

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

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Abstract

Which acquisitions lead to higher prices? We answer this question using a novel dataset of pharmaceutical acquisitions of branded, on-patent drugs from 2007–2019. Our results uncover two patterns. First, we exploit regulation that exempts low-value deals from being disclosed to antitrust authorities to show that regulatory scrutiny minimizes the effect of horizontal acquisitions, likely through a screening mechanism. Low-value deals that fall below the disclosure threshold led to an average 60 percent increase in net price, whereas remaining deals only result in a small and statistically insignificant increase in net price. Second, we find that cross-market acquisitions by large pharmaceutical companies do not lead to higher prices on average—although we cannot reject the possibility that they might have a small inflationary effect.

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“Which mergers matter?” is the question that regulators try to answer when they review the thousands of deals that are disclosed every year. A vast body of theoretical and empirical work has focused on this topic (Williamson, 1968; Jacquemin and Slade, 1989; Whinston, 2007; Asker and Nocke, 2021; Nocke and Whinston, 2022), often using retrospective analyses of past acquisitions to examine their impact (see, e.g., Kim and Singal, 1993; Hunter et al., 2008; Farrell et al., 2009; Ashenfelter et al., 2014; Kwoka, 2014). These results, however, can be hard to interpret because retrospective analyses can only examine acquisitions that are carried out. Because of regulatory enforcement by antitrust agencies, these acquisitions are likely selected to have a minor impact on market outcomes (Carlton, 2007; Kwoka, 2014). As a result, retrospective analyses might lack external validity.

One particular market where M&A activity has come under increasing scrutiny is the pharmaceutical market, with some policymakers raising concerns over the possible role of M&A activity in the significant growth of drug prices.¹ In addition, the Federal Trade Commission (FTC) has recently increased scrutiny of mergers that create “cross-market” effects, which may arise if drug manufacturers can leverage a portfolio of drugs treating different diseases to attain higher prices when bargaining with payers. However, despite the importance of this topic, empirical evidence on the effect of pharmaceutical M&A is relatively scarce for two reasons. First, traditional pharmaceutical sales datasets do not track changes in ownership structure.² Second, data on pharmaceutical market outcomes are not readily available, even in aggregate form, because most manufacturers negotiate undisclosed rebates with payers, and insurance coverage of drugs can vary substantially across plans and is therefore hard to track.

In this article, we provide evidence that is directly relevant to the antitrust debate by developing a novel source of data tracking the holder of the US marketing rights for the vast majority of branded prescription drugs from 2007–2019, which we match to detailed information on average prices net of rebates and coverage status. We find that only about one-fourth of all acquisitions in our data combine drugs treating the same

¹See, 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).

²For example, the IQVIA National Sales Perspective dataset only reports the company that is currently marketing a product.

disease, while the rest consolidate ownership of drugs that do not appear to be substitutes.³ The prevalence of cross-market deals makes the potential presence of cross-market effects a first-order issue. Next, we find that horizontal acquisitions that avoid regulatory review are followed by much larger increases in price, suggesting that government oversight plays an essential role in keeping markets competitive. Finally, we find that cross-market acquisitions have minimal impact on prices on average. However, the imprecision of our estimates means that we cannot rule out a small inflationary effect.

To build our M&A database, we rely on a combination of existing and hand-collected data. Our initial primary 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 company reporting sales changes, we compile an initial list of potential acquisitions. We supplement this list using SDC Platinum, a database of acquisitions involving US companies. Finally, we verify each deal's details by manually collecting and classifying press releases and other publicly available announcements. This verification step is vital because it allows us to identify deals in which the company responsible for pricing decisions changes. The latter category includes instances where a company acquires the U.S. marketing rights to a drug without obtaining the underlying intellectual property. The result of this data collection process is a yearly panel that monitors the current holder of the U.S. marketing rights of each drug.

Our final database contains 152 deals involving the marketing rights of 264 unique products.⁴ We identify three striking features of pharmaceutical M&A. First, the marketing rights of branded on-patent drugs are traded with high frequency. Approximately one-third of all branded drugs switch marketing companies at least once during our sample period. Second, horizontal acquisitions, which consolidate the marketing rights of products in the same therapeutic area, represent only a small minority (about 25 percent) of all deals in our dataset. Instead, most acquisitions combine products from different therapeutic areas. Finally, in many deals, the selling company transfers the US marketing rights of a given drug while retaining the underlying intellectual property of the drug that is acquired. This type of deal is often excluded from tradi-

³Throughout the rest of the article, we refer to drugs treating the same disease as being in the same "therapeutic area."

⁴We exclude from this count 24 deals made by Valeant Pharmaceuticals, a company that was investigated by the SEC for reporting fraudulent net sales numbers. The net sales numbers whose accuracy was questioned are the same ones we use in our analysis. We separately analyze Valeant's activity in Appendix C, where we present suggestive evidence that supports the validity of the SEC complaint.

tional M&A databases because they are not technically acquisitions but are an important piece of the pharmaceutical M&A landscape.

To analyze the effect of acquisitions on market outcomes, we integrate our database with drug-level data on yearly negotiated prices and insurance coverage. We obtain the data from two sources: SSR Health and MMIT Analytics. SSR Health collects net sales data from SEC filings of publicly traded drug manufacturers and estimates each drug's average market-level net price. MMIT Analytics tracks the level of coverage, known as formulary status, of drugs across the vast majority U.S. health insurance plans.⁵ This enables us to construct coverage measures at the drug-year level as proxies for drug access.⁶

We use our combined dataset to conduct a series of event studies, each focusing on a single acquired drug, evaluating the effect of acquisitions on drug prices and patient access. Our primary approach is to match acquired drugs to drugs with similar characteristics, such as years since market entry, therapeutic area, and annual sales. We then plot the distribution of the effects across all events and compare it to a placebo distribution obtained by randomly assigning a synthetic treatment to drugs that were not involved in acquisitions.

Our results are split into two parts. In the first part, we study horizontal acquisitions, which are generally seen as the most problematic type of acquisition from an antitrust standpoint. To identify horizontal acquisitions (i.e., acquisitions involving competing drugs), we use the Anatomic Therapeutic Chemical (ATC) code, a hierarchical drug classification system established by the World Health Organization. We define markets based on the first three digits of the ATC code, which groups drugs with similar chemical properties that treat the same disease. Note that drugs with multiple indications can have multiple ATC codes, meaning the same drug can overlap across multiple markets.

Our analysis shows that drugs acquired in horizontal acquisitions experience an average 20 percent increase in net price. However, consistent with the idea that the overall sample is selected, this effect is concentrated among a small subset of acquisitions

⁵MMIT tracks plans across all U.S. market segments. We compute overall coverage by using enrollment figures as weights. As of 2019, MMIT covers approximately 300 million lives.

⁶In unreported analyses, we also test the impact of acquisitions on advertising, using publicly available OpenPayments data on detailing, and direct-to-consumer-advertising data from AdSpender. Our results are inconclusive. Advertising expenditures fluctuate significantly from year to year, and all our estimated coefficients were too imprecisely estimated to yield any valuable insight. [Dubois and Majewska \(2022\)](#) analyze how advertising responds to pharmaceutical mergers using IQVIA data, and find that, on average, advertising spending falls following an acquisition.

that likely escaped regulatory scrutiny. To identify these acquisitions, we exploit a discontinuity in the reporting requirements for the Department of Justice (DOJ) and the Federal Trade Commission (FTC) set in 2000 by the Scott-Hart-Rodino Act (HSR Act). The HSR Act establishes that acquisitions below \$50 million are exempt from disclosure regardless of who is completing the deal, while acquisitions below \$200 million are exempt only if the companies pass the size-of-person test (e.g. if they are small enough).⁷ Throughout the text, we refer to these deals as “stealth” acquisitions, following the terminology used in [Wollmann \(2019\)](#). Because there are very few deals below the smaller threshold, we use the higher threshold to create an imprecise indicator of stealth acquisitions.⁸

Stealth acquisitions are followed by significantly larger increases in net price than the average horizontal acquisition. The average stealth acquisition leads to a 60 percent increase in net prices for acquired drugs, while drugs owned by the acquiring company in the same therapeutic area experience a 42 percent increase in net price. In contrast, horizontal acquisitions whose value is above the HSR threshold are followed by a smaller and imprecisely-estimated increase in net price (12 percent).

In the second part, we examine cross-market acquisitions. While cross-market acquisitions are generally considered less problematic from an antitrust perspective, recent theories of portfolio bargaining have questioned this assumption ([Dafny et al., 2019](#); [Kleiner et al., 2022](#)). According to the theory, an upstream firm (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, as long as (i) the products have common customers; (ii) the firm is able to sell its portfolio as an all-or-nothing bundle; and (iii) the payer’s objective function as a function of the number of products included satisfies specific conditions.⁹ In the case of pharmaceutical markets, the first condition is satisfied for all drugs because health plans enroll patients who take medications from a large number of markets. However, the second condition may not hold. Our formulary data reveals that full portfolio exclusions are extremely rare. In addition, the fact that different agents negotiate prices

⁷Both thresholds are adjusted annually for inflation. Currently, the two thresholds are set at \$101 and \$403 million respectively.

⁸Our data does not allow us to conduct the size-of-person test accurately, so some deals below the threshold may still need to be reported to the FTC.

⁹For prices to increase, the payer’s objective function needs to be concave in the number of drugs made available. Cross-market mergers can lead to price *reductions* if portfolios consist of complementary drugs (the payer’s payoff function is convex). See the theoretical section in [Dafny et al. \(2019\)](#) for details.

and handle distribution may also make exclusions harder to enforce through bargaining alone. However, we also find a weak, but significant correlation in the probability of exclusion across drugs owned by the same company, which suggests that partial bundling could occur.¹⁰

Empirically, our event study analysis suggests that cross-market acquisitions by larger companies do not have a significant effect on price. The average effect of these deals is almost exactly zero, although the estimate is imprecise, preventing us from ruling out a small inflationary effect. The empirical evidence on prices, combined with our results on formulary coverage across firm portfolios, suggests one of two possibilities. Either bundling drugs occurs too rarely to show up in the data, or the shape of the payer's objective function is not very concave, and bundling does not result in much higher prices.

This paper makes three contributions. First, it 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., 2020). Our work is among a group of recent papers that focus on the differential impact of stealth acquisitions on market outcomes (Cunningham et al., 2021; Wollmann, 2021; Morzenti, 2022). A conceptually related paper is Bhattacharya et al. (2022), 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 cross-market mergers.

Second, our paper is part of a literature studying the impact of consolidation in the pharmaceutical market. Our contribution to this literature is two-fold. First, by compiling a detailed database of acquisitions, we document extensive M&A activity involving branded, on-patent drugs and characterize the nature of this consolidation activity. Second, by focusing on the effect of consolidation on the price and coverage of branded drugs, our effort complements research that focuses primarily on the generic market (Hammoudeh and Nain, 2019; Bonaime and Wang, 2022; Chen et al., 2022), as well as papers studying the impact of acquisitions on R&D (Higgins and Rodriguez, 2006; Cunningham et al., 2021) and advertising (Dubois and Majewska, 2022).

Finally, our paper contributes additional evidence to the ongoing debate on the effects of cross-market acquisitions. Contrary to recent evidence from hospital markets

¹⁰We stress that this evidence is correlational, and may be driven by unobserved factors, such as selection into the types of drugs owned by the same company.

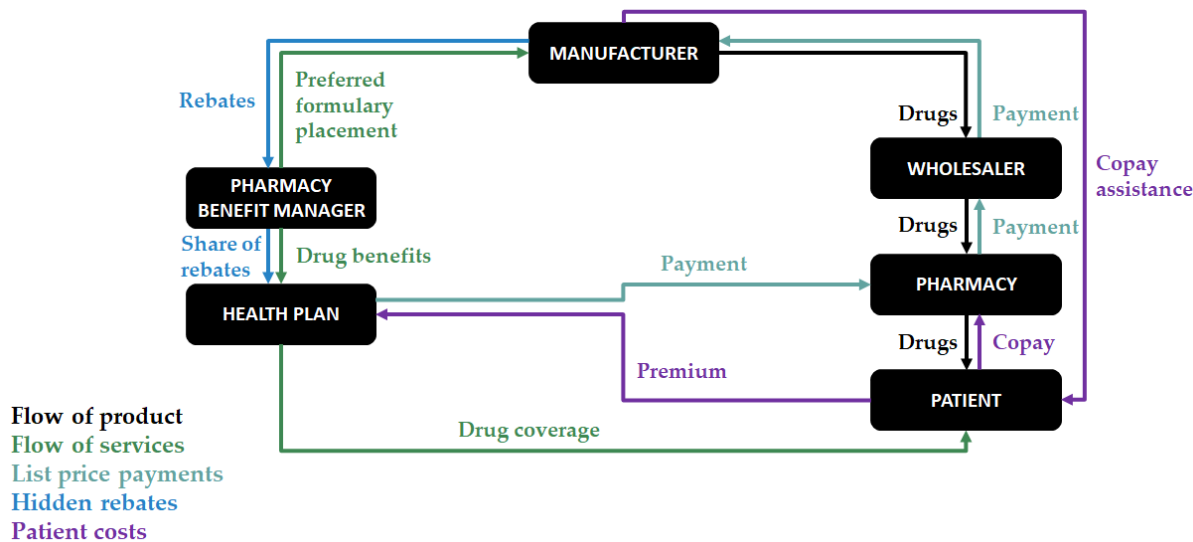


Figure 1: Stylized diagram of drug market relationships

(Dafny et al., 2019; Brand et al., 2023), we do not find that cross-market acquisitions affect prices. Differences in the bargaining structure of pharmaceutical markets relative to hospital markets may explain the differing results.

The rest of the paper is organized as follows. Section 1 discusses institutional details and data. Section 2 provides an overview of M&A activity in the pharmaceutical market. Section 3 describes our methodological approach. Section 4 presents results on how market outcomes respond to horizontal mergers. Section 5 presents results on how market outcomes respond to cross-market mergers. Section 6 concludes.

