Mergers and Advertising in the Pharmaceutical Industry

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January 2026†

Abstract

In many industries, the market structure determines the level of both price competition and promotional activities. We study how price and advertising strategies change when firms merge in pharmaceutical markets in the US. We show that across all drug markets, although mergers do indeed increase prices, advertising spending decreases after a merger. Merger simulations that do not account for advertising reductions may thus lead to biased price effects. Considering a merger of two large pharmaceutical companies in an antimicrobial drug market, we estimate a structural model of supply and demand and simulate the merger effect under different magnitudes of advertising changes. We find that the merger effect on prices is lower when accounting for advertising decreases than when ignoring them. We also provide welfare evaluations either using static consumer surplus or accounting for the dynamic consumer surplus effect of innovation that larger industry profit incentivizes.

Keywords: Merger, Advertising, Drugs, Welfare, Innovation

JEL Codes: I10, L22, L41

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†We would like to thank Matthew Grennan, Julian Reif and the participants in the seminars and conferences at Toulouse, the MaCCI Annual Conference in Mannheim, the Stockholm School of Economics brown bag seminar, the European Economic Association conference in Milan, the EARIE conference in Vienna, the IIOC conference in Washington, DC, and the American Society of Health Economics conference. The authors gratefully acknowledge the financial support of the ANR under grants no. ANR17-EURE-0010 (Investissements d'Avenir program) and ANR-16-CE36-0004 as well as the European Research Council (ERC) and the European Union (grant agreement No 101141890 — EHCI).

1 Introduction

Competition authorities frequently use ex ante simulations to evaluate the anticompetitive effects of mergers in terms of higher prices or lower rates of innovation (European Commission, 2015). When firms with overlapping market activities merge, prices typically increase due to reduced competition, increasing producers' profits at the expense of consumers. However, firms may use other strategic tools, such as promotion, in which case a change in market structure may have more ambiguous effects, as such a change changes both price and advertising strategies. For example, a merged firm does not need to engage in the business-stealing promotion of previously rival products, potentially leading to less advertising. The change in firms' profits, as well as welfare effects, may thus depend on advertising decisions. Moreover, regarding consumer welfare, in addition to the usual possible cost synergies that can compensate for the negative effect of the increased market power of a merger, higher industry profits might spur welfare-improving future innovation. Thus, the trade-off concerning merger decisions depends on the elasticity of innovation to industry profits, on variable profits, and on promotional spending.

In this work, we study mergers in the pharmaceutical industry. First, we show reduced-form results on the effect of mergers on both prices and promotional spending across all drug classes in the US. Our results suggest that average prices do indeed increase after a merger but that advertising spending sometimes decreases, which can be welfare improving when these decreases reduce wasteful spending for business stealing. Second, we study the role of advertising in a specific market that experienced a merger. Using the case of the merger between Pfizer and Wyeth, whose activities overlapped in the market for antimicrobial drugs, we estimate a structural model of supply and demand with firms competing in terms of both pricing and advertising. We use these estimates to simulate the counterfactual price equilibrium without the merger and at different levels of advertising. We find that the merger effect on prices is greater when we account for the equilibrium advertising changes of firms than when we do not. This finding shows that the price increase observed after the Pfizer–Wyeth merger for their own products (Zyvox and Tygacil) is greater than what would have been simulated ex ante with fixed advertising levels because the level of advertising changed after the merger.

This study draws attention to the promotional spending strategies in oligopoly competition that affect the price equilibrium and that are thus important when considering the effect of the market structure on prices. It shows that competition policy balancing the short- and long-term effects of the profits of innovating firms should also consider how mergers affect promotional strategies in addition to price competition. As stated by the Federal Trade Commission,[1] ex post analyses using data from both before and after mergers can help us learn how completed mergers affect prices and innovation. We add to this discussion the concern for how they affect promotional strategies. Our results can provide guidance regarding methods of analysis that may help distinguish mergers that are likely to negatively affect consumers from those that are not. European Commission (2015) summarizes lessons from the European Commission's Directorate-General for Competition review of European merger decisions. While recommending the structural merger simulation methods for ex ante evaluation, it mentions that when specifying a demand model for differentiated products, it is common to assume price as the strategic variable but that the structural model can be modified to allow for advertising or quality as an additional strategic variable. In addition to this recommendation, such analysis has not been conducted in the case of advertising in the pharmaceutical sector. Using pre- and post-merger data, we avoid complex simulations of the dynamic equilibrium changes to advertising that would need to be carried out for a purely ex ante evaluation. Instead, we show that merger simulations should consider the possible advertising strategy scenarios.

Our counterfactual estimation suggests that the effect of the change in advertising on profits is approximately 30% of the total merger effect for the merged firm, prompting us to reflect on the long-term dynamic effects of the merger on welfare. We propose a simple calculation that accounts for the effect of higher profits on future innovation using external evaluations of the elasticity of innovation to profits. We then use our market evaluation of the increase in consumer surplus obtained by the introduction of a new product to propose welfare evaluations of these expected future innovations. Note that this evaluation does not rely on intermediary steps of innovative activities, which can be affected by the market structure, as shown by Cunningham et al. (2021). Rather, it simply projects the effects of profitability on the future market entry of new products, which can be even greater if companies can be promised greater profits without changing the market structure.

[1] See https://www.ftc.gov/policy/studies/merger-retrospectives.

Literature Our paper relates to several strands of literature on mergers.

Merger effects on aspects other than pricing strategies In addition to the standard literature on merger simulation and price effects (Nevo, 2000; Björnerstedt and Verboven, 2016), this study is related to the literature on the modeling of merger effects in markets where firms not only compete in terms of prices but also can relocate products or change promotional strategies. Unless multiproduct firms sell complements (Song et al., 2017), the price effects of mergers usually increase prices. Indeed, Song et al. (2017) show that a merger between two pharmaceutical companies selling drug complements in cocktail treatments may lead to a price reduction contrary to the standard upward pricing pressure because firms internalize the situation of substitution between standalone products. Otherwise, some studies have focused on product repositioning. Theoretically, just as product repositioning can mitigate the anticompetitive effects of a merger (Gandhi et al., 2008), advertising changes can also do so. For example, Fan (2013) shows that merger simulation that ignores product relocation can be misleading. With respect to advertising, the literature on its relationship with the market structure has found opposite results. Chandra and Weinberg (2018) use the 2008 merger of Miller and Coors in the US beer brewing industry to examine how local concentration affects firms' advertising behavior, finding that higher local market concentration increases advertising. However, there are fewer studies on merger effects in pharmaceutical markets. Leheyda et al. (2011) is one of the few studies to investigate ex post the effects of a pharmaceutical merger, namely, that of Pfizer and Pharmacia in 2003 in the Swiss market. This evaluation confirmed the predictions of the Swiss Competition Commission that this merger had very small effects on prices and product development, mostly because both companies had only slight overlaps. Otherwise, the literature on mergers in the pharmaceutical industry has focused more on their effects on innovation, obtaining slightly mixed results. Finally, Tenn et al. (2010) examines the impact of ignoring promotional competition in the form of displays in supermarkets or in newspapers when predicting the effects of mergers using structural models of price competition. They find that ignoring this form of static promotional competition significantly biases demand price elasticity and thus underestimates the price effects of a merger. They also show that post-merger promotional activity matters for merger effects.

Merger effects on innovation The literature has recently addressed the dynamic effects of mergers from a theoretical perspective. Jullien and Lefouili (2018) discuss the various positive and negative effects of mergers on innovation and shed light on the circumstances under which the overall impact of a merger on innovation may be either positive or negative. Moreover, Motta and Tarantino (2021) provide some theoretical conditions under which mergers of firms that compete in terms of prices and investments have a positive effect on total investment and consumer surplus. However, these conditions do not allow for additional strategic tools of competition, such as advertising. Furthermore, Régibeau and Rockett (2019) address the question of whether mergers, in addition to raising issues about product market competition, raise concerns when firms have substantial innovation programs, arguing that the efficiencies brought by innovation can justify a more lenient policy toward innovation-intensive mergers. These authors distinguish directed versus nondirected product market innovation as a key determinant of whether the negative effects of a merger between companies with product overlap should be considered stronger compared to other types of mergers.

