horizontal consolidation, we consider what happens when the single-product manufacturer acquires its competitor product from the fringe manufacturer. Under this scenario, the manufacturer bargains jointly for both products with the PBM.

If the single-product manufacturer in market j acquires its competitor from the fringe manufacturer, its bargaining problem with the PBM becomes

$$\max_{L_j^{m+o}} \left[\phi\left(\mathcal{F}\right) - L_j^{m+o} - \phi\left(\mathcal{F}_j''\right)\right] \times \left[L_j^{m+o}\right]$$

where the "disagreement" formulary $\mathcal{F}_j''$ excludes both products in market j. The solution yields

$$L_j^{m+o} = \frac{1}{2}\left[\phi\left(\mathcal{F}\right) - \phi\left(\mathcal{F}_j''\right)\right]$$

Notice that in this case, contracts cannot include contingencies because the same manufacturer owns both products and negotiates an all-or-nothing deal. Hence, the same equilibrium price occurs regardless of whether contingent rebates are present, leading to our second result.

Result 2. Consolidation leads to larger increases in prices when contracts contain contingencies.

A.5 Effect of cross-market consolidation with and without price contingencies

To mimic cross-market consolidation, we assume that two single-product manufacturers merge, and then negotiate jointly with the PBM. If the single-product manufacturers in markets j and k merge, their joint bargaining problem could be set up as

$$\max_{L_{j+k}^m} \Big[\phi\left(\mathcal{F}\right) - L_{j+k}^m - p_j^o\left(\mathcal{F}\right) D_j^o\left(\mathcal{F}\right) - p_k^o\left(\mathcal{F}\right) D_k^o\left(\mathcal{F}\right) - \\ \left(\phi\left(\mathcal{F}_{jk}'''\right) - p_j^o\left(\mathcal{F}_{jk}'''\right) D_j^o\left(\mathcal{F}_{jk}'''\right) - p_k^o\left(\mathcal{F}_{jk}'''\right) D_k^o\left(\mathcal{F}_{jk}'''\right)\right)\Big] \times \left[L_{j+k}^m\right]$$

where the disagreement formulary $\mathcal{F}'''_{jk}$ excludes both products owned by the merged manufacturer. The solution yields

$$L^m_{j+k} = \frac{1}{2}\left[\phi\left(\mathcal{F}\right) - \phi\left(\mathcal{F}'''_{jk}\right) - \left(p^o_j\left(\mathcal{F}\right) D^o_j\left(\mathcal{F}\right) - p^o_j\left(\mathcal{F}'''_{jk}\right) D^o_j\left(\mathcal{F}'''_{jk}\right)\right)\right.$$
$$\left. - \left(p^o_k\left(\mathcal{F}\right) D^o_k\left(\mathcal{F}\right) - p^o_k\left(\mathcal{F}'''_{jk}\right) D^o_k\left(\mathcal{F}'''_{jk}\right)\right)\right] \quad \text{(A4)}$$

Under non-contingent prices, this merger leads to higher prices as long as

$$\phi\left(\mathcal{F}\right) - \phi\left(\mathcal{F}'''_{jk}\right) > \phi\left(\mathcal{F}\right) - \phi\left(\mathcal{F}'_{j}\right) + \phi\left(\mathcal{F}\right) - \phi\left(\mathcal{F}'_{k}\right)$$

i.e., $\phi\left(\cdot\right)$ is submodular.[38] Under contingent prices, the key question to ask is: how do contingencies affect the excess payments to excluded products? We consider market j (analogous considerations apply to market k). The extra payment in market j is given by

$$p^o_j\left(\mathcal{F}'''_{jk}\right) D^o_j\left(\mathcal{F}'''_{jk}\right) - p^o_j\left(\mathcal{F}\right) D^o_j\left(\mathcal{F}\right)$$

If contingencies are only within-market—e.g., $p^o_j\left(\mathcal{F}'''_{jk}\right) = p^o_j\left(\mathcal{F}'_j\right) > p^o_j\left(\mathcal{F}\right)$—cross-market acquisitions yield the same effects as in Dafny et al. (2019). That's because the extra spending on fringe products under the joint bargaining case is the same as the split bargaining case. Hence, the only channel for higher prices is through $\phi\left(\cdot\right)$.

Conversely, cross-market contingencies can play a role if the fringe manufacturer has signed a contract that gives a lower price for excluding a product owned by a competing manufacturer in a different market (conversely, lower prices contingent on including other products in the portfolio do not affect the disagreement payoff in this situation). If such contracts are in place, then the extra payments to the fringe manufacturer will be lower when excluding the portfolio of the merged firm, which in turn weakens the portfolio bargaining effect identified in Dafny et al. (2019).

Result 3. Cross-market consolidation leads to lower prices under contingent rebates, as long as contingencies include additional rebates for excluding non-competing products owned by competing manufacturers.

[38] These are the same conditions laid out in Dafny et al. (2019).

Table A1: Sample selection criteria

	Individual deals	Individual drugs	Drug-deal combinations
Total	184	340	414
Excluding Valeant	151	262	314
Excluding drugs fully missing price data	147	245	293
Excluding drugs missing price data around time of event	83	154	169

B Data Construction & Additional Resources

B.1 Sample exclusions

In this section, we report the criteria that lead us to exclude certain deals and drugs, and the number of exclusions.

A large number of deals are excluded because they involve drugs owned by Valeant Pharmaceuticals, a company that was very active in the years between 2010 and 2015. We also exclude a handful of products for whom we have no pre-LOE price data. Finally, the largest exclusion , or no price data around the time of acquisition (which makes it impossible to run our event-study).

B.2 Estimation of net prices

Our estimated net prices come from SSR Health, which calculates them by comparing quarterly net sales reports on 10-Q and 10-K SEC filings to invoice sales and units sold from Symphony Health.[39]

The estimated net prices are calculated as net sales divided by units sold. This estimate is best understood as the average revenue that a firm receives from the sale of one unit of the drug, rather than the average price paid by an insurance company. In particular, our estimate includes copay coupons, and other concessions manufacturers make directly to patients.

Moreover, the calculation of net price can be affected by two sources of measurement error. The first source of measurement error arises from the difference in the timing of

[39]Symphony Health data are similar to the National Sales Perspective dataset from IQVIA.

when sales are recorded by drug manufacturers versus when they are recorded by Symphony Health. Drug manufacturers record sales when drugs are picked up by wholesale distributors. Conversely, the Symphony Health data is built through surveys of pharmacies and hospitals, so it records sales when patients receive prescriptions. This discrepancy in data reporting means that there is a lag between when the two sales are recorded. Crucially, this lag may fluctuate due to changes in inventory, resulting in fluctuations in net price. To minimize this concern, we aggregate sales at the yearly level, following both recommendations from SSR Health and suggestions from Ippolito and Levy (2022).

The second source of measurement error arises because data for drug sold through specialty pharmacies or administered by physicians in outpatient and inpatient settings tends to be underreported in Symphony Health, but not in 10-K filings.[40] Systematic underreporting of units sold can result in net prices that are consistently higher than list prices, which in turn implies negative rebates—a clear impossibility.

Neither error is conceptually problematic for our empirical design, because they are fundamentally orthogonal to acquisitions—our event of interest.[41] However, underreporting can cause large relative fluctuations in prices for drugs with low baseline sales, with units sold varying by up to two orders of magnitude from year to year, which can have an impact on the empirical analysis.

To minimize the impact of these fluctuations on our analysis we use two approaches. First, we correct estimated net price using a one-sided winsorization filter that reduces the net price of drugs with very negative implied rebates. We use an asymmetric filter that reduces overly negative estimated rebates because high fluctuation in prices are always tied to drugs whose net sales exceed their invoice sales. Conversely, drugs that have very high discount rates are the least likely to have measurement error issues: they have low (accurately reported) net sales and very high invoice sales, which, even if they were off by some small amount, would not result in substantially different net prices. Second, we confirm that all our net price results are consistent with results on list prices. List prices are measured without error because they are posted by firms and easily observable.

[40] IQVIA's National Sales Perspective Dataset suffers from similar issues, which are noted also in Kakani et al. (2020) and Feng et al. (2023). The solution adopted by those two papers is to limit the sample of drugs used in the analysis. This solution is not viable for us because we aim to provide a complete look at the pharmaceutical market.

[41] In theory, there could be additional errors tied to net sales reporting around the time of the acquisition. However, this error does not have a clear direction. Moreover, we do not include the year of acquisition in our core analysis.

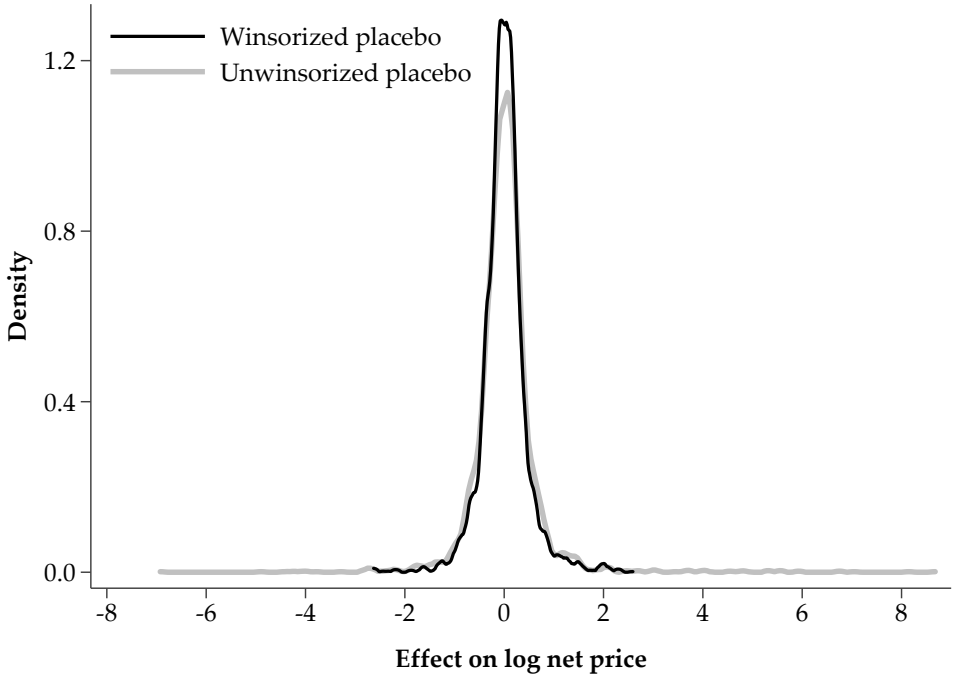


Figure A1: Placebo distribution of winsorized vs. unwinsorized net price

Notes: A plot of the distribution of placebo effects based on estimates of $\beta_{1,k}$ from Equation 2, using winsorized and unwinsorized net prices as the two outcomes.