1 Prescription Drug Markets: Institutional Details & Data

1.1 Price-Setting in the Pharmaceutical Market

We begin with a brief description of how the prices of branded drugs are set. Figure 1 provides an overview of the interactions between the various agents in this market.¹¹ Effective prices of branded drugs depend on two factors: posted list prices and nego-

¹¹The description is accurate for drugs sold through retail channels (e.g., through pharmacies). For drugs that are administered by physicians in outpatient and inpatient settings, the hospital would replace the pharmacy in the distribution chain, and, occasionally, group purchasing organizations for hospitals would take on the role of PBMs.

tiated rebates. List prices are set by manufacturers, and apply to the entire U.S. market. List prices 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 list price.

The most commonly used measure of list price is Wholesale Acquisition Cost (WAC), which is a price posted by drug manufacturers. WAC is not based on actual transactions, but it closely matches the average price paid by wholesalers who distribute the drug to pharmacies (Levinson, 2005). However, despite being the most commonly referred-to price in popular media, list prices rarely determine the real cost of branded drugs for health plans.

Effective net prices arise from the combination of the manufacturer-set list price and 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 1.¹²

PBMs and manufacturers negotiate drug prices by trading off higher rebates for better placement on prescription drug formularies—tiered menus of drugs that determine health plan drug coverage. A typical formulary will have at least three tiers: a low cost-sharing tier for generic drugs, a middle tier for preferred brand drugs, and a higher tier for non-preferred brand drugs. Additional tiers can provide more separation between groups of branded products, and for more expensive specialty drugs. Crucially, while the specific out-of-pocket cost associated to each tier is determined by the health plan, tiers determine the relative cost-sharing of drugs—e.g., a drug in a lower tier will always have a lower out-of-pocket cost than a drug in a higher tier.

Rebates and formulary placement are determined jointly through a bargaining process that begins with manufacturers sending grids of rebate bids (expressed as a percentage discount off the list price) that are contingent on the formulary status of a drug, and of that drug's competitors. Formulary arrangements that place drugs on a better tier relative to their competitors are assigned higher rebate bids.¹³ After receiving

¹²Several recent papers have proposed models of PBM behavior. See, e.g., Feng and Maini (2019); Conti et al. (2021).

¹³For more details on manufacturer and PBM negotiations, see the Insulin Report of the Senate Finance Committee ([https://www.finance.senate.gov/imo/media/doc/Grassley-Wyden%20Insulin%20Report%20\(FINAL%201\).pdf](https://www.finance.senate.gov/imo/media/doc/Grassley-Wyden%20Insulin%20Report%20(FINAL%201).pdf), retrieved May 27, 2021).

bids from all manufacturers and potentially some back and forth negotiations, PBMs pick their preferred formulary arrangements and organize them into standardized “national” formularies.¹⁴ Each PBM then sends their formulary offerings to health plans, who evaluate them based on generosity and expected spending.¹⁵ While many health plans simply pick one of the national formularies, they also have the option to make any changes in coverage they deem necessary.¹⁶ Any deviations from the national formulary will also result in a different rebate, in accordance to the rebate grids submitted by the manufacturer. Occasionally, PBMs can exclude drugs from their formularies altogether. In these cases, health plans that wish to offer the drug as part of their insurance packet would need to either pay list price or switch to a different PBM.

1.2 Data on Pharmaceutical Market Outcomes

To analyze the market outcomes described in the previous section, we assemble a detailed dataset with information on prices, sales, and formulary coverage at the drug-year level. Our data comes from two sources. Data on sales and prices comes from SSR Health, a consulting company specializing on the pharmaceutical market. Data on formulary coverage comes from MMIT Analytics, a company that aggregates information on drug tiering and restrictions from health plan formularies.

Data on sales and prices SSR Health provides quarterly data on list prices, estimated average net-of-rebates prices, and net sales of branded prescription drugs. The database contains information for a little over 1,000 branded drugs, from 2007–2019, which covers almost all of US branded drug spending.¹⁷ The main exception is drugs marketed by privately-owned companies, which are not required to disclose information to the SEC. However, the vast majority of pharmaceutical companies are publicly traded, so

¹⁴Occasionally, PBMs also engage in back-and-forth negotiations with manufacturers to extract higher rebates than those submitted initially.

¹⁵PBMs also compete on additional aspects, for example by offering pharmacy mail delivery services and claims management. In addition, several PBMs are now vertically integrated with insurance companies, although they still offer services to third parties. Some PBMs also offer standalone drug plans on the Medicare Part D marketplace.

¹⁶In our data, custom formularies cover approximately 50 percent of lives across the commercial, health exchange and Medicare segments, while national formularies cover around 40 percent of lives. The remaining fraction of lives are covered under “processor” agreements, where the PBM does not directly negotiate prices, but simply acts as a processor of claims.

¹⁷Data is not available for all drugs in all periods. Over time, as more firms have started reporting drug-specific earnings on their SEC filings, the sample has expanded. Occasionally, drugs are also dropped, mainly because of patent expiration.

this restriction does not affect the interpretation of our results. In 2018, SSR Health covered ~90 percent of U.S. invoice sales, and ~80 percent of U.S. net sales.¹⁸

Estimated average net-of-rebates prices in the data are calculated as the ratio of net sales, which SSR Health collects from SEC filings of publicly traded firms, and volume sales, which are sourced from a third-party, Symphony Health.¹⁹ Because sales and volume numbers come from different datasets, the resulting net price series can display measurement error in the form of large fluctuations from quarter to quarter. Moreover, the estimates from Symphony Health tend to under-count the volume of drugs that are distributed through non-traditional channels, like specialty pharmacies. As a result, estimated net prices for some drugs tend to be implausibly large, and, in some cases, consistently above list prices—which implies a negative average rebate. To reduce the scope of these issues we take two steps. First, we aggregate quarterly data to the year level. This greatly reduces the issue of fluctuation. Second, we cap estimated rebates at the 5th percentile of the observed distribution, which removes the most extreme outliers.²⁰ We also use the SSR Health data to calculate yearly invoice sales and volume for all drugs.²¹

We exclude from our sample of analysis drugs owned by Bausch Health (formerly Valeant Pharmaceuticals). We do this because we have reason to believe that Valeant’s data is inaccurate. The company was investigated by the SEC in 2016 for improper revenue recognition and misleading disclosures in SEC filings—the same ones SSR Health uses to collect data on net sales. In our analysis of Valeant’s drugs, included in Appendix C, we find circumstantial evidence supporting the SEC’s claim: net sales for products acquired by Valeant spike in the year of acquisition before returning to baseline in years after that. However, we do not find a concurrent spike in quantity sold (data on which comes from a third-party, and not Valeant itself).

Data on formularies We also acquired data on formulary coverage from MMIT Analytics. The MMIT database covers almost exactly the same set of drugs covered by the

¹⁸As discussed in [Feng et al. \(2023\)](#), these numbers come from comparing total spending in the SSR Health data to figures in an IQVIA report on 2018 US drug spending (IQVIA, 2019).

¹⁹The Symphony Health data is analogous to IQVIA’s National Sales Perspective datasets, which is more commonly used in economic research.

²⁰We describe the issue and the winsorization procedure in more detail in Appendix A, where we also show how this adjustment, while significantly reducing the noise in the data, does not materially affect our results. For a more detailed guide on working with SSR Health data, see also [Ippolito and Levy \(2022\)](#).

²¹These fields are not identical to the Symphony Health data, which we do not have direct access to, but are backed out from the data that SSR Health does make available.

SSR Health data, but only from 2011–2019.²² The data contain monthly snapshots at the level of a drug and a health insurance plan. According to MMIT, the data cover all health insurance plans in the U.S. across commercial insurance, Medicare, Medicaid, and the ACA health exchanges.

For each drug and health plan we observe the formulary tier of the drug, and any restrictions placed by the formulary, such as prior authorization (PA, requiring physicians to submit a form to the insurer before prescribing a drug), and step therapy (ST, prohibiting prescribing the drug as a first-line therapy). In addition, we also observe the number of lives covered by each health plan, and the structure of each formulary, which helps us in understanding the relative standings of drugs in the formulary and in making comparisons across formularies.

We use the data to construct several lives-weighted measures of formulary coverage at the drug-year level, based on whether: (i) a drug is covered on a formulary; (ii) whether the formulary places PA or ST restrictions on prescriptions; and (iii) whether a drug is covered on a preferred formulary tier. We also calculate a single “average tier” summary metric following a procedure described by [Geruso et al. \(2019\)](#).²³ We restrict our attention to three segments of the US market: commercial insurance, Medicare, and Health Exchanges (we exclude Medicaid, which is subject to strict coverage requirements that might make it less responsive to acquisitions). Together, these three segments make up almost 80 percent of covered lives in the US.

2 Overview of M&A Activity in the Pharmaceutical Market

2.1 Data on M&A deals

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. To build this data, we rely on two primary data sources, which we supplement with additional hand-collected data. Our first source is again SSR Health. In the process of recording net sales data from SEC filings, SSR keeps track of any switch in the company reporting sales of a given drug. In most cases, these switches indicate that the company

²²The 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.

²³For more details on this procedure, see [Appendix A](#).

Table 1: Characteristics of pharmaceutical deals in our sample

		Overall	Acquisitions by larger company	Acquisitions by smaller company
Count		150	93	57
w/ same ATC-3 drugs		40	28	12
Value of transaction (\$ mill.) ²⁴	mean	5,340	6,391	1,946
	median	941	1,453	153
w/ same ATC-3 drugs	mean	9,355	10,630	3,408
	median	3,655	5,084	650
Number of products	mean	2.12	2.54	1.44
	median	1	1	1
w/ same ATC-3 drugs	mean	3.4	4.18	1.58
	median	1.5	2	1

in charge of pricing and marketing has changed. We compile a first 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.

Our second source of data is SDC Platinum, a database that reports deals between firms. We isolate a subsample of the database containing deals that involve at least one company in our data or whose description includes the name of a drug in our sample.

We then perform a manual match of the two databases, confirm details of each deal manually by searching press-releases and other publicly available documents online. Through this process we also fill in additional details, such as the financial terms of the deal.

Finally, from this set of transactions, we drop purely financial deals (such as cash payments or royalty streams) that do not involve the transfer of marketing rights and deals that only involve drugs whose patents had already expired.

2.2 Characteristics of M&A Activity in the Pharmaceutical Market

Our final dataset includes 150 deals involving the marketing rights of 261 distinct patent-protected branded drugs, representing around one third of all drugs in our sample. 42 drugs are acquired more than once, with one product acquired four times.

²⁴Data available for 110 out of 150 deals

Table 1 presents some basic summary statistics. M&A activity in the pharmaceutical market presents significant heterogeneity in the dollar value associated with the transaction and the sizes of the companies involved. The average acquisition has a value of approximately \$5.3 billion. However, this masks substantial variation. Our data includes a handful of very large mergers—such as the Merck-Schering Plough merger of 2009, the Pfizer-Wyeth merger of 2009, and the Actavis-Allergan merger of 2015—as well as many acquisitions of drugs either with low sales or that are close to loss-of-exclusivity. Figure 2 provides a different visualization of these patterns, by arranging deals according to the size of the target and acquiring companies (measured by net sales in the four quarters prior to the acquisition), and the future stream of sales of the assets involved.

We highlight two interesting patterns. First, only about 25 percent of acquisitions would classify as traditional horizontal acquisitions—that is, acquisitions that combine substitute products—while the rest are best classified as cross-market acquisitions. We define substitutes as drugs sharing the same 3-digit Anatomical Therapeutic Chemical code (ATC-3), a common classification used in the economics literature. The first three digits of the ATC code define the anatomic and therapeutic/pharmacologic subgroup of a drug. Most drugs have 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 real substitute products (type II error).²⁵

While cross-market acquisitions are generally thought to be less problematic for antitrust, this conventional wisdom has been challenged in recent years (Dafny et al., 2019; Kleiner et al., 2022), leading to renewed scrutiny on these kinds of deals from the FTC, including the recent challenge of the acquisition of Horizon Pharmaceuticals by Amgen.²⁶ This provides additional motivation for our analysis.

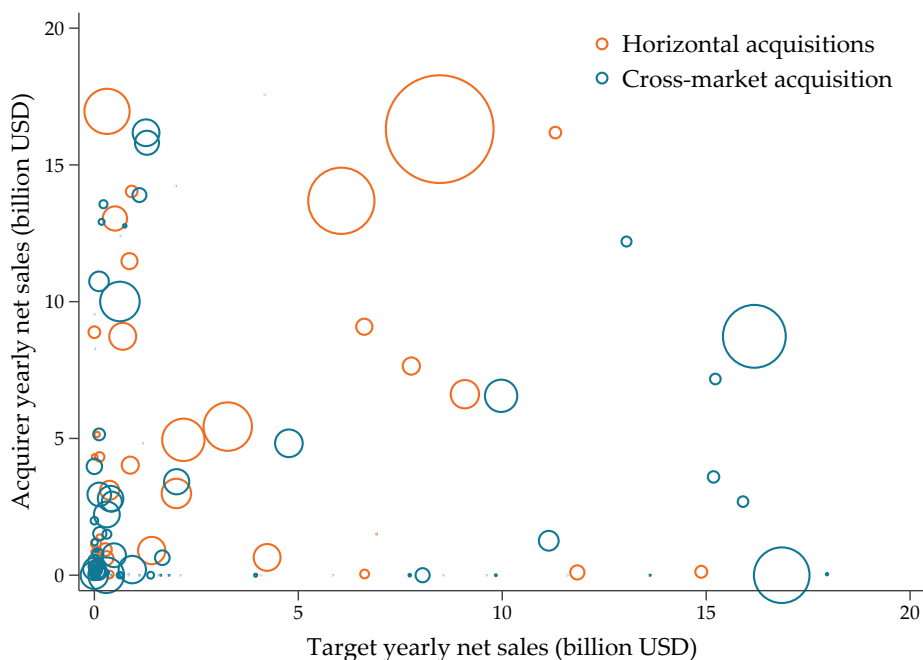
Second, it is not uncommon for small companies to acquire drugs owned by a larger company. These deals, which appear on the bottom-right of Figure 2, are often single-drug acquisitions and tend to be smaller than average.