Empirically, Ornaghi (2009) finds that mergers between large companies have a negative effect on competitors' research and development (R&D) in the therapeutic areas of the mergers. Moreover, Haucap et al. (2019) find negative effects of mergers on innovation, as measured by patent citations in markets with high R&D intensity. Comanor and Scherer (2013) provide suggestive evidence of the negative effects of mergers on innovation. However, Grabowski and Kyle (2008) show that the size of a company is important for the late-stage development of pharmaceutical R&D projects; hence, mergers have a positive effect. European Commission (2020) analyze 149 mergers and acquisitions (M&As) between 2010 and 2013 and find that they increase the number of discontinuations of drug development projects while accelerating the progression of continued projects through clinical trial phases, except in disease classes where targets and acquirers overlap. Morgan (2001) discusses the public policy concern about the potential effects of mergers on innovation. A comparison of the approaches taken by the EU and the US in three recent major pharmaceutical mergers reveals that the EU appears to place more explicit emphasis on effects in downstream markets than the US does, indicating that the dynamic effects of mergers on innovation are more uncertain. Furthermore, Cunningham et al. (2021) show that acquired drug projects are less likely to be continued when they overlap with the acquirer's product portfolio. Thus, the dynamic effects of mergers are a legitimate

concern that should be accounted for when considering the benefits in terms of future innovation and larger profits in more concentrated industries.

Merger simulations Our merger simulation method relies on the demand estimation and supply-side modeling of the competition among firms in oligopolies, which is a common approach (Nevo, 2000; Björnerstedt and Verboven, 2016; Weinberg and Hosken, 2013; Miller and Weinberg, 2017). Ex ante simulations have been shown to provide realistic predictions of the merger effect. As in our case, where we observe the merger and can compare counterfactuals to the observed market equilibrium post-merger, Weinberg and Hosken (2013) compare the price effects obtained through simulation of the merger using pre- and post-merger data. They show that some discrepancies between observed and simulated price effects can come from the modeling of demand or conduct but establish that advertising is not the source of such discrepancies in the mature market studied. Pharmaceutical drug markets may differ because of the innovative nature of products and the lifecycle of patent protection, making advertising potentially very valuable and for a limited period of time in such markets. Moreover, Björnerstedt and Verboven (2016) analyze a large merger in the Swedish market for analgesics that resulted in a large price increase. They show how structural model simulation allows us to predict merging firms' price responses and that cost increases or partial collusion may explain the overestimation bias in predictions of the price change of nonmerging firms.

Advertising of pharmaceuticals The literature has studied the main determinants of advertising in the pharmaceutical industry: drug age, market size, and quality. In a theoretical framework, Bhattacharya and Vogt (2003) show that prices should be expected to increase and advertising spending should decrease over the course of the lifetime of a drug. Moreover, Lakdawalla et al. (2013) show that advertising levels are higher when the market size is larger with the implementation of Part D health insurance. de Frutos et al. (2013) use a Hotelling model of price and advertising competition between prescription drugs of different qualities. Allowing consumers to differ in terms of brand loyalty, these authors show that brand advertising is a strategic substitute and that better drugs are more expensive and more advertised for the purpose of generating brand loyalty. Another strand of literature focuses on the determinants of the content and role of advertising. Dave (2013)

reviews the literature on the effects of pharmaceutical advertising and finds that direct-to-consumer (DTC) advertising is mostly informative and market expanding, whereas physician advertising is more persuasive. Anderson et al. (2013) find that ad information content is higher for higher-quality brands but lower for brands with a higher market share. The closest to our paper, the literature that associates advertising with changes in the market structure focuses on patent expirations. Lakdawalla and Philipson (2011) find that the decrease in advertising following patent expiration leads to a short-run decrease in consumer welfare. Similarly, Castanheira et al. (2019) explain the fact that generic entry often leads to a drop in quantity, while prices drop due to the impact of the reduction in promotional efforts on the market equilibrium.

Given that we are also interested in understanding the consequences of changes in promotional efforts, our study is related to the literature on the effects of advertising. Lakdawalla (2018) underlines that as advertising increases profitability, innovation and advertising become complements. Anderson et al. (2016) focus on comparative advertising; their analysis of the over-the-counter (OTC) analgesics market shows that comparative advertising negatively affects competitors targeted in ads more than they benefit the advertiser, generating excessive levels of advertising. Finally, David et al. (2010) report that detailing worsens the match between drugs and patients, increasing the number of reports of adverse events.

Structure of the paper In Section 2, we present the data and some reduced-form difference-in-differences results for the correlations among mergers, prices and advertising decisions on all drug classes in the US. Section 3 shows the results of the estimation of a full structural model in a given drug market, highlighting the role of advertising in the overall merger effect. Subsection 3.1 describes the market and advertising data. Subsection 3.2 then presents the demand model used for the market for antibiotic drugs in which Pfizer and Wyeth overlapped prior to their merger. Subsection 3.3 presents the oligopoly structural supply model and its full estimation. In Section 4, we show our main counterfactual simulation results, and Section 5 concludes the paper. Additional robustness checks and details are provided in Appendix A.

2 Reduced-form empirical analysis

We start by documenting some general evidence on the correlation between prices and advertising spending with mergers across all drug classes in the US. The analysis uses all drug markets from 2002 to 2014 and all mergers and acquisitions of firms owning those products to document the merger effects on average prices and advertising.

The direction of the merger effect on advertising is difficult to predict. On the one hand, higher profit margins can increase the returns to advertising. On the other hand, if merging firms were engaging in substantial business-stealing advertising before the concentration took place, the net effect of the merger could be a decrease in advertising. We use our data to determine whether we can identify a broad trend in this effect across many mergers.

Without cost synergies or other changes in market demand, the expected effect on prices is an increase compared to a counterfactual situation without the merger. Empirically, the effect will depend on whether the control group, supposedly unaffected by the merger, is not subject to spillovers. Thus, it is an empirical question of whether the data allow us to identify the effect on prices. The identification of the effect on prices also depends on merger-related changes in other strategic variables that affect the demand shape. For this reason, investigating the effect of mergers on advertising is also important.

2.1 Data sources and construction

We use sales data from IMS Health MIDAS (now called IQVIA), which provides data on the quarterly wholesale-level revenues and quantities sold for each drug in a country from 2002 to 2014. The dataset covers all wholesale transactions in different sectors (for the US, these are clinics, drugstores, federal facilities, food stores, health maintenance organizations (HMOs), home health care, long-term care facilities, mail services and nonfederal hospitals), disaggregated at the form (mode of administration) and strength levels. We aggregate over these two dimensions to obtain a dataset in which the unit of observation is a product-quarter.[2]

Using only this dataset for merger analysis is impossible, as it retains the ownership structure only

[2]Quantities are summed by using their levels in standard units to ensure comparability between forms and strengths.

from the previous period in the sample. This implies that these data do not allow us to observe M&As among companies that market some drugs. Therefore, we match the sales data with the Citeline Pharma Projects dataset from Informa, a comprehensive dataset of drug development projects until marketing that allows us to observe all drugs whose first marketing started after 1980. The dataset also contains the ownership history for each entry. We also match the sales data with the MedTrack data from Informa, which records all deals in the biotech industry. The MedTrack data allow us to identify 144 M&As involving companies with drugs with some US sales over the 2002-2014 period. This number of M&As is comparable to that identified in Cunningham et al. (2021) using another data source (Thomson Reuters SDC Platinum supplemented by Thomson Reuters RecapIQ, now called Cortellis Deals Intelligence). We match Pharma Projects data with the sales data on molecule and brand names using a fuzzy string matching algorithm (and manual corrections when necessary). If a molecule exists in both branded and generic forms, then we match only the branded entries in the sales data. As Pharma Projects tracks drugs released only after the 1980s, we miss information on some older molecules (this is the case, for example, for the following molecules, all of which were developed in the 1960s: cefazolin and its combinations, lincomycin, and spectinomycin).

