Fighting Fire with Fire: On Allowing Mergers of Large Buyers to Counter Seller Market Power*

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Abstract

We study the implications of allowing mergers of buyers that consolidate large customer bases to counter seller market power. We exploit the 2012 merger of the two largest U.S. pharmacy benefit managers (PBMs), a transaction that aggregated bargaining power over 150 million consumers and was approved with the aim to counter the pricing power of large pharmaceutical companies. Exploiting geographic variation in market concentration, we find that the merger's increase in buyer power led to a 4% reduction in prices paid to pharmacies by health insurers for branded drugs in highly exposed states, with effects lasting over two years and strongest in more competitive drug-product markets. We show, however, that new agency costs arise when dominant buyers squeeze intermediaries in multi-layered supply chains. Following reimbursement reductions, pharmacies responded by reducing package sizes, a strategy that increases revenue via more frequent prescription refills. This response increased transaction costs for consumers, reducing medication adherence, which in turn resulted in increased emergency room visits for these same patients. We estimate that the resulting medical costs offset the direct financial savings from increased bargaining power. Our findings highlight the double-edged nature of buyer consolidation: it disciplines sellers but in multi-layered supply chains additional agency costs arise that can ultimately harm consumers.

Keywords: Countervailing Market Power; Mergers; Pharmaceutical Markets

JEL Classification: L41; I11; L11

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1. Introduction

A central concern in antitrust policy is firms' ability to exercise market power in selling goods and services. Dating back to at least Stigler (1950), a prevailing view in economics has held that firms often acquire such power by merging with competitors. Guided by this view, competition authorities have historically focused on reviewing horizontal mergers among sellers to safeguard competitive market conditions. However, economic theory also recognizes a countervailing force: buyer power—e.g., arising from buyer consolidation—could discipline dominant suppliers and promote competition (Galbraith, 1954, 1952). Recognizing this force, competition authorities at times consider allowing mergers of buyers to create countervailing market power in order to "fight fire with fire."[1]

However, buyer consolidation can be a double-edged sword because buyer power is typically exercised within multi-layered supply chains and hence its consequences go beyond bilateral price negotiations between a large buyer and large seller. In many sectors transactions pass through multiple intermediaries—e.g., distributors, processors, and retailers. These intermediaries shape how countervailing buyer power propagates through the supply chain and often determine consumer outcomes. For these reasons, it is important to study the effects of buyer consolidation to better understand the efficacy of competition authorities approving mergers to fight fire with fire. In particular, it is important to better understand how buyer consolidation influences intermediary behavior as well as product variety, service quality, and cost pass-through to consumers.

Studying countervailing market power faces a number of challenges. For one, large-scale mergers that have the potential to offset seller dominance are rare because competition authorities closely scrutinized mergers among larger buyers.[2] Further complicating matters, researchers rarely observe the consumer outcomes stemming from countervailing power. Aside from data challenges for consumers, the consequences for them are mediated through intermediaries' pricing and product decisions, making it hard to measure the ultimate effects on consumer welfare. As a result, it is rare to find empirical settings that allow researchers to simultaneously observe buyer consolidation, intermediaries' strategic responses, and downstream consumer outcomes. We overcome these challenges by studying a setting that provides exceptional transparency into how buyer power propagates through intermediaries to consumers—the U.S. prescription drug market.[3]

[1] Reflecting this idea, the European Union's merger framework recognizes countervailing buyer power as a mitigating factor when assessing whether a merger would significantly impede effective competition (European Commission, 2004).

[2] See, e.g., 2023 Merger Guidelines (U.S. Department of Justice and Federal Trade Commission, 2023).

[3] Although our analysis focuses on the pharmaceutical drug market, the underlying economic structure is common in many industries with multi-layered supply chains. Sectors such as consumer packaged goods, elec-

The U.S. prescription drug market is ideally suited to studying these dynamics. On one side of this market, branded drug manufacturers hold substantial seller market power, protected by patents and associated intellectual property rights. On the other side, Pharmacy Benefit Managers (PBMs) act as intermediaries for the buyers that ultimately pay for drugs (e.g., insurers and employers), leveraging an intangible but key asset: their formularies, which determine market access for millions of patients. By granting or denying formulary placement, PBMs can negotiate rebates and discipline seller power.

Importantly, however, PBM behavior also affects the supply chain. Pharmacies depend on inclusion in PBM networks to sustain prescription volume and thus face strong incentives to accept PBM contract terms. Because pharmacies are the final point of contact with patients, their responses directly shape the prices, package sizes, and refill patterns for consumers. Thus, the PBM setting allows us to answer the question: how does powerful-buyer consolidation affect not only upstream prices, but also the behavior of intermediaries and, ultimately, the outcomes for downstream consumers?

To answer this question, we take advantage of the 2012 merger between Express Scripts and Medco—the two largest PBMs in the U.S. at the time—which resulted in a single firm negotiating drug prices on behalf of nearly 150 million individuals. The transaction was highly controversial: critics argued it would diminish competition among pharmacies and restrict patient access, while supporters relied on buyer power, claiming that greater scale would strengthen PBMs' bargaining leverage and ultimately reduce drug costs for consumers.[4] After an extensive investigation, the Federal Trade Commission (FTC) allowed the merger to proceed. At the same time, Commissioner Julie Brill dissented, arguing that the merger raised competitive concerns in both the PBM and specialty pharmacy markets and warranted closer scrutiny (Brill, 2012). This merger—one of the largest horizontal mergers of buyers in recent history and the largest-ever consolidation of customer capital at the time—provides a well-suited setting to study how countervailing buyer power is transmitted through intermediaries to consumers.

To isolate the effects of buyer consolidation, our research design utilizes local differences in exposure to this merger. We do so by exploiting the merger's heterogeneous geographic impact—based on pre-existing differences in state health insurance markets—in a difference-in-differences framework. This approach compares differences in drug prices and downstream

tronics and appliances, automotive, industrial equipment, office supplies, building materials, and technology solutions similarly feature intermediated transactions, retailers that sell to final consumers, and manufacturers that influence end-user demand through mechanisms such as coupons, rebates, or bulk discounts.

[4]See, e.g., testimony before the Senate Judiciary Committee (2012), which argued that the Express Scripts–Medco merger "has the potential to reduce prescription drug costs for consumers by increasing bargaining power with manufacturers." Available at: https://www.govinfo.gov/content/pkg/CHRG-112shrg72806/html/CHRG-112shrg72806.htm.

market conduct in states with high pre-existing exposure to the two merging PBMs against those with low exposure.[5] Using this design, we first document the direct impact on prices. We then use granular pharmaceutical and medical claims data to trace consequences along the supply chain, examining how pharmacies altered their dispensing behavior and, in turn, how these changes ultimately affected patient medication adherence and health outcomes.

Starting with the direct effect of the merger on drug prices, we examines the primary argument made in favor of the merger: that enhanced buyer power would enable the consolidated PBM to lower prices for dispensed drugs.[6] Using comprehensive Medicaid drug-level price data, we compare price changes in states experiencing large increases in PBM market concentration to those in states with little or no change in concentration. We find that the merger led to an average price reduction of 3.6% for branded drugs after the merger in highly-exposed states relative to states with low exposure to the merger, and that these effects persist at least 10 quarters after the consummation of the merger. States most exposed to the merger realized on average savings of $17.60 per branded-drug claim over our sample period. Furthermore, these effects are nearly 30% stronger (i.e., 4.6% or $22.50 lower per branded-drug refill) in more competitive drug markets, defined as markets with many closely related substitute drugs. Taken together, these results indicate that buyer consolidation reduces prices, but the effects are not uniform across products and depend on the ex ante degree of product market competition, a dimension that is likely relevant for assessing the competitive consequences of buyer consolidation.

Next, we utilize a unique feature of our setting. In particular, the timing of the merger allows an investigation into how enhanced buyer power affected outcomes of a well-documented generic drug-maker cartel that formed in 2013, one year after the merger. The idea of this analysis is to examine countervailing buyer power in a situation in which seller power had newly formed (rather than taking seller power as given, as our prior analysis did).[7] Generic drug manufacturers contract directly with pharmacies. PBMs, however, still reimburse pharmacies for generic prescription claims and can therefore exert influence on prices by denying claims for higher-priced generic drugs. Thus pharmacies would be better off not stocking cartelized generics, which in turn creates price pressure on such drugs in markets with higher PBM buyer power. Using a stacked difference-in-differences design that exploits nearly one

[5] We also develop a continuous measure of exposure to this merger and find similar results throughout our analyses using this alternative treatment measure.

[6] Throughout the paper, we use the term "prices" to refer to the reimbursements that insurers pay pharmacies for prescription drug claims.

[7] Reduced prices for branded drugs in our prior analysis could also be a symptom of other externalities of the merger—e.g., improvements in insurance network relationships—rather than countering powerful sellers. Thus, our results that the PBM merger muted the impact of a generic drug-maker cartel reinforces the interpretation that the merger lowered prices by countering seller market power.

hundred generic drug cartel events, we find substantially larger price reductions in treated states during the post-merger cartel period: prices of cartelized drugs are approximately 30% lower in states highly exposed to the merger. This evidence suggests that countervailing buyer power can disrupt collusive pricing by sellers. We also find no such differential price effects during a similar generic drug cartel that occurred several years before the merger, essentially serving as a placebo test.

Having established the price effects of the merger, we now turn to the important question of intermediary behavior. Our finding that the merger led to lower drug prices reimbursed to pharmacies raises questions about how pharmacies strategically respond and what consequences these actions ultimately have for consumers. Retail pharmacies face significant uncertainty about how much a PBM will reimburse for a given prescription filling. Furthermore, the increased leverage from the Express Scripts-Medco merger increased the PBM's negotiating power with pharmacies, allowing it to lower reimbursements. Pharmacies cannot easily adjust their prices in response, but they can turn to alternative margins of adjustment—most notably, the quantity dispensed per fill. Each dispensing event generates a fixed fee (and, typically, a patient co-pay), so pharmacies can partially offset reduced per-unit margins by filling prescriptions in smaller package sizes and thereby increasing the number of refills.

To formalize these dynamics and generate testable predictions, we develop a simple model. The model highlights that pharmacies face a trade-off between maximizing per-unit drug margins and capturing fixed fees from each dispensing event (i.e., a fill or refill). Post PBM merger, reimbursement rates decline and the per-unit margin shrinks, making the fixed fee revenue from each individual fill relatively more profitable. The model predicts that pharmacies strategically reduce package sizes to increase refill frequency. This change is only seemingly minor, as it increases the "refill burden" due to more frequent pharmacy visits and additional transaction costs, which in turn predicts a reduction in patient medication adherence.

Consistent with our framework's prediction, we find that pharmacies located in counties more exposed to the merger dispensed packages that are about 8% smaller than those in less exposed counties, with the largest reductions occurring among pharmacies with weaker pre-merger bargaining positions. This strategic response led to a corresponding 10% increase in the number of refills required by patients, consistent with the theoretical prediction that lower reimbursements induce pharmacies to adjust dispensing behavior in ways that shift transaction frequency rather than prices.

We next examine the implications of this strategic pharmacy response for consumers. Our framework predicts that the induced shift toward smaller package sizes can increase

patients' refill burden and impede adherence. Using patient-level prescription claims data, we estimate the net impact of the merger on medication adherence. We find that patients in highly exposed counties are 3.3% less likely to remain adherent to their prescribed regimens relative to those in low-exposure counties. This result is present even when comparing drugs included on the merged PBM's formulary to those excluded from the PBM's formulary within the same patient in highly-exposed counties, ruling out confounding effects related to unobserved health conditions or patient heterogeneity.

Finally, we examine whether the documented financial savings due to lower input prices are offset by higher medical costs resulting from the degradation in patient adherence shown. To explore the consequences of reduced adherence for patients' health outcomes, we join patients' drug claims data (by enrollee ID) to their medical claims data, allowing us to observe whether a patient's reduction in medication adherence is associated with an increase in their subsequent hospitalizations. We use the number of emergency room visits as our main measure and find, using a two-stage regression model, that a one-standard deviation change in the predicted reduction in adherence estimated in our first-stage model is associated with an increase of 0.28 emergency room visits in the subsequent 90 days in our second-stage model. We estimate this increase in emergency room visits translates into additional medication-adherence related healthcare costs of $207.6 million to $622.8 million in the U.S. every year. Although insurers bear most of these costs, we further show that patients' out-of-pocket spending—driven by incremental co-insurance costs—exceeds their average savings from lower insurance premiums.

Taken together, our findings highlight the complex tradeoffs inherent to "fighting fire with fire," or allowing buyer consolidation to combat seller market power. We provide novel evidence that consolidating buyer power can lower input prices and even counter explicit collusion by suppliers. However, these pecuniary benefits come at a cost. In multi-layered supply chains, pressure applied by dominant buyers does not simply serve to counter dominant sellers. It also propagates through connected intermediaries, generating new conflicts and distorting consumer-facing market conduct. This tradeoff—where squeezing margins in one part of the chain triggers degraded service in another part of the chain—poses a significant challenge for antitrust enforcement. By documenting how financial savings on input prices can ultimately translate into adverse health outcomes for patients, our results highlight the importance of antitrust authorities considering consequences beyond nominal price effects. In multi-layer markets, merger review hinges on understanding how market power is transmitted across the supply chain and how mechanisms that limit rent extraction affect the quality of goods and services delivered to consumers.

Our findings make several contributions to the literature, which we detail in Section

2. Section 3 discusses our institutional setting. Section 4 describes our data and presents descriptive statistics. Section 5 presents our empirical strategy and discusses our results on the effects of the merger on prices. Section 6 introduces a theoretical framework for our empirical analyses of pharmacy responses and patient choices, and presents the results. Additional analyses are provided in Section 7, and Section 8 concludes.

2. Related Literature and Contribution

Beginning with Galbraith (1954, 1952), a growing theoretical literature considers the role of buyer power as a countervailing force to counter seller market power (e.g., Chipty and Snyder, 1999; Dix and Lensman, 2022; Iozzi and Valletti, 2014; Loertscher and Marx, 2019; Snyder, 1996). However, empirical evidence of such countervailing market power is relatively scarce (e.g., Bhattacharyya and Nain, 2011; Ellison and Snyder, 2010; Fee and Thomas, 2004). Furthermore, most of these studies focus on the direct effects of enhanced buyer power on input prices—motivated by the notion that lower procurement costs may ultimately be passed through to consumers in the form of lower retail prices.[8] Although recent empirical studies generally find that stronger buyer power lowers input prices (e.g., Barrette et al., 2022; Decarolis and Rovigatti, 2021), whether and to what extent these cost savings benefit end consumers remains an open question. Our study addresses this gap by providing empirical evidence on how enhanced buyer power affects both prices and downstream consumer outcomes.

Another contribution of our study is to show that intermediaries in the supply chain represent a key channel through which enhanced buyer power can ultimately affect consumers. While prior research has largely examined the consequences of stronger buyer power in settings dominated by concentrated sellers, many industries are in fact organized through one or more intermediary layers that separate upstream producers from downstream buyers.[9] By documenting that pharmacies respond to reductions in reimbursements by adjusting package sizes—thereby increasing the frequency of refills—our study underscores the importance of examining the behavior of other firms along the supply chain when assessing the broader effects of changes in buyer market power. In this way, we also contribute to a growing literature that studies the effects of intermediary concentration along the supply chain (e.g.,

[8]This reasoning has also become increasingly salient in merger proceedings, where merging buyers often invoke potential consumer pass-through as a justification for consolidation (e.g., Kirkwood, 2012; Steptoe, 1993).

[9]Although our analysis centers on the prescription drug industry, comparable vertical structures are common in sectors such as consumer packaged goods, electronics and appliances, automotive, agriculture and farming, industrial equipment, office supplies, building materials, and technology—where manufacturers sell through intermediaries while simultaneously offering end-buyers incentives such as rebates or coupons.

Decarolis and Rovigatti, 2021; Lin and Wang, 2025; Salz, 2022). Although this work generally finds that greater intermediary concentration reduces input prices, it provides little evidence on whether, or through what mechanisms, these changes are transmitted through the supply chain to end consumers.

Our findings are also relevant for the extensive literature that examines how vertical and contractual arrangements in healthcare markets shape prices, medical access, and welfare. Recent work in this literature has documented how consolidation and bargaining among healthcare intermediaries, such as PBMs, insurers, hospital systems, and group purchasing organizations, shape the allocation of surplus across market participants (e.g., Brot-Goldberg et al., 2022; Che, 2025; Gowrisankaran et al., 2015; Gray et al., 2023; Grennan, 2013; Ho and Lee, 2017, 2023; Lin and Wang, 2025; Yde, 2025).[10] While this literature largely focuses on *ex-ante* bargaining over premiums and network inclusion, we isolate the *ex-post* operational distortions. We contribute to this literature by showing that greater PBM market power induces pharmacies to adjust their dispensing behavior, and provide novel evidence on how countervailing market power in the presence of multilayered supply chains raises patients' costs at the ultimate point of care. Furthermore, by demonstrating that these dispensing adjustments ultimately reduce patient medication adherence, which in turn leads to a subsequent increase in emergency room visits, we document an important downstream consequence of "fighting fire with fire" on the overall quality of patient care.

This paper also contributes to a broad literature in corporate finance and industrial organization examining how product market consolidation affects consumer welfare (e.g., Cooper et al. (2019); Cunningham et al. (2021); Eliason et al. (2020); Fathollahi et al. (2022); Garmaise and Moskowitz (2006); Kamepalli et al. (2022); Sapienza (2002)). In particular, our work is closely related to Bonaimé and Wang (2024), who show that mergers among prescription drug manufacturers in already concentrated markets lead to higher prices and changes in innovation outcomes. We contribute to this line of inquiry by showing that consolidation at the opposite end of the supply chain—i.e., among buyers—likewise has implications for consumer welfare in prescription drug markets, albeit through a distinct mechanism operating via other intermediaries along the supply chain.[11]

Finally, our setting highlights the unique economic consequences of consolidating intangible customer capital. In this regard, our study adds to a growing literature on the consequences of consolidating intangible capital (e.g., Cunningham et al., 2021; Kamepalli et al., 2022; Kepler et al., 2025). Unlike mergers that primarily consolidate tangible assets,

[10] For a comprehensive review of this literature, see Gaynor et al. (2015).

[11] Also closely related to our study is Gray et al. (2023), who study the vertical integration of PBMs and insurers. In line with concerns that such integration can disadvantage competitors, they document that insurers purchasing PBM services from rival firms experienced higher premiums following a 2015 merger.

the consolidation of formulary control amplifies a key "gatekeeper" asset that allows the merged firm to credibly threaten exclusion by manufacturers and steer patients, thereby disciplining upstream sellers while simultaneously squeezing downstream intermediaries. Our results show that the specific type of capital consolidated can fundamentally reshape competitive dynamics. This insight has direct policy relevance: because antitrust authorities often screen mergers based on the size of the target's balance sheet—which typically omit customer-related intangibles (Kepler et al., 2025)—current regulatory frameworks may overlook transactions that materially alter supply-chain behavior and downstream market dynamics.

3. Institutional Setting

3.1. Pharmaceutical Drug Industry

Pharmaceutical drug expenditures in the U.S. totaled $450 billion in 2023—or 1.6% of the gross domestic product—an increase of nearly 22% from 2019 (Centers for Medicare & Medicaid Services, 2020, 2024). These growing costs are financed by private insurance, which accounts for about two-thirds of spending, and public insurance (e.g., Medicare and Medicaid), which accounts for the remaining third. Both private and public insurers pay these costs via reimbursements for claims submitted by pharmacies on medications provided to insured consumers.

As illustrated in Appendix A, pharmacies play a key role in the pharmaceutical drug industry supply chain—along with drug manufacturers, insurers, and pharmacy benefit managers. The pharmaceutical industry's supply chain shares many similarities with standard business-to-business vertical supply chains. At the top of the supply chain, drug manufacturers develop, produce, and distribute medications to the market. Pharmacies acquire both branded and generic drugs from these manufacturers and dispense them to consumers. Patients select a pharmacy where healthcare providers send their prescriptions, and they cover part of the cost through co-pays. Pharmacies then seek reimbursement for the remaining balance from pharmacy benefit managers, who administer and reimburse claims on behalf of insurers at the bottom of the supply chain.

3.2. Pharmacy Benefit Managers

Pharmacy Benefit Managers (PBMs) play an important role within the U.S. pharmaceutical market, functioning as intermediaries among insurers, employers, manufacturers, and pharmacies. PBMs' core responsibilities include the design and administration of prescription drug benefit plans, negotiation of manufacturer rebates and discounts, development of

formularies (i.e., lists of covered medications), and the establishment of contractual arrangements with both retail and mail-order pharmacies to facilitate drug distribution.

PBMs exert considerable economic influence due to their ability to aggregate purchasing power on behalf of millions of insured individuals. By negotiating directly with pharmaceutical manufacturers, PBMs secure rebates in exchange for favorable placement of drugs on formularies. This formulary management not only affects net drug prices—i.e., reimbursement costs net of rebates—and the competitive landscape of therapeutic markets, but also has downstream implications for patient access, physician prescribing patterns, and the financial outcomes of both drug manufacturers and dispensing pharmacies.