Impact of winsorization on analysis

The main effect of the winsorization procedure is to improve the precision of the estimated net price year-to-year changes. To show this effect we plot the placebo distribution using winsorized net price and unwinsorized net price (Figure A1). Whereas the distribution are both symmetrical and largely comparable, the unwinsorized distribution has a significantly larger support, which includes a magnitude of almost ten in both direction.[42]

To ensure that our correction does not affect the results of our analysis, we compare the estimated coefficients for stealth horizontal acquisitions plotted in the distribution in Figure 3 to the estimated coefficients when we do not winsorize net price (Figure A2). Almost all coefficients lay on the 45-degree line, except in a few instances where the unwinsorized coefficient appears more extreme (negative or positive) than what we estimate using the winsorized price.

[42] A magnitude 10 effect on log price is equivalent to a change in price of 20,000 times relative to baseline, which, even for pharmaceuticals, is unrealistic—Martin Shkreli faced widespread public condemnation for increasing the price of daraprim 55-fold.

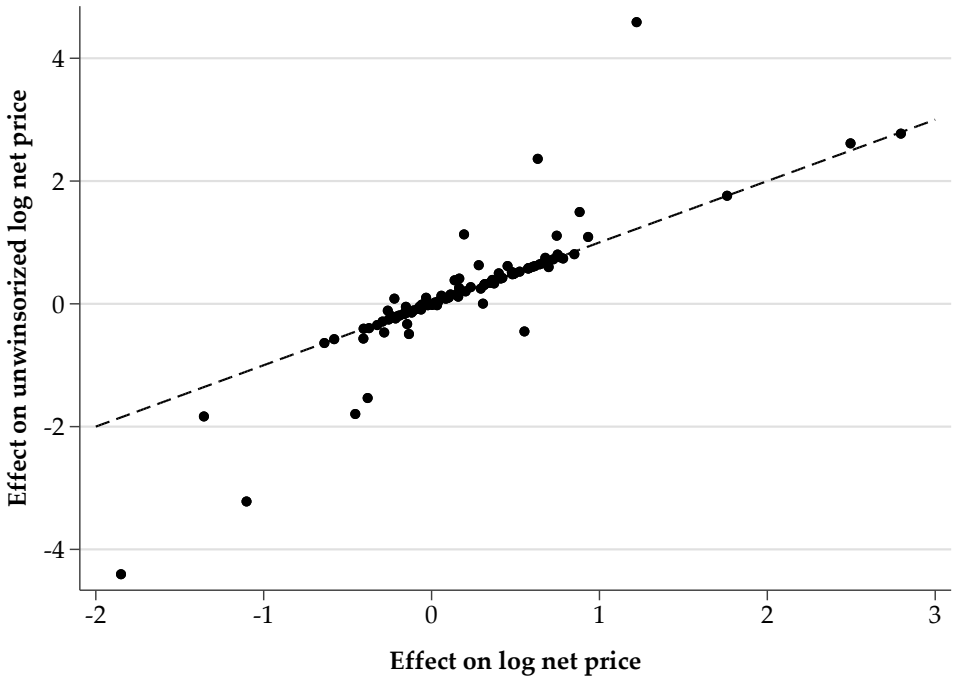


Figure A2: Effect of horizontal acquisitions on winsorized vs. unwinsorized net price

Notes: A plot of the distribution of effects based on estimates of $\beta_{1,k}$ from Equation 2, using winsorized and unwinsorized log net prices as the two outcomes. Each data point represents the estimated response for a drug acquired in a stealth acquisition.

Correlation between impact of acquisitions on net and list price

As an additional robustness check, we also compare the size of the effect of an acquisition on net price on the size of the effect on list price. Figure A3 displays the results for the set of 169 acquired drugs in our sample. List prices are reported by the company so they are measured without error.[43] We find that the effect on net price is about 20 percent smaller than the effect on list price on average, and the two are tightly correlated.

B.3 Calculation of coverage generosity

We briefly describe the steps we take to arrive at drug-year level measures of insurance coverage. For more details on trends in the MMIT data, see Appendix A.1 of Feng and Maini (2023), which uses the same measure of coverage generosity.

1. For each drug and year, we use the data from the February data entry for each plan-

[43]Through the SSR Health data we can recover a product-level list price. Occasionally, this price represents the average across multiple formulations of the same product. Year-to-year fluctuations of the within-product share of each formulation can then introduce some amount of measurement error from year to year, but we expect this effect to be small.

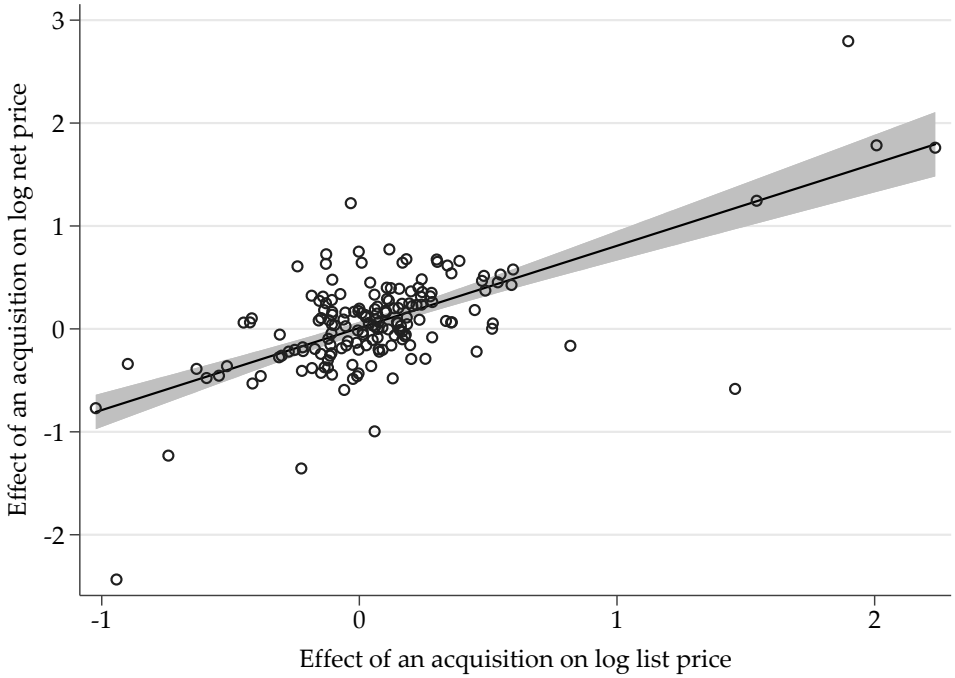


Figure A3: Correlation between effect of acquisition on net and list price

Notes: A plot of the distribution of effects based on estimates of $\beta_{1,k}$ from Equation 2 for a set of 168 acquired drugs, using log wholesale acquisition cost (WAC) and log net prices as the two outcomes. Each data point represents the estimated response for an acquired drug.

drug-year to measure coverage and enrollment for the year.

   (a) This is based on discussions with the data provider that January data is sometimes unstable in terms of lives covered.

   (b) For drugs that do not enter the dataset until later in the year (e.g., new entry), we take the first month of the year in which they have data.

   (c) We exclude plans that are Medicaid plans

2. In 2014, there is some duplicate data that we remove (these have plan type equal to "PBM OFFERING").

   (a) This is based on discussions with the data provider.

3. Next, we convert the raw coverage information into an aggregate measure, following Geruso et al. (2019):

   (a) We use the "universalstatus" variable provided by MMIT to create the coverage measure

(b) We mark drugs as "not covered" (value of 1) if the status variable is "Not covered drugs tier" or "Unknown coverage"

(c) We mark drugs as "restricted" (value of 2) if the "pa_st" variable is one (prior authorization or step therapy) or if the status variable is "Prior authorization required"

(d) We mark drugs as "medical tier" (value of 3) if the status variable is "Medical"

(e) We mark drugs as "non-preferred specialty" (value of 4) if the status variable is "Injectable drugs tier", "Non-preferred specialty drugs tier", or "Specialty drugs tier"

(f) We mark drugs as "preferred specialty" (value of 5) if the status variable is "Preferred specialty drugs tier"

(g) We mark drugs as "non-preferred brand" (value of 6) if the status variable is "Covered Drugs Tier", "Non-preferred brand drugs tier", or "Non-preferred generics and non-preferred brands"

(h) We mark drugs as "preferred brand" (value of 7) if the status variable is "Generic drugs tier", "Non-preferred generic drugs", "Non-preferred generics and preferred brands", "Preferred brand drugs tier", "Preferred generic drugs tier", "Preferred generics and preferred brands", "Value brand drugs tier", "Value generic drugs tier", "Zero co-pay tier"

(i) Based on these values, we also create additional binary variables such as excluded (coverage measure equal to 1) to provide evidence on portfolio negotiations

4. We then aggregate these coverage measures to a drug-year level, weighting by the lives covered by each plan.

B.4 Creation of matched control groups

To generate matched control groups we rely on the built-in Stata command "cem". We use this command to build up to five different sets of matched control groups for each drug.[44]

The five sets of matched controls are based on:

1. Age

[44] This includes both treated drugs, and non-treated drugs. We use the matched controls for non-treated drugs to calculate the placebo distribution.

2. Age and ATC-1 code
3. Age, ATC-1 code, and firm size
4. Age, ATC-1 code and net sales
5. Age, ATC-1 code, firm size, and net sales.

Age is measured on the year of acquisition (for both the treated drug and the control drugs). For firm size, we divide firms into small, medium, and large firms based on their average yearly sales over the time-span of our data (2007–2019). Firms with fewer than 250 million in yearly sales are considered small, and firms with greater than 2.5 billion in yearly sales are considered large. To create net sales categories, we use log net sales in the year before the acquisition. Matching on ATC-1 code is exact.