Finally, we obtain advertising data from IMS Health Global Promotional Track, which provides monthly advertising expenditures for each drug by media (detailing, DTC advertising, marketing publications in journals, and promotion in meetings) at the country level for the US from 2005 to 2014. Similar to the Pharma Projects data, we match these data to our main dataset using product names and a fuzzy string matching algorithm.

The IMS data allow us to observe the quarterly wholesale revenues and quantities of each drug that we use to compute average wholesale prices by quarter. However, several issues need to be considered in the careful measurement of wholesale average prices. First, revenues concern the products sold by the manufacturer in a given period, while quantities are the units dispensed to patients in the same period (Kakani et al., 2020). Given that some establishments might hold stocks of medicines, we account for the discrepancy in the timing of recording revenues and quantities by using a smoothed version over three quarters of the price (see Appendix Section A.1 for details). Moreover, revenues are computed using list prices, but payers may negotiate wholesale-level rebates, which are confidential. Anecdotally, the rebates for high-price patent-protected products can be

substantial. Kakani et al. (2020) show that toward the end of our sample period, average rebates were approximately 32% but varied widely between ATC4 classes and could even be as low as 7% (if any) and as high as 64%. Moreover, rebates change over time. The IMS data provide sales values and volume for nine different channels: clinics, food stores, long-term care hospitals, drugstores, HMOs, mail services, federal facilities, home health care, and nonfederal facilities. We notice that clinics and federal facilities both have lower wholesale list prices and experience less of an increase in those prices over time. In contrast, food stores and drugstores usually have the highest wholesale prices. This pattern is quite common for all drugs. Thus, for each drug, we use the ratio of the minimum wholesale price observed across all channels to the average wholesale price across all channels, except clinics and federal facilities, as an approximation of the average rebate that must be used if prices are equal to the net price in these two lowest price channels (see Appendix Section A.1 for details). We then test the robustness of our results to different measurement assumptions regarding prices, and in particular, we replicate our results closely using gross prices.

Table 2.1 shows the descriptive statistics of the data after matching and price corrections for all Anatomical Therapeutic Chemical (ATC) level 1 classes on revenues and advertising spending.[3] Advertising spending is minimal for some ATC classes; however, it can represent 5 to 8% of total wholesale revenue for others. Generic companies typically advertise very little for their own products, probably because their margins are too low for advertising to be valuable.

[3]In the ATC classification system, active substances are classified in a hierarchy with five different levels. The system has fourteen main anatomical/pharmacological groups or 1^{st} levels. Each ATC main group is divided into 2^{nd} levels, which can be either pharmacological or therapeutic. The 3^{rd} and 4^{th} levels are chemical, pharmacological or therapeutic subgroups, and the 5^{th} level is the chemical substance.

Table 2.1: *Descriptive Statistics*

ATC1 Class	Revenue Total	Revenue Branded	Revenue Generic	Advertising Spending
A Alimentary tract and metabolism	31,580,451	26,410,085	5,170,366	1,192,218
B Blood and blood-forming organs	16,540,304	14,239,303	2,301,001	430,340
C Cardiovascular system	32,587,329	25,663,821	6,923,508	1,714,614
D Dermatologicals	6,226,835	3,167,750	3,059,085	211,310
G Genito-urinary system and sex hormones	13,312,437	10,058,359	3,254,078	1,222,688
H Systemic hormonal preparations	4,974,800	3,879,543	1,095,257	85,490
J General anti-infectives systemic	27,157,499	16,906,791	10,250,708	540,866
K Hospital solutions	269,904	11,811	258,094	54
L Antineoplastic & immunomodulating agents	34,567,375	33,001,658	1,565,717	441,623
M Musculo-skeletal system	8,656,680	6,848,730	1,807,949	794,882
N Nervous system	52,426,765	41,641,471	10,785,295	2,428,259
P Parasitology	322,992	169,448	153,544	12,419
R Respiratory system	20,448,037	17,207,132	3,240,905	1,294,998
S Sensory organs	5,431,783	4,399,132	1,032,651	293,434

Notes: Revenues and advertising in 1,000 US$ per year over the 2005-2013 period.

2.2 Difference-in-Differences Evidence of Merger Effects on Wholesale Prices and Advertising

We first use all the data on wholesale-level prices for all drug classes in the US from 2002 to 2014, advertising expenses for all drugs (available starting in 2005) and the 144 M&As that took place in this period to evaluate how prices and advertising are correlated with mergers. We define markets using the ATC level 4 classification. We observe, on average, 12 deals per year, ranging from 3 (in 2013) to 20 (in 2010) per year. These deals are mostly acquisitions: only 5 (3.5%) are mergers, 70% are 100% acquisitions, and the rest are majority acquisitions. MedTrack provides the deal value for 134 of these mergers, with a mean of 3.78 bn US$, and Pfizer–Wyeth is the largest of these deals, at 68 bn US$ (the 5^{th} largest deal to date). We consider mergers that correspond to the case where both parties are marketing competing products, which happens in only 14 deals (2 mergers, 8 100% acquisitions and 4 majority acquisitions) with 24 firms participating. Defining a product at the brand, company, active ingredient, dosage, form and strength, these deals affect 194 competing products of the merging firms and 1,930 products of other firms marketed in the same ATC4 classes (out of slightly over 20,000 products in total). 76 of the merging products are advertised after a merger.

In the majority of these transactions, the Federal Trade Commission (FTC) ordered divestitures of certain product lines. These products are excluded from our treatment group, as the algorithm that we use to recover ownership changes works only for products that belong to the merged firm after the merger.[4] Table A.2 in Appendix A.3 shows some descriptive statistics of the sample of products and time periods used in the reduced-form exercise, indicating that we have many markets (defined at the ATC4 level) in which firms that merge have overlapping products. Mergers of competitors affect 42 out of the 493 ATC4 markets. Table 2.2 shows how the classes with mergers compare to those that are unaffected. While the differences are not statistically significant, markets (ATC4 classes) where competitors merge have a higher mean number of products with lower generic penetration and a higher mean product price but lower per-product sales value.

Table 2.2: *Descriptive Statistics of the Difference-in-Differences Dataset*

	ATC4 classes with mergers	ATC4 classes without mergers
Number of products	43.75	18.48
	(48.34)	(34.09)
Market share generic (value)	0.39	0.58
	(0.33)	(0.42)
Market share generic (volume)	0.66	0.68
	(0.31)	(0.40)
Product sales ($1000s)	5,446.70	7,736.50
	(28,356.46)	(55,347.27)
ATC Class sales ($1000s)	316,912.96	160,515.73
	(581,695.69)	(422,235.29)
Product wholesale price	27.88	22.43
	(214.17)	(235.11)

Notes: Means and standard deviations across quarters are in parentheses. ATC4 classes with mergers are only those with the products of the two merging companies.

We estimate a set of difference-in-differences regressions to quantify the changes in prices and advertising following a merger. Our strategy is similar to that of Bhattacharya et al. (2023), who study merger effects in the grocery retail industry, and to that of Dafny et al. (2012), who investigate the price effects of insurance mergers. Bhattacharya et al. (2023) estimate the merger effect first as the

[4]In practice, these products will be assigned in our dataset to the company that they were divested to for the entirety of the sample period and, thus, are treated as nonmerging products.

departure from the premerger trend in the prices of each product. Then, they use a control group via geographic markets where merging parties constitute a small share of total sales. The identification strategy is based on the idea that trends in demand or cost are gradual; thus, the deviations from the trend at the time of a merger should be due to that merger. Dafny et al. (2012) use markets with low predicted changes in hospital concentration after the merger as control groups. Bonaimé and Wang (2024) and Hammoudeh and Nain (2022) also use difference-in-differences regressions to study the effect of mergers on drug prices. The differences in the data sources and specifications used in these two papers lead to opposite results. Our analysis, which is based on yet another data source and a different methodology, confirms Bonaimé and Wang (2024)'s price increase.