PBMs also contract with dispensing entities such as pharmacies. A PBM's market size and concentration allows it to set reimbursement rates and participation criteria for pharmacy networks. Moreover, a PBM's dual capacity—as both purchaser (from manufacturers) and payer (to pharmacies)—affords them with significant control over the cost, accessibility, and distribution of prescription medications. As such, PBMs play an influential role in structuring pharmaceutical spending and determining the broader economic dynamics of the U.S. drug supply chain.

3.3. The Express Scripts-Medco Merger

To investigate the effects of large buyer consolidation, we study the April 2012 merger of the two largest PBMs at the time—Express Scripts and Medco—which resulted in a single firm, with over 50 percent market share in the U.S., administering insurance claims and negotiating prescription drug prices on behalf of roughly 150 million U.S. residents (National Community Pharmacists Association, 2012).

Several features of the merger make it ideal to study the consequences of powerful buyer consolidation. First, mergers of large horizontal rivals are rare, largely because antitrust regulators heavily scrutinize and typically block such deals. Consistent with this scrutiny, the Express-Medco merger, which ranks as one of the largest in the U.S. over the past twenty-five years, initially underwent an eight-month antitrust investigation by the DOJ and FTC (Federal Trade Commission, 2012). Second, as shown graphically in Online Appendix OA.B, the merger increased state-level PBM market concentrations and HHIs by amounts that far exceed those viewed as anticompetitive in regulators horizontal merger guidelines. In particular, the Express Script-Medco merger immediately increased HHIs in the affected states by more than 1,000 on average. To put this in perspective, an increase in HHI of 100 points or more in an already highly concentrated market is presumed by the FTC and DOJ to enhance market power.[12] Finally, not all states were impacted by the merger; and some

[12]See p.5 of the 2023 U.S. Merger Guidelines (U.S. Department of Justice and Federal Trade Commission,

states were impacted significantly more than others. Such heterogeneity exists because each state regulates its own health insurance market, which in turn creates state-level variation in the concentration and makeup of these markets.

4. Data Sources, Sample Construction, and Descriptive Statistics

This section describes our data sources, and outlines how we construct our sample, and discusses descriptive statistics.

4.1. Data Sources

Data on all prescription drugs manufactured for sale in the U.S. come from the National Drug Code (NDC) Directory (the "Directory"), which is published and updated daily by the Federal Drug Administration (FDA). Drugs listed in the Directory have a unique 11-digit NDC code, which identifies the manufacturer, drug name, dosage, strength, and package size. We merge the Directory data, by NDC code, to Medicaid State Drug Utilization Data files, which—following Starc and Wollmann (2025)—are our source of NDC-level prices and quantities at the state level.[13]

We obtain PBM data from Clarivate, a private provider whose Pharmacy Benefit Evaluator files provide detailed county-level information on the number of covered people by health insurer and their associated PBM. To calculate state-level PBM market shares, we aggregate the number of covered people for each insurer across all counties within a state. These state-level shares are central to our drug price analysis. For patient-level tests, we leverage county-level variation in PBM market power, allowing us to conduct our analysis at a more granular level across nearly 3,000 counties across the United States.

We obtain prescription drug consumer-level data from the Merative™ MarketScan® Research Databases, one of the largest databases of U.S. prescription drug claims, containing a comprehensive panel of deidentified data on over 273 million patients. These data enable us to observe patient claims at the patient-drug product-pharmacy level, and include information on the number of days supplied, refills, and whether the purchase was through a retail pharmacy or mail order. These data also provide information on the geographic location and ownership characteristics of pharmacies. In addition, we obtain medical claims data

2023) for additional information about the levels and changes of HHI that are considered problematic to the DOJ and FTC.

[13]Drug utilization data containing NDC-level total expenditures and number of prescriptions are reported by all 50 states and the District of Columbia on a quarterly basis to the Centers for Medicare & Medicaid Services. Expenditures reported are pre-rebate, not net of manufacturer rebates; however, the federal Medicaid drug rebate is uniform nationwide.

from the same source, including records of inpatient, outpatient, and emergency department services. The consistent patient identifiers across the drug and medical claims files allow us to observe subsequent health outcomes.

4.2. Defining our Sample of Drugs

The prescription drugs we include in our sample come from the 2012 Express Scripts National Preferred Formulary (NPF), which identifies the brand-name and generic medications that may be covered under the health plans administered by Express (ES). The NPF is updated annually based on reviews of clinical research and cost evaluations of available medicines. For 2012, the NPF contained over 400 brand-name and generic medications, which we present in Online Appendix OA.A. We manually join these data to NDC product codes.

4.3. Defining Markets

We define markets for our sample at two geographic levels: state and county. For analyses of drug price changes, we use state-level markets, since Medicaid reports drug-specific expenditures and quantities at that level.[14] For analyses of pharmacy and patient choices, we use county-level markets, as PBM market shares vary across counties and our claims data identify pharmacy locations and dispensing behavior.

In our state-level analysis of drug prices, we classify states as either most (treatment) or least (control) exposed to the merger. To construct these groups, we aggregate county-level PBM market shares to the state level for 2010 (pre-merger) and 2013 (post-merger).[15] This procedure identifies four treatment states (Louisiana, Missouri, Vermont, and West Virginia) and three control states (Florida, Maryland, and Minnesota).

In our analysis of pharmacy and patient choices surrounding the merger, we examine all counties across the United States. We classify a county as most exposed tp the merger if it satisfies two conditions: (1) the change in ES's market share from the pre- to post-merger period lies in the top quartile across all counties, and (2) the level of ES's market share also lies in the top quartile across all counties post-merger. This classification approach is analogous to the premerger review guidelines used by the FTC and DOJ to assess potential anticompetitive effects of mergers based on both the level and change in market shares. We apply the same logic to identify counties least exposed to the merger—those in the bottom quartiles of both market-share change and post-merger market-share level. These two sets of counties comprise the sample used in our analyses of pharmacy and patient responses to the

[14]County-level Medicaid drug utilization data are not publicly available. A direct request to a state Medicaid agency confirmed that such data are unavailable at the county level.

[15]Data on PBM market shares in 2011, the year immediately preceding the merger, are incomplete.

merger. As shown in Table 2, Panel B, the most and least exposed groups include 464 and 597 counties, respectively, comprising nearly 120,000 unique patients with claims covering approximately 560 drug products dispensed by over 15,000 pharmacies. We also conduct these analyses with an alternative sample that expands the number of control counties to 2,218 (for a total of 2,682 counties), representing over 400,000 unique patients with claims for roughly 608 drug products dispensed by over 40,000 pharmacies.

4.4. Descriptive Statistics

Table 1 presents statistics on changes in Express Scripts market shares before and after the merger for our treatment and control groups. The average post-merger market share level (change) was 64.9% (28.1%) for treatment states, and 7.4% (2.3%) for control states. Panel B shows that states most exposed to the merger tend to have smaller populations and lower GDPs compared to those least exposed. Table 2, Panel A, reports summary statistics for our state-level analyses of drug prices. Of the more than 58,000 observations, approximately 55% represent treatment states, and about half of this sample fall within the post-merger period. The average price of brand-name drugs is $429.02.

Panel B of Table 2 presents summary statistics for our county-level analyses. In our tests of package sizes, conducted at the claims level in counties most versus least exposed to the merger, we have more than 1.8 million observations across 15,232 pharmacies. When expanding the analysis to include all counties, the sample increases to approximately 6.8 million observations across 40,492 pharmacies. For our patient-level tests of refill behavior, we observe the behavior of 172,000 patients in the counties most and least exposed to the merger, and this expands to roughly 612,500 patients when all counties are included in the control group.

5. Buyer Consolidation and Prices

This section examines how drug prices changed following the merger. We begin by documenting how the merger shifted state-level market shares of Express Scripts, as well as the state-level Herfindahl–Hirschman indices (HHIs) of the PBM market. We then describe our empirical strategy and conduct our baseline test. Next, we identify drugs whose product markets are most likely to be affected by the merger. We conclude by investigating the impact of the merger on drug prices around a drug cartel.

5.1. Shift in Market Shares

Our empirical strategy relies on local differences in exposure to the merger. Consistent with such local differences, Table 1, Panel A shows that Express Scripts' market share in

treatment states rose by roughly 28 percentage points on average following the merger, reaching an average post-merger share of about 65%. In contrast, Express Scripts' average market share in control states was only 5.15% before the merger and increased modestly by 2.6 percentage points (to 7.41%) afterward. To measure the resulting change in the terms of market concentration, Online Appendix OA.B, Panel B, presents HHIs for treatment and control states before and after the merger. In 2010, the average HHI in treatment states exceeded 3,000—nearly twice the level that classifed as highly concentrated by the DOJ and FTC—and by 2013, it approached 5,000. The average increase of 1,700 HHI points is seventeen times greater than the 100-point threshold that the FTC and DOJ consider indicative of enhanced market power. In contrast, market concentration in control states remained largely unchanged over the same period.

5.2. Effect on Prices

To evaluate the extent to which the merger enhanced Express Scripts' influence as a dominant buyer and resulted in lower nominal prices, we compare the prices of identical drugs—produced by the same manufacturer—sold in states impacted by the merger versus those unaffected. Doing so allows our empirical strategy to control for for manufacturer and drug-specific factors—such as packaging, dosage, and quality—while leveraging local differences in market share induced by the merger. For our analysis, we measure the average log prices for our sample of brand drugs each quarter, and normalize the prices of each drug series to zero in the quarter of the merger (*Price*).

Figure 1 presents our results from plotting normalized drug prices around the merger separately for treatment and control states from our sample (we highlight the quarter of the merger with a vertical dashed line). Three noteworthy features emerge from this plot. First, drug prices in treatment and control states exhibit similar trends during the years before the merger, including in the quarter-to-quarter price differences. Second, the average price of drugs in treatment states decreased by about 5 percent within two quarters after the merger relative to control states, and this difference remained constant for the subsequent two years. Third, the post-event trends, including the quarter-to-quarter price differences, follow a very similar path after their initial divergence immediately after the merger.

To address concerns that other factors could confound the relation between the merger and prices, we next estimate the following model:

$$Price_{i,s,t} = \beta_0 + \beta_1 Treatment(State)_s \times Post_t + \theta_i + \gamma_s + \tau_t + \epsilon_{i,s,t}, \tag{1}$$

where the dependent variable *Price* is the log price of drug i in state s during year-quarter t. The variable *Treatment(State)* is an indicator variable that takes the value of 1 if the state

is a treated state, and zero if it is a control state. *Post* is an indicator that takes the value of 1 if the observed price is in a year-quarter after the merger, and 0 otherwise. We perform our analysis within manufacturer-drug-package-dosage, and include fixed effects at the drug (i.e., NDC) level (θ_i). This allows us to take advantage of the availability of unique National Drug Codes assigned by the FDA. We control for other potential confounding effects, using state and year-quarter fixed effects, denoted γ_s and τ_t, respectively. Standard errors are clustered at the drug (NDC) level.[16] In equation (1), *Treatment(State)* $\times$ *Post*, captures the average change in drug prices in states whose market concentrations increase substantially due to the merger relative to prices in states whose market concentrations see little to no increase due to the merger.

Table 3, Panel A, presents the regression results from estimating equation (1). In column (1), the estimate of our main variable of interest *Treatment* $\times$ *Post* is -0.032 and is statistically significant at the 1% level, indicating that in the ten quarters after the merger quarter, drug prices in treatment states are on average 3.2 percentage points lower than those in control states. In column (2), we replace the drug level and year-quarter fixed effects with a drug $\times$ year-quarter fixed effect. This allows us to examine changes in nominal drug prices in treated versus control states for identical drugs at the same point in time, which helps alleviate the concern that confounding events, such as the expiration of drug patents, may be driving the results. The coefficient on *Treatment(State)* $\times$ *Post* is -0.036 and remains statistically significant at the 1% level. These results indicate that even within the same manufacturer, drug, package, and dosage, drug prices in states most exposed to the merger are lower relative to those that were least exposed. In terms of savings, our results suggest that states most exposed to the merger saved approximately $17.60 per filled prescription on average.[17]

To validate our findings, we conduct placebo analyses in which we randomly draw a quarter from a uniform distribution between the beginning of the sample period and 2012Q1; we restrict the draw to this period to avoid contamination from the actual treatment. Next, we randomly assign four states to the treatment group and the remaining three states to the control group for the placebo tests. We present results of this analysis in Online Appendix OA.C. Based on 1,000 replications, the average placebo effect is close to zero, as shown in Panels A and B, which correspond to our findings columns (1) and (2), respectively. In contrast, the red lines in the figures indicate the actual estimated coefficients, which are

[16] We do not cluster standard errors at the state level because the number of states is small (seven). In settings with few clusters, cluster-robust standard errors are known to substantially overreject the null due to serial correlation (Bertrand et al., 2004a).

[17] We estimate the on average savings using mean price of branded drugs in our sample, $489.02, reported in Panel A of Table 2 and multiplying by the coefficient, -0.036, in column (2)

statistically different than zero (i.e., p-value=0.057 and 0.034, respectively).

An embedded assumption in our research design is that, in the absence of the merger, any trends in drug prices between treatment and control states would remain constant. While this parrallel trends assumption is inherently untestable, we estimate the following model to test for differential premerger trends in drug pricing:

$$Price_{i,s,t} = \sum_{t=-10, t\neq 0}^{10} \beta_t Treatment(State)_s \times Time_t + \theta_i + \gamma_s + \tau_t + \epsilon_{i,t}, \tag{2}$$

where the dependent variable and fixed effect structure from equation (1) are the same, and we replace *Treatment(State)* × *Post* with a series of ten year-quarter indicators before and after the merger that we interact with *Treatment*. We set the exclusion period to the quarter before the merger was completed. Results from equation (2) are reported in columns (3) and (4) of Panel A, Table 3. Across both columns, we find no evidence of premerger trends in drug prices. However, as shown in column (4), starting in the second quarter following the merger and continuing through the tenth quarter, prices for identical drugs are between 2.3 and 5.1 percentage points lower on average in treated states compared to control states. To illustrate this pattern graphically, we plot the coefficients from column (4) in Figure 2.

Panel A of Table 1 also shows that states differ in the degree to which they were exposed to the merger. Accordingly, we convert our binary measure *Treatment* into a continuous measure and re-estimate Equations (1) and (2). We report the results in Online Appendix OA.G. The magnitude of the coefficient in column (2) indicates that a 10 percent increase in market share reduces prices by 1.88 percent on average. In columns (3) and (4), we again find no evidence of premerger trends in prices, and show that these effects start in the second quarter after the merger and persist until the tenth quarter.

5.3. Effect of Prices of Drugs with Substitutes

Our results in Table 3, Panel A suggest that drug prices are lower in those states most affected by the merger. We next conduct a test to provide additional evidence to support this inference. Thus far we have considered the impact of increased PBM market power on all branded drugs. However, the merger likely affected drug markets differently depending on the *ex ante* level of competition in each particular drug market—particularly with regard to the availability of substitute drugs. For example, branded drugs with many substitutes are likely to experience greater downward price pressure compared to those with few substitutes. To test this, we begin by identifying plausible substitutes for each branded drugs in our sample, allowing us to construct a product market for each branded drug in our sample. The intuition behind this approach is to classify drugs with therapeutic/pharmacological uses as a drug

product market. We describe further details of this process in Online Appendix OA.D. Next, we use our data on drug prices and quantities to calculate HHIs for each of the constructed drug product markets. We then classify markets into high or low concentration markets based on an indicator for whether the drug market HHI is above versus below median HHI. Thus, markets with below (above) median drug market HHI have relatively more (fewer) substitutes.

Figure 3 illustrates the average drug prices in markets with HHIs below the median, indicating markets with many substitutes (Panel A), and those with HHIs above the median, indicating markets with few substitutes (Panel B). Notably, pre-merger prices follow similar trends in both low- and high-concentration markets. Furthermore, for both market concentration types, pre-merger prices in treatment states closely align with those in control states. However, the average price of drugs in treatment states decreases more starkly in low-concentration markets with many substitutes compared to high-concentration markets with few substitutes in the years following the merger.

Panel B of Table 3 results from estimating equations (1) and (2) separately for low- and high-concentration markets, allowing for a direct comparison of the difference in magnitude. Results from our regression models, inclusive of state and drug-year-quarter fixed effects, are presented in all four columns. In column (1), the coefficient for β_1 is -0.046, whereas in column (3), it is -0.030, suggesting that, on average, low-concentration drug markets with many substitutes in treatment states experience more than 50% the price reduction compared to high-concentration drug markets with few substitutes within the same states.[18] The year-quarter estimates from our dynamic-effects models, shown in columns (2) and (4), reveal a similar pattern. Starting in the second quarter following the merger, prices in low-concentration markets with many substitutes are 4.2 percentage points lower in treated states compared to control states. This price gap remains through the tenth quarter after the merger, suggesting long-lasting effects of the merger. In contrast, we do not observe similar effects in high-concentration markets with few substitutes.[19]

5.4. Impact of Merger on Generic Prescription Drug Cartel

Next, we study whether the rise in PBM market power provided additional, unforeseen, benefits to buyers. Here, we take advantage of a generic prescription drug cartel that formed

[18] A difference-in-coefficients test is significant at the 10 percent level.

[19] In Online Appendix OA.C, Panels C and D, we present results from placebo analyses. Panel C displays our coefficient of interest from column (1) relative to the distribution of coefficients from 1,000 replications using randomly drawn event quarters. The mean estimate from placebo estimates is zero; in contrast, our coefficient is statistically significant (at the 1 percent level) from zero. Panel D displays our coefficient from column (3) relative to the mean coefficient from 1,000 replications. We find that the coefficient is not statistically different from zero, consistent with the notion that price decreases in high concentration markets were more difficult to achieve relative to low concentration markets.

in the second quarter of 2013, approximately one year after the merger of Express Scripts and Medco, and continued until at least 2015, when a government investigation commenced into the cartel. Details of the cartel, including the participants, drugs, and dates have been well-publicized and are documented in a 510-page legal complaint that was filed collectively by nearly all U.S. states and Puerto Rico in 2019 (State of Connecticut et al., 2019).

The 2019 Complaint alleges that many of the largest generic prescription drug manufacturers colluded to significantly increase the prices of hundreds of generic drugs, in some cases by more than 1,000%. Importantly, each allegation in the complaint specifies the dates, companies involved, and the drugs in question, including details such as drug substance composition, delivery method, release mechanism, and strength. This information enables the construction of over 100 distinct drug cartelization events that vary by time, participant, and drug, which we analyze using a stacked-event study design. The complaint also indicates that, although the cartel operated on a national scale, participants understood that raising prices would be more challenging in certain markets. This informative motivates us to investigate whether increasing prices was more difficult in states with greater PBM market power.

Online Appendix OA.E provides a further explanation of our analysis, including a catalog of key events included in our stacked-event study design. We begin our empirical analysis of how heightened PBM market power shaped the impact of the generic prescription drug cartel by plotting the average log prices for the sample of generic prescription drugs mentioned in the Complaint as being subject to price-fixing against calendar time in quarters. We normalize each price series to zero in the quarter of the cartel price fixing event.

Figure 4, Panel A, presents results from this analysis (we highlight that quarter with a vertical dashed line). We find that prices of generic drugs that were subsequently cartelized exhibit similar pre-cartel trends in treatment and control states. After a drug is cartelized, prices in all states increase immediately for roughly two quarters but then begin to diverge for the next two years. Notably, prices in treatment states increase at a slower rate relative to those in control states. To highlight the extent of the price difference, we re-estimate Equation (1) for this stacked-event study sample. Results are displayed in Panel B of Figure 4. Prices of cartelized drugs are initially lower (by 6.4 percentage points), and trending upwards (to just 1.7 percentage points lower), in treatment states before the cartel event quarter but then decrease shortly after they are cartelized. At the widest point, ten quarters after the event quarter, cartelized drug prices are on average nearly 30 percentage points lower in treatment states with high exposure to the PBM merger relative to price in control states with low exposure to the PBM merger.

Although alternative explanations for the observed price divergence cannot be entirely

ruled out, any potential confounding variable or event would need to account for price differences across more than 100 distinct events, occurring at various times and involving different drugs and price fixing cartel members. Nevertheless, to provide additional support for our inferences, we exploit a smaller generic prescription drug cartel involving topical drugs that formed in 2009, nearly three years before the merger of Express Scripts and Medco. Details of the cartel, including the participants, drugs, and dates are documented in a 593-page legal complaint that was filed collectively by nearly all U.S. states and Puerto Rico in 2020.

We analyze sixteen cartel events in a similar stacked-event study design, starting with the first event in Q1 2009 and ending with the last event in Q1 2011, to study how drug prices were affected by this cartel prior to the PBM merger we study. The average log prices are plotted in Panel A of Online Appendix OA.F. Prices in treatment and control states exhibit similar pre- and post-trends, with no identifiable divergence in prices after cartel event quarters. Results for estimates of Equation (2) are presented in Panel B of Online Appendix OA.F. Again, we find no evidence of a consistent price divergence between treatment and control states after following these pre-merger cartel events.