Finally, Table 2 reports some basic summary statistics on the acquired drugs in our sample, and compares them to drugs that were never acquired. Drugs that are acquired

²⁵As a robustness check, we repeat our analysis of horizontal acquisitions using ATC-4 as the definition of therapeutic class. We recover almost identical results (see Appendix B.6).

²⁶See the FTC's 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.

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 invoice sales in the quarter immediately 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 cross-market acquisitions. Finally, the size of each marker is proportional to the total invoice sales of all drugs acquired in the year immediately following the acquisition.*

experience faster list and net price growth, but have lower net sales, and comparable formulary coverage to other drugs.

3 Methodological Approach

We use a matching-based approach to estimate the impact of mergers on market outcomes. 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 select control drugs that: (i) share the same general therapeutic area, measured by ATC-1 code, as drug j ; (ii) have been on the market a similar number of years (“age”) at the time of acquisition k ; and (iii) in the year prior to acquisition k generate similar revenue.²⁷ This helps con-

²⁷We measure age as years from launch and revenue using sales net of rebates.

	Non-acquired drugs		Acquired drugs					
			Overall		Acquired by larger company		Acquired by smaller company	
	median	IQR	median	IQR	median	IQR	median	IQR
Avg. net sales (million USD)	195.99	[45.80; 584.60]	152.00	[40.10; 367.25]	155.20	[41.00; 362.85]	123.62	[26.37; 387.70]
Annual WAC growth	6.80%	[2.4%; 11.4%]	8.70%	[3.5%; 13.9%]	8.50%	[3.3%; 13.8%]	9.90%	[5.4%; 15.4%]
Annual net price growth	3.30%	[-5.5%; 11.8%]	5.30%	[-4.2%; 16.0%]	5.20%	[-4.2%; 16.1%]	7.30%	[-3.4%; 18.7%]
Fraction covered	0.85	[0.76; 0.94]	0.84	[0.77; 0.92]	0.84	[0.77; 0.92]	0.83	[0.77; 0.93]
Fraction unrestricted	0.67	[0.43; 0.78]	0.68	[0.50; 0.77]	0.68	[0.51; 0.77]	0.61	[0.44; 0.73]
Fraction preferred	0.14	[0.05; 0.30]	0.14	[0.06; 0.29]	0.13	[0.06; 0.28]	0.14	[0.05; 0.28]
N	683		243		198		58	

Note: all statistics reported at the drug-year level.

Table 2: Summary statistics for drugs in our sample

trol for general trends in different therapeutic areas, secular lifecycle trends in market outcomes, and differences between small and large drugs.²⁸

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 (Roth et al., 2023). The main concern with this assumption is that acquisitions are not random, and acquiring companies may be targeting drugs with better long-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, which is discussed in detail in Appendix B.7, return estimates that are similar to those found in our main specification. The second assumption is that the drugs included in the control group are not affected 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). We do not find any evidence of spillover effects in our analysis. We also note that if such as spillover existed, it would most likely generate a conservative bias on our coefficients of interest.

In order to obtain reliable estimates, we also require that the treated drug report data in the year before and year after the acquisition (for a total of at least three years of

²⁸We require each matched control sample to have at least five drugs. If we cannot find a sample that is sufficiently large, we drop the revenue requirement. When that is not enough either, we drop the ATC-1 requirement. We exclude from the matched control any drug that was acquired, and drugs that are owned by companies who make a horizontal acquisition below the HSR threshold and that share the same ATC-3 code with an acquired drug, because we estimate that these drugs also experience an increase in price.

data). Imposing these requirements reduces our overall sample of events to 178 drugs-acquisition pairs. Of these, 71 are matched based on age and year, 79 are matched based on age, year, and ATC-1, and 18 are matched based on age, ATC-1, and revenue.

Using the matched samples, we conduct a difference-in-difference analysis. Formally, we run regressions of the form:

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

where j indexes the drug, t indexes the year, and k the drug involved in the acquisition event. α_j are drug fixed effect, Post_t is an indicator for time periods after the acquisition, and $\beta_{1,k}$ is the main coefficient of interest. The outcomes we study include net price, volume sold, and population-weighted average formulary tier. We apply a log transformation to the first two variables. We also report results on list price, net sales, and other formulary coverage variables (fraction covered, fraction unrestricted, and fraction preferred) in Appendix B.1. We do not include year fixed-effects because each matched control panel is balanced on years. We include the three years before and after the acquisition and exclude the year of the acquisition. The exclusion accounts for the fact that acquisitions happen at different times during the year, and we do not want to make an assumption as to when the price can respond.

To aggregate the estimates from our individual event-study regressions, we calculate the average effect of all acquisitions (or subgroups of acquisitions with similar characteristics). The average effect is conceptually equivalent to the output of a stacked regression, but with the advantage of being able to use custom weights to calculate more efficient averages. In our case, we weigh each coefficient by the inverse of its standard error. This returns our best estimate as

$$\hat{\beta}_1 = \frac{\sum_k \frac{1}{\hat{\sigma}_{2,k}^2} \hat{\beta}_{1,k}}{\sum_k \frac{1}{\hat{\sigma}_{2,k}^2}} \quad (2)$$

where $\hat{\sigma}_{2,k}$ is the (estimated) standard error of $\hat{\beta}_{1,k}$. The standard error of equation 2 is

$$\hat{\sigma}_1 = \sqrt{\frac{1}{\sum_k \frac{1}{\hat{\sigma}_{2,k}^2}}} \quad (3)$$

To illustrate the variation in response size across deals, we plot the distribution of coefficients $\hat{\beta}_{1,k}$. To help distinguish between noise and signal in the coefficients, 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.

As an alternative approach, and to evaluate how prices evolve over time after acquisitions, we estimate effects using approaches suggested by the recent two-way fixed-effects (TWFE) literature. We provide both simple estimates of the level change in the outcome variable and also follow [Sun and Abraham \(2021\)](#) in estimating time-varying treatment effects. These analyses yield very similar results to our main approach, and we report them in [Appendix B.5](#).

4 Price and Access Response to Horizontal Acquisitions

We present estimates associated with horizontal acquisitions, which standard theory predicts to have inflationary effects. In addition, we also study volume and insurance coverage effects to gain a more complete picture of the effect of acquisitions. Finally, we provide breakdowns by whether the value associated with the deal falls below FTC reporting thresholds, in order to assess the role played by regulators.

4.1 Effect on Net Price

[Figure 3](#) plots the distribution of the treatment effects for horizontal acquisitions, based on a sample size of 50 drug-year events. We find that these events have a large but imprecisely-estimated positive effect on price. The weighted average effect is 0.20, corresponding to roughly a 22 percent increase, but with a standard error of 0.20.

The majority of 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. The FTC screens these deals to prevent anti-competitive ones from being carried out. As a result, most of the deals in the sample are likely selected to have a small effect.

To eliminate the role of selection, we isolate deals below the HSR threshold, and plot their distribution separately in [Figure 4](#).²⁹ The results suggest that selection plays a big role. The eight products acquired in deals that fall below the HSR threshold experience an average increase in log net price of 0.5, corresponding to a 65 percent in-

²⁹We do not know the value of every deal. We treat missing values as if their value was above the HSR threshold. Only two horizontal acquisition have missing values. Including them in either sample does not affect the results.

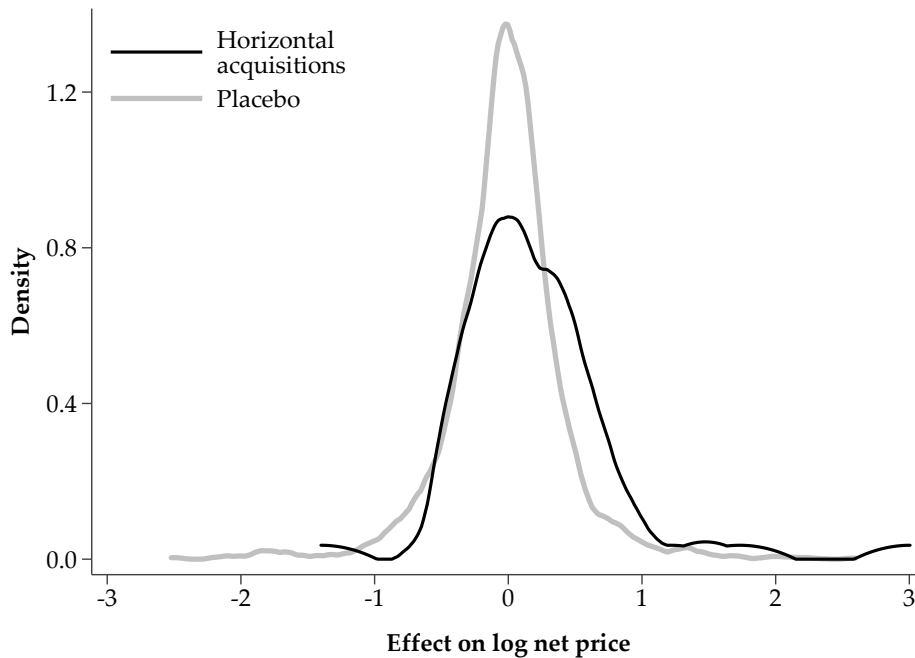


Figure 3: Distribution of net price changes across horizontal acquisitions

crease in net price. The effect is statistically significant, with a standard error of 0.19. Conversely, deals above the HSR threshold experience an average increase of 0.14 (or a 15 percent increase in net price). The difference between the two estimates is statistically significant, and the latter estimate is not statistically significant from 0 (standard error is 0.20).

4.2 Effect on Access: Volume and Formulary

We also examine the impact of horizontal acquisitions on volume sold and formulary access, in order to better understand market structure and implications for patient welfare.

Figure 5 plots the distribution of volume (Panel A) and coverage (Panel B) for horizontal acquisitions below and above the HSR threshold, as well as the placebo distribution. Overall, horizontal acquisitions result in slightly lower volume sold and worse formulary coverage. However, unlike with net price, we do not find obvious differences across the two types of acquisitions. The distributions for both the volume and coverage effects are similar and centered around slightly more negative values than the placebo distribution, but, when we calculate efficient averages, these effects appear to

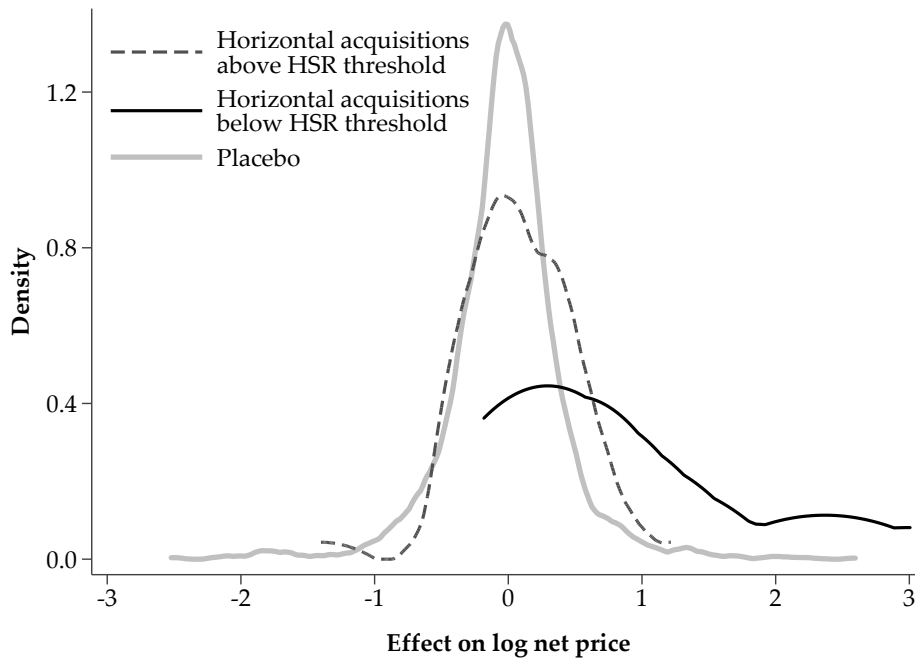


Figure 4: Distribution of net price changes across horizontal acquisitions; deals above and below the HSR threshold

be noisy and not statistically different from zero.³⁰ Deals above the HSR threshold are followed by lower volume sold and formulary coverage, but both estimates are imprecise.

4.3 Spillover effects of Horizontal Acquisitions

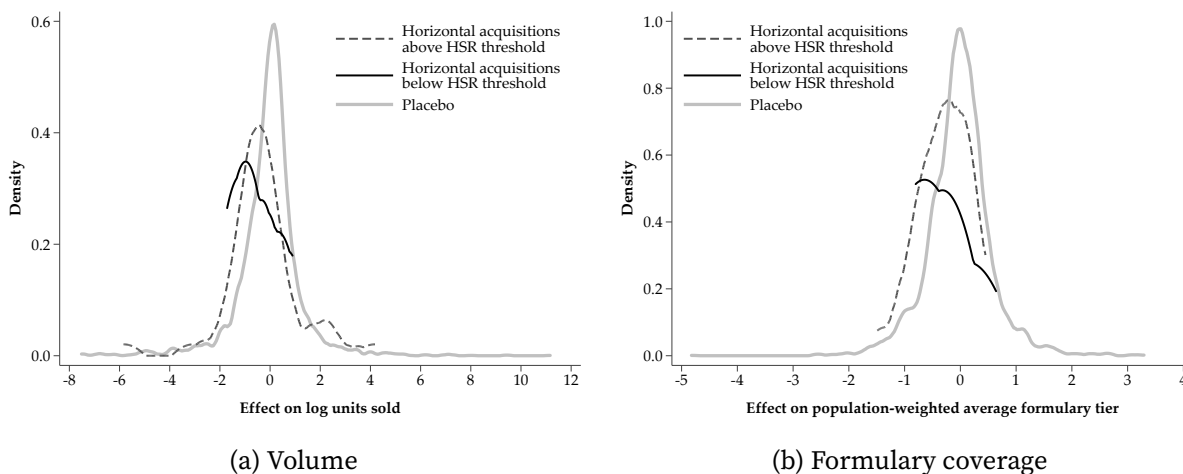
Overall, the evidence from the last two sections suggests that firms that make acquisitions that are not subject to close regulatory scrutiny can achieve large price increases without losing volume and formulary coverage. Conversely, deals that are scrutinized by regulatory authorities have a much smaller impact on price.