In our basic specification, we include the effect of the merger on both products directly involved in the transaction and their rivals in the same ATC4 class. We also include product and quarter fixed effects and time-varying controls related to the age of the product and the intensity of competition within the ATC4 class, with the number of products in the same ATC4 class. Indeed, Starc and Wollmann (2023) have shown the role of product entry in preventing cartels from increasing prices too much. Similarly, entry can discipline the price increase effects of mergers. In addition to standard two-way fixed effects (TWFE) regressions, we provide estimates of the merger effect obtained using the methodology proposed by Callaway and Sant'Anna (2021), as our setting is a straightforward example of staggered treatment.

Finally, we also control for the endogeneity of the merger decision as follows. Indeed, the merger decision of firm $f(j)$ may be timed to coincide with a patent expiration or the anticipation of the introduction of new drugs in the market of drug j, that is, unobservables affecting the pricing or advertising decision.

Thus, we correct for this endogeneity problem using a control function approach where the decision of a firm to merge with another one is explained by its overall R&D pipeline that concerns other markets than the one of a particular drug. Thus, if we find some variables of the research pipeline of a firm explain the merger decision, we can exclude that they affect the product market prices of a drug owned by that firm, except through the merger effect. To do so, we estimate the probability of a firm engaging in a merger with a competitor based on the state of its R&D pipeline (number of projects at each stage of development, recent progress and discontinuations)

and product portfolio (number of products, their age, patents expirations) and then include this estimate in our difference-in-differences regressions. Indeed, we know that the R&D pipeline is an important determinant of mergers and acquisitions in the pharmaceutical industry (Danzon et al. (2007a); Guadalupe et al. (2012); Cunningham et al. (2021)). Appendix A.2 provides details on the control function estimation.

Table 2.3 presents a stylized example that explains how drugs are assigned to the treatment and control groups. In this example, firms A and B merge, and drugs D1 and D2 are the treated products, as they belong to the merging firms and are in the same market. Drugs D3 and D4 are rival products, as they are in the same market as the merging products. Drugs D5-D10 constitute the control group, even though D5 and D9 belong to firms that own the rival products, and D8 belongs to the merging firm A. Consequently, we compare the outcomes of the products directly affected by the transaction (competing products of the merging firms) and the outcomes of products indirectly affected by the merger (rivals of the merging products) to the outcomes of products in ATC4 classes that were not affected by the merger.

Table 2.3: *Treatment and control groups in case of a merger of Firm A and Firm B*

Market	X				Y			Z		
Product	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Owner	A	B	C	D	D	E	F	A	C	G
Group	**treated**		**rivals**		**control**					

In our baseline specification, we regress the outcome variable Y_{jt} for drug j in quarter t on a set of treatment dummies and controls:

$$Y_{jt} = \underbrace{\gamma_m}_{\substack{\text{merger effect}\\ \text{on merging}\\ \text{products}}} \times \underbrace{D^m_{jt}}_{\substack{\text{merging products}\\ \text{after a merger}}} + \underbrace{\gamma_r}_{\substack{\text{merger effect}\\ \text{on the rivals}\\ \text{of merging}}} \times \underbrace{D^r_{jt}}_{\substack{\text{rivals of merging}\\ \text{after a merger}}} + \underbrace{h(\hat{P}(D^m_{jt}=1))}_{\text{control function}} + \lambda X_{jt} + \alpha_j + \delta_t + \varepsilon_{jt} \tag{2.1}$$

where D^m_{jt} is a dummy variable equal to one if product j belongs to a firm that merged with the owner of its competitor before quarter t and D^r_{jt} is a dummy variable equal to one if product j belongs to the same ATC4 class as the merging products before quarter t. $\hat{P}(D^m_{jt}=1)$ is the estimated probability that the owner of j has engaged in a merger of competitors and $h(.)$ a parametric control

function. The control variables X_{jt} are the time to patent expiration, a set of dummy variables controlling for the age of the drug (in years), the number of products at time t in ATC4 class $c(j)$ of drug j, and a dynamic term that captures the effect of past advertising spending. In practice, we use the lagged advertising stock $a_{jt-1} = \sum_{\tau \leq t-1} \delta^{t-1-\tau} e_{j\tau}$ with $\delta = 0.5$, instrumented by the second and third lags of $\log(e_{jt})$ following Arellano and Bond (1991). δ_t are quarter fixed effects, and α_j are product fixed effects.

The coefficients γ_m and γ_r are the effects of the merger on the outcome variable, which can be interpreted as causal under the assumption that time-varying unobservables are not correlated with selection into the merger. Given that we control for product fixed effects, many other observables that vary over time and the estimated probability of having merged, the causal effect estimates are biased only if time-varying unobservables are correlated with price and the merger or if time-invariant unobservables (which vary within a molecule and market and are not controlled for by other observable product characteristics) are correlated with prices and the merger event (for example, some unobserved information about product quality that happens to affect prices and advertising decisions and is correlated with the merger). Typically, however, pharmaceutical mergers are believed to be driven by the need to restructure the firm's product portfolio due to a patent expiration or a negative shock in the R&D pipeline (Danzon et al., 2007b), accounted for by our control function, rather than the benefits from concentration in an existing product market.

To examine the effect of the merger over time, we estimate a specification in which we allow the merger effects γ_m and γ_r to be different in the short term (during the first 3 years after the merger) and in the long term (3 years or more since the transaction).

Columns (1)-(2) of Table 2.4 show the results of the estimation of Equation (2.1) on log prices $\log(p_{jt})$.[5] The coefficient estimate of γ_m (*Post merger* in the table) shows a significant 12.6% (= $\exp(0.119)$) increase after the merger and a significant 10.7% (= $\exp(0.102)$) increase for competing products (γ_r, *Post merger, rivals* in the table) in the baseline specification. The decomposition into the effect during the 3 years post-merger (short term) and after (long term) shows that the effect for the merging products remains the same in the long term. These results are consistent

[5]Table A.4 in Appendix Section A.3 shows the same regression on prices as that in Table 2.4, except that it uses nondiscounted gross prices that do not account for rebates. The results in the two tables are extremely similar.

with the findings of Bonaimé and Wang (2024), who use data from a survey on acquisition costs by retail pharmacies from a more recent period (2013 to 2019) and confirm an average slight price increase after a merger.[6] Our results are also consistent with the findings of Feng et al. (2023) for horizontal acquisitions, whose sample largely overlaps with ours but extends until 2019. In the grocery retail sector, merger effects are of a smaller magnitude, with prices increasing by 1.5% in the US (Bhattacharya et al., 2023), even if they find considerable heterogeneity. In pharmaceutical markets, products based on on-patent molecules having exclusivity rights and differentiation across products of different molecules can explain why merger effects can be greater.

However, this merger effect on prices may also depend on other strategic variables chosen by firms, like advertising spending, including the "stock" of advertising reached before the merger. Indeed, advertising varies over time and, in particular, with a change in ownership. This implies that the merger effect on prices may be very heterogeneous according to advertising choices, while our reduced form estimates only their average effect.

To estimate the effect of a merger on advertising, we regress the log of per-product advertising expenditures $\log(e_{jt})$ on the same set of variables as that used in Equation (2.1).[7] We restrict the sample to products that were advertised at any moment during the period studied, and we estimate γ_m using only the products that were advertised before the merger.

Columns (3)-(4) of Table 2.4 present the results of the estimation. The coefficient estimate in column (3) shows a very large and significant decrease of 49% ($= 1 - \exp(-0.673)$) in advertising expenditure on the products involved in the merger after the merger, but no significant effect for rival products. The decomposition of the effect between the short and long terms in column (4) shows that the effect is stronger three years after the transaction. Table A.3 in Appendix A.3 shows that the decrease is observable in most advertising channels, except DTC advertising and spending in meetings where there is no significant change after the merger, but the largest part of the advertising spending in this market is in detailing (65% of total advertising spending of products involved in the mergers studied).

[6] Additionally, Bonaimé and Wang (2024) focus on the effect on the products of the acquirer and do not control for time fixed effects beyond deal fixed effects. Their control group is composed of similar drugs from the same company from markets that do not overlap with the target company.