B.5 Pharmaceutical deals challenged by the FTC, 2007–2019[45]

Table A2: Pharmaceutical deals challenged by the FTC, 2007–2019

Companies involved	Approval Date	Summary	Links
Mylan Lab./E. Merck oHG	11/01/2007	The FTC required several divestitures in generic markets	http://www.ftc.gov
Schering-Plough Corp./Organon BioSciences N.V	12/28/2007	The FTC required divestiture of three poultry vaccines, but no human pharmaceutical products	http://www.ftc.gov
King Pharma., Inc./Alpharma, Inc	02/02/2009	The FTC required King to divest one drug (Kadian, morphine sulfate) to Actavis	http://www.ftc.gov
Schering-Plough Corp./Merck & Co., Inc.	10/29/2009	The FTC required Schering-Plough to sell assets related to rolapitant, a molecule they were developing	http://www.ftc.gov
Pfizer, Inc./Wyeth	01/25/2010	The FTC required divestitures in animal markets, but no human pharmaceutical products	http://www.ftc.gov
Watson Pharma. Inc./Actavis, Inc	12/14/2012	The FTC required divestiture of 18 generic drugs to Sandoz and Par Pharmaceuticals	http://www.ftc.gov
Actavis, Inc./Warner Chilcott plc	12/04/2013	Actavis was required to divest three oral contraceptives and one osteoporosis drug.	http://www.ftc.gov
Valeant Pharma. Int., Inc./Precision Dermatology, Inc	08/20/2014	The FTC required Valeant and Precision to divest two drugs: Tretin-X and Retin-A	http://www.ftc.gov
Novartis AG/GlaxoSmithKline, PLC	01/13/2015	The FTC required Novartis to divest the product Habitrol	http://www.ftc.gov
Endo Int. plc/Par Pharma. Holdings, Inc	10/10/2015	The FTC required divestiture of several generic products.	http://www.ftc.gov

[45]Source: http://www.ftc.gov, retrieved March, 2023.

C The Case of Valeant

C.1 Background

Valeant Pharmaceuticals (currently Bausch Health) is a Canadian-American pharmaceutical company. Between 2010 and 2015, the company gained notoriety for engaging in a large number of acquisitions and significantly increasing the prices of the drugs it acquired.[46] These price increases were met with widespread condemnation in popular media, and ultimately resulted in investigations into Valeant's pricing practices in Massachusetts and New York.[47]

Separately, questions arose around the company's accounting practices, and specifically the way it recorded revenue in the mandatory filings that publicly-traded companies need to submit to the Securities and Exchange Commission (SEC). The SEC questioned both the way Valeant was skirting generally accepted accounting principles (GAAP) in recognizing revenue on their SEC filings, and their ties to Philidor, a specialty pharmacy that distributed many of Valeant's drugs.[48] A case study published by the Stanford Graduate School of Business (McNichols and Foroughi, 2017) described these accounting irregularities as follows:

> *"A highly acquisitive company, some observers questioned whether Valeant was hiding the underlying fundamentals of the business in order to deliver promised growth. By not providing clear revenue numbers in the years following acquisitions, and by failing to provide any sort of consistency in reporting, analysts were left with no way to accurately assess the performance of acquisitions or the underlying business. In its 2011 Form 10-K, for example, Valeant provided revenues attributed to certain acquisitions (PharmaSwiss, Sanitas AB, etc.); however, these disclosures disappeared in Valeant's 2012 annual filings for both 2011 and 2012 acquisitions."* (McNichols and Foroughi, 2017, p. 8)
>
> *"Channel stuffing" refers to the practice of shipping more goods to distributors and retailers along the distribution channel than end users, and is often used to accelerate*

[46] See, e.g., https://www.wsj.com/articles/pharmaceutical-companies-buy-rivals-drugs-then-jack-up-the-prices-1430096431, accessed April 4, 2024, or https://www.nytimes.com/2015/10/05/business/valeants-drug-price-strategy-enriches-it-but-infuriates-patients-and-lawmakers.html, accessed April 4, 2024.

[47] See https://www.nytimes.com/2015/10/15/business/valeant-under-investigation-for-its-drug-pricing-practices.html, accessed April 4, 2024.

[48] See, e.g., https://www.fiercepharma.com/pharma/sec-raises-red-flags-over-valeant-s-use-non-gaap-measures, accessed April 4, 2024, and https://www.wsj.com/articles/valeant-under-investigation-by-sec-1456779650, accessed April 4, 2024.

revenue recognition in order to provide a short-term lift in profit. In the fourth quarter of 2015, Valeant reported that sales of omeprazole/sodium bicarbonate, a drug for gastrointestinal diseases, and Glumetza, a diabetes treatment, rose significantly (triple 3Q15 sales); but the number of prescriptions actually dispensed to patients declined in that same quarter, according to Symphony Health Solutions, a health care data and analytics company." (McNichols and Foroughi, 2017, p. 12)

Eventually, Valeant's market capitalization plummeted from $85.6 billion in July 2015 to less than $5 billion at the end of 2016.[49]

The company was also sued by shareholders who claimed that they were misled about the company's financial performance. Valeant eventually settled with shareholders for $1.21 billion in 2018, and in 2020, the company agreed to pay $1.875 billion to settle criminal charges related to its fraudulent accounting practices. Valeant changed its name to Bausch Health Companies in 2018.

C.2 Background on Valeant Acquisitions

Our data shows that, between 2007 and 2019, Valeant Pharmaceuticals International, Inc. completed 24 acquisitions that involved over 90 on-patent branded drugs (Table A3).[50] All but three of these acquisitions occurred between 2010 and 2015. Compared to the rest of the deals in our sample (Table 1 in the main text), acquisitions by Valeant are smaller in terms of overall value but include more drugs. These patterns confirm the informal narrative of Valeant as targeting smaller, potentially under-managed assets.

As discussed in the previous section, another important component of Valeant's acquisition strategy was increasing the price of acquired drugs. Our data confirms this impression as well. Figure A4 plots the effect of a Valeant acquisition on list and net price of acquired drugs. Although the net price data reported by Valeant is likely unreliable, we find that both list and net prices increase by approximately 0.3 log points (about 35%).

C.3 Evidence of net sales manipulation

"A highly acquisitive company, some observers questioned whether Valeant was hiding the underlying fundamentals of the business in order to deliver promised growth.

[49] See https://www.theglobeandmail.com/globe-investor/valeant-passes-rbc-as-canadas-largest-company-by-market-value/article25642880/, accessed April 4, 2024, and , accessed April 4, 2024.

[50] Notice that our numbers likely underestimate the extent of Valeant's activity, because we do not count generic drugs, off-patent branded drugs, and some on-patent branded drugs acquired from privately-owned companies.

Table A3: Characteristics of Valeant pharmaceutical deals

		Acquisitions by Valeant	Acquisitions of Valeant products
Count		24	8
Value of transaction ($ mill.)	mean	1,719	247
	median	332	76
Number of products	mean	3.75	1.13
	median	2	1

Notes: all statistics reported at the deal level. Acquisitions are considered horizontal if at least one acquired drug shares an ATC-3 code with a drug owned by the acquiring company.

> *By not providing clear revenue numbers in the years following acquisitions, and by failing to provide any sort of consistency in reporting, analysts were left with no way to accurately assess the performance of acquisitions or the underlying business. In its 2011 Form 10-K, for example, Valeant provided revenues attributed to certain acquisitions (PharmaSwiss, Sanitas AB, etc.); however, these disclosures disappeared in Valeant's 2012 annual filings for both 2011 and 2012 acquisitions."* (McNichols and Foroughi, 2017, p. 8)
>
> *"Channel stuffing" refers to the practice of shipping more goods to distributors and retailers along the distribution channel than end users, and is often used to accelerate revenue recognition in order to provide a short-term lift in profit. In the fourth quarter of 2015, Valeant reported that sales of omeprazole/sodium bicarbonate, a drug for gastrointestinal diseases, and Glumetza, a diabetes treatment, rose significantly (triple 3Q15 sales); but the number of prescriptions actually dispensed to patients declined in that same quarter, according to Symphony Health Solutions, a health care data and analytics company."* (McNichols and Foroughi, 2017, p. 12)

SSR Health, our data provider, collects information on net sales from various sources, including the SEC filings that Valeant was allegedly manipulating during some of the years in our sample period. Although we cannot obtain direct evidence of manipulation by simply looking at data trends, we can still attempt to identify any uncharacteristic patterns in net sales by comparing trends in log net sales and log units sold for all products acquired by Valeant. To do so, we regress each variable on drug fixed effects and time fixed effects relative to the year of acquisition (we don't use a control group for this analysis). We plot the results of this analysis in Figure A5. Panel A shows the pattern in net sales. In the year of acquisition, acquired products display an average increase in net sales of around 0.5,

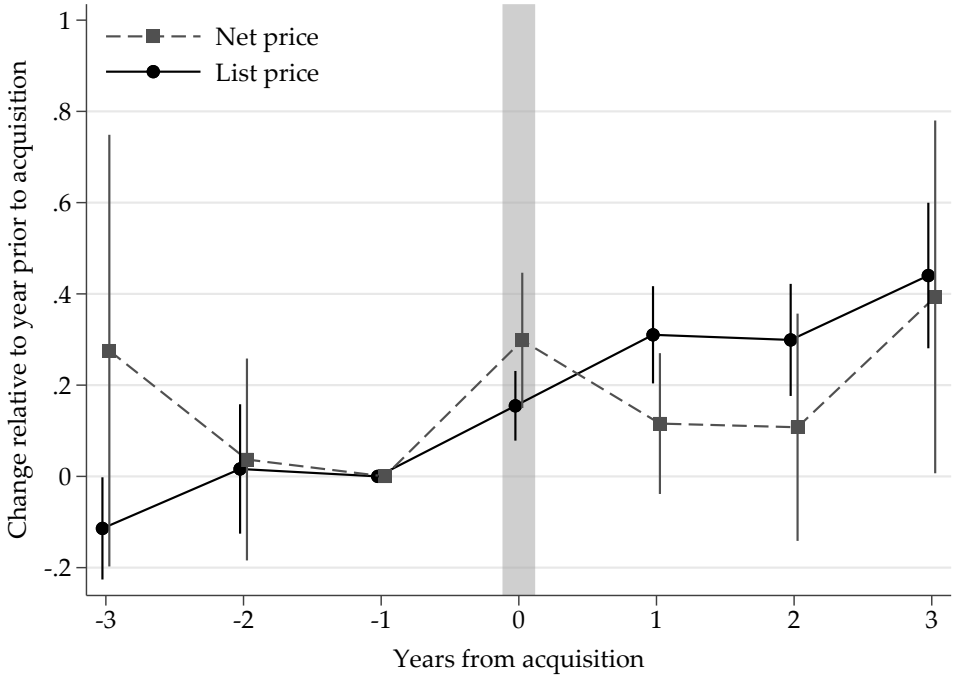


Figure A4: Effect of Valeant Acquisitions on list and net prices

Notes: We report estimates of β_t in Equation 1, focusing on log net price and log wholesale acquisition cost ("list price"). The sample consists of drugs acquired by Valeant Pharmaceuticals. We also report 95 percent confidence intervals for each estimate.

or 65 percent). After acquisition, sales fall back to baseline. However, units sold displays a very different pattern. We see no break from trend in the year of acquisition, and units sold actually fall in subsequent years.