Collectively, our results in this section indicate that the merger had a meaningful impact on prices in markets most exposed to the consolidation. Furthermore, our evidence also suggests that the magnitude of these effects varies systematically with market structure. Drug-product markets with a larger number of competitors, such as (1) brand drugs with many substitutes and (2) generic drugs, experience substantially larger price declines than more concentrated markets, underscoring the central role of market structure in shaping the effects of buyer power.

Moreover, given that brand drugs represent about 83% of total Medicaid spending on drugs (Park, 2022), our results suggest substantial savings to state-level Medicaid spending on brand drugs in the states most exposed to the merger. However, comment letters submitted to the FTC and DOJ during their antitrust investigation of the deal highlight numerous potential unintended consequences of allowing the merger, as do concerns voiced during a hearing regarding the merger before members of the U.S. House of Representatives [20] We next explore these unintended consequences.

6. Pharmacy Responses and Patient Choices

Our findings thus far indicate that the merger reduced nominal drug prices in states that were highly exposed to increases in PBM market shares due to the merger. However, such reduc-

[20]For additional details, see National Community Pharmacists Association (2011) and United States House of Representatives Committee on the Judiciary (2011).

tions in reimbursed prices would impact pharmacy margins upstream, thus raising questions about how pharmacies strategically respond to recover lost profits, and how these responses in turn affect patients. To formalize these dynamics and generate testable predictions, we now present a simple theoretical model that links reimbursement rates, pharmacy dispensing incentives, and patient medication adherence.

6.1. Theoretical Framework

To formalize how pharmacies adjust their dispensing behavior when reimbursements decline following a merger, we develop a model of pharmacy incentives in choosing a prescription package size. Consider a setting in which a patient must consume a total quantity of medication $Q > 0$ over the course of treatment. Although physicians determine the drug and overall prescribed quantity, pharmacies ultimately decide the size of each individual fill. A key assumption—consistent with real-world practice—is that pharmacies may choose to partially fill prescriptions (e.g., Berger, 2016). Let $s > 0$ denote the size of each prescription fill, which in turn determines the number of pharmacy visits (i.e., refills) required to dispense the total course. The implied number of fills given package size s is

$$N = \frac{Q}{s}$$

For each fill, the patient pays a co-payment $k > 0$ and the pharmacy receives a fixed dispensing fee $f > 0$ along with a per-unit reimbursement p from the PBM. The pharmacy incurs a per-unit wholesale acquisition cost w, which it pays to the drug manufacturer (or distributor). The per-visit profit to the pharmacy when dispensing package size s is therefore

$$\pi(s) = k + f + ps - ws$$

where $k + f$ represents the per-visit payment (from the patient and PBM) and $(p - w)s$ represents the per-unit margin times the quantity dispensed in a given fill.

However, patients may not fully adhere to the scheduled number of refills.[21] We construct a function that captures how the rate of completing any given scheduled refill declines with both the copay amount k and the number of scheduled visits $N = Q/s$. We specify adherence per scheduled fill as

$$A(k, N) = \exp(-\beta_1 k - \beta_2 N)$$

[21] For example, poor medication adherence is estimated to account for 33 to 69 percent of medication-related hospital admissions in the United States, with associated annual costs ranging from $100 billion to $300 billion (Benjamin, 2012; Osterberg and Blaschke, 2005). In fact, there is a specific diagnostic code (Z91.141) available to hospitals to record "patient's other noncompliance with medication regimen due to financial hardship."

where $\beta_1, \beta_2 > 0$ capture sensitivity to copayments and to refill burden (e.g., travel or mail-order costs). In an extreme case, a patient with $\beta_1 = \beta_2 = 0$ would adhere perfectly, but in general $0 < A(k, N) \leq 1$. The actual number of visits completed by the patient is thus

$$N \cdot A(k, N) = \frac{Q}{s} \exp\Big(- \beta_1 k - \beta_2 \frac{Q}{s} \Big)$$

The pharmacy's total profit from dispensing the required quantity Q is therefore

$$\begin{aligned} \Pi(s) &= \pi(s) \cdot N \cdot A(k, N) \\ &= \big(k + f + (p - w)s\big) \frac{Q}{s} \exp\Big(- \beta_1 k - \beta_2 \frac{Q}{s} \Big) \end{aligned}$$

The pharmacy chooses s to maximize $\Pi(s)$. Differentiating and setting the first-order condition equal to zero yields the condition

$$\beta_2 Q(f + k) + \big(\beta_2 Q(p - w) - (f + k)\big)s = 0$$

Solving for the optimal package size gives

$$s^* = \frac{Q\beta_2(f + k)}{(f + k) - Q\beta_2(p - w)}$$

For the interior solution, we impose the condition $f + k > Q\beta_2(p - w)$ which ensures that the denominator is positive and the optimal s^* lies in the feasible range.[22]

To study how PBM reimbursement affects the chosen package size, differentiate s^* with respect to p. Since only the denominator depends on p, we obtain

$$\frac{\partial s^*}{\partial p} = \frac{Q^2\beta_2^2(f + k)}{\big((f + k) - Q\beta_2(p - w)\big)^2} > 0$$

When reimbursement p declines, the per-unit margin $(p - w)$ shrinks as well. Consequently, dispensing larger quantities in a single fill becomes less profitable for the pharmacy, while generating additional dispensing events becomes relatively more attractive. The optimal

[22] This condition guarantees the existence of an interior optimum by requiring that the total per-fill payment $(f + k)$ is sufficiently large relative to the product $Q\beta_2(p - w)$. Intuitively, $(f + k)$ reflects the value the pharmacy derives from a dispensing encounter, whereas $Q\beta_2$ captures the patient's cumulative sensitivity to refill burden over the full treatment. When $(f + k)$ is large enough compared to $Q\beta_2(p - w)$, the pharmacy faces a meaningful trade-off between generating revenue from additional fills and preserving adherence, and therefore optimally selects an interior package size s^*. If the inequality fails, the pharmacy does not benefit from increasing the dispensing frequency because the adherence penalty dominates the per-fill revenue benefit. In such cases, no interior balancing point exists and the optimum lies at a boundary, typically the larges package size that minimizes refill burden.

package size s^* therefore falls when p decreases, prompting the pharmacy to provide smaller fills and more frequent refills to offset lost revenue through additional dispensing fees (f) and copays (k). This adjustment raises patients' refill frequency and, in turn, increases refill burden and reduces adherence.

In summary, our theoretical framework predicts that (1) lower reimbursements lead pharmacies to dispense smaller package sizes, which (2) increase the frequency of refills and, consequently, (3) reduce patient adherence.[23]

6.2. Economic Incentives for Pharmacies

Our theoretical framework predicts that lower reimbursements induce pharmacies to adjust their dispensing behavior, but this mechanism is only plausible if the underlying incentives are economically meaningful. In particular, pharmacies must be able to offset lost reimbursement revenue by generating additional income through more frequent dispensing. In section 5.2, we estimate that reimbursements decline by approximately \$17.60 on average, implying that any response must compensate for this loss. Two direct sources of incremental revenue are dispensing fees and patient co-payments, both observed at the claim level in our data. The mean (median) dispensing fee is \$1.80 (\$1.35), and the mean (median) co-payment is \$30.90 (\$25). Together, these components yield an expected \$32.70 in incremental revenue per dispensing event, exceeding the average reimbursement reduction. This magnitude suggests that pharmacies can plausibly recoup lost reimbursement revenue by increasing the number of refills through smaller package sizes.

6.3. Empirical Strategy

To empirically test the three core predictions of our theoretical framework, we combine county-level data on Express Scripts' market shares (before and after the merger) with claims-level data containing de-identified information (e.g., medication adherence), pharmacy identifiers, and drug codes. This structure allows us to perform the analysis at the patient–drug–pharmacy level, thereby tracking how the same patient's prescriptions for a given drug product are filled at the same pharmacy over time. Our empirical design exploits cross-county variation in the change in Express Scripts' market share induced by the merger—comparing counties where the merger led to a substantial expansion in Express Scripts' presence (treatment group) with those where its market share remained largely unchanged (control group). We measure changes in package sizes, refill frequencies, and adherence using this quasi-experimental variation. The analysis focuses on branded prescription

[23] Indeed, $N \cdot A(k, N)$ for s^* is strictly smaller than $\frac{Q}{s^*}$.

drugs included in Express Scripts' formulary in the year preceding the merger.

6.4. Packaging and Refills

We begin by testing the first prediction from our theoretical framework that when reimbursement prices decline, pharmacies will offset revenue losses by increasing revenue from alternative sources, such as dispensing fees and in-store retail sales. One way pharmacies can pursue this is by increasing the frequency of customer visits—e.g., by encouraging more frequent refills via partial fills of prescriptions. In practice, pharmacists can partially fill prescriptions (e.g., providing a 1-month supply of medication instead of a 6-month supply), for example, due to limited inventory.[24] To explore whether pharmacies in counties most exposed to the merger are associated with reduced package sizes (and thus increased dispensing and co-pay fees), we estimate the following difference-in-differences specification:

$$PackageSize_{i,p,j,t} = \beta_0 + \beta_1 Treatment(County)_c \times Post_t + \theta_{k,p,j} + \tau_t + \epsilon_{i,p,j,t}, \qquad (3)$$

where $PackageSize_{i,p,j,t}$ denotes the size of the prescription drug package filled, standardized across the same drug product (i.e., NDC, excluding the last two digits), for drug i dispensed by pharmacy p to patient j in year-month t. $Treatment(County)_c$ is an indicator that takes the value of 1 if the county-level (1) change in Express Scripts' market share following the merger is in the top quartile across all counties, and (2) the post-merger level of Express Scripts' market share is in the top quartile, and 0 otherwise. $Post_t$ is an indicator that takes the value of 1 if the year-quarter t is after the merger quarter (2012 Q2), and 0 otherwise. We include a patient-drug product-pharmacy fixed effect, $\theta_{k,p,j}$, to observe changes in package sizes for the same patient purchasing the same drug product at the same pharmacy across time. We also include a year-quarter fixed effect, τ_t, to control for other potentially confounding effects related to trends and seasonality in prescription filling behavior. Standard errors are clustered at the drug (NDC) and county levels.

Our theoretical model predicts a negative coefficient on β_1, reflecting the expectation that pharmacies in counties most exposed to the merger reduce package sizes following the merger. Consistent with this prediction, in Table 4 column (1), which includes over 1.8 million claims from counties most and least exposed to the merger, we find that β_1 is negative (-0.011) and statistically significant at the 10 percent level. In column (2), which includes an expanded sample of approximately 6.8 million claims across 2,682 counties, our main coefficient of interest remains negative (-0.010) and statistically significant at the 10

[24]Partial fills and refills are legally allowed, as long as the remaining balance is dispensed within the prescription's validity period (typically 6 to 12 months), the total quantity dispensed does not exceed the amount prescribed, and each partial fill is properly documented.

percent level.[25] These magnitudes suggest that, on average, pharmacies in the most affected counties dispensed packages approximately 8% smaller relative those in the least affected counties, and about 6% smaller relative to all other counties.

Figure 5 plots coefficients from estimating a model that replaces $Post_t$ with a series of year-quarter indicators interacted with $Treatment(County)_c$. We find no evidence of any differential pre-trends in package sizes, as the estimated coefficients in the pre-merger period fluctuate around zero each period and are statistically indistinguishable from zero. In contrast, we observe a sharp decline in package sizes in the counties most affected by the merger beginning in the first quarter after the merger, and this difference persists for roughly two and a half years. By late 2014, package sizes increase noticeably.[26] A plausible explanation for this reversion is that, around this time, PBMs began incorporating medication adherence into their pharmacy performance evaluation metrics, after the Centers for Medicare & Medicaid Services (CMS) tied Medicare Part D plan bonuses to adherence measures. Once adherence became financially consequential for plans, PBMs gained incentives to realign pharmacy behavior by rewarding higher adherence performance (U.S. Federal Trade Commission, 2024), prompting pharmacies to dispense larger package sizes to improve adherence rates.

In order for a strategy of reducing package size to increase pharmacy profits, reductions in package size must lead to more frequent refills. An increase in refill frequency would generate additional revenue for pharmacies through dispensing fees and co-pays, and could also lead to greater in-store retail sales. To explore this possibility, we study drug refills at the patient–pharmacy–drug product–time period level. Time periods are grouped into two categories—pre-merger and post-merger—so that each observation corresponds to a unique combination of patient, pharmacy, drug product, and time period. We conduct tests using four balanced time windows centered on the merger quarter (–1 to +1 quarter, –2 to +2 quarters, –3 to +3 quarters, and –4 to +4 quarters), allowing us to compare refill frequency within equally-sized windows around the merger event for the same patient, purchasing the same drug product, at the same pharmacy. We estimate the following empirical specification:

$$NumRefills_{k,p,j,t} = \beta_0 + \beta_1 Treatment(County)_c \times Post_t + \theta_{k,p,j} + \tau_t + \epsilon_{k,p,j,t}, \qquad (4)$$

where $NumRefills_{k,p,j,t}$ denotes the number of refills of drug product k dispensed at pharmacy p for patient j over time period t; and $Treatment(County)_c$ and $Post_t$ are defined

[25] In Online Appendix OA.I, column (1) we replace $Treatment(County)_c$ with a continuous measure $Exposure_c$, which captures the degree to which a county was exposed to the merger in the pre-period, and continue find a negative coefficient of -0.029.

[26] Confidence intervals in the last quarter of the sample period include 0, which helps explain why our coefficients from these tests are only significant at the 10 percent level.

as previously described. We include a patient-drug product-pharmacy fixed effect, $\theta_{k,p,j}$, as well as an event period fixed effect, τ_t. Standard errors are clustered at the drug (NDC) and county levels.

Columns (1) through (4) of Table 5 present results for the sample comprising counties most and least affected by the merger. In column (1), which examines a [-1,+1] quarter window around the merger, we find a statistically significant increase—at the 1 percent level—in the number of refills for patients in counties most exposed to the merger relative to those least exposed. Widening the time horizons of the windows of analysis in columns (2) through (4) shows that the estimated effect remains positive, statistically significant, and increases monotonically in magnitude. These results suggest that refill frequency rises persistently over longer horizons following the merger. Using the results from column (4), the magnitude of the coefficient (0.406) indicates that refills increased by over 12% in counties most exposed to the merger.

In columns (5) through (8), we show results for the sample comprising all counties and find that the results continue to hold. Using this same sample in Online Appendix OA.I, we replace $Treatment(County)_c$ with our continuous measure $Exposure$ and continue find a positive and statistically significant relationship—at the 1 percent level—between our main variable of interest, $Exposure_c \times Post_t$, and the number of refills across all four window horizons in columns (2) through (5).

6.5. Bargaining Power

Overall, our results on smaller package sizes and increased refill frequency are consistent with pharmacies changing their strategies to recoup lost profits following reductions in nominal drug prices being reimbursed following the PBM merger. To provide further evidence of this change in pharmacy strategy, we next test whether such behavior is most pronounced among pharmacies that are likely most affected by the PBM merger. The credibility and costliness of being excluded from a PBM's pharmacy network hinge on the relative bargaining power between the PBM and the pharmacy (or pharmacy chain). Consequently, an increase in PBM market power following the merger should most strongly affect pharmacies with weaker bargaining positions. To measure a pharmacy's bargaining power, we proxy for it using the pharmacy's market share—defined as the number of claims filled by that pharmacy as a percentage of all pharmacy claims within the same county. We then take the inverse of this measure and use it in the following triple difference-in-differences model to test whether pharmacies with weaker bargaining power respond to the merger by reducing

package sizes:

$$\begin{aligned} PackageSize_{i,p,j,t} = \beta_0 &+ \beta_1 Treatment(County)_c \times Post_t \times MarketShare(Inverse)_p \\ &+ \beta_2 Treatment(County)_c \times Post_t \\ &+ \beta_3 Treatment(County)_c \times MarketShare(Inverse)_p \\ &+ \beta_4 Post_t \times MarketShare(Inverse)_p \\ &+ \beta_5 Treatment(County)_c + \beta_6 Post_t + \beta_7 MarketShare(Inverse)_p \\ &+ \theta_{k,p,j} + \tau_t + \epsilon_{i,p,j,t} \end{aligned} \tag{5}$$

Results from estimating this model are presented in column (1) of Table 6. Consistent with the notion that pharmacies with weaker bargaining power are more likely to be affected by decreased reimbursements and thus have stronger economic incentives to reduce package sizes, we find a negative and statistically significant relationship between our main variable of interest, $Treatment(County)_c \times Post_t \times MarketShare(Inverse)_p$, and package sizes.

In columns (2) through (5) of Table 6, we extend this analysis to to explore the impact of the merger on the number of refills for pharmacies with weaker bargaining power, using the following triple difference-in-differences model:

$$\begin{aligned} NumRefills_{k,p,j,t} = \beta_0 &+ \beta_1 Treatment(County)_c \times Post_t \times MarketShare(Inverse)_p \\ &+ \beta_2 Treatment(County)_c \times Post_t \\ &+ \beta_3 Treatment(County)_c \times MarketShare(Inverse)_p \\ &+ \beta_4 Post_t \times MarketShare(Inverse)_p \\ &+ \beta_5 Treatment(County)_c + \beta_6 Post_t + \beta_7 MarketShare(Inverse)_p \\ &+ \theta_{k,p,j} + \tau_t + \epsilon_{k,p,j,t} \end{aligned} \tag{6}$$

Column (2) of Table 6 reports estimates for a [-1,+1] quarter window around the merger and shows a statistically significant positive relationship between our main variable of interest, $Treatment(County)_c \times Post_t \times MarketShare(Inverse)_p$, and the number of refills. Thus, pharmacies in treated counties most affected by the mergers are significantly more likely to increase the number of prescription refills following the merger when the pharmacy has weak bargaining power. This result is robust—and increases in magnitude—as we expand the time horizon of our analysis to wider windows in columns (3), (4), and (5), respectively.

6.6. Patient Choices

Our empirical analysis so far has focused on the strategic decisions of pharmacies, finding that pharmacies in counties most affected by the merger (1) reduce package sizes, which results in (2) an increase in the number of refills, and that these effects are more pronounced when (3) pharmacies have weaker bargaining power. We next investigate the extent to which the ultimate consumers (i.e., patients) in this market are affected by the changes in pharmacy behavior associated with the merger.

6.6.1. Medication adherence

Our theoretical model predicts that as pharmacies provide patients with smaller package sizes—thereby increasing the number of refills—the additional costs born by patients, such as more co-pays or travel costs to fill prescriptions, may lead to some patients discontinuing their medications prematurely. To explore this possibility, we examine whether counties most affected by the merger are associated with reduced medication adherence by estimating the following difference-in-differences model:

$$\begin{aligned} ReducedAdherence_{i,p,j,t} = \beta_0 + \beta_1 Treatment(County)_c \times Post_t \\ + \beta_2 Treatment(County)_c + \beta_3 Post_t + \theta_{k,p,j} + \tau_t + \epsilon_{i,p,j,t}, \end{aligned} \tag{7}$$

where the dependent variable *ReducedAdherence* is an indicator variable that takes the value of 1 if patient j does not refill a drug i at pharmacy p within 30 days following the end of the originally-prescribed days' supply, and 0 otherwise. $Treatment(County)_c$ and $Post_t$ are defined as previously described. We include a patient-drug product-pharmacy fixed effect, $\theta_{k,p,j}$, as well as a year-quarter fixed effect, τ_t in all specifications. Standard errors are clustered at the drug (NDC) and county levels.

Our theoretical framework predicts that patients in counties most affected by the merger—i.e., where package sizes decrease and the number of refills increase—are more likely to stop refilling their medications. Thus, we expect a positive coefficient on β_1. Consistent with this prediction, column (1) of Table 7 Panel A, which includes over 1.8 million claims from counties most (treatment group) and least (control group) affected by the merger, shows that β_1 is positive (0.008) and statistically significant at the 10 percent level. Given an average baseline non-refill rate of 0.24, this coefficient implies that adherence worsens by approximately 3.3% in counties most exposed to the merger. In column (2), which includes an expanded sample of approximately 6.8 million claims across 2,682 counties, our main coefficient of interest remains positive (0.022) and statistically significant at the 1 percent level.

One potential concern with this analysis is that we cannot control for unobserved patient-level factors—such as mortality—that could independently explain lower adherence in counties most affected by the merger. To address this concern, we estimate an alternative specification that compares the likelihood of reduced adherence for drugs included on the Express Scripts formulary versus those excluded from its formulary. In this analysis, we restrict the sample to patients who have filled at least one prescription on and one off of Express Scripts' formulary, and limit our sample to counties most affected by the merger. This analysis therefore tests whether, within these counties, patients are more likely to fail to refill drugs on the Express Scripts formulary relative to drugs excluded from it. In particular, we estimate the following specification:

$$\begin{aligned} ReducedAdherence_{i,p,j,t} = \beta_0 + \beta_1 Treatment(Drug)_i \times Post_t \\ + \beta_2 Treatment(Drug)i + \beta_3 Post_t + \theta_{k,p,j} + \tau_t + \epsilon_{i,p,j,t}, \end{aligned} \tag{8}$$

where the dependent variable *ReducedAdherence* is an indicator variable that takes the value of 1 if patient j does not refill a drug i at pharmacy p within 30 (or 60 or 90) days following the end of the originally prescribed days' supply, and 0 otherwise. $Treatment(Drug)_i$ and $Post_t$ are defined as previously described. We include a patient-drug product-pharmacy fixed effect, $\theta_{k,p,j}$, as well as a year-quarter fixed effect, τ_t. Standard errors are clustered at the drug (NDC) and county levels.