[7] In practice, given the many zeros in our data, we define the dependent variable as $\log(1 + e_{jt})$.

Table 2.4: *Price and Advertising Spending Changes Post Merger*

	(1) $\log(p_{jt})$	(2) $\log(p_{jt})$	(3) $\log(e_{jt})$	(4) $\log(e_{jt})$	(5) $P(e_{jt}>0)$
Post merger (γ_m)	0.124***		-0.673***		-0.113***
	(0.020)		(0.103)		(0.020)
Post merger, rivals (γ_r)	0.087***		0.210		0.035
	(0.014)		(0.138)		(0.022)
Post-merger, short term (γ_m^{short})		0.098***		-0.362***	
		(0.018)		(0.092)	
Post merger, long term (γ_m^{long})		0.099***		-0.682***	
		(0.020)		(0.136)	
Post merger, short term, rivals (γ_r^{short})		0.043***		0.261*	
		(0.010)		(0.122)	
Post merger, long term, rivals (γ_r^{long})		0.095***		0.156	
		(0.014)		(0.133)	
Advertising Stock $t-1$	0.011***	0.012***	0.468***	0.468***	0.065***
	(0.001)	(0.001)	(0.014)	(0.014)	(0.002)
Observations	399,849	399,849	53,018	53,018	53,018
R-squared	0.001	-0.001	-4.120	-4.119	-2.287

*Notes: The dependent variables are the log average price ($\log(p_{jt})$), log advertising spending ($\log(e_{jt})$) and a dummy for non-zero advertising spending ($P(e_{jt}>0)$). All regressions include product and quarter fixed effects, the estimated probability of having merged, as well as control variables: dummies for the age of the drug, the time left to patent expiration, and the number of products in the same ATC4 class. Standard errors are clustered at the ATC3×quarter level. *** for $p<0.001$, ** for $p<0.01$, and * for $p<0.05$.*

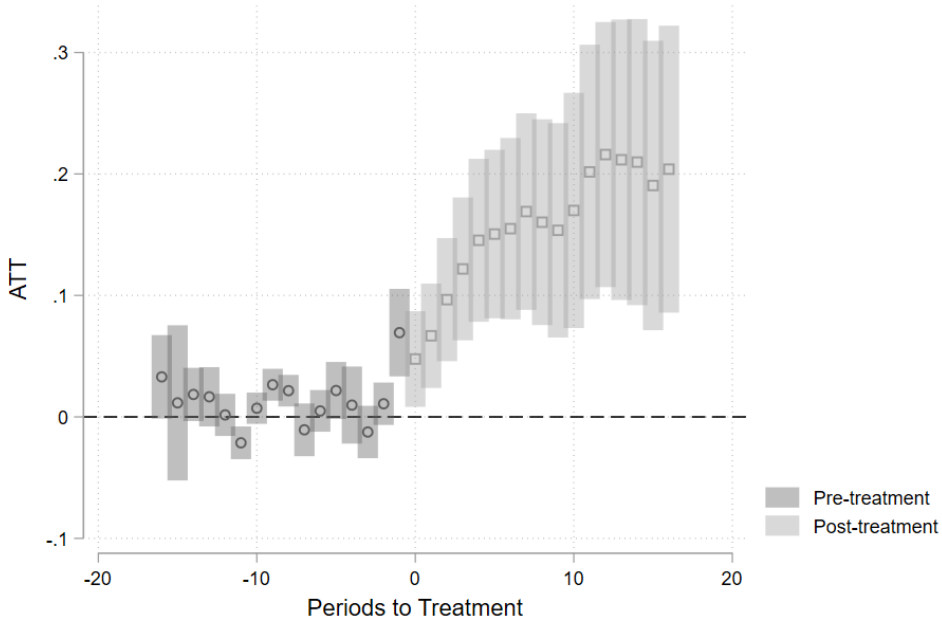
Finally, in column (5) of Table 2.4 we apply the same specification to a dummy variable for observations with non-zero advertising spending. We obtain a 10.7% decrease in the probability of advertising spending, suggesting that mergers decrease advertising at the extensive margin, driving the expenses on some products to zero.

As the mergers occurred at different times over the sample period, our results thus far rely on the assumption that the treatment effects are homogeneous. For prices, we can account for the heterogeneity of these treatment effects due to the staggered nature of the treatment using the technique proposed by Callaway and Sant'Anna (2021). We estimate the merger treatment effects using the same specification as in column (1) of Table 2.4: we include the dummy for the effect of the merger on competitors and use the same control variables. Our control group consists of not-yet-treated and never-treated units. To implement the IV strategy, we first regress the lagged stock of advertising on the exogenous variables and instruments and then include both the lagged stock of

advertising and the residuals from this regression in the main model.

Accounting for the staggered nature of the treatment gives us an average treatment effect on the treated of 8.6% (0.086 with a 0.029, significant at the 5% level). Figure 2.1 presents the event study estimates obtained for changes in prices. The price increase starts from the quarter immediately before the merger and remains significant for four years following the transaction.

Figure 2.1: *Event Study Estimates of the Merger Effect on Prices and Advertising Spending*



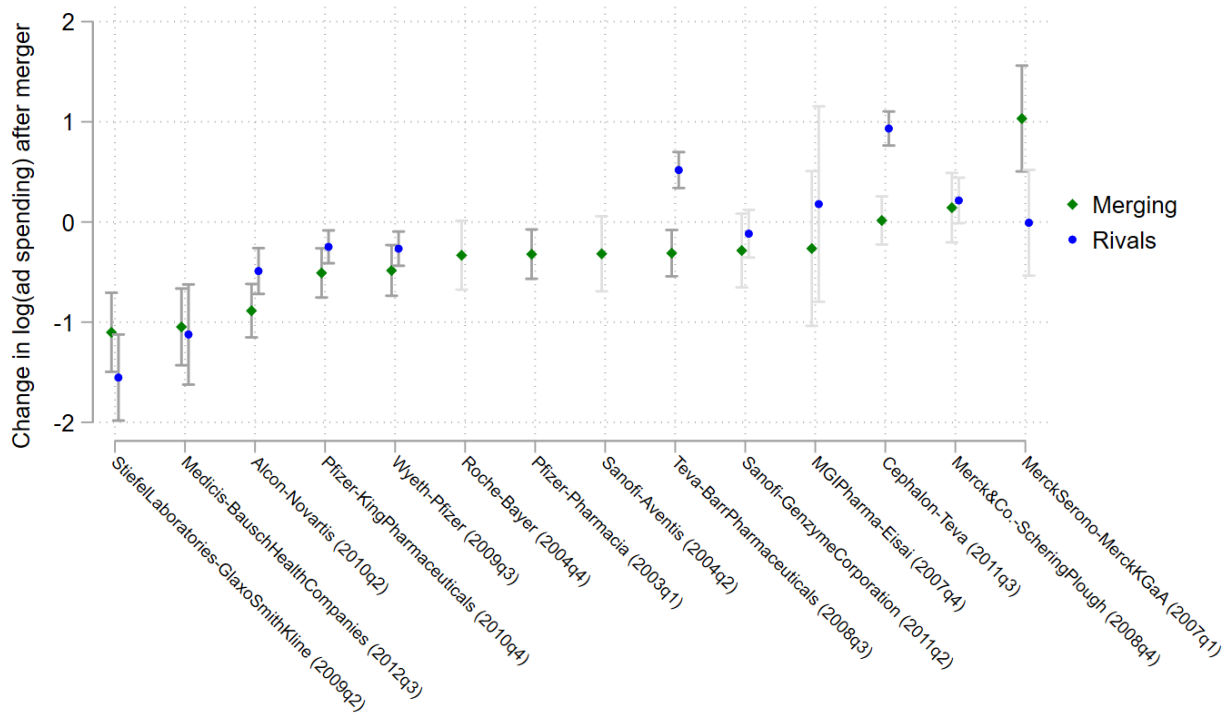
Notes: Point estimates and 95% confidence intervals follow Callaway and Sant'Anna (2021) with a varying base period: in the pretreatment periods, the base period is the immediately preceding period.