This short-term increase in revenue in the year of acquisition is consistent with the characterization of Valeant's behavior in the quotes at the beginning of this section, which allege that Valeant was accelerating revenue recognition on SEC filings to appear more profitable. The long-term downward trend in volume sold after the acquisition is consistent with a sustained market response to Valeant's practice of sharply increasing drug prices for all acquired drugs.

D Robustness Checks

D.1 Using ATC-4 to define horizontal acquisitions

In Figure A6, we replicate Figure 4 using ATC-4, rather than ATC-3, to define overlap in therapeutic class. Although this definition results in a much smaller set of deals (51 drug-deal units, of which 7 fall below the HSR threshold), the estimates are qualitatively similar

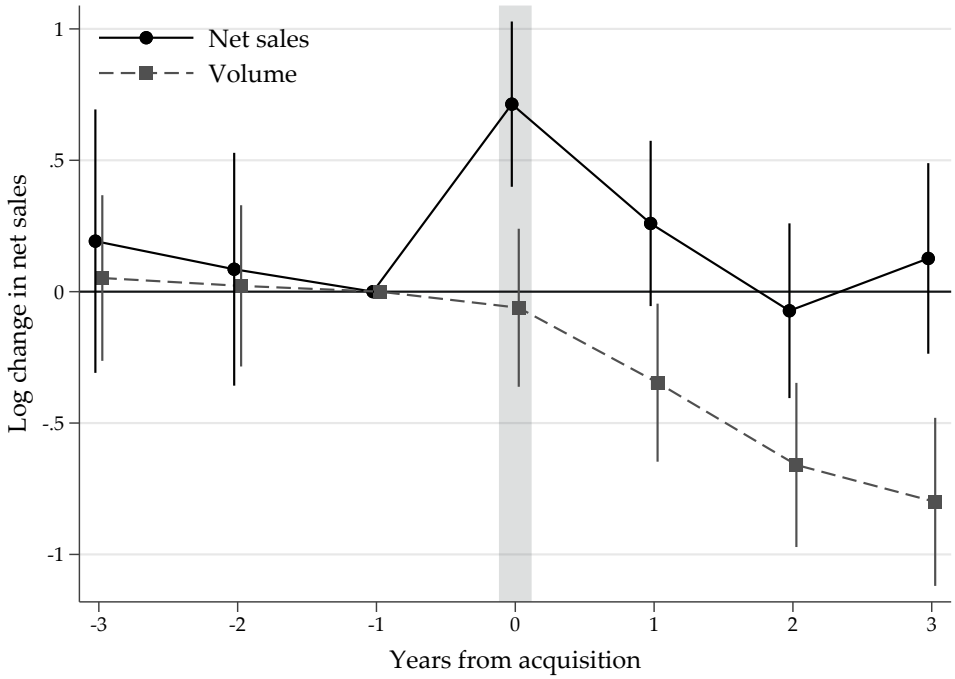
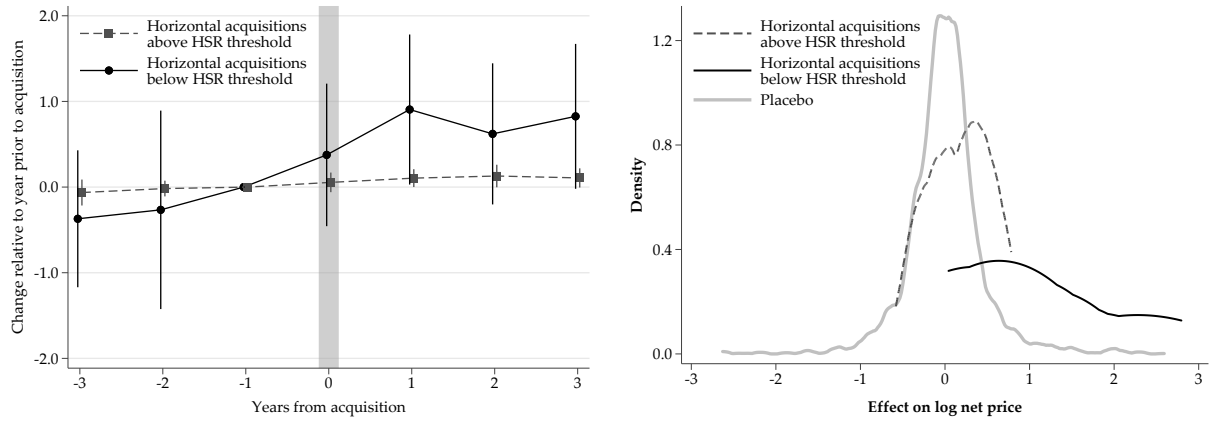


Figure A5: Trends in net sales and volume after acquisition by Valeant

Notes: We report estimates of β_t in Equation 1, focusing on log net sales and log units sold ("volume"). The sample consists of drugs acquired by Valeant Pharmaceuticals. We also report 95 percent confidence intervals for each estimate, with standard errors clustered at the drug level.



(a) Stacked DiD

(b) Distribution of Effects

Figure A6: Replication of Figure 4 using ATC-4 as therapeutic class

Notes: Panel A reports estimates of $\beta_t$in Equation 1, focusing on the log net price response of acquired drugs that overlap with an acquirer's drug's ATC-4 classification, and breaking out acquired drugs by whether the value of their associated horizontal merger is above or below the higher HSR threshold. We also report 95 percent confidence intervals for each estimate. Panel B reports the distribution of $\beta_{1,k}$ estimates from Equation 2 for the same drug-events, and also displays the distribution of estimates from a placebo study. All standard errors are clustered at the drug level.

to those from our core analysis, and imply even larger impacts on net prices.

D.2 Allowing for differential trends

To check that our result on horizontal acquisitions is not driven by differential trends in net prices, we repeat the event studies, but allow the matched control group and the treated drug to have differential linear trends. Figure A7 compares coefficients from this approach versus the core analysis. We find that the two coefficients are highly correlated (the slope of the best fit line is 0.80), and only a handful of coefficients are significantly different.

D.3 Changing the matching algorithm

Finally, we test the robustness of our results to changes in our matching algorithm.

Sensitivity of the results to using different sets of matching variables

In our main analysis, we use coarsened exact matching with up to four variables to create a matched control group: (i) Age, (ii) ATC-1, (iii) firm size, and (iv) net sales. Matching on all four variables often results in empty or very small matched cohorts. Hence, to obtain

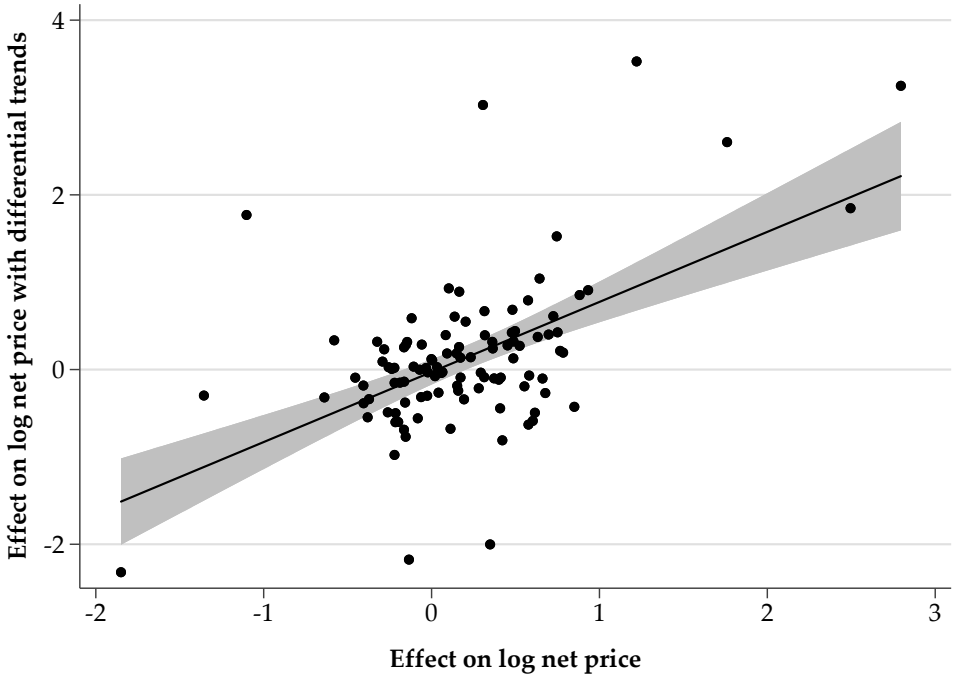


Figure A7: Effect of horizontal acquisitions with and without linear trends

Notes: A plot of the distribution of effects based on estimates of $\beta_{1,k}$ from Equation 2, focusing on the log net price response and comparing estimates recovered with and without including differential linear time trends for treatment and control group. Each data point represents the estimated response for a drug acquired in a stealth acquisition.

the most accurate results, we use the cohort group that is matched across the highest number of variables that includes at least 5 drugs.