Next, we investigate spillover effects of small horizontal acquisitions. We study drugs owned by the acquiring company that share at least one ATC-3 code with the acquired drugs. Figure 6 plots the distribution of our results, based on a sample of ten drug-year events.

We find that these products experience a sharp increase in price as well, albeit a noisier one. The estimated average effect is 0.36, or a 43 percent increase in price, but

³⁰We report these results and others in a summary table in Appendix B.4 (Table 4).

Figure 5: Distribution of volume and coverage changes across horizontal acquisitions; deals above and below the HSR threshold



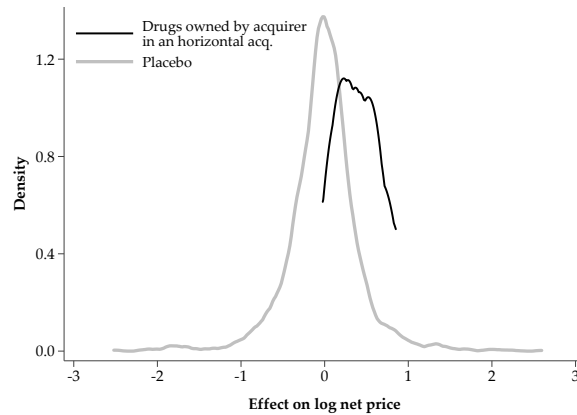
with a standard error of 0.28. As in the case of acquired products, we find that, while the distributions suggest an increase in volume and a decline in formulary coverage, neither of the estimates is distinguishable from zero.

Appendix B.2 reports estimates of the response of other products that compete with the acquired products, but are not directly involved in the deal. The price of drugs in the same ATC-3 where a stealth acquisition took place experience an average declines in log net price by 0.05, with a standard error of 0.19. Drugs with the same ATC-4 as drugs directly involved in the deal (either acquired or owned by the acquiring company) experience an average decrease in log price of 0.04, with a standard error of 0.23. These results suggest that any spillover effects of these deals are likely to be small.

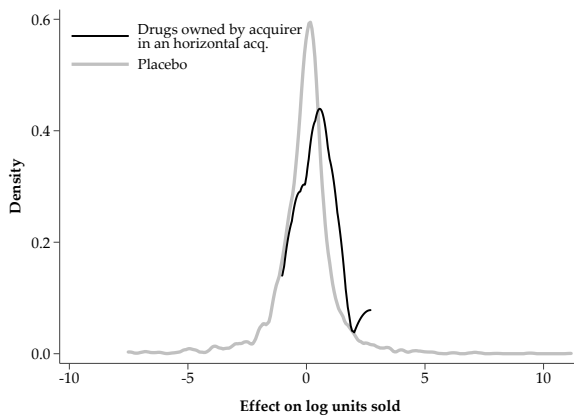
4.4 Discussion: why do stealth acquisitions have a much larger effect on price?

Our analysis of the effect of horizontal acquisitions of patent-protected branded drugs uncovers a stark difference between stealth acquisitions and acquisitions that were disclosed to the FTC, despite the fact that both sets of acquisitions include drugs that share the same ATC-3 code. This difference raises an important question: what characteristics of stealth acquisitions make them more likely to have an inflationary effect?

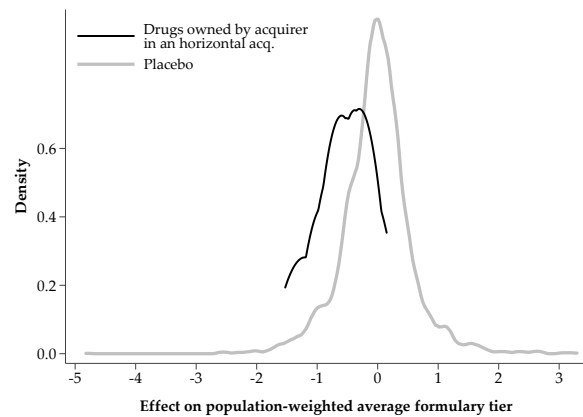
We conjecture that stealth acquisitions are unobservably more likely to include drugs that are closer substitutes, even within an ATC-3 code. To confirm this intuition,



(a) Net Price



(b) Volume



(c) Formulary coverage

Figure 6: Distribution of net price changes across horizontal acquisitions; products owned by the acquiring company

we use a different classification variable, provided to us as part of the MMIT dataset. This classification does not depend on the ATC code, and is much more granular than ATC-3.³¹ We find that 37.5 percent (3 out of 8 products) of stealth acquisitions but only 6.8 percent (3 out of 44) of regular acquisitions result in overlaps at the MMIT Therapeutic Class level.³²

Our interpretation of this suggestive evidence is that drug manufacturers are much less likely to engage in horizontal acquisitions of closely related products when they

³¹In our product sample there are 175 distinct ATC-3 codes and 509 unique Therapeutic Classes as defined by MMIT.

³²Stealth acquisitions are also slightly more likely to overlap in ATC-4 (50 percent, or 4 out of 8, versus 36 percent, or 16 out of 44).

have to disclose the acquisition to the FTC—presumably because they expect the FTC to block it, or to require divestments that would negate the strategic gains from the acquisition.³³

5 Effect of Cross-Market Acquisition

In our second set of analyses, we study acquisitions of drugs in different markets. These acquisitions represent the vast majority of the deals in our sample.

5.1 Portfolio Bargaining: Evidence from Exclusions

While cross-market acquisitions are generally thought to be less problematic than horizontal acquisitions for antitrust purposes, recent models of portfolio bargaining based on negotiations between hospitals and insurers suggest that these kind of acquisitions can lead to higher prices under some conditions.

The key insight of the bargaining literature is that a firm that owns products across multiple market can extract higher prices in negotiations under three conditions. The first condition is that the products must have a common customer. In the case of hospitals and insurers, the common customer might be an employer with offices in multiple locations. In the case of the pharmaceutical market, the case is even more clear cut: every insurer offers plans that must cover drugs across all therapeutic areas. The second condition is that the firm must be willing to bundle products across markets and withdraw them from the negotiation unless they are all covered on the formulary. The third and final condition is that the payer's payoff function is concave in the number of drugs covered. In other words, the losses from losing access to multiple drugs is higher than the sum of losses from losing each drug individually.

In our data, we see only partial evidence that this second condition might hold for pharmaceutical companies. Using our formulary data, we find that most formulary exclusions affect drugs whose marketing company also owns other products included in the formulary (Figure 7). Exclusions of a company's entire portfolios are very rare, and almost entirely confined to firms marketing 2 or 3 drugs.³⁴

³³We consider this to be primarily a selection-into-acquisition effect because the FTC has not blocked any proposed pharmaceutical acquisitions in a long time, although it recently sued to block the proposed Amgen-Horizon merger.

³⁴These firms represent around 80 percent of all full exclusion events.

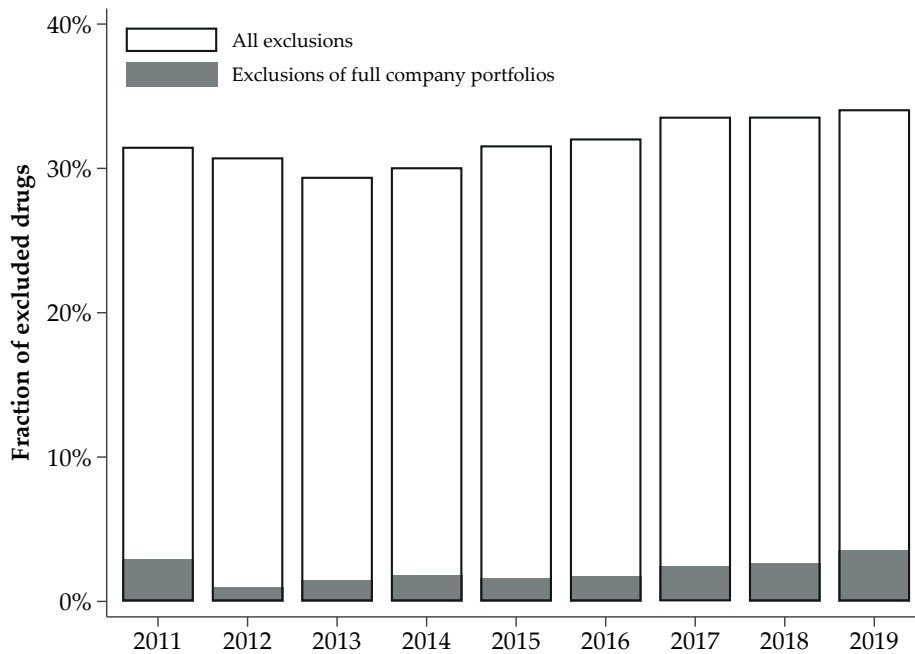


Figure 7: Exclusion rate of drugs across formularies

Even though full formulary exclusion appears rare, we note that partial cross-market tie-ins may still occur. To test whether partial tie-ins exist, we look for evidence of joint partial exclusions within a firm’s portfolio. To do so, 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 excluded. As controls we include year, drug, and formulary fixed effects. The results suggest a weak, but statistically significant effect that implies that a products are approximately 2 percent more likely to be excluded if they are owned by a company that has another excluded product (Table 3). We stress, however, that this evidence is purely correlational. Ultimately, the question of whether cross-market deals can lead to higher prices remains an empirical one.

5.2 Impact of cross-market acquisitions by larger companies

To test for the presence of portfolio effects, we examine cross-market deals where the acquirer is a larger company. To identify such deals, we create a binary “larger acquirer” classification based on a comparison of the net sales of the acquiring and target companies in the four quarters prior to the acquisition. We also include in this

Table 3: Correlation in Exclusion Rates at the Company-Formulary-Year level

	(1)	(2)	(3)
Indicator for other excluded product from the same company	0.0622 (0.0005)	0.0191 (0.0006)	0.0237 (0.0006)
Fixed effects	Drug, Year, Formulary	Drug, Formulary-Year	Drug-Year, Formulary-Year
Observations	4,777,663	4,777,663	4,777,663
R ²	0.439	0.459	0.494

sample all company acquisitions, because these types of deals will always result in the acquired products becoming part of larger portfolio.

Panel A of Figure 8 shows the distribution of the effect of cross-market acquisitions on price. The average effect is -0.003 —essentially zero. The distribution is also remarkably similar to the placebo distribution. However, the standard error of the average is large, at 0.21. The noisiness in the estimate means that while we do not find evidence of portfolio effects, we are unable to reject the possibility that cross-market acquisitions may have a small inflationary effect. Panels B and C of Figure 8 document responses in volume and coverage. Both distributions also match the placebo distribution very closely.

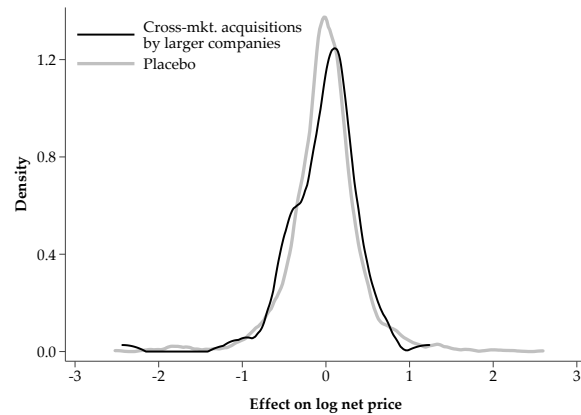
The lack of significant cross-market effects could be due to various structural aspects of pharmaceutical markets. We highlight three. First, as shown in the evidence on exclusions in Figure 7, drug companies do not appear to systematically negotiate over whole portfolios. This finding is consistent with qualitative evidence we collected through discussions with former PBM and pharmaceutical executives— all of whom noted that negotiations are typically conducted separately by disease area.³⁵ However, we note that partial bundling schemes that involve a subset of a company’s drugs.³⁶

Second, because the distribution and negotiation channels are separate, a PBM could disagree with a drug manufacturer, but still be able to have its enrollees access the drugs through a retail pharmacy at list price. This would make it very difficult for manufacturers to enforce full exclusion.³⁷ A more integrated system could potentially

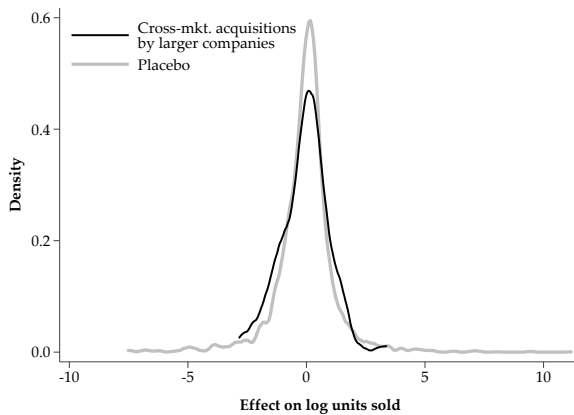
³⁵Many pharmaceutical companies are organized into divisions based on disease area, and there are often separate negotiation teams for each division.

³⁶See, e.g., the allegation in the recent Regeneron-Amgen lawsuit: <https://www.fiercepharma.com/pharma/regenerons-cholesterol-drug-war-heats-antitrust-lawsuit-over-amgens-bundling-scheme>, retrieved July 25, 2023.

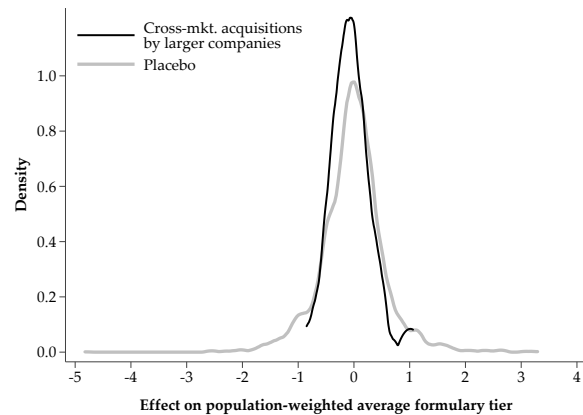
³⁷For the PBM, the only loss from the disagreement would be the lack of rebates, which would be less damaging than complete exclusion.