For the analysis of advertising spending, we do not have enough statistical power in our sample to implement Callaway and Sant'Anna (2021).[8] Instead, we run a series of difference-in-differences regressions applying Equation (2.1) merger by merger (using IVs for the lagged advertising stock) and each time removing observations already treated by a different merger. For each regression, we restrict the sample to the ATC3 classes that are affected by the merger. Figure 2.2 presents the results of this estimation. Across the different transactions, the effect on advertising spending of the products involved in the merger is negative, with only one statistically significant exception. For the mergers with the strongest negative effect, the effect on rivals' advertising spending is also negative.

[8] In almost all of the individual group-time regressions that are used to calculate the ATT, we would have less than 5 treated observations.

Figure A.3 in Appendix A.3 shows that for all of the individual transactions, we obtain a significant positive effect on prices, close to the average effect in Table 2.4, but not significant for the point estimates that are the smallest in magnitude.

Figure 2.2: *Estimates from the merger by merger regressions: advertising spending*



Notes: Point estimates and 95% confidence intervals.

While the classical price increase effect of reduced competition is precisely estimated, the effect on advertising decisions appears to be important but heterogeneous across mergers. Our data and the complexity of the setting, where individual products are affected by mergers multiple times, do not allow us to explore this heterogeneity in greater depth. Overall, the evidence suggests that mergers allow firms to reduce their advertising spending because of lower competition between substitute products within an ATC4 class market. To the best of our knowledge, this evidence on advertising across all drug classes in the US from 2005 to 2014 has not been documented before.

A merger effect on advertising implies a further possible effect not only on the demand shape and

consumer welfare but also on equilibrium prices and firm profits driven by changes in advertising spending. However, the uncertainty about the magnitude of the merger effect on advertising and the interrelatedness of its impacts on the other outcomes motivate a focus on a specific merger case and structural model estimation.

3 Structural model of a market with a merger

The trade-off faced by competition policy in the pharmaceutical industry is between allowing higher firm profits to stimulate innovation and reducing health care spending. To establish the contribution of the merger-driven change in advertising to the change in profits and consumer welfare, we develop a model of supply and demand for a market of antibiotics in which a merger occurred in late 2009, considering the role of advertising.

The acquisition of Wyeth by Pfizer in October 2009, valued at $68 billion, is the fifth largest transaction of its kind to date (European Commission, 2015). Regulatory reviews of the merger have investigated several markets in which Pfizer and Wyeth had potentially competing products (e.g., treatments for renal cell carcinoma and Alzheimer's disease, antidepressants, and antibiotics), ultimately concluding that the transaction did not raise anticompetitive concerns in human health product markets.

Following the medical literature (Choo and Chambers, 2016; Welte and Pletz, 2010), we consider the Pfizer molecule linezolid, under the brand name Zyvox, and the Wyeth tigecycline molecule, under the brand name Tygacil, as competitors in the market concerning methicillin-resistant Staphylococcus aureus (MRSA) infections. This market definition diverges from the ATC4 market definition typically used by competition authorities, but it is justified by the approved indications overlapping over several drugs in this MRSA market. Appendix A.5 details the definition and justification of this market definition.

3.1 Descriptive statistics

Table 3.1 presents some summary statistics for the set of products in the market considered. Our sample contains 22 unique molecules. On average, there are 18.58 molecules marketed per quarter,

with 11.94 being genericized and 14.29 with a branded product (toward the end of the sample, for 6 molecules, there are only generic products). During the period of our sample, 3 new molecules entered (tigecycline in 2005, telavancin in 2009 and ceftaroline and fosamil in 2011), and 2 molecules lost patent protection and experienced generic entry (ceftriaxone in 2005 and cefepime in 2007). Four of the branded drugs and all of the generic drugs experienced no advertising spending.

High levels of resistance to some antibiotics can change the substitution patterns or the incentives to prescribe certain products. As shown in Figure A.4 in Appendix A.4, Staphylococcus aureus infections in the US do not show any resistance to linezolid or vancomycin, and their resistance to other products in our sample has not been systematically tracked. Recent medical studies, mostly conducted after the period of our analysis, have found instances of resistance of MRSA infections to antibiotics in the sample. However, such instances remain rare (e.g., Kaur and Chate (2015); Liu et al. (2021)).

Table 3.1: *Summary Statistics of the MRSA Market*

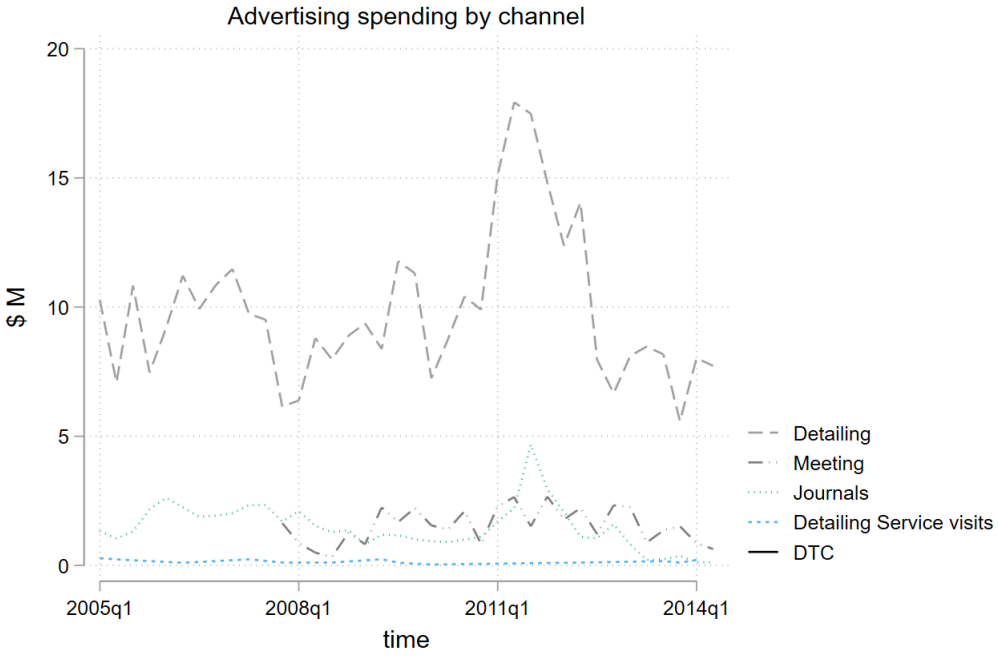
	Mean	SD	Median	N
Nongeneric products				
Sales value (list prices)	26394.00	57101.97	2461.86	884
Sales value (after rebates)	19383.20	42790.73	1684.35	884
Sales volume	536.22	932.20	168.50	884
Net price	34.97	55.18	11.43	884
Ad spending	828.35	1578.43	0.00	572
Generic products				
Sales value (list prices)	13661.03	21797.32	4600.68	523
Sales volume	1972.55	2702.83	323.00	523
Net price	10.57	6.36	9.41	523
Firm level				
Sales value (list prices)	29220.53	57506.59	4864.42	1043
Sales value (after rebates)	23278.49	44085.45	4263.55	1043
Ad spending	454.28	1383.26	0.00	1043
Sales volume	1443.58	2180.71	349.00	1043
Market entries	0.01	0.12	0.00	1043
Number of products	1.35	0.80	1.00	1043

Notes: Sales values and advertising spending per quarter are expressed in 1,000s of US$, and sales volumes per quarter are expressed in standard units.

Pharmaceutical companies have a particular interest in advertising antibiotics to physicians, as for many infections, the standard of care is to follow an *empirical therapy*. In this approach, the

physician makes an educated guess and prescribes an initial course of an antibiotic while waiting for the results of laboratory tests that can more precisely guide further treatment. Indeed, as shown in Figure 3.1, most of the advertising spending in the market considered in our analysis is devoted to detailing.

Figure 3.1: *Market-Level Advertising Spending by Channel (J1X+J1D2+J1F)*



At the level of individual molecules, the same pattern holds (see Figure A.5 in Appendix A.4): the bulk of advertising expenditures is used for detailing, and changes over time are also the consequence of changes in spending on detailing, as the other channels remain stable.