Panel B of Table 7 presents results. Across all three specifications—which extend the allowable gap between the last and next refill from 30 to 60 to 90 days—we find that patients are significantly more likely to fail to refill Express Scripts–formulary brand drugs relative to other drugs that the same patient refills at the same pharmacy.

6.6.2. Reduced adherence and health outcomes

Finally, we examine the degree to which the financial savings achieved via lower input-prices that we document following the merger are offset by higher medical costs resulting from the degraded medication adherence we find. Poor medication adherence accounts for an estimated 33 to 69 percent of medication-related hospital admissions in the United States, with associated annual costs ranging from $100 billion to $300 billion (Benjamin, 2012; Osterberg and Blaschke, 2005). A key advantage of our data is that we can directly link patients' prescription drug claims to their medical claims, enabling us to test whether reductions in adherence are associated with an increase in hospitalizations.

Because medication adherence is potentially endogenous to patients' underlying health status, we estimate the effect of adherence on hospitalization using a two-stage least squares

(2SLS) framework that isolates plausibly exogenous variation in adherence. In the first stage, we estimate the following specification:

$$\begin{aligned} ReducedAdherence_{i,p,j,t} = \beta_0 &+ \beta_1 Treatment(County)_c \times Post_t \\ &+ \beta_2 Treatment(County)_c + \beta_3 Post_t \\ &+ \beta_4 Age_{j,t} + \beta_5 PriorERVisits_{j,t-1} \\ &+ \theta_{k,p,j} + \tau_t + \epsilon_{i,p,j,t}, \end{aligned} \tag{9}$$

where the dependent variable *ReducedAdherence* is an indicator variable that takes the value of 1 if patient j does not refill a drug i at pharmacy p within 30 days following the end of the originally-prescribed days' supply, and 0 otherwise. $Treatment(County)_c$ and $Post_t$ are defined as previously described. Factors that may be correlated with emergency room visits such as the patient's age and prior emergency room (ER) visits—defined as the number of ER visits in the past month—are included as controls in our first stage. We include a patient-drug product-pharmacy fixed effect, $\theta_{k,p,j}$, as well as a year-quarter fixed effect, τ_t in all specifications. Standard errors are clustered at the drug (NDC) and county level. Results showing a positive and statistically significant association between $Treatment(County)_c \times Post_t$ and *ReducedAdherence* are reported in Panel A of Table 8.

In the second stage, we estimate the effect of reduced medication adherence on subsequent hospitalizations. Specifically, in the following equation, we regress the number of ER visits in period $t+1$—defined as a 90-day window—on the predicted reduction in adherence in period t, obtained from estimates in our first stage, in the following regression specification:

$$\begin{aligned} NumberERVisits_{i,p,j,t+1} = \beta_0 &+ \beta_1 \widehat{ReducedAdherence}_{i,p,j,t} \\ &+ \beta_2 Age_{j,t} + \beta_3 PriorERVisits_{j,t-1} \\ &+ \theta_{k,p,j} + \tau_t + \epsilon_{i,p,j,t}, \end{aligned} \tag{10}$$

We control for the patient's age and for prior ER visits (in the past month). We also include a patient-drug product-pharmacy fixed effect, $\theta_{k,p,j}$, as well as a year-quarter fixed effect, τ_t in all specifications. Standard errors are clustered at the drug (NDC) and county level. Columns 1 and 2 of Panel B, Table 8, report the results.

In column 1, where are dependent variable is the number of ER visits in the next 90 days, the coefficient on the patient's predicted reduction in adherence obtained from our first stage is positive and statistically significant at the 5 percent level. The magnitude of the coefficient (0.887) indicates that a one-standard deviation increase in predicted reduced adherence from the first stage is associated with an additional 0.28 emergency room visits

for the same patient in the next 90 days.[27]

In columns 3 and 4, the outcome is an indicator variable for an emergency room visit in the next 90 days. We continue to find a positive and statistically significant coefficient on the patient's predicted reduction in adherence obtained from our first-stage estimation. In economic terms, the coefficient from column 3 (0.361) indicates that a one-standard deviation increase in predicted reduced adherence from the first stage is associated with an 11.6% higher probability of an emergency room visit in the next 90 days.[28]

6.6.3. Estimating the Hospitalization Costs of Reduced Adherence

Prior estimates place annual U.S. hospitalization costs attributable to reduced medication adherence between $100 billion and $300 billion (Benjamin, 2012; Osterberg and Blaschke, 2005). In our sample, 14.7% of U.S. counties (462 of 3,144) are classified as highly exposed to the merger. As shown in Panel A of Table 8, the predicted rate of reduced adherence in these counties is 0.008 higher, corresponding to a 3.3% increase relative to the mean reduced-adherence rate of 24%. Applying this increase to the estimated effect of reduced adherence on the probability of an emergency room visit (0.361, column 3 of Panel B) implies a 1.2% increase in ER visits for patients in highly exposed counties. Combining these estimates yields an implied annual increase in hospitalization costs ranging from $207.6 million (14.7% $\times$ 1.2% $\times$ $100 billion) to $622.8 million (14.7% $\times$ 1.2% $\times$ $300 billion).

6.7. Estimating the Net Effects to Consumers

Our analysis of branded-drug prices shows an average 3.6% reduction in reimbursements to pharmacies in states most exposed to the merger. While these savings may be passed through to insured patients in the form of lower premiums, our evidence suggests they may also induce responses by affected pharmacies that ultimately raise consumer costs. Assessing the net effect on consumers is therefore essential.

We begin by examining insurer–state–level data on insurance premiums to test whether consumers in highly exposed states experience slower premium growth. Consistent with this hypothesis, we find that premiums in the most-exposed states grew by 2 percentage points less than in the least-exposed states over the two years following the merger. Had premiums increased at the same rate, consumers in the most-exposed states would have paid

[27] Computed as 0.28=0.32*0.887; where 0.32 is standard deviation of predicted reduced adherence, and 0.887 is the main coefficient in the second stage.

[28] Computed as 0.116=0.32*0.361; where 0.32 is standard deviation of predicted reduced adherence, and 0.361 is the main coefficient in the second stage.

an additional \$75 (or \$37.50 per year).[29]

Because patients face two distinct decisions—whether to continue or discontinue refilling their prescriptions—we estimate the merger's net effects separately for each case. For patients in highly exposed states who continue to refill, the benefits of lower insurance premiums must be weighed against the expected costs associated with additional refills, such as travel and out-of-pocket payments. For patients who discontinue their medication, savings from lower premiums, reduced cost sharing, and less travel must be balanced against the expected increase in future healthcare costs borne by the patient.

For patients who continue to refill, column 4 of Table 5 shows that the average patient in a county highly exposed to the merger fills 0.41 additional prescriptions over the four quarters following the merger. Although we do not observe patients' contracted co-insurance rates, we can bound expected out-of-pocket costs using typical co-insurance rates for brand drugs of 20 to 30 percent. Using the sample's average per-prescription reimbursement of \$429 as a benchmark, this implies an increase in expected out-of-pocket spending of approximately \$35 to \$53 over the post-merger year.[30] By comparison, the estimated reduction in insurance premiums over the same period is roughly \$38. Taken together, and abstracting from additional travel costs, the increase in expected out-of-pocket spending for continuing patients outweighs the premium savings on average.

For patients who reduce adherence, our estimates from subsection 6.6.3 indicate that the probability of an ER visit increases by 1.2% on average for patients in highly exposed counties. Given the average cost of an ER visit for a 48 year old (i.e., the mean age of a patient in our sample) is estimated to be \$880 (in 2021 dollars) (Roemer, 2024), the incremental expected out-of-pocket costs for a patient are \$2 to \$4, assuming co-insurance rates of 20-30 percent.[31] This calculation, however, abstracts from other economically meaningful costs, including ambulatory care, follow-up costs, prescription changes, and lost wages. Consequently, the net consumer impact of reduced medication adherence is likely to exceed the savings from lower insurance premiums.

[29] These savings are comparable in magnitude to those estimated by Che (2025), who study the effects of PBM buyer power on insurance premiums in a different setting.

[30] Expected out-of-pocket costs are calculated as the product of the estimated increase in the number of refills (0.41), the sample-average per-prescription reimbursement (\$429), and assumed co-insurance rates of 20–30 percent. Because co-insurance is typically applied to list prices rather than reimbursement amounts, and list prices are generally lower, these calculations should be interpreted as conservative lower-bound estimates.

[31] Expected out-of-pocket costs are calculated as the product of the estimated increase in the probability of an ER visit (1.2%), the estimated cost of an ER visit (\$880), and assumed co-insurance rates of 20–30 percent.

7. Additional Analyses and Discussion

In this section, we analyze why changes in pharmacy behavior emerge only after the merger. We also consider a potential but unlikely response by Express Scripts—namely, lowering dispensing fees in reaction to pharmacies' behavior. In addition, we examine how adherence incentives may counteract or limit such adjustments by pharmacies. Finally, we discuss the role of drug-manufacturer rebates paid to insurers through their PBMs, and other forms of consolidation that are occurring in the industry.

7.1. Pre-Merger Dispensing Behavior

One might wonder why pharmacies did not dispense smaller package sizes prior to the merger. Recall that our model predicts an inverse relationship between package size and reimbursement rates. When the per-unit reimbursement p increases, the per-unit margin $(p - w)$ rises, which increases the denominator of s^* and thus shifts the optimal package size upward. Higher unit profitability diminishes the relative gain from increasing the number of dispensing events, leading pharmacies to optimally dispense larger package sizes. As our price analysis shows, the merger increased the market power of Express Scripts, enabling the PBM to reduce reimbursements to pharmacies for the same drugs. Consequently, the merger serves as a natural shock that lowers p and shifts pharmacies' optimal package-size decisions.

7.2. Dispensing Fees

Given the reduction in package sizes we find after the merger in the areas most affected by the merger, one potential way to curb such behavior would be for PBMs to reduce or withhold dispensing fees. However, two factors limit this possibility. First, dispensing fees are typically fixed amounts specified in pharmacy contracts (see Online Appendix OA.J for a copy of an Express Scripts contract). Second, for Medicaid prescriptions—where reimbursements are administered at the state level—minimum dispensing fees are established by law, preventing PBMs from lowering them.[32]

To verify these institutional constraints empirically, we estimate a difference-in-differences regression comparing dispensing fees in counties most versus least exposed to the merger. The dynamic coefficients, reported in Online Appendix OA.K, show a slight upward trend prior to the merger but no systematic divergence afterward, indicating that dispensing fees remained stable and did not decline in the counties most exposed to the merger.

[32] Dispensing fees for each state are available here: https://www.medicaid.gov/medicaid/prescription-drugs/downloads/medicaid-prescription-reimbursement.pdf.

7.3. Adherence Incentives

A natural extension of our analysis is to consider how adherence incentives influence pharmacies' dispensing decisions. Because patients are sensitive to refill frequency—more frequent refills tend to lower adherence—effective adherence incentives must ultimately encourage pharmacies to reduce refill frequency, such as by dispensing larger package sizes.

In practice, PBM adherence incentives typically take one of three forms: (1) performance bonuses, paid quarterly or annually to pharmacies meeting adherence benchmarks; (2) fee withholds, where a portion of reimbursement is initially withheld and later released contingent on achieving adherence targets; and (3) preferred network tiering, which rewards high-performing pharmacies through increased prescription volume via enhanced network placement.

As shown in Figure 5, package sizes begin to rise toward their per-merger levels near the end of 2014, coinciding with the broader rollout of adherence incentive programs. Our theoretical framework provides a lens to interpret this pattern: whether through annual bonuses, released withholds, or improved network access, these mechanisms all make pharmacy profits increasing in adherence. Since our model predicts that adherence declines with smaller package sizes, these incentives naturally motivate pharmacies to revert toward dispensing larger packages. This pattern suggests that sufficiently strong adherence incentives can offset the profit losses associated with lower reimbursement rates or higher wholesale costs.

7.4. Drug Manufacturer Rebates

An increase in PBMs' buyer power is likely to affect the rebates that drug manufacturers pay to secure placement on preferred tiers of PBM-administered formularies.[33] Because rebates are proprietary and unobservable in our data, we cannot test this channel directly. However, using proprietary data from a single drug plan, Ho and Lee (2023) shows that granting PBMs greater flexibility in formulary tiering can substantially increase rebate payments.

If rebates rise following the merger, manufacturers may attempt to recoup these losses by increasing wholesale prices charged to pharmacies. Such price increases would disproportionately affect pharmacies with weaker bargaining power. Although our data do not allow us to disentangle pharmacy responses to lower reimbursements from responses to higher wholesale acquisition costs, both mechanisms arise from the same underlying shift in buyer power induced by the merger.

[33] Appendix A illustrates how rebates flow from manufacturers to PBMs and are subsequently shared with insurers.

7.5. Vertical Integration

A growing literature studies the effects of vertical integration along the pharmaceutical supply chain, including insurer–PBM, PBM–pharmacy, and insurer–PBM–pharmacy integration. An important advantage of our setting is that no economically meaningful vertical integration events occurred during our sample period (Q4 2009 to Q4 2014), making it unlikely that our results are confounded by contemporaneous forms of consolidation. Notable vertical integration events—such as CVS's (a pharmay chain) acquisition of Caremark (a PBM)—occurred in 2007, roughly two years before the start of our sample period and about five years prior to the Express Scripts–Medco merger. Consistent with this, we examine CVS/Caremark's PBM market shares before and after 2012 and find them to be similar in counties most exposed to the merger relative to those least exposed: CVS/Caremark held an average market share of roughly 10 percent in both sets of counties prior to the merger, remaining essentially unchanged in counties least exposed and declining to roughly 5 percent in counties most exposed.[34] Nevertheless, it is useful to consider how vertical integration, including smaller-scale arrangements not directly observed in the data, could affect our inferences.

For example, Yde (2025) documents that pharmacies owned by PBMs receive higher reimbursement rates, consistent with cross-subsidization. If some pharmacies in highly exposed counties are subsidized by PBMs other than the merged entity, then the average pharmacy response to reduced reimbursements should be attenuated in those counties, as subsidized pharmacies should be relatively less affected by the merger. This implies that our estimates of changes in package sizes, refill frequency, and downstream patient health outcomes likely represent lower-bound effects.

8. Conclusion

This paper examines the economic implications of allowing the the consolidation of large buyers to counter the market power of dominant sellers—i.e., "fighting fire with fire." By exploiting the 2012 consolidation of Express Scripts and Medco as a natural experiment, we provide causal evidence on how such countervailing market power operates within a complex, multilayered U.S. pharmaceutical supply chain.

We find a significant reduction in nominal drug prices in states most affected by the merger, particularly for branded drugs with available substitutes where PBMs can generate competition. Furthermore, we document a novel spillover effect of powerful buyer consolidation: the merged firm's market power was sufficient enough to disrupt explicit upstream

[34]The next major integration event occurred in 2018, when Cigna (an insurer) acquired Express Scripts.

collusion. During a generic drug cartel following the merger, price increases were significantly dampened in high-exposure states, suggesting that powerful buyers can serve to countervail coordinated seller price fixing.

However, we also show that these benefits from the merger generated unintended upstream distortions. Because PBMs transmit price pressure through multilayered intermediaries rather than directly to consumers, the merger squeezed pharmacy margins, prompting a strategic change in dispensing behavior. To formalize the intuition of these forces we develop a theoretical framework, in which we predict and find that pharmacies responded to lower reimbursements by reducing package sizes to trigger more frequent dispensing fees, co-pays, and retail shopping. This operational response transferred an increased refill burden to patients that led to a reduction in medication adherence, which in turn leads to a subsequent increase in emergency room visits for the same patients. These findings reveal a critical agency conflict in multilayered vertical markets: when intermediaries are squeezed by powerful buyers, they may recover profits through operational adjustments that erode service quality and harm end consumers.

Our findings are relevant for antitrust policy and the regulation of competition in healthcare markets. The Federal Trade Commission's recent scrutiny of PBMs, for example, highlights concerns about their market power and its effects on the pharmaceutical supply chain. While the PBM merger we study achieved its purported goal of lowering nominal drug costs, it did so by reshaping the incentives of the supply chain in ways that ultimately compromised patient care. This suggests that antitrust evaluations of buyer consolidation in multilayered supply chains cannot rely solely on input price effects or assume perfect pass-through of nominal price changes. Instead, results from our study suggest the importance of regulators considering the "gatekeeper" role of dominant firms' intangible assets like formularies and how the exercise of market power propagates through intermediaries. As sectors continue to consolidate across healthcare markets and beyond, understanding these effects where savings in one level of a supply chain create distortions in another—is essential for assessing the full implications of "fighting fire with fire."

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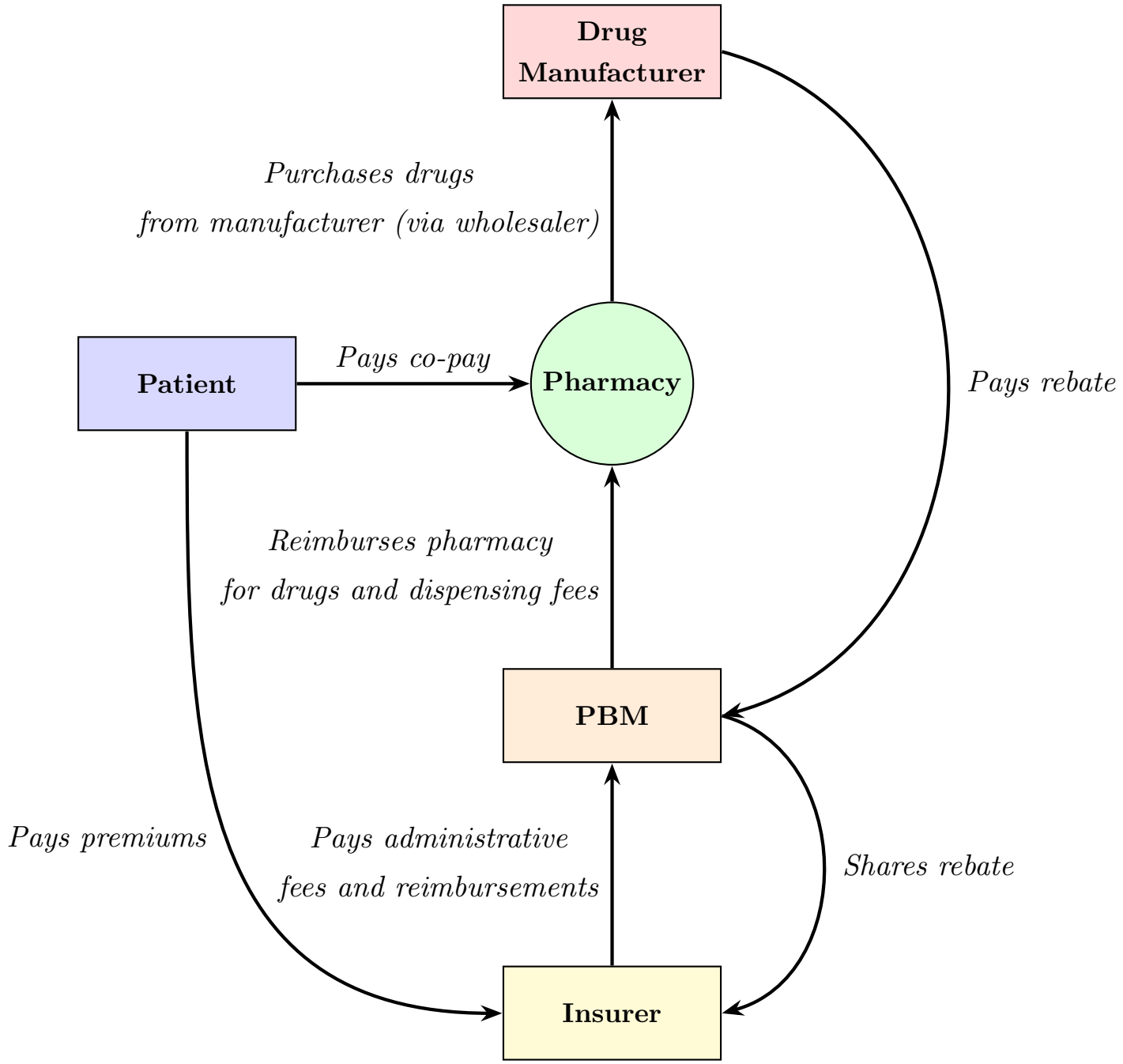
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Appendix A. Pharmaceutical Industry Supply Chain

This figure depicts the supply chain in the pharmaceutical drug industry. Arrows indicate the flow of payments.