(a) Net Price



(b) Volume



(c) Formulary coverage

Figure 8: Distribution of changes in outcomes across acquisitions by larger companies

lead to larger cross-market effects.³⁸

Third, because payers are negotiating over hundreds of branded drugs, losing a few drugs from one manufacturer might not be enough to push the payer to a very concave part of its payoff function. Without concavity, cross-market effects disappear.

5.3 Discussion: why do cross-market acquisitions take place?

Our analysis of cross-market acquisitions uncovered very small effects, which raises the question of why so many cross-market acquisitions take place in the pharmaceu-

³⁸For example, if a drug manufacturer also owned a pharmacy, it could more credibly threaten to block access for a given PBM's enrollees. From 2013 to 2015, Valeant Pharmaceuticals owned a specialty pharmacy that was distributing its drugs: <https://www.nytimes.com/2015/10/31/business/valeant-pharmaceuticals-philidor.html>, retrieved July 25, 2023.

tical market. Based on our reading of press releases and articles surrounding various deals, we conclude that cross-market acquisitions of branded drugs roughly fall into four categories.

Acquisitions that arise as part of larger deals: The vast majority of cross-market acquisitions arise as a byproduct of larger deals that appear to have different targets. Oftentimes, the real target of the acquisition is a product in the R&D pipeline of the acquired company. For example, in 2017, Takeda Pharmaceutical acquired Ariad Pharmaceuticals for a little over \$5 billion dollars. Articles published around the time of the acquisition mention Ariad's sole marketed product, Iclusig (ponatinib, a drug approved for the treatment of leukemia), as an important asset in the transaction. However, Iclusig recorded only a little over \$100 million in US sales in 2016, an amount that likely does not justify the high price tag on the acquisition. Instead, Takeda's main target was likely Ariad's rich oncology pipeline, including brigatinib, a treatment for lung cancer in the final stages of development that was touted as a potential blockbuster at the time.³⁹

In several other instances, cross-market acquisitions arise from large mergers, such as Pfizer-Wyeth (2009, involves 11 products in our data), Merck-Schering-Plough (2009, involves 18 products), Allergan-Actavis (2015, involves 24 products), and Shire-Takeda (2019, involves 15 products). These mergers likely have strategic motivations that go beyond any individual drug market.

Acquisitions that lead to cost-efficiencies: These acquisitions closely resemble horizontal acquisitions, but appear based on cost efficiencies that can be achieved even when products are not substitutable. For example, in January 2014, Forest Laboratories acquired the marketing rights to the drug Saphris (asenapin maleate, ATC code N05AH05) from Merck Co.. In press releases announcing the deal, Merck Co. justified the divestiture as part of a cost-cutting plan. By selling Saphris, they were able to let go of about 150 members of their sales force.⁴⁰ Conversely, Forest may have been better positioned than Merck Co. to market Saphris, despite being a smaller company. Forest's portfolio at the time of the acquisition included several products targeting the central nervous system (CNS). Forest's CEO Brent Saunders explained the acquisition by stating: "We

³⁹See <https://www.reuters.com/article/us-ariad-pharm-m-a-takeda-pharma/japans-takeda-to-buy-u-s-cancer-drug-maker-ariad-in-5-2-billion-deal-idUSKBN14T1F7>, retrieved March 2023. Brigatinib launched in 2017 under the brand name Alunbrig, but did not bring in significant sales in the first three years after approval, peaking at \$44 million in 2019, the last year of our data.

⁴⁰See <https://www.fiercepharma.com/sales-and-marketing/merck-cutting-150-its-saphris-sales-team-after-selling-drug-to-forest-for-240m>, retrieved March 2023.

are pleased to gain access to another commercial product in the CNS category. With Viibryd and our soon to be launched product, Fetzima, Saphris complements our current position in psychiatry and gives us access to the important schizophrenia segment.”⁴¹ Note that, while the language suggests the existence of some form of synergy, it also rules out a direct horizontal motive by pointing to the schizophrenia segment as separate: both Viibryd (ATC code N06AX24) and Fetzima (ATC code N06AX28) are used to treat major depressive disorder.

Targeted acquisitions of potential blockbuster products: In several instances, larger companies will acquire small biotech companies that own assets they believe will be very successful in the future. For example, Celgene acquired Abraxane (paclitaxel) in 2010 through the acquisition of the company Abraxis Biosciences. At the time of acquisition, Abraxane was approved for breast cancer, but was also being tested in clinical trials for a series of additional indications.⁴² Celgene eventually obtained approval for lung cancer in 2012, and pancreatic cancer in 2013. These two additional indications helped grow net sales from around \$300 million in 2011 to about \$600 million in 2014, despite the net price of the treatment remaining relatively stable.

Acquisitions that return the marketing rights to the patent owner: In a few cases, acquisitions are best interpreted as deals that return the drug to the company that owns the underlying intellectual property. For example, Copaxone (glatiramer acetate) was developed by Teva (an Israeli company focused primarily on the generic market) but initially marketed in the US by other companies, because Teva lacked the necessary workforce to support its marketing.⁴³

6 Conclusion

Retrospective analyses of merger and acquisition (M&A) activities have long been a staple of economic research. In this study, we undertake a detailed retrospective analysis of the pharmaceutical market, an industry that has been receiving increased atten-

⁴¹See <https://www.businesswire.com/news/home/20131202005452/en/Forest-to-Acquire-U.S.-Marketing-Rights-to-Saphris%C2%AE-asenapine-from-Merck>, retrieved March 2023.

⁴²See <https://www.fiercebiotech.com/financials/celgene-strikes-2-9b-deal-to-acquire-abraxis>, retrieved March 2023.

⁴³See <https://www.thepharmaletter.com/article/sanofi-stops-marketing-teva-s-copaxone-in-usa>, retrieved March 2023.

tion from policymakers and regulators, partly because of underlying trends in price growth.

Our first contribution is to characterize the landscape of pharmaceutical M&A involving branded drugs. Transactions are quite frequent, and they exhibit significant heterogeneity in terms of transaction value and size of the acquirer. In addition, we find that only a small fraction of mergers consolidate drugs treating the same disease.

Our second contribution is to answer the questions of which mergers matter and how effective are regulators. Stealth mergers have a much greater impact on prices than any other type of merger, suggesting that regulators are effective at deterring inflationary transactions. Furthermore, our findings regarding cross-market acquisitions differ from analogous analyses of the hospital market ([Dafny et al., 2019](#)), suggesting that the impact of cross-market deals depends on market structure.

The results here complement work on upstream transactions in the industry. As noted above, a common motivation for mergers in the industry is to buy drug candidates before they are approved by the FDA, an issue studied in recent work. Future work can do more to incorporate both upstream and downstream merger motivations to provide a complete picture on how regulators affect industry dynamics. The impact of mergers on workers in the industry, particularly those driving innovation, also remains an open question.

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A Data Construction

A.1 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.⁴⁴

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 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.⁴⁵ 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.⁴⁶ However, un-

⁴⁴Symphony Health data are similar to the National Sales Perspective dataset from IQVIA.

⁴⁵IQVIA's National Sales Perspective Dataset suffers from similar issues, which are noted also in [Kakani et al. \(2020\)](#) and [? \(2020\)](#). 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.

⁴⁶In 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

derreporting 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.⁴⁷ 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.

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 9). While 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.⁴⁸

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 4 to the estimated coefficients when we do not winsorize net price (Figure 10). Almost all coefficients lay on the 45-degree line.

A.2 Calculation of formulary coverage

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 \(2019\)](#), which uses the same measure of formulary coverage.

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

acquisition in our core analysis.

⁴⁷We 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.

⁴⁸A 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.

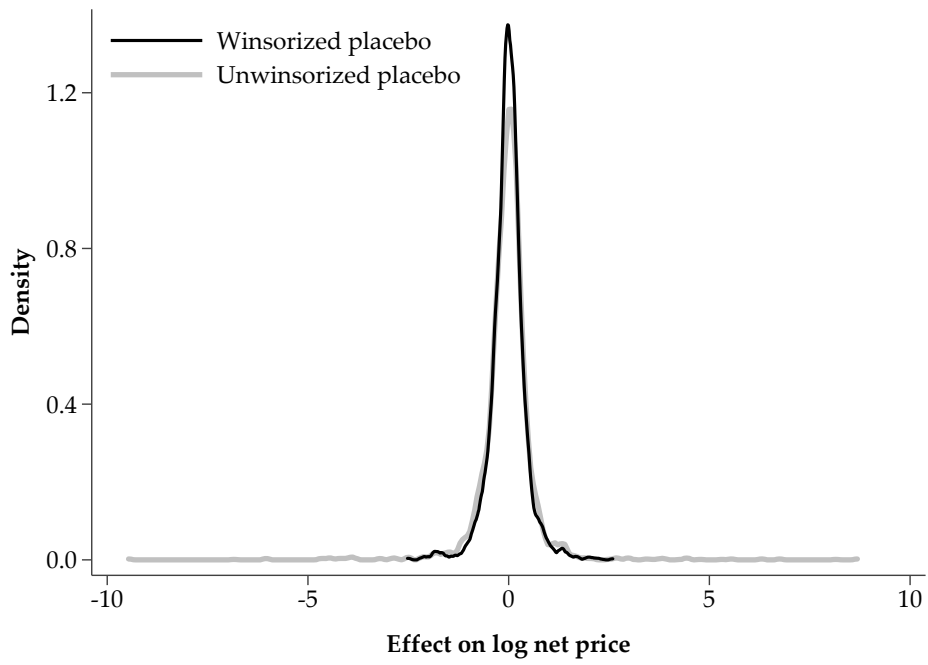


Figure 9: Placebo distribution with winsorized and unwinsorized net price

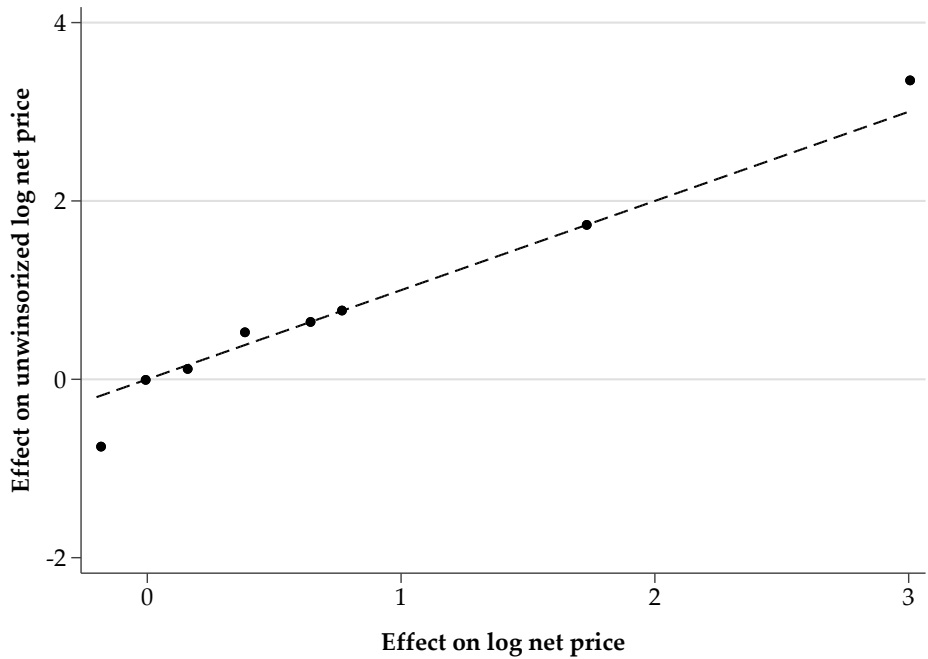


Figure 10: Effect of stealth horizontal acquisitions with winsorized and unwinsorized net price

- (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
- (a) Higher aggregate measures correspond to more generous coverage

B Additional Empirical Results and Robustness Checks

B.1 Impact of acquisitions on other variables

We report results on the impact of various type of acquisitions on list price. While 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. Hence, checking that list price and net 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.

Correlation between impact of acquisitions on net and list price

As a first robustness check, we regress the size of the effect of an acquisition on net price on the size of the effect on list price. Figure 11 displays the results. 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.

Effect of acquisitions on list price

Figures 12, 13, and 14 display how log list price changes (i) after a horizontal acquisition below and above the HSR threshold, (ii) after a horizontal acquisition below the HSR threshold for drugs owned by the acquiring company, and (iii) after a cross-market acquisition by a larger company. All three graphs closely mimic the results of their corresponding figures in the main text (Figures 4, 6, Panel A, and 8 respectively).