To account for a potentially persisting effect of advertising in demand estimation, instead of current advertising spending, we use a lagged advertising stock (following Erdem et al. (2008), David et al. (2010), David and Markowitz (2015) and Dubois et al. (2018)),[9] defined for drug j at the beginning of quarter t as the discounted sum of past flow spending $e_{j\tau}$:

$$a_{j,t} = \sum\nolimits_{\tau<t} \delta^{t-1-\tau} e_{j\tau}$$

[9]Dubois et al. (2018) via an increasing concave transformation of the stock variable in the demand specification. An alternative functional form that we tested, used in Dubé et al. (2005) and Shapiro (2018), defines the stock of advertising as $a_{jt} = \sum_{i\leq t} \delta^{t-i} \sinh^{-1}(e_{jt})$, where $\sinh^{-1}(x) = \log\left(x + \sqrt{1+x^2}\right)$.

In the main empirical analysis, we use a decay parameter by quarter of $\delta = 0.5$, and we drop the first year of the data in the demand estimation to begin the analysis in 2006, to avoid the initial value problem (since $0.5^4 = 0.0625$, advertising spending prior to 2005 is not considered important). Figure A.6 in Appendix A.4 shows the evolution of these stocks over time by product.

3.2 Demand model

We then estimate the demand in this market using a random coefficient logit model. Following Berry (1994); Berry et al. (1995); Nevo (2001), we specify the random utility for each drug $j \in \{1, .., J_t\}$ of ATC4 class c for patient i in period t as

$$u_{ijt} = \delta_{m(j)} - \beta_i p_{jt} + \gamma_j(\mathbf{a}_{t-1}) + \alpha \mathbf{x}_{jt} + \zeta_{ct} + \xi_{jt} + \varepsilon_{ijt} \tag{3.1}$$

where $\delta_{m(j)}$ is a molecule fixed effect, p_{jt} is the price of the drug, $\mathbf{x}_{jt}$ is a vector of observed characteristics, ζ_{ct} are class-period-specific effects, ξ_{jt} is an unobserved demand shock for product j at t, and ε_{ijt} is consumer i's deviation from the mean utility of taking drug j in period t. Moreover, we allow advertising to affect demand using the stock of past advertising expenditures, as in Dubois and Lasio (2018), but with a more general specification including spillover effects, as in Dubois et al. (2018). We may interpret the demand model as resulting from decision utility maximizing by the prescribers without necessarily interpreting these decision utilities as experience utility relevant to the patient welfare as in Dubois et al. (2018). Denoting $\mathbf{a}_{t-1}$ the vector of the beginning of period $t-1$ advertising expenditure stock, we specify

$$\gamma_j(\mathbf{a}_{t-1}) = \gamma a_{j,t-1} + \Gamma \sum\nolimits_{k \neq j} a_{k,t-1}$$

for product j to allow for advertising spillovers of products k other than j.[10]

This implies that if $\gamma > 0$ and advertising spillovers are positive ($\Gamma > 0$), then the outside good market share is a decreasing function of any of the product advertising variables a_{jt}, which would

[10]Remark that in the study of merger in the ice cream industry, Tenn et al. (2010) account for promotion by introducing dummies for whether the product is displayed in a store or in a newspaper in a static demand model and does not allow either dynamics or spillovers across products. They however share the same idea that mergers can lead to a change in promotion activity.

mean that advertising has a market expansion effect, although it has a business-stealing effect from other competing products if Γ is not too large.[11] If $\Gamma > 0$ is large compared to γ, advertising will then be expanding the total market but not necessarily business stealing because the effect on the market share will depend on the local derivative of the exponential of the mean utility with respect to advertising, which can be larger for the cross effect than the own effect. However, with Γ equal to zero or positive but small in magnitude compared to γ, the advertising of a product will then increase its market share both at the expense of the outside good and of other products.

The model is completed by an outside good with normalized indirect utility $u_{i0t} = \varepsilon_{i0t}$. The indirect utility can then be redefined with the mean utility $\delta_{jt} = \delta_{m(j)} - \beta p_{jt} + \gamma_j(\mathbf{a}_{t-1}) + \alpha \mathbf{x}_{jt} + \zeta_{ct} + \xi_{jt}$ and deviation $\mu_{ijt} = (\beta - \beta_i)\, p_{jt}$, where $\beta \equiv E(\beta_i)$. Under the assumption that ε_{ijt} is i.i.d. extreme value type I distributed, the choice probability of alternative j by consumer i has a logit form, and the aggregate market share of product j, s_{jt}, is given by

$$s_{jt}\left(\mathbf{a}_{t-1}, \mathbf{p}_t\right) = \int \frac{\exp\left(\delta_{jt} + \mu_{ijt}\right)}{1 + \sum_k \exp\left(\delta_{kt} + \mu_{ikt}\right)} \varphi\left(\beta_i\right) d\beta_i,$$

where $\varphi(.)$, the probability distribution function of β_i, is assumed to be the normal distribution $\mathcal{N}(\beta, \sigma^2)$. We also specify the aggregate market size, which is set such that the average outside good market share is 15%. Robustness checks on the demand estimation are performed with different assumptions regarding the market size specification and the functional form of $\gamma_j(\mathbf{a}_{t-1}) = a_{j,t-1}^{\kappa} + \Gamma \sum_{k \neq j} a_{k,t-1}$ with varying κ (see Appendix A.6).

For estimation, we follow the standard approach of Berry et al. (1995) and Nevo (2001) for identifying and estimating such a model with aggregate data using moment conditions between constructed demand shock variables ζ_{jt} and instrumental variables:

$$E\left[\xi_{jt}\left(\theta\right) | \mathbf{x}_t, \mathbf{w}_t\right] \tag{3.2}$$

where θ is the vector of parameters and $\mathbf{w}_t$ denotes the instrumental variables.

Our instrumental variables combine Hausman- and BLP-style instruments. For the Hausman-

[11] In other pharmaceutical markets (see Liu et al. (2017) for HIV/AIDS combination therapies and Shapiro (2018) for antidepressants), there is also evidence of positive advertising spillovers.

style instruments, using all drugs of this market and all countries used for constructing instruments (Germany, Canada, India, Turkey, and Spain), we first regress the price of a drug on a product fixed effect and then use the residuals of the price in each of the countries other than the US as instruments, with interaction with ATC4 fixed effects. The idea of Hausman instruments is that the marginal cost of production of a drug to be sold in any country is affected by common shocks across all countries, such as shocks on input prices of active ingredients or shocks on other manufacturing costs, such as energy and labor, that affect producing facilities that deliver drugs or intermediary inputs for the many countries where the drug is sold. These cost side shocks are good instruments for prices as they are unrelated to demand variation in preferences. The countries we include both have health systems where medicines are priced freely, namely Germany until 2011, and Canada for generics. The regulation of drug prices in India, Turkey and Spain does not mean that they do not carry any information about the marginal costs, on the contrary, as pharmaceutical firms have to negotiate and justify their prices, they could be more aligned with the marginal costs.

The BLP-style instruments use the number of generics in the ATC4 class, interacted with the ATC class and year dummies, and the number of companies producing products in the same ATC4 class. Instruments for price are also good instruments for advertising expenses because advertising returns, and thus advertising decisions, depend, of course, on markups that depend on marginal costs. Finally, we also use the price of a unit quantity of advertising, which varies over time, as an instrument. Indeed, in the case of detailing, the data provide advertising expenses but also advertising units of detailing to physicians so that we can compute a unit price of detailing that varies over time and eventually across firms depending on labor costs and the difficulty of doing this detailing. As detailing is the main advertising expense in this market, total expenditures are affected by this price, which is used as an additional instrument.

Furthermore, we use optimal instruments (Chamberlain, 1987), which are conditional expectations of the derivative of the conditional-moment restriction with respect to the vector of parameters with the approximation method of Reynaert and Verboven (2014). Finally, first-stage regressions of the endogenous variables on instruments have F-statistics of 605.01 for price, 113.30 for lagged own advertising stock and 17.78 for the lagged stock of advertising of other products, reassuring us about the strength of our instruments.