To test the robustness of our results to these matching methods, we run the analysis on each of the five possible combinations of the four matching variables considered in the paper:

1. Age
2. Age and ATC code
3. Age, ATC code, and firm size
4. Age, ATC code and net sales
5. Age, ATC code, firm size, and net sales.

We then compare the results obtained with the simplest match (Age) to the results obtained when matching to the four other combinations (we do not impose any size restrictions in this exercise). Figure A8 displays the results. The estimates are very similar across

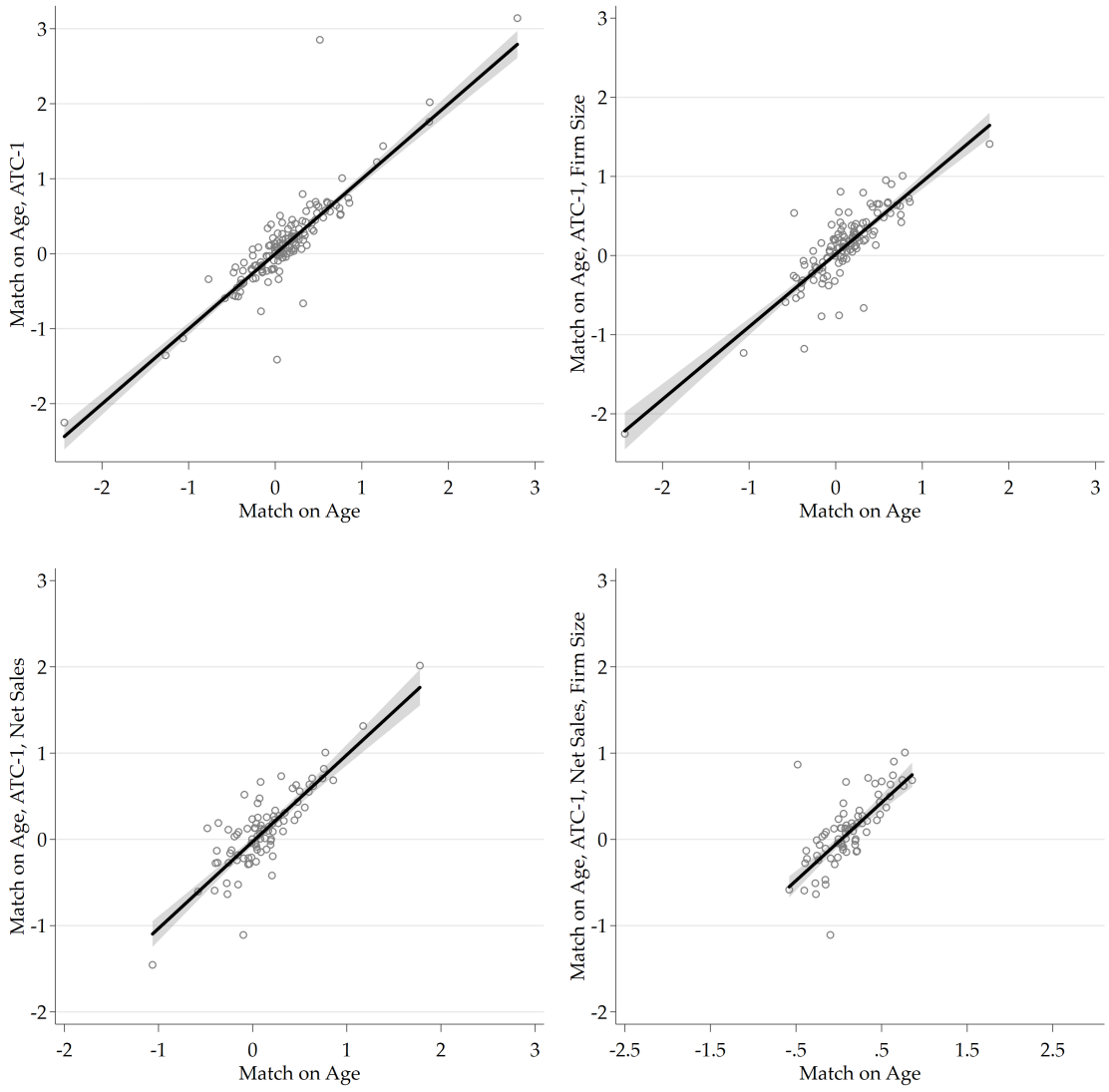


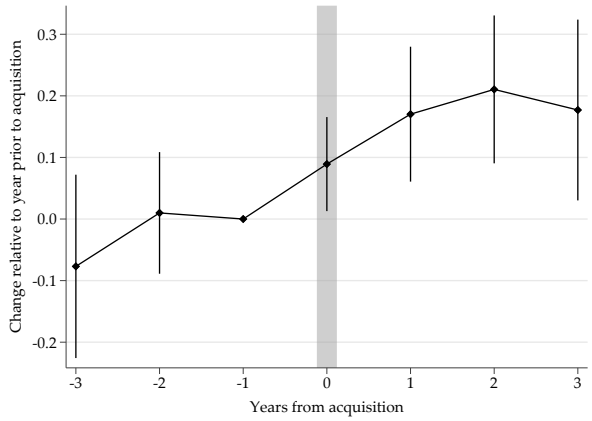
Figure A8: Correlation of coefficients across matching algorithms

the approaches, with correlations between each compared sample lying between 0.85 and 1.01.

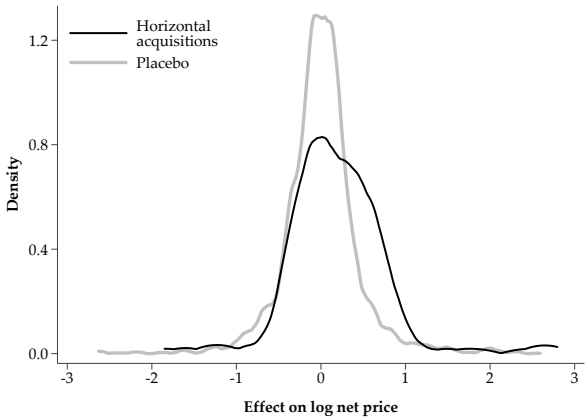
Sensitivity of the results to excluding drugs with the same ATC-3 from the matched control

A potential concern is that acquisitions might generate upward pricing pressure on other drugs competing with drugs directly involved in the acquisition. If these drugs are included in the control group, they may bias the coefficient downward. To show that this type of violation is unlikely to have a large effect on our estimates, we replicate all main figures using a matched control group that excludes drugs in the same ATC-3 as the focal

drug. The results are virtually unchanged.