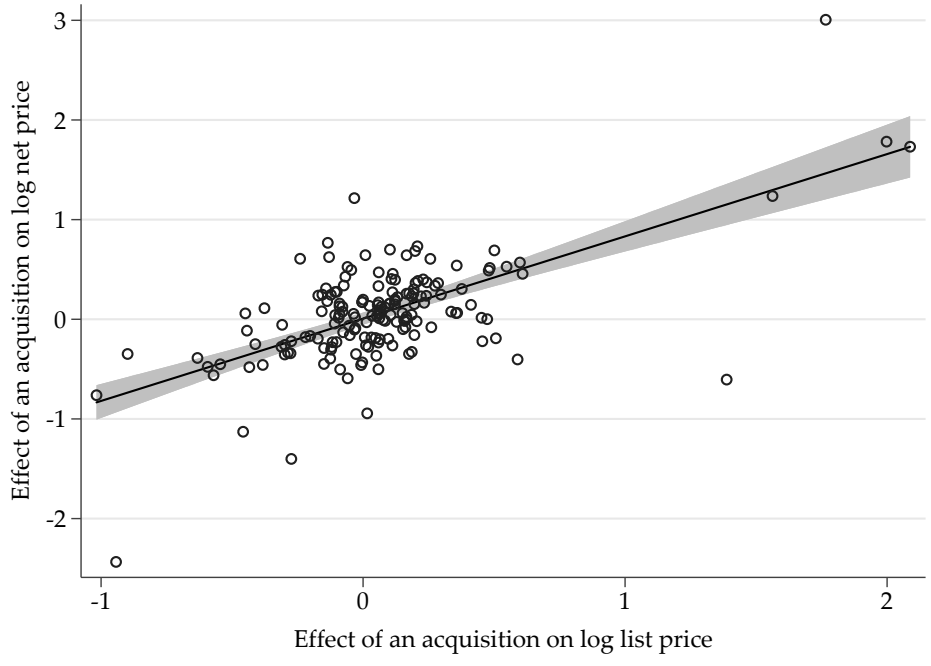


Figure 11: Correlation between effect of acquisition on net and list price

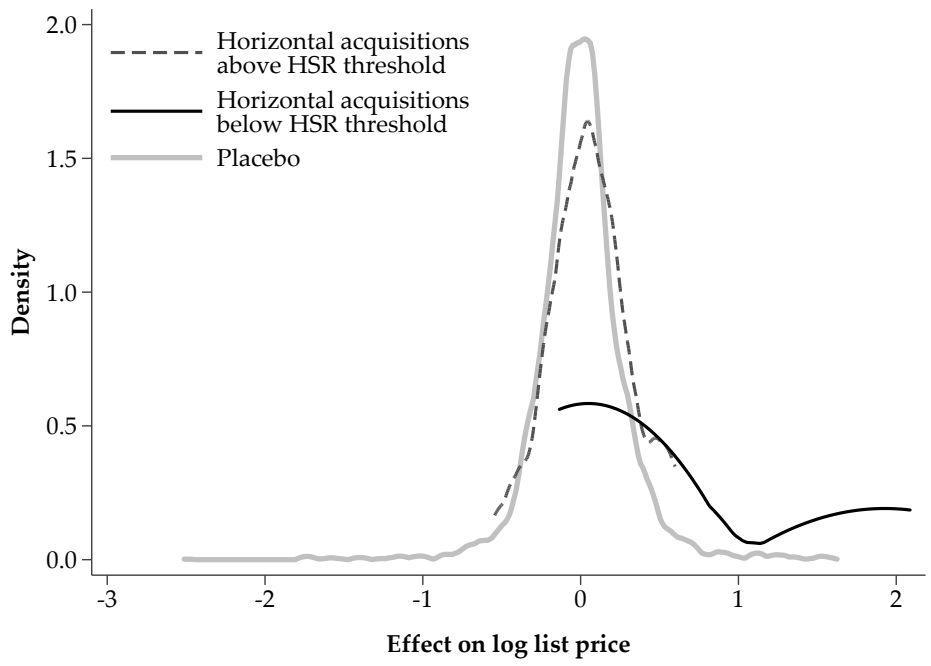


Figure 12: Distribution of list price changes across horizontal acquisitions; deals above and below the HSR threshold

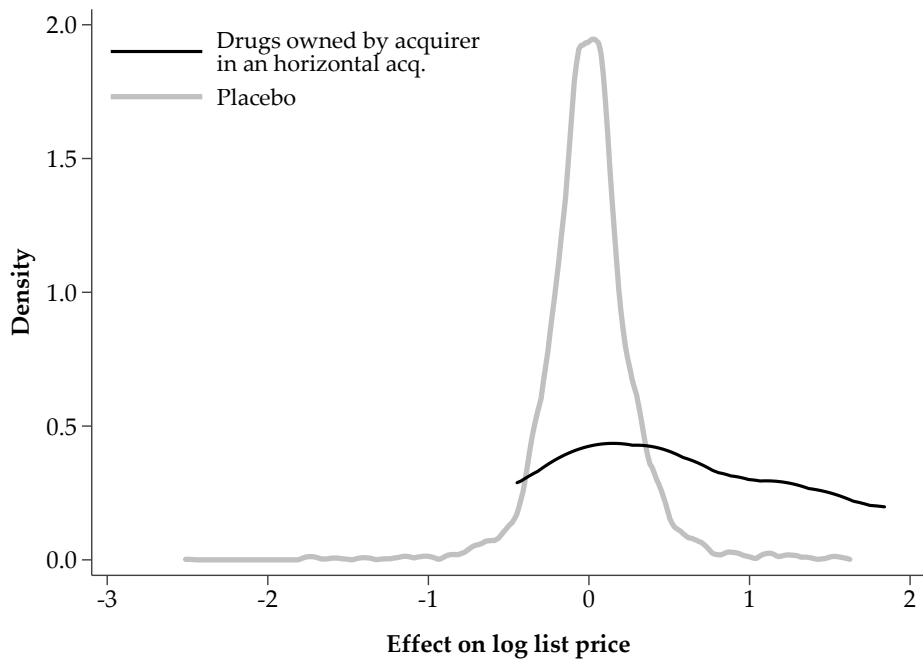


Figure 13: Distribution of list price changes across horizontal acquisitions; drugs owned by acquirer in deals below the HSR threshold

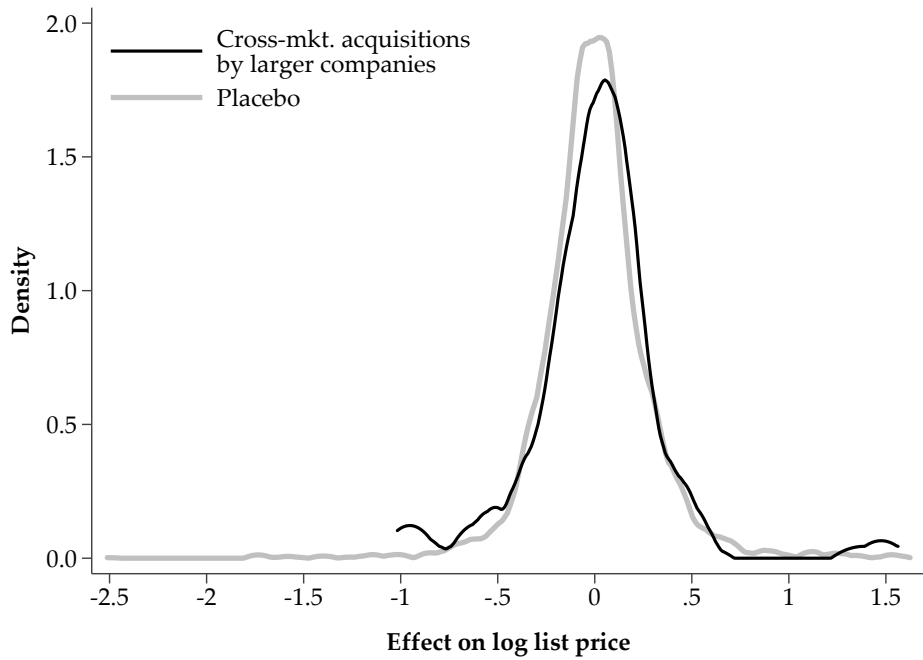


Figure 14: Distribution of list price changes across acquisitions by larger companies

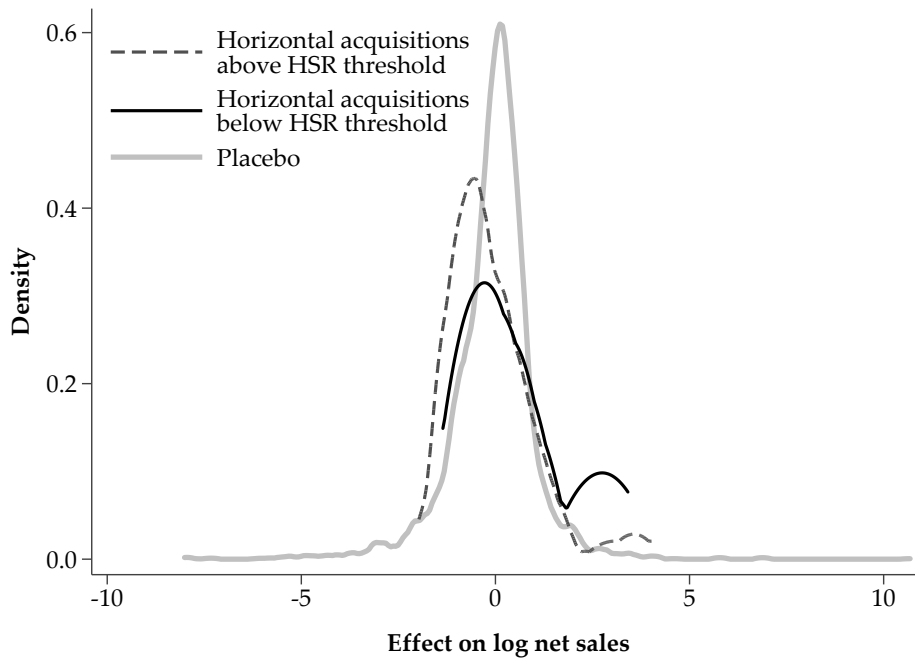


Figure 15: Distribution of net sales changes across horizontal acquisitions; deals above and below the HSR threshold

Impact of acquisitions on net sales

Figures 15, 16, and 17 show how log net sales change: (i) after a horizontal acquisition below and above the HSR threshold, (ii) after a horizontal acquisition below the HSR threshold for drugs owned by the acquiring company; and (iii) after a cross-market acquisition by a larger company. The results are noisy, but the distributions suggest that only a fraction of horizontal acquisitions below the HSR threshold translate higher prices into higher sales for either the acquired product or the product owned by the acquiring company. As expected given the results on net price, we do not detect any effect of cross-market acquisitions on net sales.

B.2 Spillover effects of acquisitions on competing drugs

Our main results show that horizontal acquisitions below the HSR threshold result in much higher prices. In this section, we check whether competing products that are not involved in these acquisition react to these changes in price. We select two types

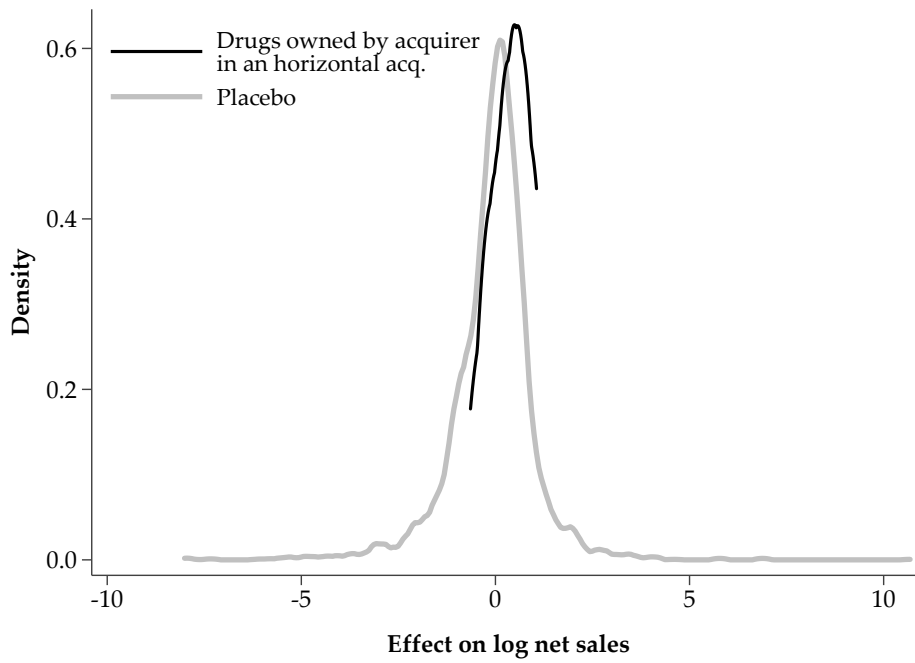


Figure 16: Distribution of net sales changes across horizontal acquisitions; drugs owned by acquirer in deals below the HSR threshold

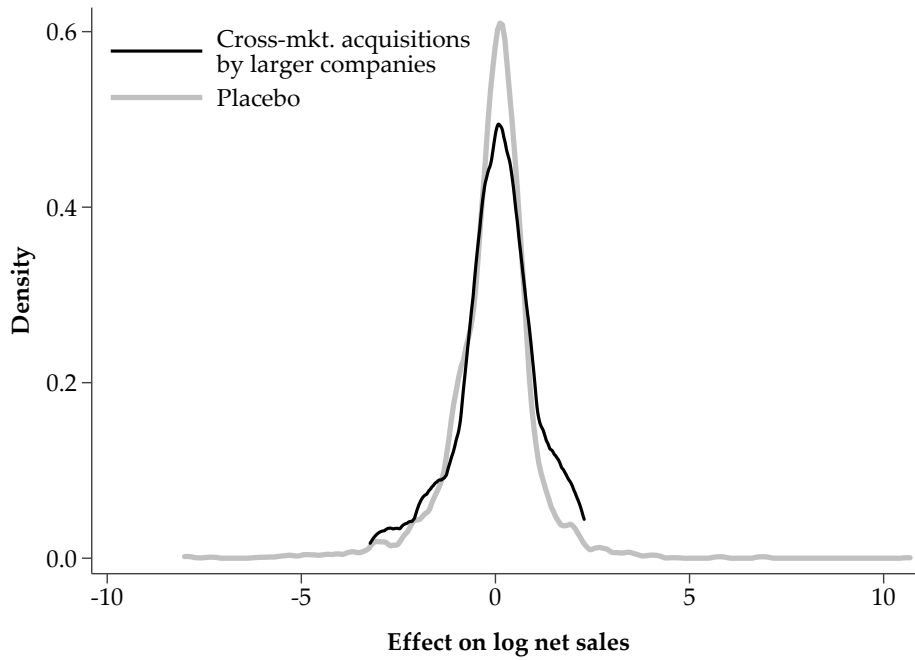
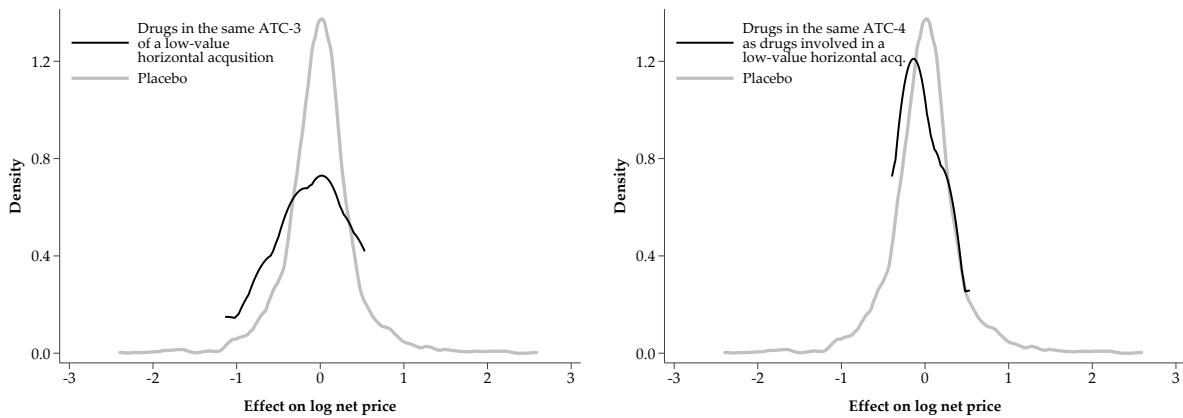


Figure 17: Distribution of list price changes across acquisitions by larger companies

Figure 18: Spillover Effects of Horizontal Acquisitions Below the HSR Threshold



(a) Spillover effect on other drugs in the ATC-3 where the horizontal acquisition took place
 (b) Spillover effect on other drugs sharing the same ATC-4 as drugs involved in the acquisition

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 18 displays our results for the two groups in Panel A and B, respectively. Our estimated coefficient for both groups is -0.05 —a small effect that is not distinguishable from zero.