Appendix B. Variable Definitions

Variable	Description	Source
Dependent variables		
Price	The log of the price of drug i in state s at year-quarter t.	MSDU
PackageSize	The drug package size, standardized across the same drug product (NDC, excluding the last two digits), measured at the insurance claim level.	MarketScan
NumRefills	Number of drug refills at the patient, pharmacy, drug product, and pre- or post-period levels. The pre- (post-) period is defined as: 1, 2, 3, or 4 quarters before (after) the treatment period.	MarketScan
Number ER Visits (Past Month)	Number of emergency room visits by the patient in the past month.	MarketScan
Number ER Visits (Next Quarter)	Number of emergency room visits by the patient in the next quarter.	MarketScan
Indicator for ER Visits (Next Quarter)	An indicator equal to 1 if the number of emergency room visits by the patient in the next quarter is greater than 0, and 0 otherwise.	MarketScan
Explanatory variables		
Treatment(State)	An indicator set to 1 if state i is in the treatment group (Louisiana, Missouri, Vermont, West Virginia), and 0 if state i is in the control group (Florida, Maryland, Minnesota).	MSDU, Clarivate
Treatment(County)	In Tables 4–6, for DiD sample 1 (i.e., High vs. Low counties), *Treatment* is an indicator that equals 1 when two conditions hold simultaneously: (i) the change in Express Scripts' market share for contract negotiations from the pre- to the post-period falls in the top quartile of the sample, and (ii) the post-period level of Express Scripts' market share for contract negotiations also falls in the top quartile; while equals 0 when the change in market share (condition i) falls in the bottom quartile of the sample. For DiD sample 2 (i.e., High vs. All other counties), *Treatment* is defined the same as in Column 1 for the treated group (i.e., equals 1 under the same two conditions), but equals 0 for all other counties.	MarketScan, Clarivate
Post	An indicator set to 1 if year-quarter t falls within the post-merger period (i.e., 2012 Q2), and 0 otherwise.	MSDU, MarketScan
Exposure	The degree to which a state's market was exposed to the merger event during the pre-period. It is calculated by summing the individual pre-period (averaged over 2010 and 2011) market shares of Express Scripts and Medco in a state and then subtracting the larger of the two shares. Market share is aggregated at the state-year level by dividing the number of commercial medical prescriptions managed by one retail PBM by the total number of commercial medical prescriptions in the state for that year.	Clarivate
PharmacyMarketShare (Inverse)	Number of claims by the pharmacy as a percentage of total number of claims by all pharmacies in the first year of the sample period (2009), multiplied by -1.	MarketScan
ReducedAdherance	An indicator equal to 1 if a patient fails to refill a drug product within 30 (or 60, 90) days after the end of the originally dispensed days' supply, and 0 otherwise.	MarketScan
Treatment(Drug)	An indicator that equals 1 if a drug is a brand drug listed on Express Scripts (ES) formulary, and 0 if a drug is not on ES formulary.	Express Scripts formulary
AGE	The patient's age at time t.	MarketScan

Figure 1. Effect on prices

This figure presents the average log price of brand drugs in treatment and control states on the y-axis against calendar quarter on the x-axis. The vertical dashed line corresponds to the merger event quarter, and prices are normalized to zero in that quarter.

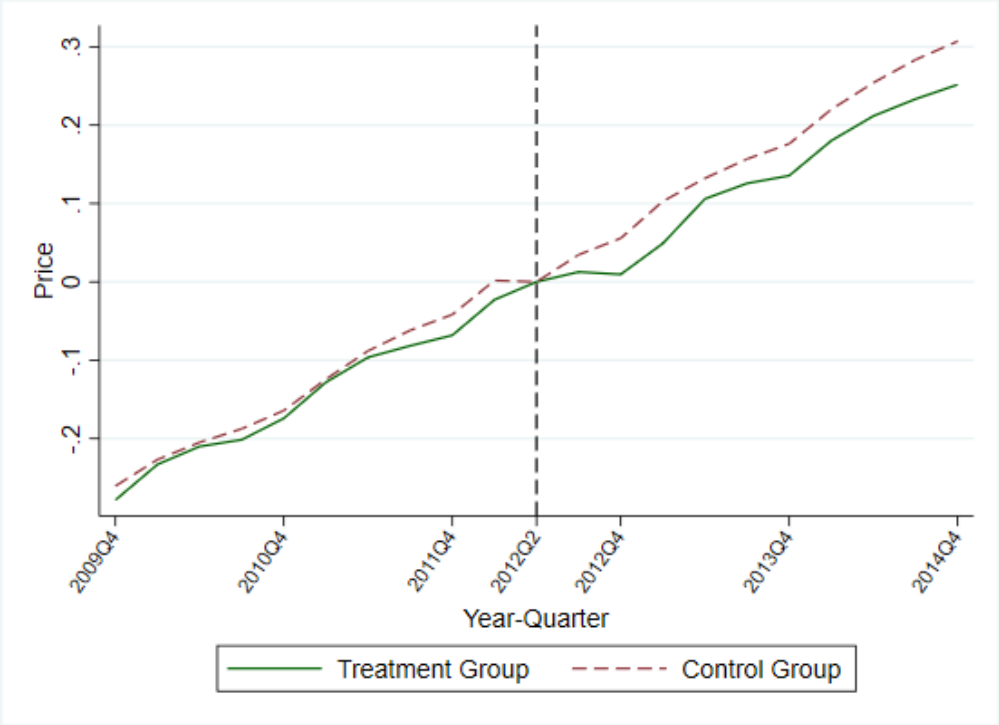


Figure 2. Dynamic effects (Brands)

This figure presents difference-in-difference coefficients for each year-quarter (with 2012Q1 as the base period) from a regression of drug price on the treatment indicator interacted with individual year-quarter indicators. The merger quarter was excluded from the estimation. The regression is at the drug-state-year-quarter level. Point estimates are derived from a regression including state and drug (i.e., NDC)-quarter fixed effects. Standard errors are clustered at the drug (i.e., NDC) level. The gray area represents a pointwise 95% confidence interval.

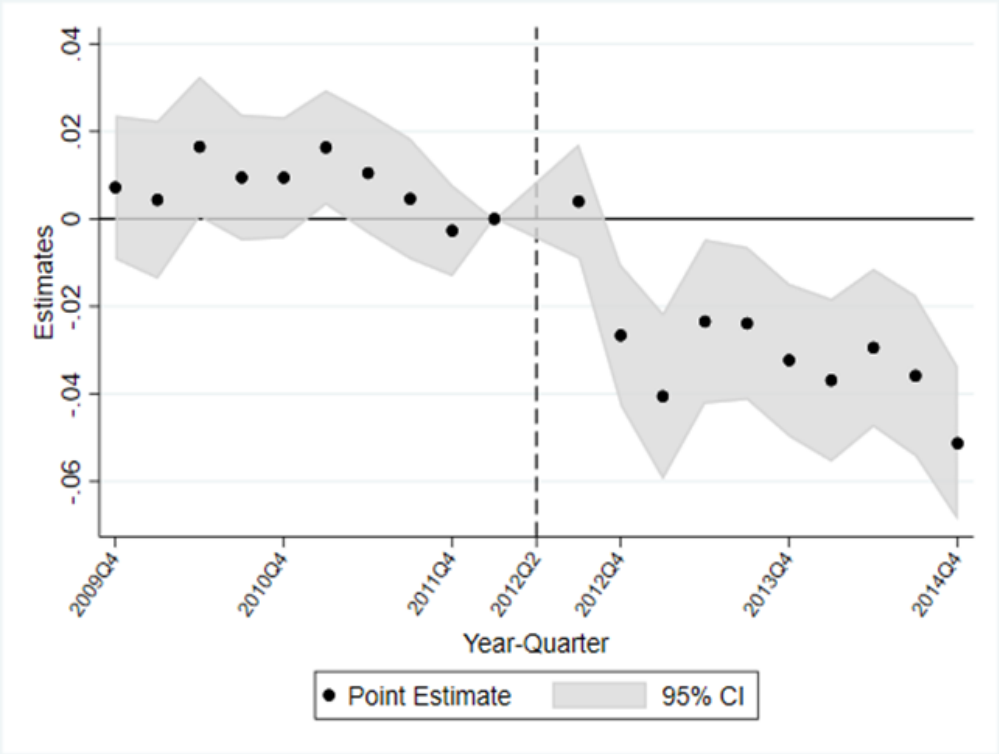
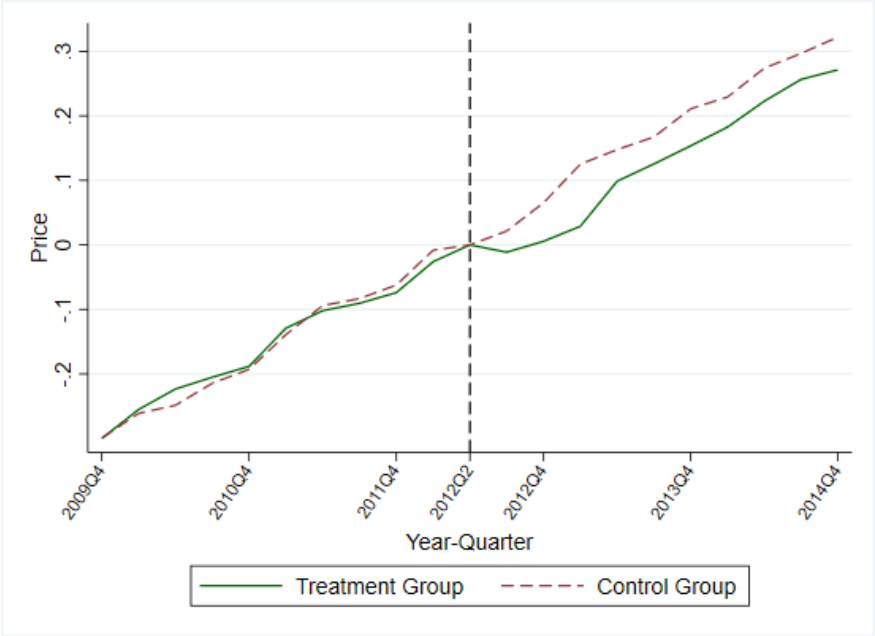


Figure 3. Effect on prices of drugs with varying substitutability

This figure presents the average log price of brand drugs with heterogeneous substitutability in treatment and control states on the y-axis against calendar quarter on the x-axis. Panel A includes brand drugs with HHI of the drug market below the median across the sample. Panel B includes those with HHI of the drug market above the median across the sample. A drug market is defined as all drugs within the same 4-digit ATC code. The vertical dashed line corresponds to the merger event quarter, and prices are normalized to zero in that quarter.

Panel A. Effect on prices of brand drugs with many substitutes



Panel B. Effect on prices of brand drugs with few substitutes

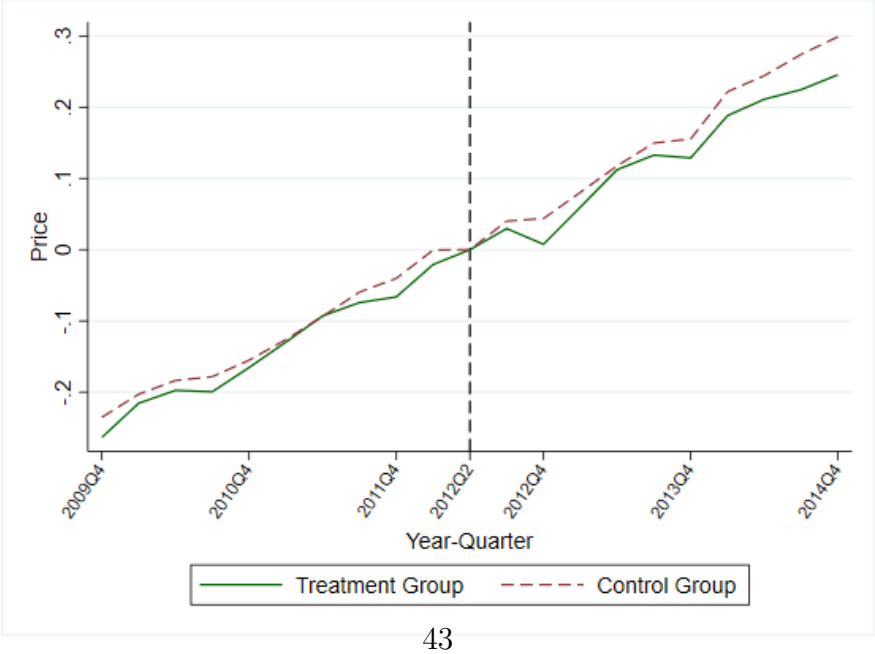
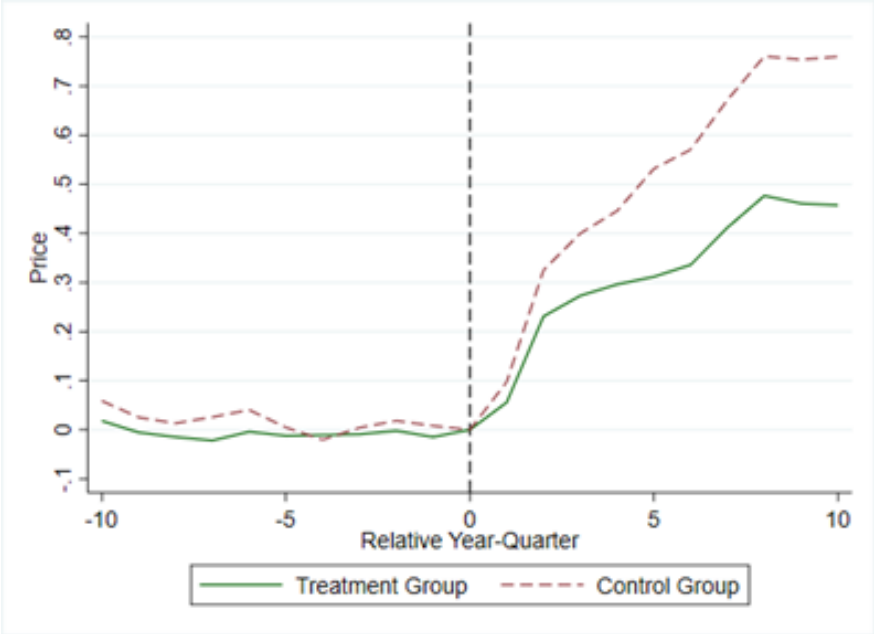


Figure 4. Effect on post-merger cartel

This table presents the dynamic trends and estimated effects on the prices of drugs within cartel groups formed after the merger event. Panel A presents the average log price of drugs within cartel groups formed after the merger event in treatment and control states on the y-axis against the quarter relative to the corresponding cartel-formation event quarter on the x-axis. The vertical dashed line corresponds to each cartel-formation event quarter, and prices are normalized to zero in that quarter. Panel B presents difference-in-difference coefficients for each quarter relative to the corresponding cartel-formation event (with the event quarter as the base year-quarter) from a regression of drug price on the treatment indicator interacted with individual relative quarter indicators. The regression is at the drug-state-relative quarter level. Point estimates are derived from a regression including state and drug (i.e., NDC)-relative quarter fixed effects. Standard errors are clustered at the drug (i.e., NDC) level. The vertical dashed line corresponds to each cartel-formation event quarter. The gray area represents a pointwise 95% confidence interval.

Panel A. Dynamic trends in prices of post-merger cartelized drugs



Panel B. Estimated effects on prices of post-merger cartelized drugs

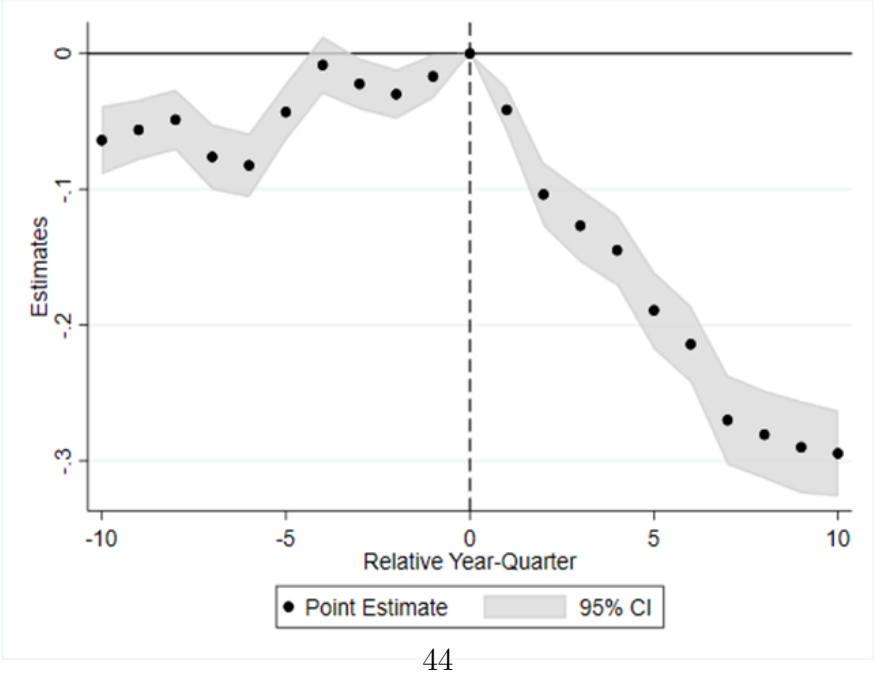


Figure 5. Package sizes

This figure presents difference-in-difference coefficients for each year-quarter (with 2012Q1 as the base period) from a regression of drug package size on the treatment indicator interacted with individual year-quarter indicators. The merger quarter was excluded from the estimation. The dependent variable is *PackageSize*, defined as the drug package size standardized across the same drug product (NDC, excluding the last two digits). *Treatment(County)* is defined as an indicator that equals 1 when two conditions hold simultaneously: (i) the change in Express Scripts' market share for contract negotiations from the pre- to the post-period falls in the top quartile of the sample, and (ii) the post-period level of Express Scripts' market share for contract negotiations also falls in the top quartile, while equals 0 when the change in market share (condition i) falls in the bottom quartile of the sample. The regression is at the insurance claim level. Point estimates are derived from a regression including patient-drug product-pharmacy, and year-quarter fixed effects. Standard errors are double clustered at the drug (i.e., NDC) and county level. The gray area represents a pointwise 95% confidence interval.

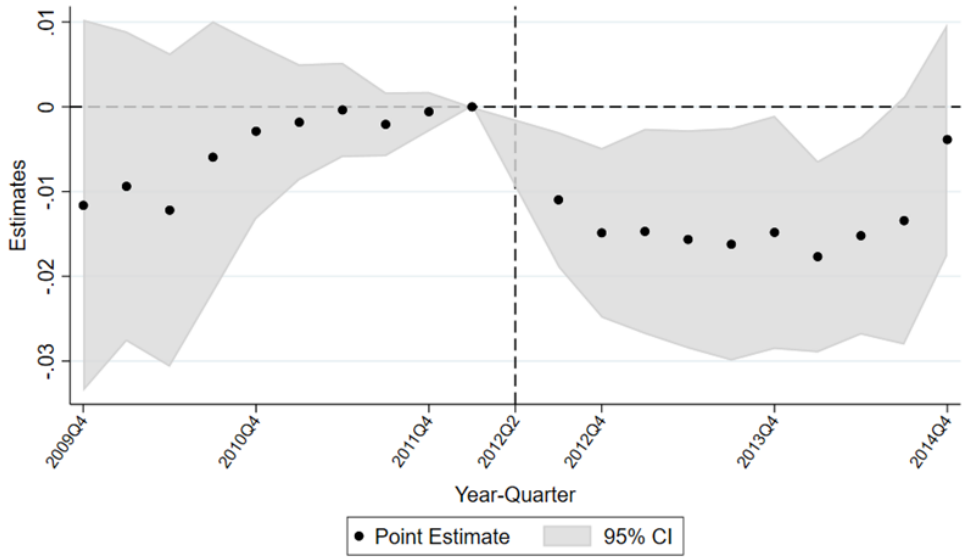


Table 1. Impact of merger on market shares

This table presents the market share of Express Scripts in the local PBM market for the treatment and control group states in our PBM data. The pre-period is measured as the year 2010, and the post-period as the year 2013.

Panel A. Market share of Express Scripts before and after the merger

Treatment States				Control States			
State	Market Share (Pre)	Market Share (Post)	Change	State	Market Share (Pre)	Market Share (Post)	Change
Louisiana	46.29%	61.68%	15.39%	Florida	4.84%	10.11%	5.27%
Missouri	30.07%	52.34%	22.27%	Maryland	4.90%	8.80%	3.90%
Vermont	54.05%	73.48%	19.43%	Minnesota	5.71%	3.32%	-2.39%
West Virginia	16.75%	72.10%	55.35%				

Panel B. Demographic characteristics of the states

Treatment States				Control States			
State	Pop. (in M)	GDP (in B)	Med. Age	State	Pop. (in M)	GDP (in B)	Med. Age
Louisiana	4.54	225.31	35.8	Florida	18.85	746.93	40.7
Missouri	6.00	259.82	37.9	Maryland	5.79	314.73	38.0
Vermont	0.63	27.41	41.5	Minnesota	5.31	274.23	37.4
West Virginia	1.85	66.00	41.3				

Table 2. Summary statistics

This table presents summary statistics for our samples. Panel A summarizes tests of prices, where the unit of observation is at the drug-state-year-quarter level. Panel B summarizes tests of package sizes and refills. For tests of package sizes, the unit of observation is at the insurance claim level, and for tests of refills, the unit of observation is at the patient-pharmacy-drug product-pre/post period level.