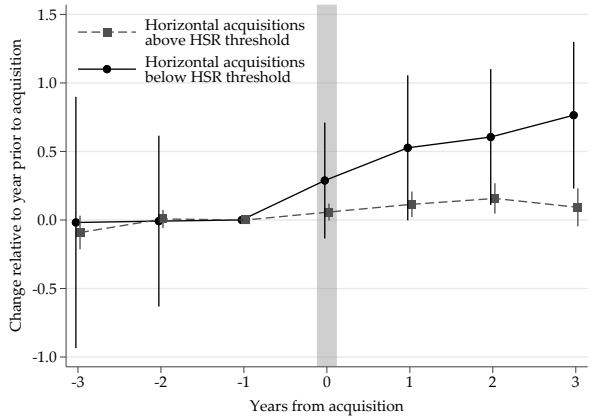


(a) Stacked DiD

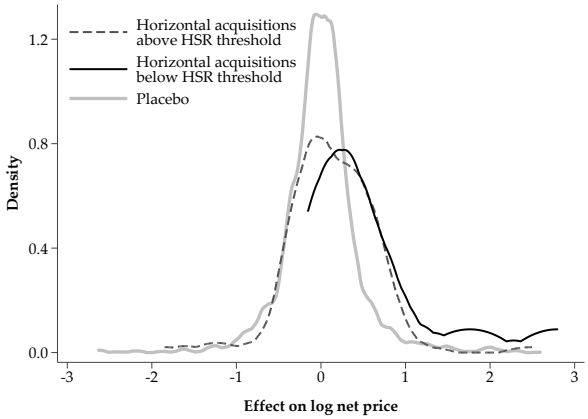


(b) Distribution of Effects

Figure A9: Replication of Figure 3

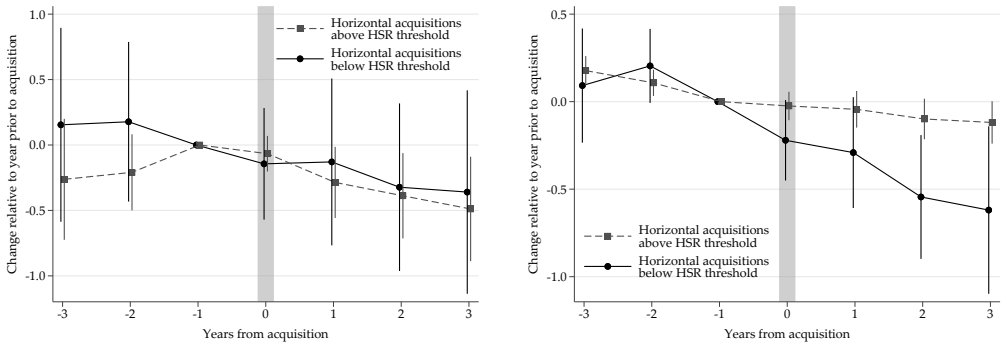


(a) Stacked DiD



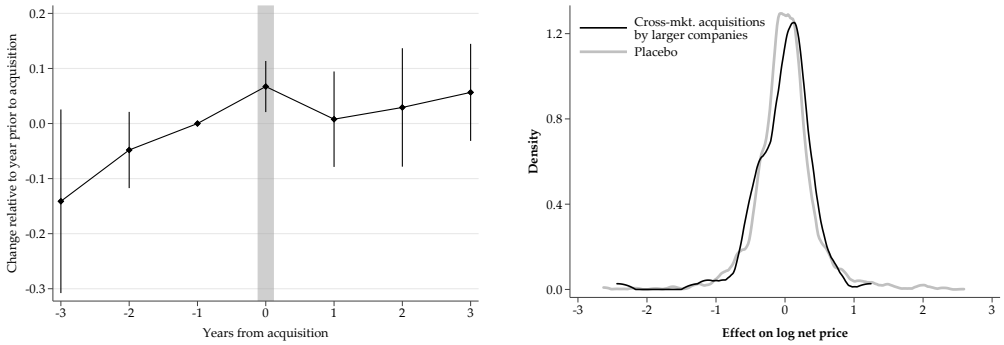
(b) Distribution of Effects

Figure A10: Replication of Figure 4



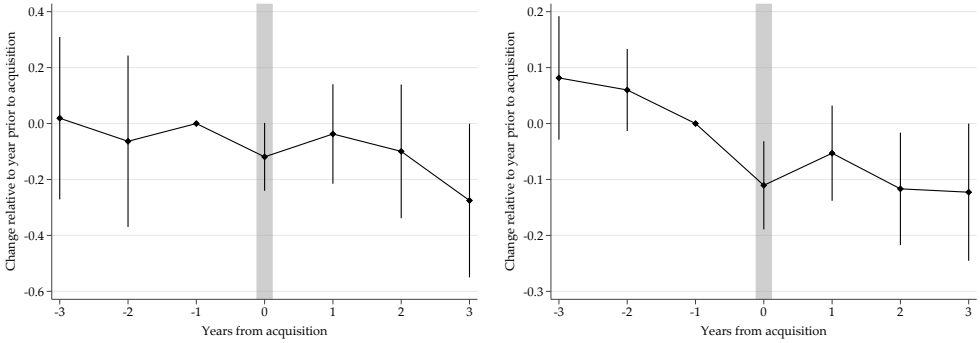
(a) Stacked DiD (Volume) (b) Stacked DiD (Coverage Generosity)

Figure A11: Replication of Figure 5



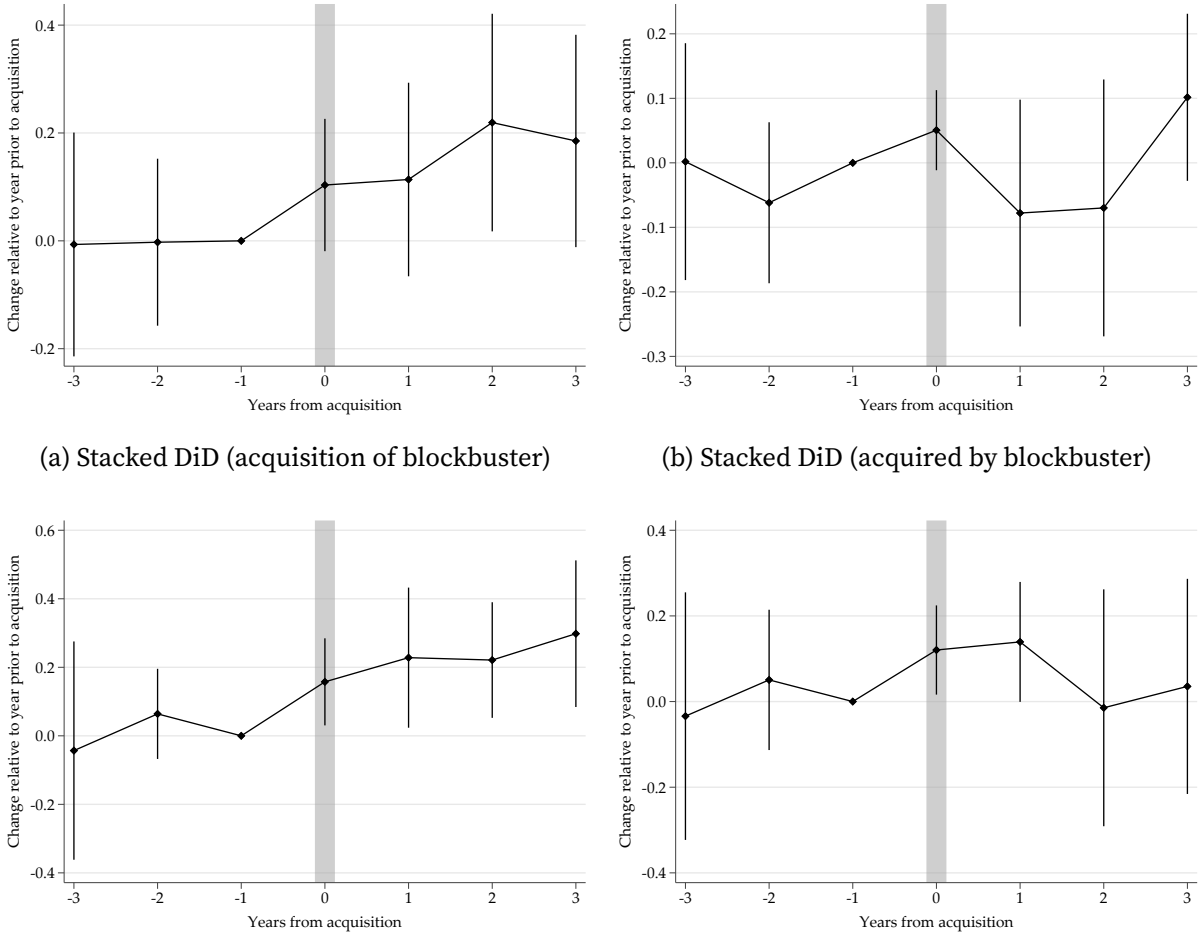
(a) Stacked DiD (Net Price) (b) Distribution of Effects (Net Price)

Figure A12: Replication of Figure 6



(a) Stacked DiD (Volume) (b) Stacked DiD (Coverage Generosity)

Figure A13: Replication of Figure 7



(a) Stacked DiD (acquisition of blockbuster)

(b) Stacked DiD (acquired by blockbuster)

(c) Stacked DiD (large portfolio expansion)

(d) Stacked DiD (large portfolio contraction)

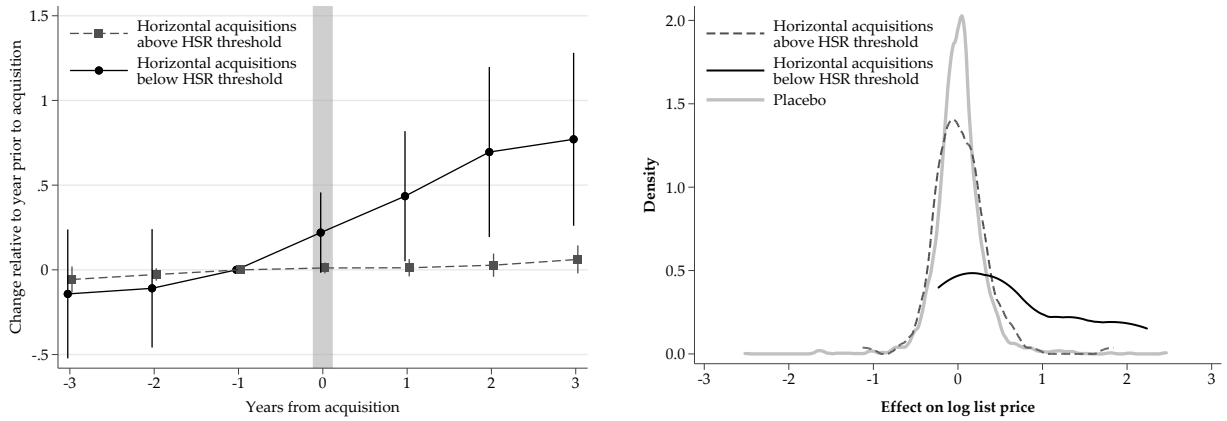
Figure A14: Replication of Figure 8

E Additional Empirical Results

E.1 Impact of horizontal acquisitions on other market outcomes

Effect of acquisitions on list price

We begin by reporting results on the impact of various type of acquisitions on list price. Although list price does not capture competitive outcomes as well as net price, it still presents a useful check, for two reasons. First, our net price data is measured with error, whereas list price data is measured without error because it is a posted price from manufacturers. In addition, list prices serve as an upperbound for net prices, so if list prices do not increase, net price responses will be bounded. Hence, checking that list price and net



(a) Stacked DiD

(b) Distribution of Effects

Figure A15: Effect of horizontal acquisitions on list price

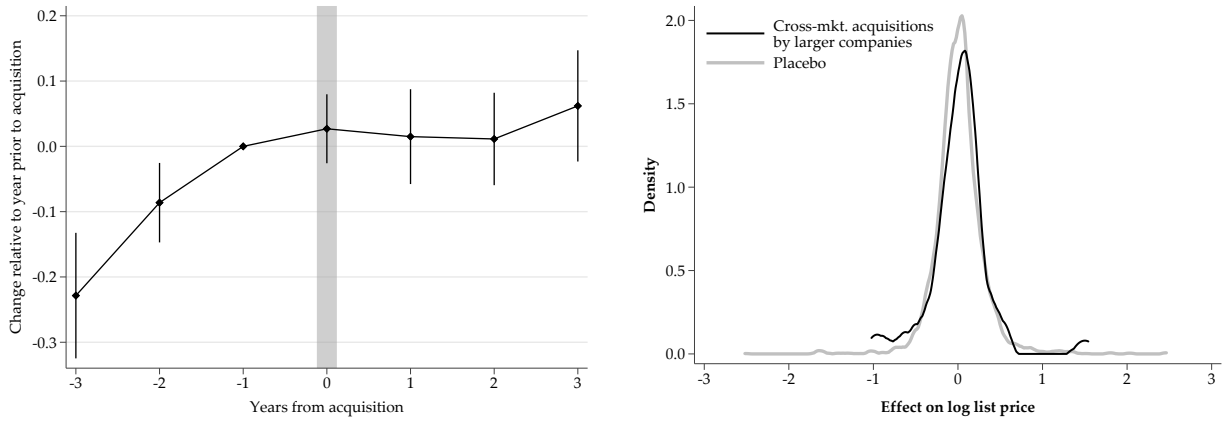
Notes: Panel A reports estimates of $\beta_t$in Equation 1, focusing on the log list price response of acquired drugs that overlap with an acquirer's drug, and breaking out acquired drugs by whether the value of their associated horizontal merger is above or below the higher HSR threshold. We also report 95 percent confidence intervals for each estimate. Panel B reports the distribution of $\beta_{1,k}$ estimates from Equation 2 across all drugs acquired in horizontal mergers of each type, and also displays the distribution of estimates from a placebo study. All standard errors are clustered at the drug level.

price effects are correlated strengthens our confidence in the net price results. Second, list price may matter independently for other outcomes such as out-of-pocket costs (Yang et al., 2020; Rome et al., 2021).