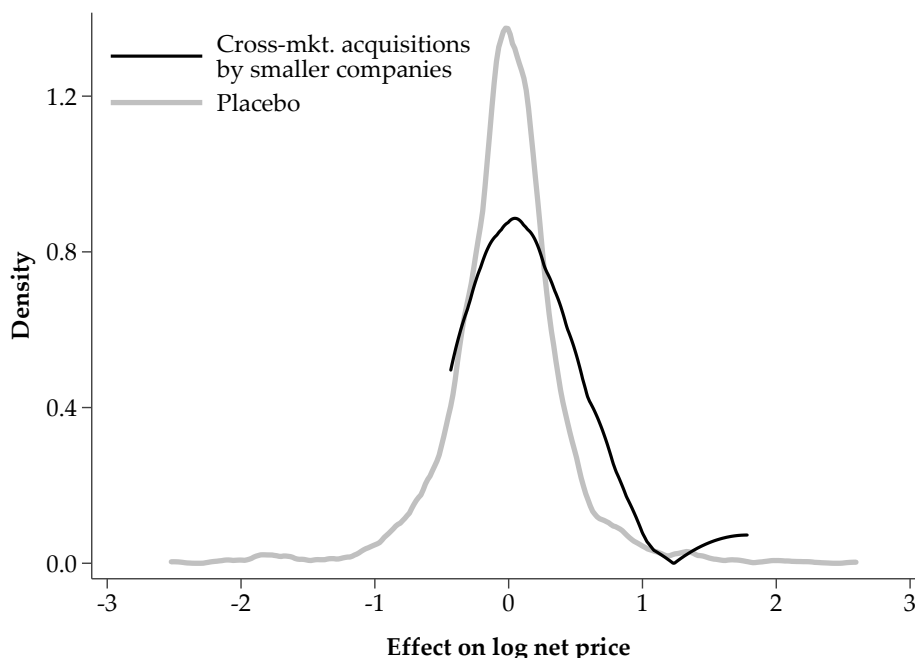
B.3 Acquisitions by smaller companies

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.

While the average effect of these acquisitions is not statistically distinguishable from zero (0.14 ± 0.22), we do find that the distribution of net price effects is shifted to the right relative to the placebo distribution (Figure 19).⁴⁹ We also find a decline in both volume (-0.67 , std. err. 0.40) and formulary coverage (-0.19 , std. err. 0.36). Figure 20 plots the distributions of these two effects. These effect suggest the existence of a selection channel whereby larger companies sell off under-performing assets to

⁴⁹A single outlier, the acquisition of Actimmune by in 2012, seems to drive a large fraction of this effect, though even without this outlier, the average would still remain positive, at 0.09 with a 0.21 standard error.

Figure 19: Distribution of net price changes across acquisitions by smaller companies



smaller companies.

B.4 Summary of average acquisition effects

B.5 Results from two-way fixed effects regression analyses

In this section, we replicate the key results of our analysis using TWFE regressions time-varying treatment effects. Following [Sun and Abraham \(2021\)](#), we estimate a regression of the form

$$y_{jt} = \alpha_i + \theta_t + \beta_t \times X_{it} \times \mathbb{I}_t + \varepsilon_{it}$$

where X_{it} is a matrix of counters for involvement in different types of deals, assuming that each type of deal has the same constant effect. We also report coefficients from a more traditional two-way fixed effect regression.

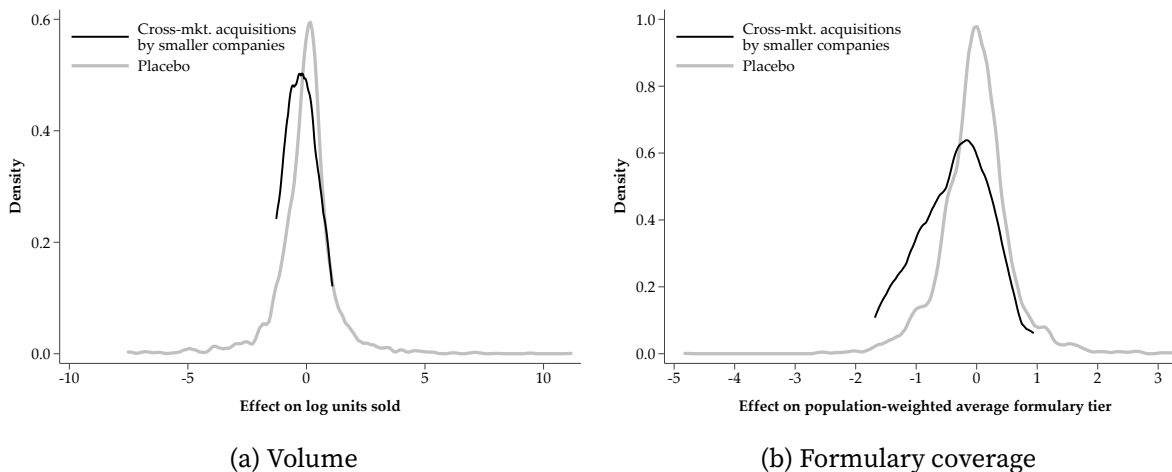
Impact of horizontal acquisitions below the HSR threshold

Figure 21 reports the change in net price following a horizontal acquisition below the HSR threshold for both acquired products (Panel A) and products owned by the acquiring company (Panel B). In both cases, we see a clear increase in net price after the

	Acquired in horizontal acquisition above the HSR threshold	Acquired in horizontal acquisition below the HSR threshold	Owned by acquirer in horizontal acquisition below the HSR threshold	Acquired in cross-market acquisition by larger company	Acquired in cross-market acquisition by smaller company	Same ATC-3 as a horizontal acquisition below the HSR threshold	Same ATC-4 as a drug involved in horizontal acquisition below the HSR threshold
Log net price	0.14 (0.20)	0.5 (0.19)	0.36 (0.28)	-0.003 (0.21)	0.13 (0.22)	-0.05 (0.19)	-0.04 (0.23)
Log list price	0.04 (0.14)	0.09 (0.17)	0.52 (0.17)	0.01 (0.13)	0.22 (0.14)	0.07 (0.11)	0.09 (0.10)
Log units sold	-0.76 (0.38)	-0.27 (0.38)	0.11 (0.70)	-0.104 (0.35)	-0.66 (0.40)	-0.71 (0.50)	-0.28 (0.55)
Log net sales	-0.33 (0.40)	-0.28 (0.45)	0.16 (0.56)	0.13 (0.38)	-0.42 (0.30)	-0.58 (0.51)	-0.25 (0.70)
Coverage rate	-0.19 (0.32)	-0.01 (0.30)	-0.58 (0.41)	-0.06 (0.33)	-0.30 (0.33)	-0.01 (0.29)	0.09 (0.27)

Table 4: Summary of average acquisition effects

Figure 20: Distribution of volume and coverage changes across acquisitions by smaller companies



year of the acquisition and no obvious pre-trends. The coefficients we recover from the traditional TWFE regression (Table 5) are also almost identical to the average effects estimated in the main text.

Impact of cross-market acquisitions

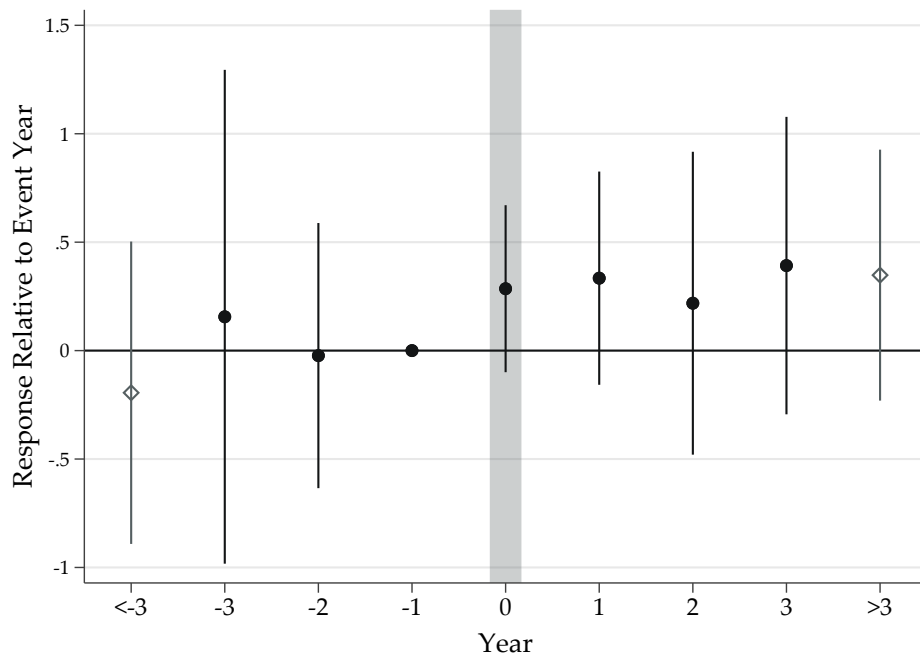
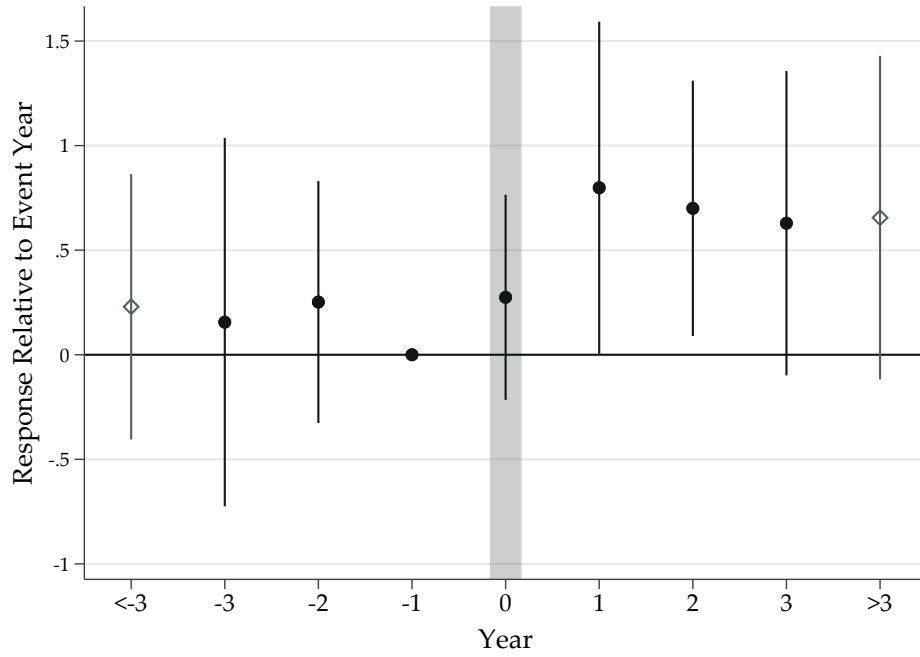
Figure 22 reports the change in net price following a cross-market acquisition by a larger company. Consistent with our main results, we do not detect an effect of cross-market acquisitions on net price. The plot also suggests the existence of some pre-trend in price. This result is also confirmed by the traditional TWFE regression, which shows a small, but insignificant effect on price.

B.6 Using ATC-4 as definition of class for horizontal acquisitions

As a robustness check, we replicate Figures 3 and 4 using ATC-4 as the definition of therapeutic class (rather than ATC-4). While this definition results in a much smaller set of deals (18 deals, of which 4 fall below the HSR threshold), the results are almost identical to our main analysis (Figure 23).