Panel A. State-level variables

	Obs.	Mean	SD	P25	Median	P75
Dependent Variables						
Price (log)	58,469	5.47	0.92	4.90	5.34	5.91
Price (raw)	58,469	429.02	926.88	133.86	207.63	367.49
Explanatory Variables						
Treatment	58,469	0.55	0.50	0.00	1.00	1.00
Post	58,469	0.46	0.50	0.00	0.00	1.00
Exposure	58,469	0.15	0.10	0.05	0.15	0.25

Panel B. County-level variables

High vs. Low counties	
Number of treatment counties	464
Number of control counties	597
Number of drug products	559
Number of patients	118,903
Number of pharmacies	15,232

	Obs.	Mean	SD	P25	Median	P75
PackageSize	1,831,577	−0.14	0.61	−0.58	0.00	0.00
NumRefills [-1 Qtr, +1 Qtr]	171,768	1.19	1.01	0.00	1.00	2.00
NumRefills [-2 Qtr, +2 Qtr]	171,768	2.03	1.78	1.00	2.00	3.00
NumRefills [-3 Qtr, +3 Qtr]	171,768	2.69	2.51	1.00	2.00	4.00
NumRefills [-4 Qtr, +4 Qtr]	171,768	3.29	3.23	1.00	2.00	5.00
PharmacyMarketShare(Inverse), Table 4 Column (1)	1,759,202	−0.12	0.20	−0.13	−0.03	−0.01
PharmacyMarketShare(Inverse), Table 4 Columns (2)-(5)	160,610	−0.15	0.23	−0.22	−0.04	−0.01
ReducedAdherence (30 Days)	1,831,579	0.24	0.43	0.00	0.00	0.00
Age	1,831,408	48.24	13.82	44.00	52.00	58.00
Number ER Visits (Past Month)	1,831,408	0.04	0.25	0.00	0.00	0.00
$\widehat{ReducedAdherance}$ *(30 Days)*	1,831,408	0.24	0.32	0.01	0.15	0.34
Number ER Visits (Next Quarter)	1,831,408	0.11	0.49	0.00	0.00	0.00
Indicator for ER Visits (Next Quarter)	1,831,408	0.07	0.26	0.00	0.00	0.00

Table 2. Summary statistics (Continued)

Panel B. County-level variables (continued)

High vs. All other counties and Exposure tests	
Number of treatment counties	464
Number of control counties	2,218
Number of counties (for Exposure tests)	2,682
Number of drug products	608
Number of patients	401,935
Number of pharmacies	40,492

	Obs.	Mean	SD	P25	Median	P75
PackageSize	6,770,254	−0.17	0.60	−0.58	0.00	0.00
NumRefills [-1 Qtr, +1 Qtr]	612,452	1.31	1.04	1.00	1.00	2.00
NumRefills [-2 Qtr, +2 Qtr]	612,452	2.25	1.86	1.00	2.00	4.00
NumRefills [-3 Qtr, +3 Qtr]	612,452	3.00	2.64	1.00	2.00	5.00
NumRefills [-4 Qtr, +4 Qtr]	612,452	3.67	3.41	1.00	3.00	6.00
ReducedAdherence (30 Days)	6,769,785	0.23	0.42	0.00	0.00	0.00
Age	6,769,785	49.02	13.37	45.00	53.00	58.00
Number ER Visits (Past Month)	6,769,785	0.03	0.23	0.00	0.00	0.00
$\widehat{ReducedAdherance}$ *(30 Days)*	6,769,785	0.23	0.37	−0.02	0.12	0.34
Number ER Visits (Next Quarter)	6,769,785	0.10	0.46	0.00	0.00	0.00
Indicator for ER Visits (Next Quarter)	6,769,785	0.07	0.25	0.00	0.00	0.00

Table 3. Effect of an increase in buyer power on drug prices

This table shows the difference-in-difference analysis of drug price between treatment states and control states. The unit of observation is drug-state-year-quarter. The dependent variable is log of the price of drug i in state s at year-quarter t. In Panel A, Columns (1) and (3) include year-quarter, drug (i.e., NDC) and state fixed effects. Columns (2) and (4) include state and drug (i.e., NDC)-YQ fixed effects. Panel B includes state and drug (i.e., NDC)-YQ fixed effects. In Panel B, Columns (1) and (2) include brand drugs with HHI of the drug market below the median across the sample. Columns (3) and (4) include those with HHI of the drug market above the median across the sample. A drug market is defined as all drugs within the same 4-digit Anatomical Therapeutic Chemical (ATC) code. Standard errors are clustered at the drug (i.e., NDC) level. In Panel B, we also report the t-statistic and p-value for a one-sided test of the difference in the main coefficient between Columns (1) and (3). See Appendix B for variable definitions. *, **, and *** indicate statistical significance at less than 10%, 5%, and 1%, respectively.

Panel A. Difference-in-difference estimates for treatment and control groups

Dependent variable:	*Price (log)*			
	(1)	(2)	(3)	(4)
Treatment(State) × Post	-0.032***	-0.036***		
	(-5.53)	(-6.29)		
Treatment(State) × Pre 10			0.002	0.007
			(0.26)	(0.86)
Treatment(State) × Pre 9			0.001	0.004
			(0.14)	(0.47)
Treatment(State) × Pre 8			0.015*	0.016**
			(1.77)	(2.01)
Treatment(State) × Pre 7			0.008	0.009
			(1.09)	(1.29)
Treatment(State) × Pre 6			0.008	0.009
			(1.14)	(1.34)
Treatment(State) × Pre 5			0.015**	0.016**
			(2.20)	(2.45)
Treatment(State) × Pre 4			0.008	0.010
			(1.11)	(1.49)
Treatment(State) × Pre 3			0.002	0.005
			(0.24)	(0.65)
Treatment(State) × Pre 2			-0.001	-0.003
			(-0.23)	(-0.51)
Treatment(State) × Post 1			0.004	0.004
			(0.61)	(0.60)
Treatment(State) × Post 2			-0.027***	-0.027***
			(-3.22)	(-3.23)
Treatment(State) × Post 3			-0.038***	-0.041***
			(-3.88)	(-4.18)
Treatment(State) × Post 4			-0.023**	-0.023**
			(-2.40)	(-2.45)
Treatment(State) × Post 5			-0.022**	-0.024***
			(-2.45)	(-2.68)
Treatment(State) × Post 6			-0.028***	-0.032***
			(-2.98)	(-3.62)
Treatment(State) × Post 7			-0.033***	-0.037***
			(-3.32)	(-3.89)
Treatment(State) × Post 8			-0.025***	-0.029***
			(-2.69)	(-3.20)
Treatment(State) × Post 9			-0.029***	-0.036***
			(-3.06)	(-3.82)
Treatment(State) × Post 10			-0.049***	-0.051***
			(-5.25)	(-5.72)
Observations	58,469	58,469	58,469	58,469
R-squared	0.946	0.957	0.946	0.957
YQ FE	Yes	No	Yes	No
Drug FE	Yes	No	Yes	No
State FE	Yes	Yes	Yes	Yes
Drug-YQ FE	No	Yes	No	Yes

Table 3. Effect of an increase in buyer power on drug prices (Continued)

Panel B. Difference-in-difference estimates for drugs with varying substitutability

Sample:	*Low concentration markets*		*High concentration markets*	
	(1)	(2)	(3)	(4)
Treatment(State) × Post	-0.046***		-0.030***	
	(-5.59)		(-3.82)	
Treatment(State) × Pre 10		0.003		0.011
		(0.26)		(0.87)
Treatment(State) × Pre 9		0.012		-0.000
		(1.14)		(-0.00)
Treatment(State) × Pre 8		0.025**		0.013
		(2.30)		(1.06)
Treatment(State) × Pre 7		0.012		0.007
		(1.25)		(0.64)
Treatment(State) × Pre 6		0.012		0.008
		(1.30)		(0.72)
Treatment(State) × Pre 5		0.020**		0.018*
		(2.03)		(1.86)
Treatment(State) × Pre 4		0.012		0.011
		(1.50)		(1.03)
Treatment(State) × Pre 3		0.010		0.004
		(1.22)		(0.40)
Treatment(State) × Pre 2		0.006		-0.007
		(0.79)		(-0.96)
Treatment(State) × Post 1		-0.012		0.010
		(-0.93)		(1.28)
Treatment(State) × Post 2		-0.042***		-0.021*
		(-3.96)		(-1.73)
Treatment(State) × Post 3		-0.056***		-0.029**
		(-4.08)		(-2.14)
Treatment(State) × Post 4		-0.029**		-0.015
		(-2.25)		(-1.14)
Treatment(State) × Post 5		-0.035***		-0.016
		(-2.72)		(-1.30)
Treatment(State) × Post 6		-0.040***		-0.027**
		(-3.53)		(-2.17)
Treatment(State) × Post 7		-0.049***		-0.026**
		(-3.30)		(-2.10)
Treatment(State) × Post 8		-0.027**		-0.029**
		(-2.11)		(-2.31)
Treatment(State) × Post 9		-0.022*		-0.035***
		(-1.88)		(-2.62)
Treatment(State) × Post 10		-0.039***		-0.056***
		(-2.82)		(-4.68)
	Difference in coefficients test: $t[H0:(1)-(3)>0] = -1.51, p < 0.1$			
Observations	20,642	20,642	32,892	32,892
R-squared	0.943	0.943	0.960	0.960
State FE	Yes	Yes	Yes	Yes
Drug-YQ FE	Yes	Yes	Yes	Yes

Table 4. Pharmacy response: Prescription drug package sizes

This table shows the difference-in-difference analysis of drug package size between treatment counties and control counties. The unit of observation is the insurance claim level. The dependent variable is *PackageSize*, defined as the drug package size standardized across the same drug product (NDC, excluding the last two digits). In Column (1), *Treatment(County)* is an indicator that equals 1 when two conditions hold simultaneously: (i) the change in Express Scripts' market share for contract negotiations from the pre- to the post-period falls in the top quartile of the sample, and (ii) the post-period level of Express Scripts' market share for contract negotiations also falls in the top quartile, while equals 0 when the change in market share (condition i) falls in the bottom quartile of the sample. In Column (2), *Treatment(County)* is defined the same as in Column (1) for the treated group (i.e., equals 1 under the same two conditions), but equals 0 for all other counties. *Post* is an indicator set to 1 if the claim date falls within the post-merger period (i.e., 2012 Q2), and 0 otherwise. Both columns include patient-drug product-pharmacy and year-quarter fixed effects. Standard errors are double clustered at the drug (i.e., NDC) and county level. See Appendix B for variable definitions. *, **, and *** indicate statistical significance at less than 10%, 5%, and 1%, respectively.

Dependent variable:	*PackageSize*	
Sample:	*High vs. Low counties*	*High vs. All other counties*
	(1)	(2)
Treatment(County) × *Post*	-0.011*	-0.010*
	(-1.78)	(-1.74)
Patient-Drug product-Pharmacy FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	1,831,577	6,770,254
R-squared	0.936	0.935

Table 5. Effect on prescription drug refills

This table shows the difference-in-difference analysis of the number of drug refills between treatment counties and control counties. The unit of observation is the patient-pharmacy-drug product- pre- (post-) period level. The dependent variable is *NumRefills*, defined as number of drug refills at the patient, pharmacy, drug product, and pre- or post-period levels. The pre- (post-) period is 1, 2, 3, or 4 quarters before (after) the treatment period. In Columns (1)-(4), *Treatment(County)* is an indicator that equals 1 when two conditions hold simultaneously: (i) the change in Express Scripts' market share for contract negotiations from the pre- to the post-period falls in the top quartile of the sample, and (ii) the post-period level of Express Scripts' market share for contract negotiations also falls in the top quartile, while equals 0 when the change in market share (condition i) falls in the bottom quartile of the sample. In Column (5)-(8), *Treatment(County)* is defined the same as in Column 1 for the treated group (i.e., equals 1 under the same two conditions), but equals 0 for all other counties. *Post* is an indicator set to 1 if the claim date falls within the post-merger period (i.e., 2012 Q2), and 0 otherwise. All columns include patient-drug product-pharmacy and event period fixed effects. Standard errors are double clustered at the drug (i.e., NDC) and county level. See Appendix A for variable definitions. *, **, and *** indicate statistical significance at less than 10%, 5%, and 1%, respectively.

Dependent variable:	NumRefills				NumRefills			
Sample:	High vs. Low counties				High vs. All other counties			
	[-1 Qtr, +1 Qtr]	[-2 Qtr, +2 Qtr]	[-3 Qtr, +3 Qtr]	[-4 Qtr, +4 Qtr]	[-1 Qtr, +1 Qtr]	[-2 Qtr, +2 Qtr]	[-3 Qtr, +3 Qtr]	[-4 Qtr, +4 Qtr]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment(County) × Post	0.061***	0.180***	0.305***	0.406***	0.055***	0.116***	0.200***	0.271***
	(3.73)	(3.93)	(3.90)	(3.70)	(4.21)	(2.91)	(2.96)	(2.91)
Patient-Drug product-Pharmacy FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Event Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171,768	171,768	171,768	171,768	612,452	612,452	612,452	612,452
R-squared	0.745	0.763	0.756	0.740	0.745	0.759	0.749	0.732

Table 6. Supply chain responses with heterogeneous bargaining power

This table presents a difference-in-differences analysis of the effect of bargaining power on package size and drug refill patterns between treatment counties, *Treatment(County)*, and control counties. The unit of observation is the insurance claim level in Column (1), and patient-pharmacy-drug product- pre- (post-) period level in Columns (2)-(5). In Column (1), the dependent variable is *Package Size*, defined as the drug package size standardized across the same drug product (NDC, excluding the last two digits). In Columns (2)-(5), the dependent variable is *Num. Refills*, defined as number of drug refills at the patient, pharmacy, drug product, and pre- or post-period levels. The pre- (post-) period is 1, 2, 3, or 4 quarters before (after) the treatment period. *Treatment* is an indicator that equals 1 when two conditions hold simultaneously: (i) the change in Express Scripts' market share for contract negotiations from the pre- to the post-period falls in the top quartile of the sample, and (ii) the post-period level of Express Scripts' market share for contract negotiations also falls in the top quartile, while equals 0 when the change in market share (condition i) falls in the bottom quartile of the sample. *Post* is an indicator set to 1 if the claim date falls within the post-merger period (i.e., 2012 Q2), and 0 otherwise. *Inverse Pharmacy Market Share* is the number of claims by the pharmacy as a percentage of the total number of claims by all pharmacies in the county in the first year of the sample period (2009), multiplied by –1. Column (1) includes patient-drug product-pharmacy and year-quarter fixed effects. Columns (2)-(5) include patient-drug product-pharmacy and event period fixed effects. Standard errors are double clustered at the drug (i.e., NDC) and county level. We also report the t-statistic and p-value for a one-sided test of the sum of the coefficients with a sample-average value of *Inverse Pharmacy Market Share* for each column. See Appendix A for variable definitions. *, **, and *** indicate statistical significance at less than 10%, 5%, and 1%, respectively.

Dependent variable:	*PackageSize*	*Num.Refills*			
Sample:	High vs. Low counties	High vs. Low counties			
		[-1 Qtr, +1 Qtr]	[-2 Qtr, +2 Qtr]	[-3 Qtr, +3 Qtr]	[-4 Qtr, +4 Qtr]
	(1)	(2)	(3)	(4)	(5)
Treatment(County) × *Post* × *PharmacyMarketShare(Inverse)*	-0.076**	0.149***	0.373***	0.534**	0.689**
	(-2.34)	(3.41)	(2.82)	(2.25)	(2.05)
Treatment(County) × *Post*	-0.015***	0.083***	0.268***	0.438***	0.585***
	(-2.69)	(4.21)	(4.54)	(4.33)	(4.13)
Post × *PharmacyMarketShare(Inverse)*	0.091***	-0.115**	-0.224*	-0.375*	-0.482*
	(3.30)	(-2.36)	(-1.66)	(-1.76)	(-1.68)
	$H0$: col.(1): $(\beta_{r1}+\beta_{r3})[Avg.\ PharmacyMarketShare(Inverse)]+\beta_{r2}>0$; col.(2)–(5): <0				
t-statistic and p-value	$t=-2.61, p<0.01$	$t=4.07, p<0.01$	$t=4.38, p<0.01$	$t=4.36, p<0.01$	$t=4.17, p<0.01$
Patient-Drug product-Pharmacy FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	No	No	No	No
Event Period FE	No	Yes	Yes	Yes	Yes
Observations	1,759,202	160,610	160,610	160,610	160,610
R-squared	0.936	0.747	0.768	0.762	0.747

Table 7. Patient response: medication adherence

This table presents the difference-in-differences analysis of medication adherence between treatment and control counties (Panel A), as well as between treatment and control drugs (Panel B). The unit of observation is the insurance claim level. In Panel A and Panel B, the dependent variable is *ReducedAdherence*, defined as an indicator equal to 1 if a patient fails to refill a drug product within 30 (or 60, 90) days after the end of the originally dispensed days' supply, and 0 otherwise. *Post* is an indicator set to 1 if the claim date falls within the post-merger period (i.e., 2012 Q2), and 0 otherwise. In Panel A, the sample consists of insurance claims for treated drugs (i.e., brand drugs listed on the Express Scripts formulary) from patients residing in both treatment and control counties. In Panel B, the sample consists of insurance claims for treatment and control drugs, among patients residing in treatment counties. These patients have at least one treatment drug (i.e., a brand drug listed on the Express Scripts formulary) and at least one control drug (i.e., a drug not listed on the Express Scripts formulary) in the post-treatment period. *Treatment(County)* is an indicator that equals 1 when two conditions hold simultaneously: (i) the change in Express Scripts' market share for contract negotiations from the pre- to the post-period falls in the top quartile of the sample, and (ii) the post-period level of Express Scripts' market share for contract negotiations also falls in the top quartile, while equals 0 when the change in market share (condition i) falls in the bottom quartile of the sample. *Treatment(Drug)* is an indicator that equals 1 if a drug is a brand drug listed on ES formulary, and 0 if a drug is not on ES formulary. Both panels include patient-drug product-pharmacy and year-quarter fixed effects. Standard errors are double clustered at the drug (i.e., NDC) and county level. See Appendix B for variable definitions. *, **, and *** indicate statistical significance at less than 10%, 5%, and 1%, respectively.

Panel A. Difference-in-difference estimates for treatment and control counties using treatment drugs

Dependent variable:	*ReducedAdherance (30 Days)*	
Sample:	*High vs. Low counties*	*High vs. All other counties*
	(1)	(2)
Treatment(County) × *Post*	0.008*	0.027***
	(1.66)	(5.62)
Patient-Drug product-Pharmacy FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	1,831,579	6,770,281
R-squared	0.409	0.399

Panel B. Difference-in-difference estimates for treatment and control drugs in the treatment county

Dependent variable:	*ReducedAdherence*		
Window:	*30 Days*	*60 Days*	*90 Days*
	(1)	(2)	(3)
Treatment(Drug) × *Post*	0.031***	0.027***	0.026**
	(3.15)	(2.84)	(2.53)
Patient-Drug Product-Pharmacy FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Observations	803,517	803,517	803,517
R-squared	0.401	0.408	0.375

Table 8. 2SLS analysis of patient emergency room visit

This table presents the two-stage least squares analysis of the effect of reduced adherence on patients' emergency room visits, using $Treatment(County) \times Post$ as the instrumental variable. The unit of observation is the insurance claim level. In Panels A and B, the sample consists of insurance claims for treated drugs (i.e., brand drugs listed on the Express Scripts formulary) from patients residing in both treatment and control counties. Panel A reports first-stage results, and Panel B reports second-stage results. In Panel A, the dependent variable is *ReducedAdherence*, defined as an indicator equal to 1 if a patient fails to refill a drug product within 30 days after the end of the originally dispensed days' supply, and 0 otherwise. *Treatment(County)* and *Post* are defined as in Table 4. Control variables include *AGE* and $Number\ ER\ Visits\ (Past\ Month)$. *AGE* is the patient's age, and $Number\ ER\ Visits\ (Past\ Month)$ is the number of emergency room visits by the patient in the past month. In Panel B, the dependent variables are $Number\ ER\ Visits\ (Next\ Quarter)$ in Columns (1)-(2) and $Indicator\ for\ ER\ Visits\ (Next\ Quarter)$ in Columns (3)-(4). $Number\ ER\ Visits\ (Next\ Quarter)$ is defined as the number of emergency room visits by the patient in the next quarter. $Indicator\ for\ ER\ Visits\ (Next\ Quarter)$ is an indicator equal to 1 if the number of emergency room visits by the patient in the next quarter is greater than 0, and 0 otherwise. Panel B includes the same set of control variables as in Panel A. Both panels include patient-drug product-pharmacy and year-quarter fixed effects. Standard errors are double clustered at the drug (i.e., NDC) and county level. See Appendix B for variable definitions. *, **, and *** indicate statistical significance at less than 10%, 5%, and 1%, respectively.