Figure A15 plots the effect of horizontal acquisitions, while A16 plots the effect of cross-market acquisitions by a larger company. All graphs closely mimic the results of the corresponding net price estimates presented in the main text (Figures 4, and 6 respectively).

Impact of acquisitions on net sales

Figures A17 and A18 show how log net sales change after a horizontal acquisition and after a cross-market acquisition by a larger company, respectively. The results are noisy but suggest that only horizontal acquisitions below the HSR threshold result in higher sales. As expected, given the results on net price, we do not detect any effect of cross-market acquisitions on net sales.



(a) Stacked DiD

(b) Distribution of Effects

Figure A16: Effect of cross-market acquisitions by larger companies on list price

Notes: Panel A reports estimates of $\beta_t$in Equation 1, focusing on the log list price of drugs acquired into a larger portfolio without creating an overlap. We also report 95 percent confidence intervals for each estimate. Panel B reports the distribution of $\beta_{1,k}$ estimates from Equation 2 across all drugs acquired into a larger portfolio without creating an overlap, and also display the distribution of estimates from a placebo study. All standard errors are clustered at the drug level.

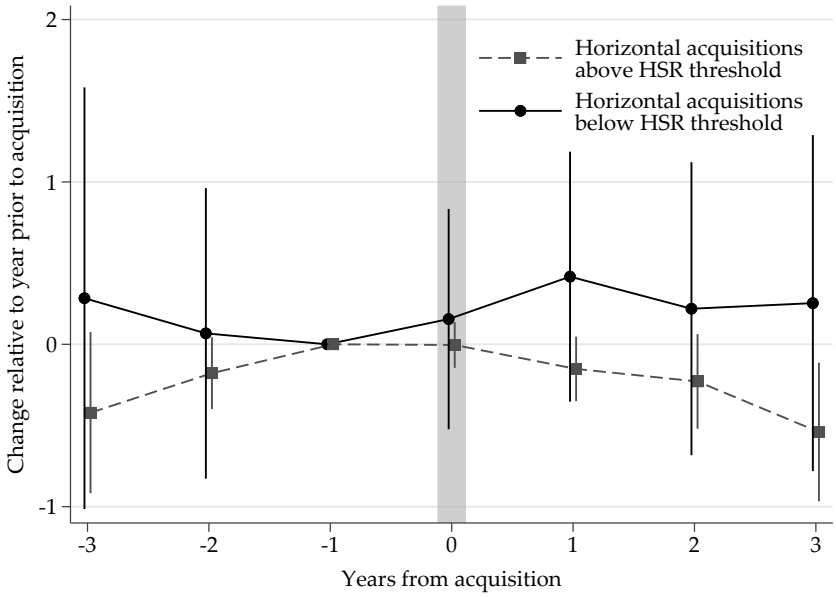


Figure A17: Effect of horizontal acquisitions on net sales

Notes: The Figure reports estimates of $\beta_t$in Equation 1, focusing on net sales of acquired drugs and breaking out acquired drugs by whether the value of their associated horizontal merger is above or below the higher HSR threshold. We also report 95 percent confidence intervals for each estimate. All standard errors are clustered at the drug level.

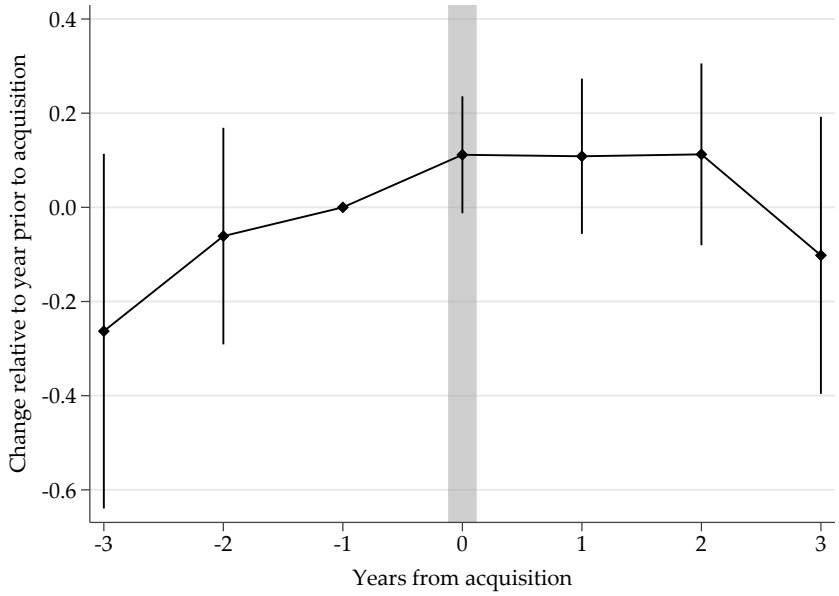
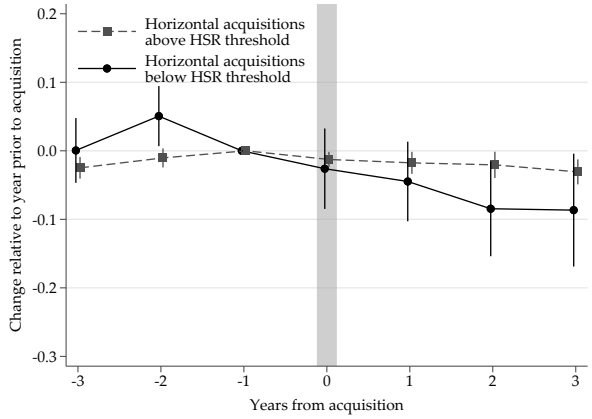


Figure A18: Effect of cross-market acquisitions by larger companies on net sales

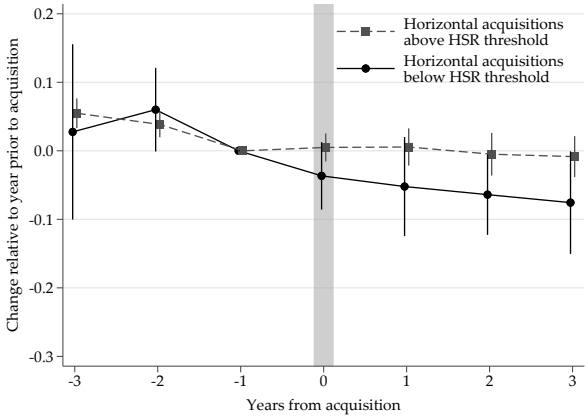
Notes: The figure reports estimates of β_t in Equation 1, focusing on the log net revenue (sales) for drugs acquired into a larger portfolio without creating an overlap. We also report 95 percent confidence intervals for each estimate. All standard errors are clustered at the drug level.

Impact of horizontal acquisitions on exclusion rates, non-financial restrictions, and preferred status

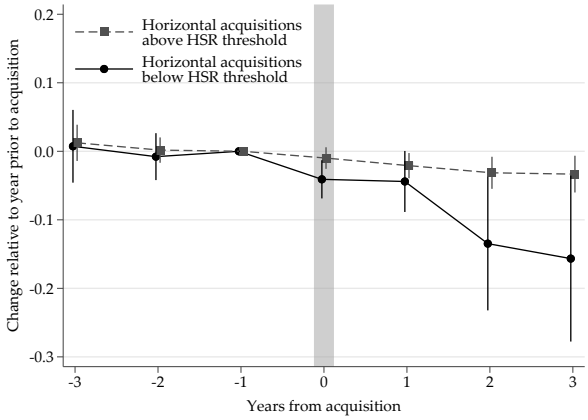
Figure A19 breaks down the effect of horizontal acquisitions on coverage rates across the three main types of formulary restrictions: exclusion, non-financial restrictions like prior authorization , and cost-sharing (proxied by placement on a preferred tier). Consistent with what shown in Figure 5, Figure A19 shows that stealth horizontal deals result in worse coverage. The effect are remarkably consistent across all types of restrictions.



(a) Stacked DiD, Fraction Covered



(b) Stacked DiD, Fraction Unrestricted



(c) Stacked DiD, Fraction Preferred

Figure A19: Effect of horizontal acquisitions on coverage restrictions

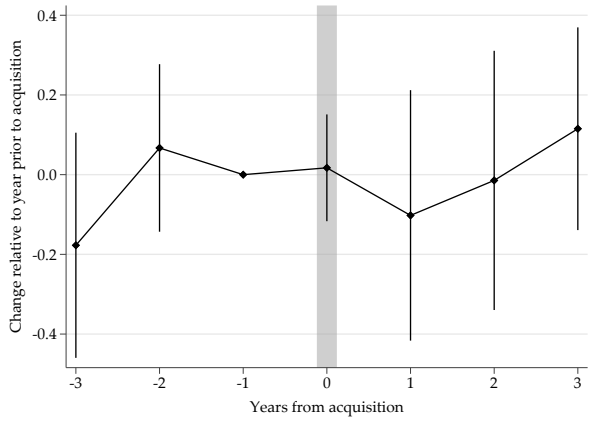
Notes: Panels A, B and C, report estimates of $\beta_t$in Equation 1, focusing on the fraction of individuals across all MMIT plans with coverage, unrestricted coverage, and preferred coverage of acquired drug, respectively, and breaking out acquired drugs by whether the value of their associated horizontal merger is above or below the higher HSR threshold. We also report 95 percent confidence intervals for each estimate. All standard errors are clustered at the drug level.

E.2 Spillover effects of acquisitions on competing drugs

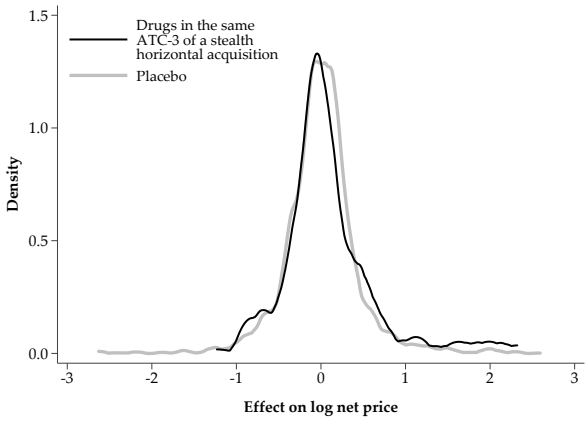
One of our results shows that stealth horizontal acquisitions result in much higher prices. In this section, we check whether competing products not involved in these acquisition react to these changes in price. We consider two groups of products: products in the ATC-3 therapeutic area where the acquisition took place, and products who share the same ATC-4 as either the acquired product or the product owned by the acquiring company.