Figure 21: Effect of horizontal acquisition below the HSR threshold on net price

(a) Acquired drugs



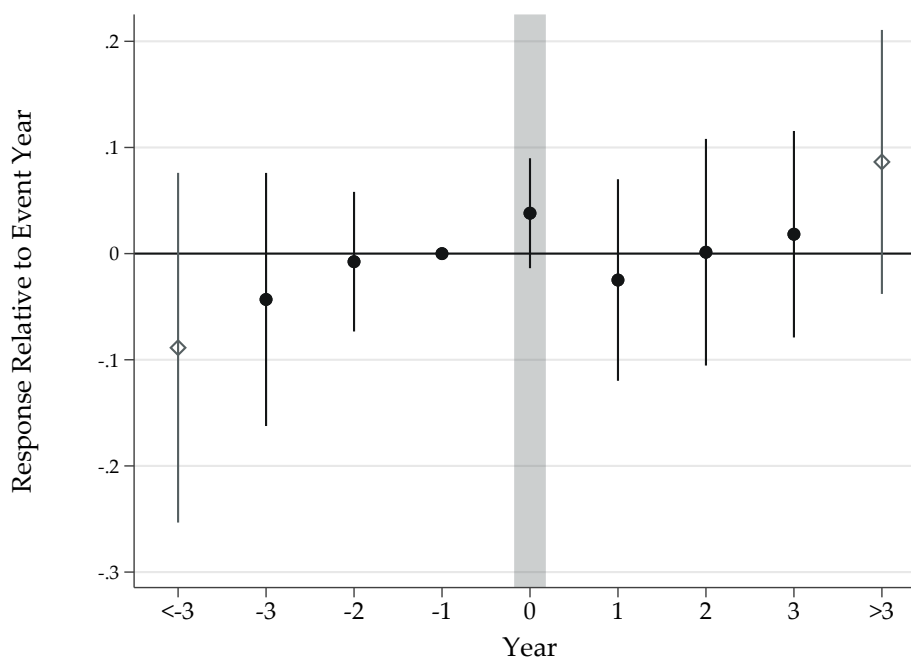
(b) Drugs owned by the acquiring company

	(1)	(2)	(3)	(4)	(5)
	Log net price	Log list price	Log units sold	Log net sales	Coverage
Acquired	0.0765 (0.0412)	0.128 (0.0320)	-0.182 (0.100)	0.0862 (0.0985)	-0.119 (0.0423)
Owned-by-acquirer	0.0491 (0.0202)	0.00118 (0.0213)	-0.131 (0.0665)	-0.125 (0.0497)	-0.00439 (0.0277)
Acquired in horizontal acquisition below the HSR threshold	0.513 (0.231)	0.297 (0.176)	0.0703 (0.425)	0.431 (0.612)	0.192 (0.176)
Owned-by-acquirer in horizontal acquisition below the HSR threshold	0.354 (0.140)	0.684 (0.206)	0.705 (0.540)	0.724 (0.321)	-0.531 (0.0842)
Product FE	X	X	X	X	X
Year FE	X	X			
Age FE			X	X	X
Observations	5,609	6,938	6,939	5,675	5,013
Adjusted R-squared	0.985	0.985	0.863	0.829	0.806

Table 5: Effect of horizontal acquisition

Figure 22: Effect of cross-market acquisitions

(a) Acquired by larger company



	(1)	(2)	(3)	(4)	(5)
	Log net price	Log list price	Log units sold	Log net sales	Coverage
Acquired by larger company	0.0694 (0.0459)	0.0932 (0.0389)	-0.164 (0.116)	-0.0671 (0.106)	-0.0357 (0.0552)
Acquired by smaller company	0.113 (0.133)	0.219 (0.0848)	-0.412 (0.317)	0.274 (0.230)	-0.295 (0.0960)
Observations	5609	6937	6938	5674	5013
Adjusted R-squared	0.985	0.985	0.898	0.877	0.834

Table 6: Effect of cross-market acquisition

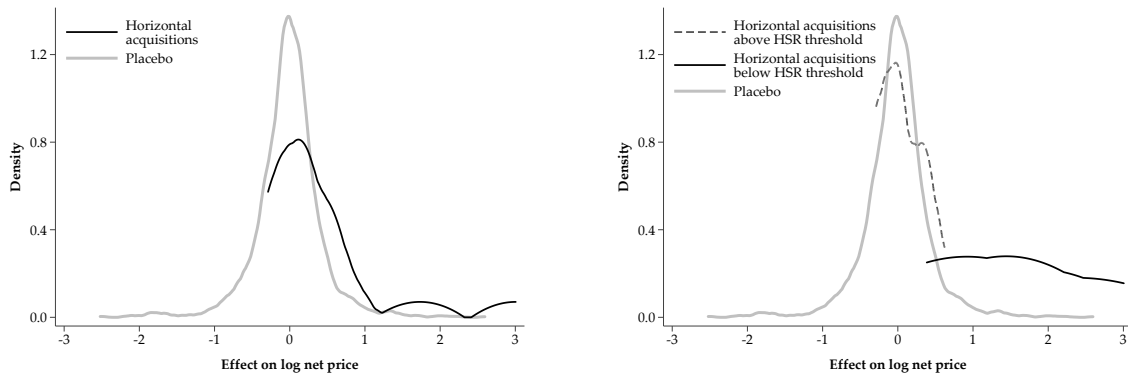


Figure 23: Replication of Figures 3 and 4 using ATC-4 as therapeutic class

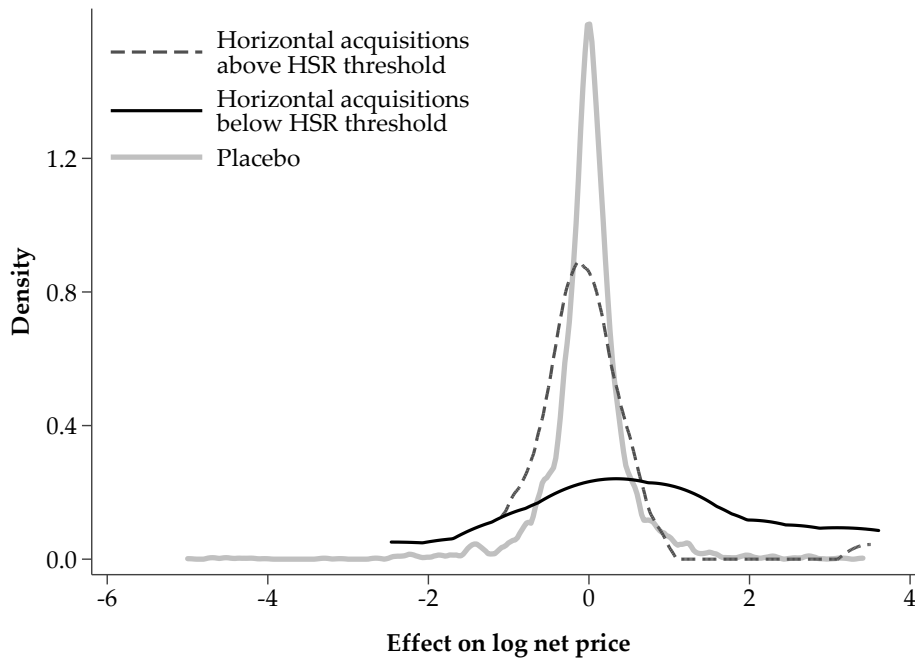


Figure 24: Distribution of net sales changes across horizontal acquisitions; deals above and below the HSR threshold

B.7 Allowing for differential trends

To check that our result on horizontal acquisitions below the HSR threshold 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. The results, shown in Figure 24, are consistent with those from our main specification.

We also check whether adding differential trends changes each coefficients significantly. Figure 25 compares each coefficient in the two types of event studies (the dashed line is the 45-degree line). We find that only one coefficient is significantly affected. The drug in question, Lenvima, is an oncology drug, whose acquirer already owned a different oncology drug, Keytruda. While Keytruda and Lenvima overlap in two indication (Renal Cell Carcinoma and Hepatocellular Carcinoma), they are also used in combination therapy in a third area (Endometrial Carcinoma). This makes them potential complements, which may justify a lower price.

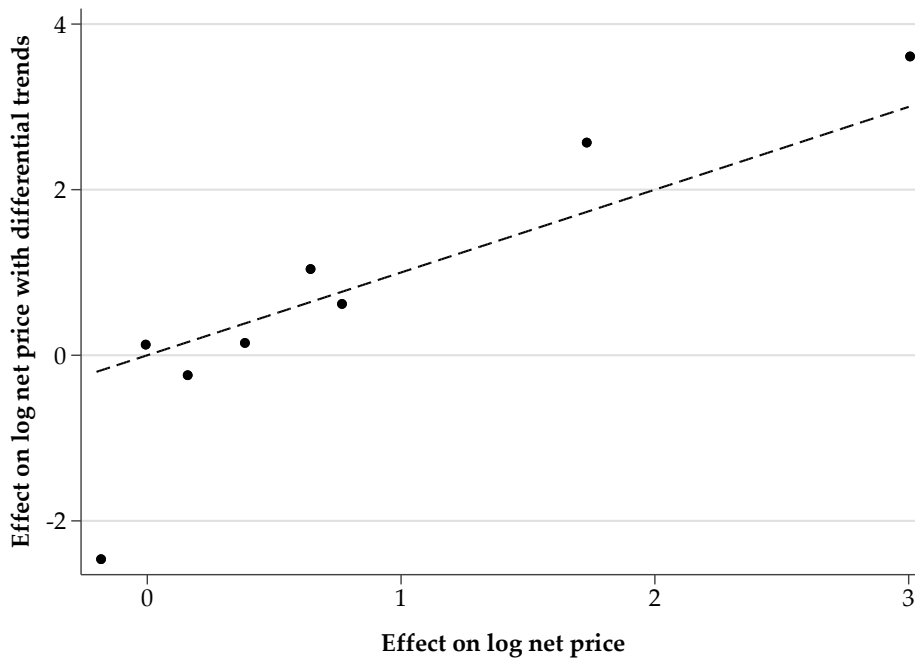


Figure 25: Distribution of net sales changes across horizontal acquisitions; deals above and below the HSR threshold

C The Case of Valeant

C.1 Background

Between 2010 and 2015, Valeant Pharmaceuticals International, Inc. engaged in a series of acquisitions that resulted in the acquisition of almost 90 drugs. During this period, the company gained notoriety for significantly increasing the prices of the drugs it acquired. In response to public outcry, investigations were launched in Massachusetts and New York into Valeant’s pricing practices. These investigations marked the beginning of a series of legal and ethical controversies that would come to define the company’s history.

In July 2015, at the height of Valeant’s success, the company boasted a market capitalization of \$81.90 billion. However, by October of that same year, the Department of Justice and the Securities and Exchange Commission had opened investigations into the company’s business practices. The investigations uncovered evidence of fraudulent accounting practices, kickbacks to doctors, and other unethical behavior.

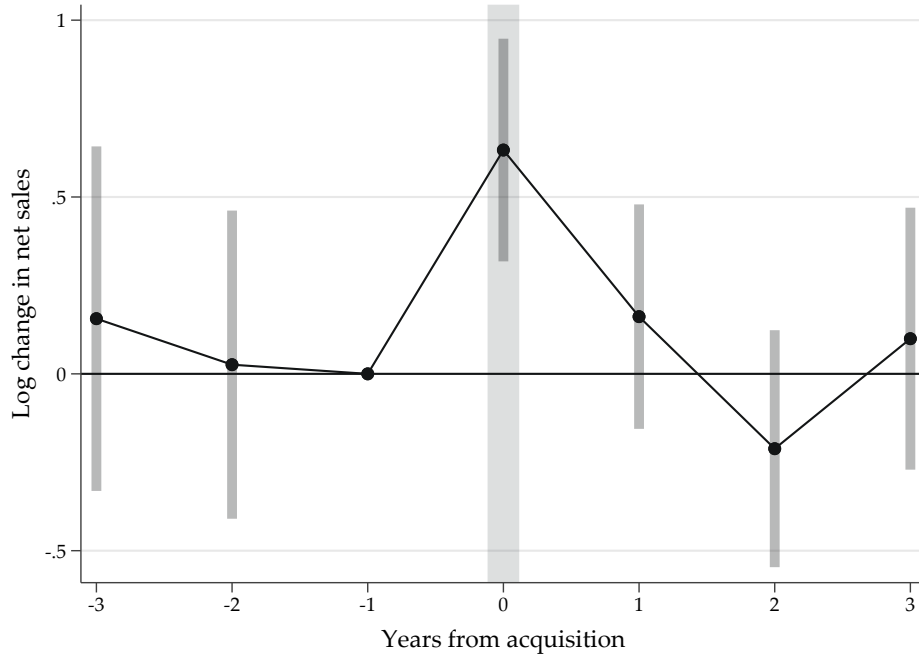
In 2016, Valeant faced congressional hearings and public outrage over its pricing

practices. 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. In part as a result of these controversies, Valeant changed its name to Bausch Health Companies in 2018.

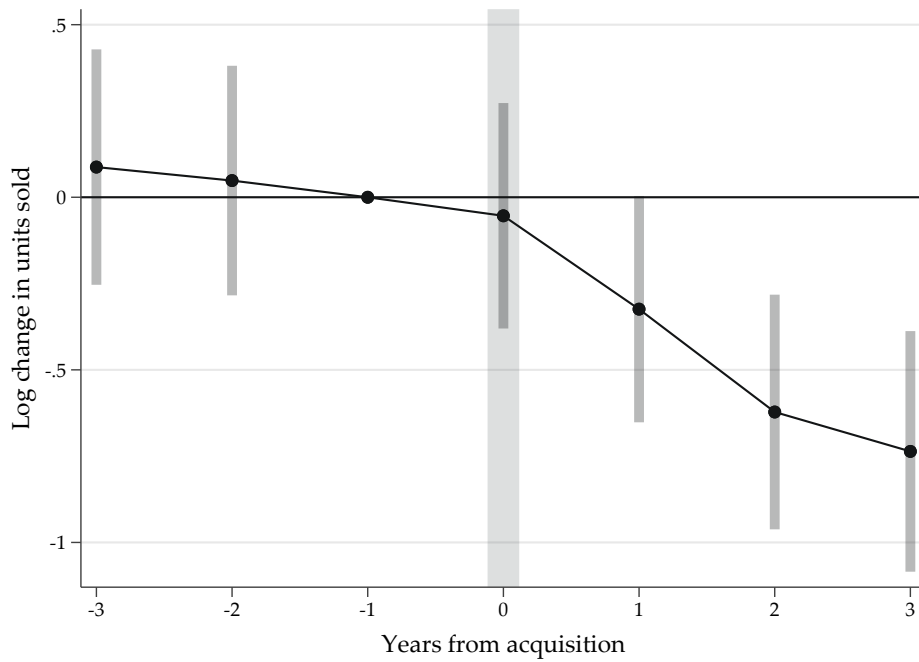
C.2 Evidence of net sales manipulation

Our data on net sales comes from the SEC filings that were disputed in litigation. To identify any uncharacteristic patterns in net sales we regress log net sales and log units sold for all products acquired by Valeant on drug fixed effects and time fixed effects relative to the year of acquisition. We plot the resulting indicators in Figure 26. 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, 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 subsequently.

The combination of these two patterns provide some suggestive evidence backing the SEC accusations.



(a) Net sales from SEC 10-K filings



(b) Units sold (sampled by data vendor)

Figure 26: Net sales and units sold around the time of acquisition, products acquired by Valeant Pharmaceuticals