Panel A. First-stage analysis of the effect of treatment on medication adherence

Dependent variable:	*ReducedAdherance (30 Days)*	
Sample:	*High vs. Low counties*	*High vs. All other counties*
	(1)	(2)
Treatment(County) × *Post*	0.008*	0.027***
	(1.68)	(5.63)
AGE	-0.023**	-0.028***
	(-2.02)	(-3.12)
Number ER Visits (Past Month)	-0.002	-0.000
	(-1.20)	(-0.29)
Patient-Drug product-Pharmacy FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	1,831,408	6,769,785
R-squared	0.409	0.399

Panel B. Second-stage analysis of the effect of predicted medication adherence on emergency room visits

Dependent variable:	*Number ER Visits (Next Quarter)*		*Indicator for ER Visits (Next Quarter)*	
Sample:	*High vs. Low counties*	*High vs. All other counties*	*High vs. Low counties*	*High vs. All other counties*
	(1)	(2)	(3)	(4)
$\widehat{ReducedAdherance\ (30\ Days)}$	0.887**	0.205*	0.361*	0.096*
	(2.32)	(1.88)	(1.80)	(1.76)
AGE	0.022*	0.016**	0.011	0.007**
	(1.69)	(2.58)	(1.47)	(2.08)
Number ER Visits (Past Month)	-0.029	-0.030***	-0.028***	-0.029***
	(-1.60)	(-4.05)	(-11.89)	(-21.08)
Patient-Drug product-Pharmacy FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	1,831,408	6,769,785	1,831,408	6,769,785
R-squared	0.381	0.354	0.267	0.251

Online Appendix

Fighting Fire with Fire: On Allowing Mergers of Large Buyers to Counter Seller Market Power

This appendix contains additional analyses and details referenced in our paper, and is organized as follows:

- List of Medications in OA.A
- Figure: Shifts in market shares and HHI in OA.B.
- Figure: Placebo analyses in OA.C
- Identifying and defining substitute drugs in OA.D.
- Generic prescription drug cartel in OA.E.
- Figure: Pre-merger cartel in OA.F.
- Table: Exposure tests in OA.G.
- Theoretical Framework Proofs in OA.H.
- Table: Packaging and refills with measure of exposure in OA.I.
- Copy of PBM contract in OA.J.
- Figure: Analysis of dispensing fee changes in OA.K.

OA.A. List of Medications

Branded medications:

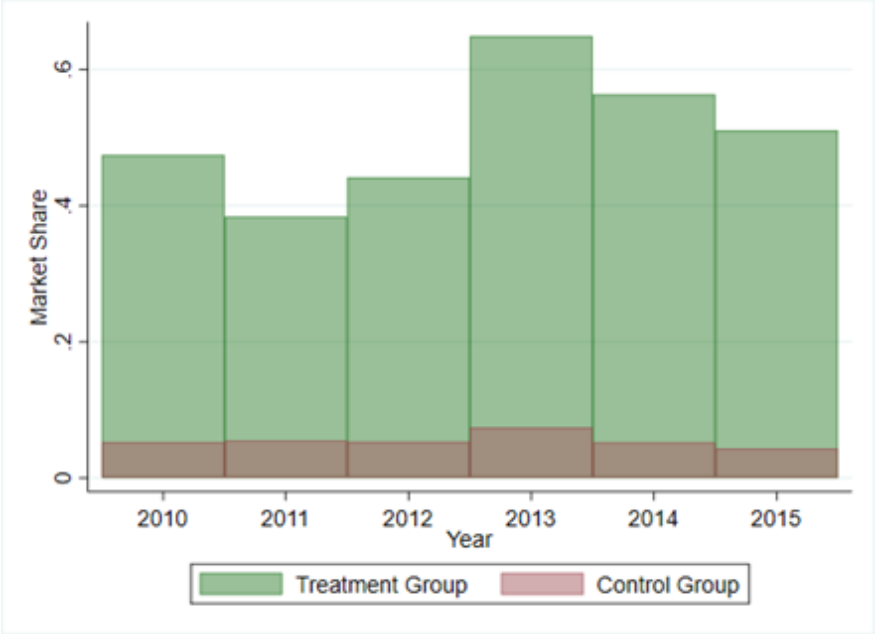
ACTOPLUS MET, ACTOS, ACUVAIL, ADCIRCA, ADVAIR DISKUS, ADVICOR, AGGRENOX, ALPHAGAN P, ALTABAX, AMITIZA, AMPYRA, AMTURNIDE, ANDRODERM, ANDROGEL, ARANESP, ARICEPT, ARIXTRA, ASACOL, ASTEPRO, ATELVIA, AVELOX, AVODART, AZASITE, AZILECT, AZOR, BENICAR, BENZACLIN PUMP, BETASERON, BONIVA, BROMDAY, BYETTA, BYSTOLIC, CANASA, CELEBREX, CETROTIDE, CIALIS, CIPRODEX, CLIMARA PRO, COLCRYS, COMBIGAN, COMBIPATCH, COPAXONE, COREG CR, CREON, CRESTOR, CRINONE, CYMBALTA, DETROL, LA, DIFFERIN, DOVONEX, DUAC, DUETACT, DULERA, EFFIENT, ELIDEL, EMBEDA, ENABLEX, ENBREL, ENDOMETRIN, EPICERAM, EPIDUO, EPIPEN, ESTRADERM, EUFLEXXA, EURAX, EVAMIST, EXELON PATCHES, EXFORGE, FINACEA, FLECTOR, FLOVENT DISKUS, FORADIL, FORTEO, FOSRENOL, GELNIQUE, GENOTROPIN, GLUCAGEN, GONAL-F (RFF), HALFLYTELY-BISACODYL, HUMALOG, HUMIRA, HUMULIN, INCIVEK, JALYN, JANUMET, JANUVIA, LAMICTAL ODT, LAMICTAL XR, LANTUS, LETAIRIS, LEVEMIR, LEXAPRO, LIALDA, LIDODERM, LIPITOR, LOTEMAX, LOVAZA, LUMIGAN, LUNESTA, LYRICA, LYSTEDA, MAKENA, MAXALT (and MLT), MENEST, METROGEL, MIGRANAL, MIRAPEX ER, MOVIPREP, MOXEZA, MUSE, NAMENDA, NASCOBAL, NASONEX, NEVANAC, NEXIUM, NIASPAN, NOVOFINE, NOVOLIN, NOVOLOG, NUCYNTA, NUEDEXTA, NUTROPIN, OPANA ER, ORTHOVISC, PATADAY, PATANOL, PENTASA, PERFOROMIST, PLAVIX, PRADAXA, PRANDIN, PREMARIN, PREMPHASE, PREMPRO, PRISTIQ, PROAIR HFA, PROCRIT, PROMETRIUM, PROTOPIC, PULMICORT, PYLERA, QVAR, RANEXA, RAPAFLO, REBIF, RENVELA, RESTASIS, RETIN-A MICRO GEL, REVATIO, SANCUSO, SAVELLA, SEREVENT DISKUS, SEROQUEL, SIMCOR, SINGULAIR, SOLARAZE, SOMATULINE DEPOT, SPIRIVA, STRATTERA, SUBOXONE, SYMBICORT, SYMBYAX, SYMLIN, TACLONEX, TAMIFLU, TAZORAC, TEKAMLO, TEKTURNA, TOVIAZ, TRACLEER, TRADJENTA, TRAVATAN Z, TREXIMET, TRIBENZOR, TRICOR, TRILIPIX, ULORIC, VAGIFEM, VALTURNA, VESICARE, VIAGRA, VICTOZA, VICTRELIS, VIGAMOX, VIIBRYD, VIMOVO, VIMPAT, VIVELLE-DOT, VOLTAREN GEL, VYVANSE, WELCHOL, XERESE, XIFAXAN, XOPENEX, ZETIA, ZOMIG, ZYCLARA, ZYLET, ZYMAXID, ZYPREXA.

Generic medications:
acetaminophen/codeine, acyclovir, adapalene, albuterol, alendronate sodium, alfuzosin er, allopurinol, amiodarone, amitriptyline, amlodipine/benazepril, amox tr/potassium clavulanate, amoxicillin, amphetamine salt combo (and er), anastrozole, antipyrine/benzocaine, arbinoxa, atenolol/chlorthalidone, azathioprine, azelastine, baclofen, balsalazide disodium, benazepril/hctz, benzonatate, brimonidine tartrate, budesonide neb susp, bupropion (12 hr, 24 hr), butalbital/apap/caffeine, calcipotriene, carbamazepine (and er), carbidopa/levodopa (and er), carvedilol, cefadroxil, cefdinir, cefprozil, cefuroxime, cephalexin, cholestyramine, chorionic gonadotropin, ciclopirox, ciprofloxacin (and er), citalopram, clarithromycin (and er), clindamycin hcl, clindamycin phosphate, clobetasol propionate, clomiphene citrate, clonazepam, clonidine, clotrimazole/betamethasone dipropionate, cyanocobalamin, cyclobenzaprine, desonide, dexamethasone, dexmethylphenidate, diclofenac sodium, dicyclomine hcl, digoxin, diltiazem (12 hr, 24 hr), divalproex sodium (and er), donepezil (and odt), dorzolamide/timolol, doxazosin, doxepin, eliphos, enoxaparin, ergocalciferol, erythromycin, erythromycin/benzoyl perox., estradiol patches (and tabs), estradiol/norethindrone acetate, etodolac, famciclovir, famotidine, felodipine er, fenofibrate, fentanyl citrate, finasteride, fluconazole, fluocinonide, fluoxetine (and dr), fluticasone nasal spray, folic acid, fosinopril/hctz, gabapentin, galantamine (and er), gemfibrozil, glimepiride, glipizide (and er), glyburide, micronized, glyburide/metformin, hydralazine, hydrochlorothiazide, hydrocodone/acetaminophen, hydrocodone/ibuprofen, hydrocortisone, hydromorphone, hydroxychloroquine, ibuprofen, imiquimod, indomethacin, ipratropium/albuterol, isosorbide mononitrate (and er), ketoconazole, ketorolac, labetalol hcl, lamotrigine, lansoprazole (and odt), latanoprost, levetiracetam, levofloxacin, levothyroxine sodium, levoxyl, liothyronine, lisinopril/hctz, lithium carbonate, losartan/hctz, lovastatin, meloxicam, metaxalone, metformin (and er), methocarbamol, methotrexate, methylphenidate, methylprednisolone, metoclopramide hcl, metoprolol/hctz, metronidazole, mirtazapine (and odt), mometasone, morphine sulfate (and er), mupirocin, mycophenolate mofetil, nabumetone, nadolol, naproxen, naproxen sodium, naratriptan, nateglinide, neomycin/polymyxin/dexamethasone, neomycin/polymyxin/hc, nitrofurantoin macrocrystal, nitroglycerin patches, nortriptyline, nystatin/triamcinolone, ofloxacin, omeprazole, ondansetron (and odt), oxcarbazepine, oxybutynin (and er), oxycodone/acetaminophen, pantoprazole, paroxetine, penicillin v potassium, phenytoin sodium (and extended), polymyxin/trimethoprim, potassium chloride (and er), pramipexole, pravastatin, prednisolone, prednisolone acetate, prednisolone sodium phosphate, prednisone, prochlorperazine, promethazine/dextromethorphan, propranolol/hctz, quinapril/hctz, ramipril, ranitidine, reprexain, ribavirin, risperidone (and odt), rivastigmine caps, ropinirole, sertraline, simvastatin, sodium fluoride, sodium sulfacetamide/sulfur, sotalol, sucralfate, sulfamethoxazole/trimethoprim, sulfasalazine, sumatriptan tab (and inj.), tamoxifen, tamsulosin, temazepam, terazosin, timolol maleate, tizanidine, tobramycin/dexamethasone, tobramycin sulfate, topiramate, trazodone hcl, tretinoin, triamcinolone acetonide, triamterene/hctz, trospium, valacyclovir, venlafaxine (and er), verapamil (and er), veripred, warfarin, zamicet, zolpidem (and er).

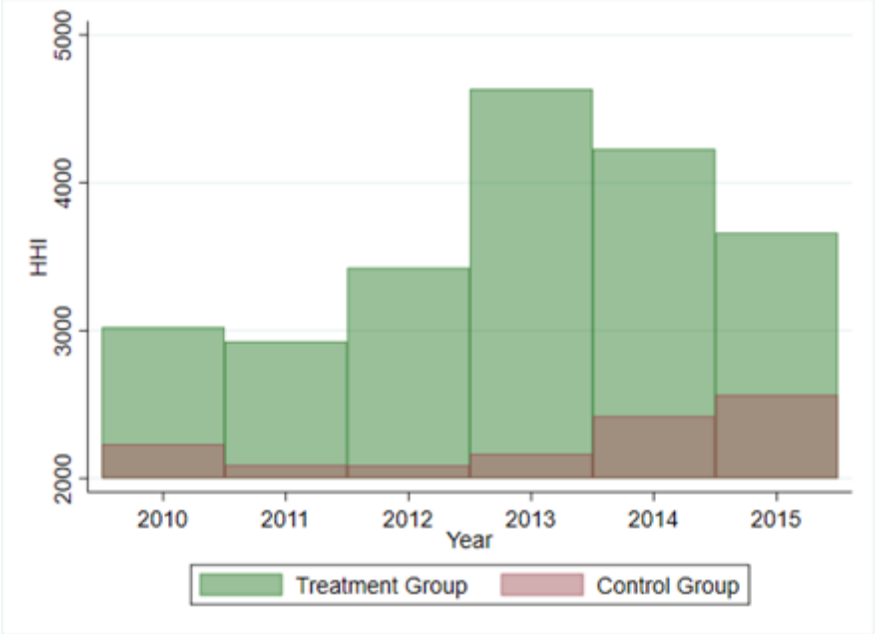
OA.B. Shifts in market shares and HHI

This figure displays the market share of Express Scripts/Medco or the HHI of the PBM market from 2010 to 2015, comparing treatment groups versus control groups. The green bar represents the value in the treatment group, while the red bar represents the value in the control group. Panel A displays the change in market share of the entity with the larger market share between Express Scripts and Medco from 2010 to 2011, and subsequently the market share of Express Scripts from 2012 to 2015 in the treatment and control groups. Panel B displays the change in HHI, calculated as the sum of the squared market percentages of each PBM in the treatment and control groups.

Panel A. Shift in market shares



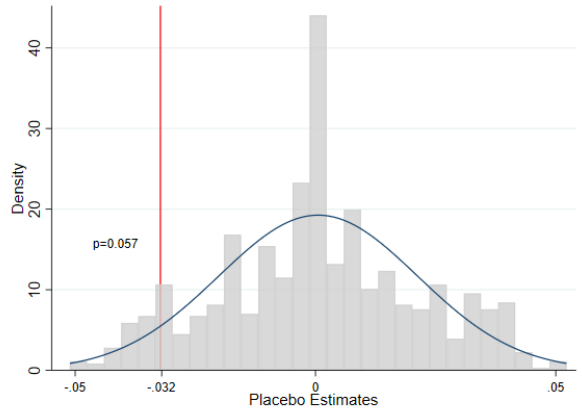
Panel B. Shift in HHI



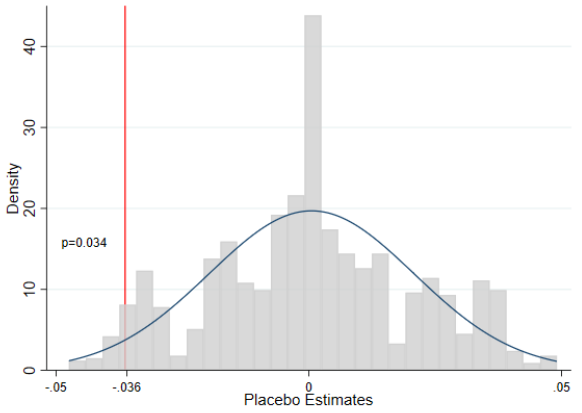
OA.C. Placebo analyses

This figure plots the actual estimates from regression models presented in Table 3 and the distribution of placebo coefficients. We use the distribution of placebo coefficients to bootstrap significance levels for our main analyses (Christensen et al. (2016); Bertrand et al. (2004b)). Specifically, we first randomly draw a quarter from a uniform distribution between the beginning of the sample period and 2012Q1; we restrict the draw to this period to avoid contamination from the actual treatment. Next, we randomly assign four states to the treatment group and the remaining three states to the control group for the placebo tests. We use 1,000 replications. In each panel, the red line indicates the actual estimated coefficient obtained from Table 3. The reported value is the one-sided p-value.

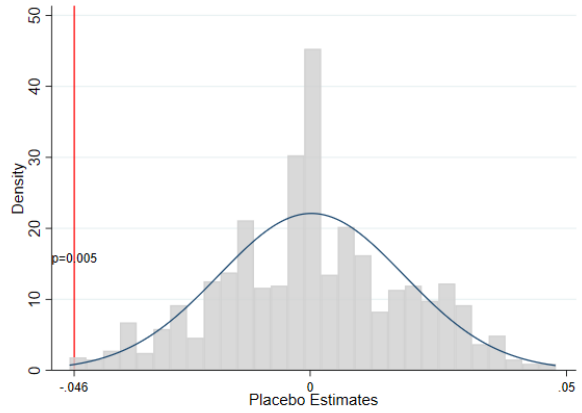
Panel A. Placebo analysis for Table 3 Panel A Column (1)



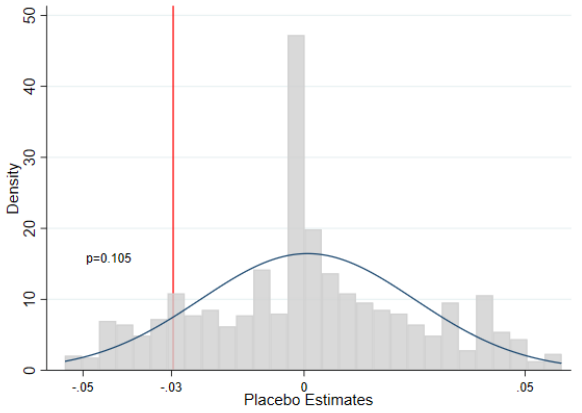
Panel B. Placebo analysis for Table 3 Panel A Column (2)



Panel C. Placebo analysis for Table 3 Panel B Column (1)



Panel D. Placebo analysis for Table 3 Panel B Column (3)



OA.D. Identifying and defining substitute drugs

In Table 3 Panel B, we separate the sample based on drugs in low-concentration market and high-concentration market, which are defined as HHI of the drug market below or above the median across the sample. The drug market is identified from drugs within the same Anatomical Therapeutic Chemical (ATC) code, following Costinot et al. (2019), Wang et al. (2023), and Allain et al. (2016).

The ATC Classification is an internationally accepted classification system for medicines that is maintained by the World Health Organization (WHO). With the ATC classification system, products are classified into groups at five different therapeutic levels. The first level of the code (1-digit) indicates the anatomical main group. The second level of the code (3-digit) indicates the therapeutic main group. The third level of the code (4-digit) indicates the therapeutic/pharmacological subgroup. The fourth level of the code (5-digit) indicates the chemical/therapeutic/pharmacological subgroup. Finally, the fifth level of the code (7-digit) indicates the chemical substance. Following Costinot et al. (2019), we use the 4-digit ATC code to define a drug market.

To obtain ATC code information, we web-scraped data from the DrugBank website. When information was missing, we supplemented it using ATC codes available from PubChem and Pharnexcloud. To calculate the drug market HHI, we sum the squared market shares (based on reimbursement amounts) for all drugs within the same 4-digit ATC code market. The reimbursement amounts for each drug are obtained from the CMS Drug Utilization data for 2011, which is one year prior to the event year.

OA.E. Generic prescription drug cartel, 2013-2015

For our analysis of the generic prescription drug cartel, we draw on detailed evidence from a 510-page legal complaint jointly filed in 2019 by nearly all U.S. states and Puerto Rico (State of Connecticut et al., 2019). The complaint documents coordinated price-fixing among a group of U.S. generic drug manufacturers that began around early 2013 and persisted until a federal investigation commenced in 2015. Starc and Wollmann (2025) find that the prices of cartelized drugs rose sharply relative to comparable non-cartelized drugs following cartel formation. Building on this evidence, we focus on cartelized drug episodes to test whether the resulting price increases differed across states—specifically, between those most and least affected by the merger one year prior to cartel formation.

The legal complaint provides detailed information on more than 100 cartel incidents, including the exact dates, affected drugs and dosages, and the firms involved. We leverage this rich variation—across drugs, timing, and participating manufacturers—to construct a stacked difference-in-differences research design. Inclusion in our sample requires observable reimbursement data for at least one treated (i.e., most affected) and one control (i.e., least affected) state both before and after the quarter in which the price increase occurred. When a drug experiences multiple price increases by the same labelers, we retain only the first event. In total, we find 96 events that meet these requirements. Illustrative examples of these cartelization events—including the generic drug name, dosage form, labeler(s), and the corresponding year-quarter—are provided below.