Figure A20 displays our results for the two groups (Panels A and C, and B and D respectively). We find a small delayed effect on drugs sharing the same ATC-4 as the drugs involved in the stealth acquisition, but nothing in drugs in the ATC-3 where the acqui-

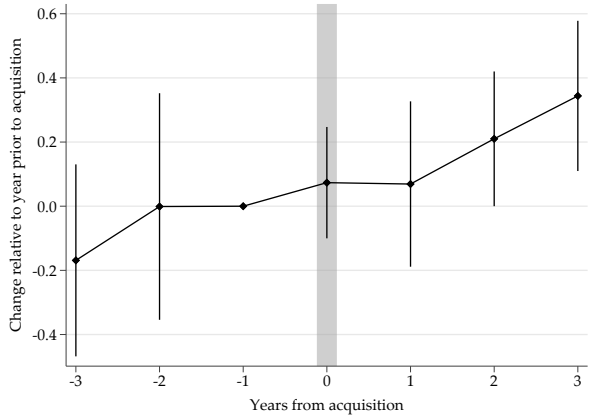
sition took place, thus further validating our choice to exclude drugs sharing the same ATC-4 from the matched control group in the main analysis.



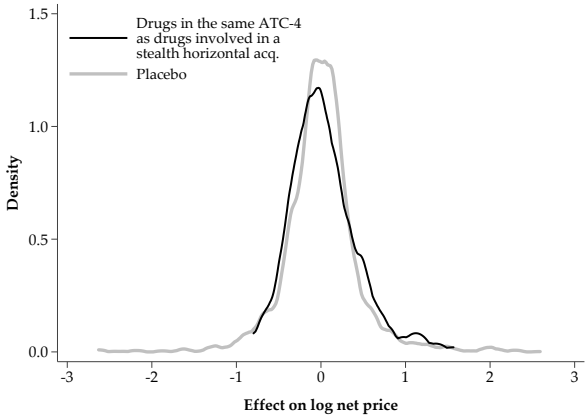
(a) Stacked DiD (ATC-3 of acquisition)



(b) Distribution of Effects (ATC-3 of acquisition)



(c) Stacked DiD (ATC-4 of involved drugs)



(d) Distribution of Effects (ATC-4 of involved drugs)

Figure A20: Spillover effect on competing drugs

Notes: Panels A and C report estimates of β_t in Equation 1, focusing on the log net price response of drugs in the same ATC-3 or ATC-4 as the overlapping drugs, respectively. We also report 95 percent confidence intervals for each estimate. Panels B and D report the distribution of $\beta_{1,k}$ estimates from Equation 2 for the same corresponding groups, and also display the distribution of estimates from a placebo study. All standard errors are clustered at the drug level.

E.3 Demand elasticity in markets where stealth horizontal acquisitions take place

Here, we provide evidence related to demand elasticity in the markets with stealth acquisitions. Because we aim to study the full set of branded drug products, detailed demand estimation is beyond the scope of our current work. Instead, we build on the quasi-experimental estimates of cost sharing elasticities from Einav et al. (2018) to provide sug-

Table A4: Market-level cost sharing elasticity comparison

	Cost sharing elasticity
Any Stealth Mergers	0.150
	(0.071)
Observations	45
R^2	0.0266

Notes: Estimates comparing cost sharing elasticities at the ATC-3 level for markets with and without observed stealth acquisitions. We report heteroskedasticity-robust standard errors.

gestive evidence. As noted in the main text, these elasticities primarily reflect extensive margin substitution rather than substitution across drugs in the same market.

We use the following procedure to arrive at a ATC-3 level cost sharing elasticity:

1. Manually create a crosswalk between branded drugs in SSR Health and the set of molecules for which Einav et al. (2018) provide cost sharing elasticities (top 100 drugs in Medicare Part D).

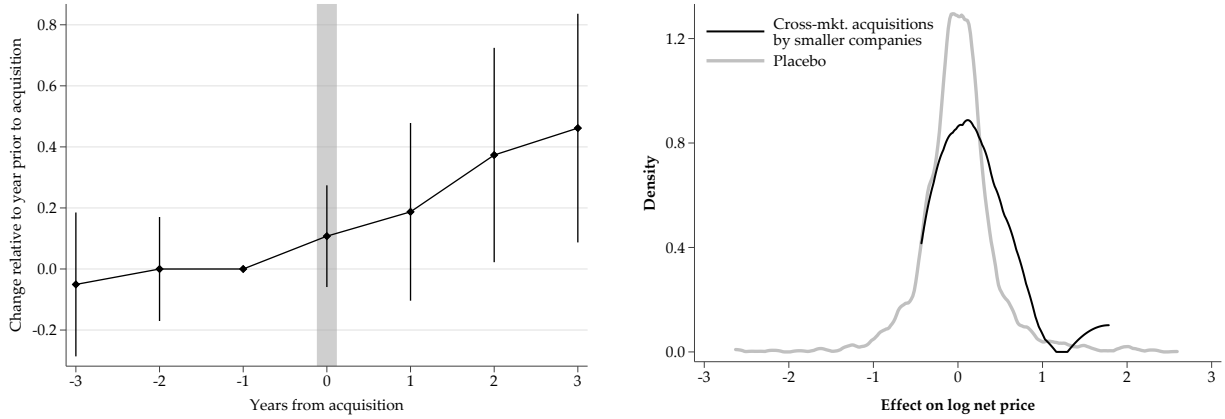
2. We attribute the basic elasticity estimate from Einav et al. (2018) to the branded drug if we find an associated molecule. We find matches for 73 branded drugs in our SSR Health data.

3. Because each drug could be in several ATC-3 markets, we expand the dataset to the drug-by-ATC-3 level.

4. Finally, we take an average elasticity across all drugs in an ATC-3 to arrive at a final estimate. We obtain elasticity estimates for 45 ATC-3 markets.

Using these estimates, we then mark whether a given ATC-3 has at least one stealth merger. We then run a simple regression comparing the demand elasticity of markets with and without an observed stealth merger. Table A4 reports the estimates. In the overall sample, the average cost sharing elasticity is -0.25. We find that stealth mergers occur in markets with less negative demand elasticities (0.15 point estimate). The effects are quantitatively large relative to baseline, and could partly explain the large net price estimates associated with stealth mergers.

We note, however, that these results are only suggestive. The ability to make stealth acquisitions is highly dependent on the revenues of products, so acquirers are not necessarily choosing across all possible therapeutic areas. Demand is also quite inelastic in general, so even if there were horizontal mergers in other markets, we may still see large



(a) Stacked DiD (Net Price)

(b) Distribution of Effects (Net Price)

Figure A21: Effect of acquisitions by smaller companies on net prices

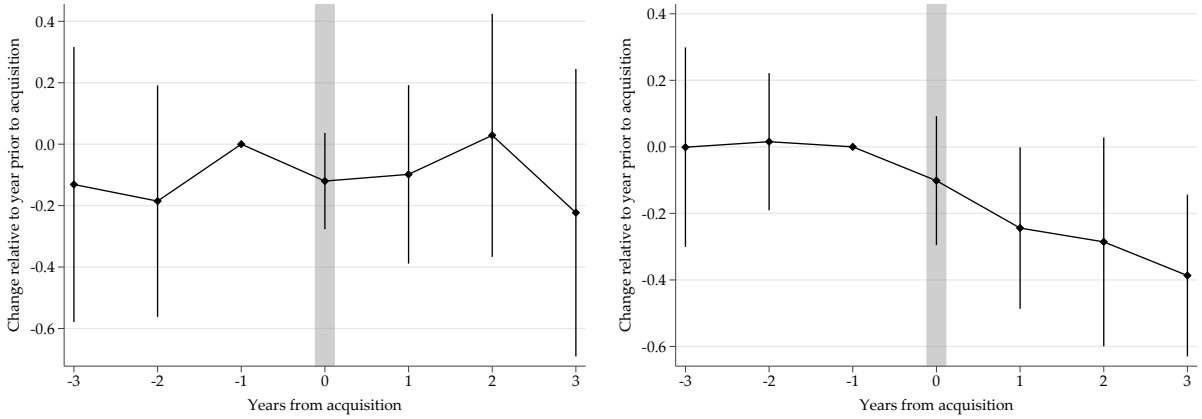
Notes: Panel A reports estimates of β_t in Equation 1, focusing on the log net price response of drugs that are acquired by a smaller company. We also report 95 percent confidence intervals for each estimate. Panel B reports the distribution of $\beta_{1,k}$ estimates from Equation 2 for the same drugs and outcome , and also display the distribution of estimates from a placebo study. All standard errors are clustered at the drug level.

price effects (but potentially not as large). Finally, Einav et al. (2018) estimate own-price elasticities. Having cross-price elasticities would provide a more complete picture on the gains from consolidation within a therapeutic area.

E.4 Acquisitions by smaller companies

Finally, in this section we report the effect of cross-market deals where a smaller company acquires drugs owned by a larger company. This group of acquisitions represents all acquisitions whose effect we have not reported already.

Figure A21 displays the results of our analysis of net price. Although the average effect is not statistically distinguishable from zero, we do find that net price starts increasing after these acquisitions, by approximately 8% per year. We do not detect a significant impact on volume (Figure A22, Panel A), but we do see some evidence of a decline in coverage generosity (Figure A22, Panel B).



(a) Stacked DiD (Volume)

(b) Stacked DiD (Coverage Generosity)

Figure A22: Effect of acquisitions by smaller companies on volume and coverage

Notes: Panels report estimates of β_t in Equation 1, focusing on the log volume and coverage generosity responses, respectively, of drugs that are acquired by a smaller company. We also report 95 percent confidence intervals for each estimate. All standard errors are clustered at the drug level.