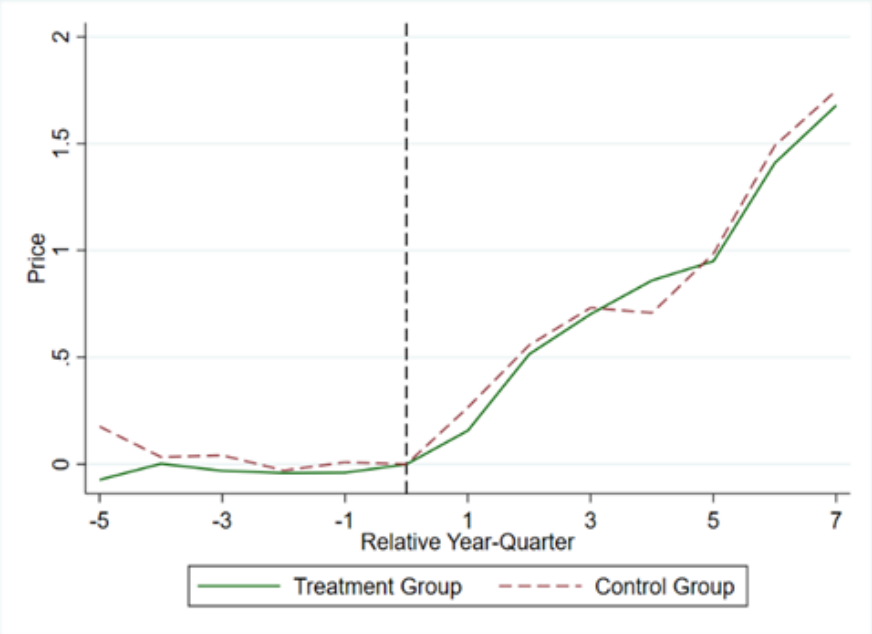
> adapalene (gel; Glenmark; 2013q2), amiloride hydrochloride and hydrochlorothiazide (tablet; Mylan, Barr; 2014q3), benazepril hydrochloride and hydrochlorothiazide (tablet, film coated; Mylan, Eon Labs; 2013q3), bethanechol chloride (tablet; Teva, Amneal; 2015q1), cefdinir (powder, for suspension; Teva, Lupin, Sandoz; 2013q3), cimetidine (tablet, film coated; Teva, Mylan; 2013q3), ciprofloxacin (tablet, film coated; Actavis; 2014q4), clarithromycin (tablet, film coated, extended release; Teva, Watson; 2014q2), clomipramine hydrochloride (capsule; Sandoz; 2013q3), clotrimazole (solution; Teva, Taro; 2014q3), cyproheptadine hydrochloride (tablet; Teva, Breckenridge; 2014q2), desmopressin acetate (tablet; Teva, Watson; 2014q3), diclofenac potassium (tablet, film coated; Teva, Mylan, Sandoz, Apotex; 2013q3), diflunisal (tablet, film coated; Teva, Rising; 2014q2), doxycycline hyclate (tablet; Teva, Par; 2014q3), enalapril maleate (tablet; Teva, Mylan; 2013q3), erythromycin ethylsuccinate (tablet; Teva, Morton Grove; 2014q2), fluconazole (tablet; Teva, Mylan; 2013q3), flurbiprofen (tablet; Teva, Mylan; 2014q3), furosemide (tablet; Teva, Mylan; 2014q3), gabapentin (capsule; Teva, Mylan; 2013q3), gemfibrozil (tablet; Mylan, Teva; 2013q4), glimepiride (tablet; Teva, Mylan; 2014q3), glipizide (tablet; Mylan, Teva; 2013q3), indapamide (tablet; Mylan, Teva; 2013q3), ketoconazole (tablet; Teva, Mylan; 2013q3), lisinopril (tablet; Teva, Mylan; 2014q2), lorazepam (tablet; Mylan, Teva; 2014q3), metformin hydrochloride (tablet; Teva, Mylan; 2013q3), metoprolol tartrate (tablet; Teva, Mylan; 2014q3), minocycline hydrochloride (capsule; Teva, Watson; 2014q3), naproxen (tablet; Teva, Mylan; 2013q3), nystatin (tablet; Teva, Perrigo; 2014q3), omeprazole (capsule; Teva, Mylan; 2014q3), ondansetron hydrochloride (tablet; Teva, Mylan; 2013q3), phenytoin sodium (capsule; Teva, Mylan; 2014q2), simvastatin (tablet; Teva, Mylan; 2013q3).

A complete list of our cartelization events can be downloaded here (insert hyperlink).

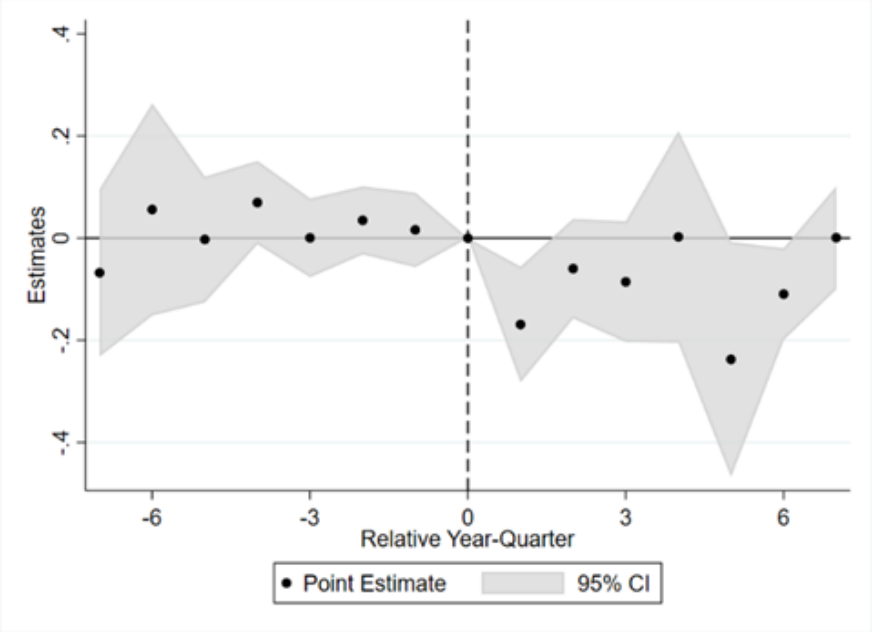
OA.F. Pre-merger cartel

This table presents the dynamic trends and estimated effects on the prices of drugs within cartel groups formed before the merger event. Panel A presents the average log price of drugs in treatment and control states on the y-axis against the quarter relative to the corresponding cartel-formation event on the x-axis. The vertical dashed line corresponds to each cartel-formation event quarter, and prices are normalized to zero in that quarter. Panel B presents difference-in-difference coefficients for each quarter relative to the cartel-formation event quarter (with the event quarter as the base year-quarter) from a regression of drug price on the treatment indicator interacted with individual relative quarter indicators. The regression is at the drug-state-relative quarter level. Point estimates are derived from a regression including state and drug (i.e., NDC)-relative quarter fixed effects. Standard errors are clustered at the drug (i.e., NDC) level. The vertical dashed line corresponds to each cartel-formation event quarter. The gray area represents a pointwise 95% confidence interval.

Panel A. Dynamic trends in prices of pre-merger cartelized drugs



Panel B. Estimated effects on prices of pre-merger cartelized drugs



OA.G. Exposure test

This table shows the difference-in-differences analysis of drug price with a continuous treatment variable. The unit of observation is drug-state-year-quarter. The dependent variable is log of the price of drug i in state s at year-quarter t. The main independent variable is the interaction term between *Exposure* and *Post* (Columns (1) and (2)), or the interaction term between *Exposure* and *Pre and Post* indicators (Columns (3) and (4)). *Exposure* is defined as the degree to which a state's market was exposed to the merger event during the pre-period. Columns (1) and (3) include year-quarter, drug (i.e., NDC) and state fixed effects. Columns (2) and (4) include state and drug (i.e., NDC)-YQ fixed effects. Panel B includes state and drug (i.e., NDC)-YQ fixed effects. Standard errors are clustered at the drug (i.e., NDC) level. See Appendix A for variable definitions. *, **, and *** indicate statistical significance at less than 10%, 5%, and 1%, respectively.

Dependent variable:	*Price (log)*			
	(1)	(2)	(3)	(4)
Exposure × *Post*	-0.176***	-0.188***		
	(-6.59)	(-7.06)		
Exposure × *Pre 10*			0.014	0.032
			(0.33)	(0.79)
Exposure × *Pre 9*			-0.002	0.008
			(-0.05)	(0.18)
Exposure × *Pre 8*			0.063	0.064*
			(1.60)	(1.66)
Exposure × *Pre 7*			0.043	0.040
			(1.21)	(1.16)
Exposure × *Pre 6*			0.050	0.054
			(1.46)	(1.61)
Exposure × *Pre 5*			0.070**	0.081**
			(2.21)	(2.57)
Exposure × *Pre 4*			0.046	0.061
			(1.29)	(1.63)
Exposure × *Pre 3*			0.005	0.019
			(0.15)	(0.57)
Exposure × *Pre 2*			-0.010	-0.019
			(-0.42)	(-0.71)
Exposure × *Post 1*			0.012	0.010
			(0.40)	(0.33)
Exposure × *Post 2*			-0.164***	-0.158***
			(-3.73)	(-3.60)
Exposure × *Post 3*			-0.191***	-0.188***
			(-3.77)	(-3.81)
Exposure × *Post 4*			-0.132***	-0.132***
			(-2.82)	(-2.88)
Exposure × *Post 5*			-0.104**	-0.100**
			(-2.34)	(-2.31)
Exposure × *Post 6*			-0.142***	-0.162***
			(-3.24)	(-3.85)
Exposure × *Post 7*			-0.190***	-0.196***
			(-3.87)	(-4.15)
Exposure × *Post 8*			-0.174***	-0.187***
			(-3.86)	(-4.21)
Exposure × *Post 9*			-0.173***	-0.198***
			(-3.75)	(-4.33)
Exposure × *Post 10*			-0.261***	-0.268***
			(-6.29)	(-6.58)
Observations	58,469	58,469	58,469	58,469
R-squared	0.946	0.957	0.946	0.957
YQ FE	Yes	No	Yes	No
Drug FE	Yes	No	Yes	No
State FE	Yes	Yes	Yes	Yes
Drug-YQ FE	No	Yes	No	Yes

OA.H. Proofs of Propositions

This section derives the pharmacy's optimal package size s^* and shows that it increases with the retail price p. We first restate the pharmacy's total profit function, simplify notation, and then differentiate with respect to s. Next, we derive the first-order condition, solve for the interior optimum, and finally compute the comparative static of s^* with respect to p.

OA.H.1. Proof of Optimal Package Size

Recall the pharmacy's total profit:

$$\Pi(s) \;=\; \big(k + f + (p-w)s\big)\frac{Q}{s}\exp\Big(-\beta_1 k - \beta_2\frac{Q}{s}\Big) \tag{11}$$

Expression (11) captures the pharmacy's total expected profit from dispensing prescriptions in packages of size s. The first term in parentheses is the per-patient gross margin, while the second term Q/s denotes the number of refill cycles. The exponential factor reflects adherence losses associated with refill frequency.

To streamline differentiation, we define the exponential component as

$$E(s) := \exp\Big(-\beta_1 k - \beta_2\frac{Q}{s}\Big) > 0 \tag{12}$$

so that we can rewrite the profit function compactly as

$$\Pi(s) = Q \cdot \frac{f + k + (p-w)s}{s} \cdot E(s) \tag{13}$$

All parameters $f, k, p, w, Q, \beta_1, \beta_2$ are treated as exogenous constants.

To find the optimal s, we differentiate (13) with respect to s. Since $\Pi(s)$ is a product of two functions of s (i.e., a rational term and the exponential $E(s)$) we apply the product rule:

$$\Pi'(s) = Q\left[\left(\frac{d}{ds}\frac{f + k + (p-w)s}{s}\right)E(s) + \frac{f + k + (p-w)s}{s}\cdot E'(s)\right] \tag{14}$$

The next two derivatives are straightforward and will be computed separately. First, differentiating the term inside the parentheses gives

$$\frac{d}{ds}\left(\frac{f + k + (p-w)s}{s}\right) = \frac{(p-w)\cdot s - (f + k + (p-w)s)\cdot 1}{s^2} = -\frac{f + k}{s^2} \tag{15}$$

Second, differentiating (12) with respect to s yields

$$E'(s) = E(s)\cdot\frac{d}{ds}\left(-\beta_1 k - \beta_2\frac{Q}{s}\right) = E(s)\cdot(-\beta_2)\left(-\frac{Q}{s^2}\right) = E(s)\cdot\frac{\beta_2 Q}{s^2} \tag{16}$$

Substituting (15) and (16) into (14) gives

$$\Pi'(s) = Q\left[-\frac{f + k}{s^2}E(s) + \frac{f + k + (p-w)s}{s}\cdot\frac{\beta_2 Q}{s^2}E(s)\right] \tag{17}$$

Factoring out the common positive term $QE(s)/s^2$, we obtain

$$\Pi'(s) = QE(s) \cdot \frac{1}{s^2}\left[-(f+k) + \frac{f+k+(p-w)s}{s}\beta_2 Q\right] \tag{18}$$

Placing the terms over a common denominator s^3 gives a more compact expression:

$$\Pi'(s) = QE(s) \cdot \frac{1}{s^3}\left[-(f+k)s + \beta_2 Q\big(f+k+(p-w)s\big)\right] \tag{19}$$

Combining all components and expanding $E(s)$, we can write

$$\Pi'(s) = Q \cdot \frac{\beta_2 Q\big(f+k+(p-w)s\big) - (f+k)s}{s^3} \exp\Big(-\beta_1 k - \beta_2 \frac{Q}{s}\Big) \tag{20}$$

Setting $\Pi'(s) = 0$ in (20), the exponential factor and other positive terms (i.e., Q and s^3) drop out, so that the first-order condition (FOC) is equivalent to setting the numerator equal to zero:

$$\beta_2 Q\big(f+k+(p-w)s\big) - (f+k)s = 0 \tag{21}$$

Expanding and collecting terms in s gives

$$\beta_2 Q(f+k) + \beta_2 Q(p-w)s - (f+k)s = 0 \quad \Longrightarrow \quad \beta_2 Q(f+k) + \big(\beta_2 Q(p-w) - (f+k)\big)s = 0 \tag{22}$$

Solving (22) for s yields the unique optimal package size:

$$\boxed{s^* = \frac{Q\beta_2(f+k)}{(f+k) - Q\beta_2(p-w)}.} \tag{23}$$

Expression (23) defines the optimal package size s^* as a function of the exogenous parameters of the model.

OA.H.2. Proof of the Relationship Between the Optimal Package Size and Price

This section establishes the positive relationship between optimal package size and price. To do so, we perform a comparative static exercise by differentiating s^* with respect to p.

Since only the denominator of (23) depends on p, differentiating with respect to p yields

$$\frac{\partial s^*}{\partial p} = Q\beta_2(f+k) \cdot \frac{d}{dp}\left(\frac{1}{(f+k) - Q\beta_2(p-w)}\right) = Q\beta_2(f+k) \cdot \frac{Q\beta_2}{\big((f+k) - Q\beta_2(p-w)\big)^2} \tag{24}$$

Thus,

$$\boxed{\frac{\partial s^*}{\partial p} = \frac{Q^2\beta_2^2(f+k)}{\big((f+k) - Q\beta_2(p-w)\big)^2}} \tag{25}$$

Because every term in the numerator of (25) is positive and the denominator is squared (and thus also positive), we have

$$\frac{\partial s^*}{\partial p} > 0$$

Hence, the optimal package size is strictly increasing in price p.

OA.I. Packaging and refills tests with exposure measure

This table shows the difference-in-difference analysis of drug package size and drug refill patterns with a continuous treatment variable. The unit of observation is the insurance claim level in Column (1), and patient-pharmacy-drug product- pre- (post-) period level in Columns (2)-(5). In Column (1), the dependent variable is *PackageSize*, defined as the drug package size standardized across the same drug product (NDC, excluding the last two digits). In Columns (2)-(5), the dependent variable is *NumRefills*, defined as number of drug refills at the patient, pharmacy, drug product, and pre- or post-period levels. The pre- (post-) period is 1, 2, 3, or 4 quarters before (after) the treatment period. *Exposure* is defined as the degree to which a county's market was exposed to the merger event during the pre-period. *Post* is an indicator set to 1 if the claim date falls within the post-merger period (i.e., 2012 Q2), and 0 otherwise. Column (1) includes patient-drug product-pharmacy and year-quarter fixed effects. Columns (2)-(5) include patient-drug product-pharmacy and event period fixed effects. Standard errors are double clustered at the drug (i.e., NDC) and county level. See Appendix A for variable definitions. *, **, and *** indicate statistical significance at less than 10%, 5%, and 1%, respectively.

Dependent variable:	*PackageSize*	*NumRefills*			
	(1)	(2) [-1 Qtr, 1 Qtr]	(3) [-2 Qtr, 2 Qtr]	(4) [-3 Qtr, 3 Qtr]	(5) [-4 Qtr, 4 Qtr]
Exposure × *Post*	-0.029	0.214***	0.677***	1.202***	1.692***
	(-1.61)	(4.46)	(5.12)	(5.19)	(5.13)
Patient-Drug product-Pharmacy FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	No	No	No	No
Event Period FE	No	Yes	Yes	Yes	Yes
Observations	6,770,254	612,452	612,452	612,452	612,452
R-squared	0.935	0.745	0.759	0.749	0.733

OA.J. PBM contract for dispensing fees

This section of the Online Appendix contains an exhibit of "Pharmacy Reimbursement Rates" included in an executed Pharmacy Benefit Management Agreement between Express Scripts, Inc. and Oklahoma City Municipal Facilities Authority. Part I of the exhibit outlines reimbursement terms, including the per-prescription dispensing fee paid to participating pharmacies.

Exhibit A-1

Pharmacy Reimbursement Rates

I. Participating Pharmacy Reimbursement Rates (Does Not Apply to Specialty Products)

	2-Tier Plan Design or 3-Tier Plan Design Less than $15.00 Copay Differential ESI National Preferred Formulary
Network	**Minimum 50,000 Participating Pharmacy Network**
Ingredient Cost - Brand *Single Source Generic Drugs are priced as brands*	Lesser of AWP – 16.75%, or U&C
Ingredient Cost - Generic *Single Source Generic Drugs are priced as brands*	Lesser of AWP – 16.75%, MRA or U&C
Ingredient Cost - Compound Drugs	Lesser of U&C or combined AWP plus applicable service fee
Dispensing Fee/Rx	$1.50
Administrative Fee/Rx	$0.00

II. Mail Service Pharmacy Pricing (Does Not Apply to Specialty Products)

	2-Tier Plan Design or 3-Tier Plan Design Less than $15.00 Copay Differential ESI National Preferred Formulary	
	1-34 Days' Supply	**35-90 Days' Supply**
Ingredient Cost - Brand Drugs *Single Source Generic Drugs are priced as brands*	AWP – 16.75%	AWP – 23.5%
Ingredient Cost – Generic Drugs	AWP - 16.75% or, if lower, MRA	AWP - 23.5% or, if lower, MRA
Ingredient Cost - Compound Drugs	Combined AWP plus applicable service fee	
Dispensing Fee/Rx *Subject to change for changes in delivery rates*	$1.50	$0.00
Administrative Fee/Rx	$0.00	$0.00
Minimum Rate / Rx	$8.99	$8.99

III. Specialty Products. Sponsor may elect the CuraScript exclusive or open option as described below:

(a) Exclusive. CuraScript is the exclusive provider of Specialty Products for the reimbursement rates shown on the CareLogic Drug List for CuraScript - Exclusive. Any Specialty Product dispensed from a pharmacy other than CuraScript (for example, limited distribution products not then available through CuraScript or overrides) will be reimbursed at ESI's standard "open" network Specialty Product rates shown below. Upon CuraScript acquisition of limited distribution products, Members will obtain prescriptions through CuraScript.

(b) Open. Specialty Products shall be available through CuraScript and Participating Pharmacies for the CareLogic Drug List for CuraScript – Open and Participating Pharmacy reimbursement rates.

OA.K. Analysis of dispensing fee changes

This section of the Online Appendix contains the figure presenting difference-in-difference coefficients for each year-quarter (with 2012Q1 as the base period) from a regression of drug dispensing fee on the treatment indicator interacted with individual year-quarter indicators. The merger quarter was excluded from the estimation. The dependent variable is *DispensingFee*, defined as the dispensing fee scaled by ingredient costs. *Treatment(County)* is defined as an indicator that equals 1 when two conditions hold simultaneously: (i) the change in Express Scripts' market share for contract negotiations from the pre- to the post-period falls in the top quartile of the sample, and (ii) the post-period level of Express Scripts' market share for contract negotiations also falls in the top quartile, while equals 0 when the change in market share (condition i) falls in the bottom quartile of the sample. The regression is at the insurance claim level. Point estimates are derived from a regression including patient-drug product-pharmacy and year-quarter fixed effects. Standard errors are double clustered at the drug (i.e., NDC) and county level. The gray area represents a pointwise 95% confidence interval.