Table 3.2: *Demand Model Estimates*

		Coefficients	Standard errors
Price	β	-0.23239	0.01797
	σ	0.10009	0.00805
Advertising stock	γ	0.00029	(0.00011)
Advertising spillover	Γ	0.00006	(0.00004)
Patent dummy		2.91049	(0.70448)
Age information dummy		-0.97752	(0.32199)
Time since patent expiration		-0.19803	(0.03024)
Time to patent expiration		-0.17126	(0.02936)
Patent information dummy		0.81700	(0.44162)
Quarter 1 after entry		-0.54235	(1.18058)
Quarter 2 after entry		-1.30352	(0.42442)
Quarter 3 after entry		-0.17182	(0.42008)
Quarter 4 after entry		-0.10796	(0.41044)
ATC4 $\times$ year fixed effects		✓	
N		956	

Notes: The age information dummy indicates that the age of the product is at least the maximum observed in the data because entry is prior to the sample. The patent information dummy is a dummy equal to one or zero to control for the case where the patent expiration date is unknown in the data because the patent already expired at the beginning of our sample. Time to patent expiration is $(t^{expiration} - t)$ *for products with a known patent expiration date, and time since patent expiration is an additional effect for expired products,* $(t - t^{expiration})$.

Table 3.2 shows the main parameter estimates of our preferred demand model.[12] We control for molecule fixed effects as well as ATC4-specific year fixed effects, which are not shown in the table but are precisely estimated. Notably, as we have many generic companies with small market shares and, thus, strong competition across generics within a molecule, we do not account for the generic name differentiation of the same molecule and aggregate generic products of the same molecule within a single generic-molecule product. Doing so does not prevent us from accounting for the fact that multiple firms compete in price with the same generic when using firms' price equilibrium conditions to identify marginal costs (see the details in Appendix Section A.7). The demand estimation results show a price coefficient that is significantly negative with a variance parameter that is also precisely estimated. The own advertising effect is positive and significant. The advertising spillover is also positive and significant but lower in magnitude than the own effect. This finding suggests that in this

[12]See Table A.6 for a robustness check with respect to market size, the stock parameter in Table A.5, and the rebates in Table A.7.

market, advertising has a market-expanding and business-stealing effect. As the advertising content could eventually change nature after the merger, we also interact the advertising variables in the demand model with the pre- and post-merger period dummies. In Table A.8, we find that both Γ and γ are not statistically different before and after the merger, thus keeping a single coefficient in the main model. The dummy variable for the product being on patent is positive but not statistically significant. The variable time to patent expiration captures the diffusion of the drug. When this variable decreases, the drug value increases. This variable is negative after patent expiration, but the time since patent expiration interacted with the patent expiration dummy eliminates this effect, as the time since patent expiration has a significant negative effect of the same magnitude. We also include a dummy variable for age exceeding the maximum observed age (because our age measure is censored for drugs already present in 2002 and for which we do not observe the entry date). Finally, we introduce dummy variables for the drug being in the first, second, third, or fourth quarter of entry, showing a negative effect relative to later periods, which, however, is statistically significant only for the second quarter after entry. These negative effects are consistent with the fact that the diffusion of drugs after market entry is not immediate. Instead, it seems to stabilize after three quarters because the fourth quarter effect is the smallest and later quarter fixed effects are always smaller and nonsignificant when introduced in the model.

This demand model allows us to recover own and cross-price elasticities for all products and quarters, as well as the advertising elasticities of demand.

Table 3.3 shows the own and cross-price mean elasticities of the main products, showing that Zyvox's own price elasticity is approximately -2.8, whereas that of Tygacil is -4.3. These two products have some of the largest cross-price elasticities in this market, particularly Tygacil's price with respect to Zyvox's price. The fact that Zyvox reacts less strongly to the price of Tygacil can be rationalized by the fact that Zyvox has a wider set of indications than does Tygacil, as the former is more frequently prescribed for pneumonia.

Table 3.4 shows the advertising semi-elasticities of the main products that advertise,[13] with own

[13]With $\gamma > \Gamma > 0$, advertising own elasticities are necessarily positive because

$$\frac{\partial s_{jt}}{\partial a_{jt}} = \gamma \int s_{ijt}(1 - s_{ijt})\varphi(\beta_i)\, d\beta_i - \Gamma \int s_{ijt}(\sum\nolimits_{k \neq j} s_{ikt})\varphi(\beta_i)\, d\beta_i$$

Table 3.3: *Own and Cross-Price Elasticities (Main Products)*

	Cefazolin(gen)	*Cefepime(gen)*	*Cefoxitin(gen)*	*Ceftriaxone(gen)*	*Cubicin*	*Maxipime*	*Tygacil*	*Vancocin*	*Vancomycin(gen)*	*Zyvox*
Cefazolin(gen)	**-0.496**	0.008	0.007	0.118	0.000	0.011	0.001	0.031	0.098	0.003
Cefepime(gen)	**0.574**	**-3.785**	0.122	**0.617**	0.002	0.142	0.092	0.401	**0.703**	0.342
Cefoxitin(gen)	**0.619**	0.141	**-3.415**	**0.588**	0.001	0.112	0.051	0.318	**0.627**	0.174
Ceftriaxone(gen)	0.460	0.033	0.027	**-1.502**	0.000	0.038	0.007	0.108	0.289	0.020
Cubicin	0.003	0.030	0.008	0.008	**-1.211**	0.006	0.109	0.018	0.014	**0.976**
Maxipime	**0.620**	0.110	0.075	**0.550**	0.000	**-3.103**	0.035	0.269	**0.567**	0.116
Tygacil	0.331	0.324	0.154	0.463	0.025	0.159	**-4.294**	0.449	**0.608**	**1.183**
Vancocin	**0.620**	0.109	0.075	0.548	0.000	0.094	0.035	**-2.917**	**0.564**	0.114
Vancomycin(gen)	**0.548**	0.054	0.042	0.415	0.000	0.056	0.013	0.160	**-1.960**	0.040
Zyvox	0.224	0.312	0.137	0.342	0.058	0.136	0.306	0.381	0.471	**-2.829**

Notes: This table shows the elasticities of market shares of products (in rows) to the prices of products (in columns). The results are rounded to the third digit. Entries with elasticities equal to 0.000 are, in fact, positive but are lower than 0.0005. Own elasticities and cross-elasticities above 0.5 are in bold.

semi-elasticities of one hundred thousand US$ in advertising stock between 0.96% and 2.63%. Thus, one hundred thousand US$ in additional advertising spending increases market share (or quantity sales) by 2.39% for Tygacil for the current quarter. As our specification of the advertising stock effect uses a decay factor of 0.5, market share is increased by approximately 1.19% one quarter later, by 0.6% two quarters later and by 0.3% three quarters later. Zyvox and Cubicin, which are the products with the highest advertising spending in our sample, have the lowest own semi-elasticities, which is consistent with decreasing returns to advertising.

The cross-elasticities are of a much smaller magnitude, and they mimic the price semi-elasticities. In particular, of the top four cross-elasticities, three are with respect to Zyvox's advertising. This result suggests that Zyvox's advertising is particularly effective in presenting it as a good substitute for the other products.

and $\int s_{ijt}(1-s_{ijt})\varphi(\beta_i)\,d\beta_i > \int s_{ijt}(\sum_{k\neq j} s_{ikt})\varphi(\beta_i)\,d\beta_i$ because $\sum_{k\neq j} s_{ikt} = 1 - s_{ijt} - s_{i0t} < 1 - s_{ijt}$, but cross-elasticities can be positive or negative because

$$\frac{\partial s_{jt}}{\partial a_{j't}} = \int s_{ijt}(\Gamma - \gamma s_{ij't})\varphi(\beta_i)\,d\beta_i - \Gamma \int s_{ijt}(\sum\nolimits_{k\neq j'} s_{ikt})\varphi(\beta_i)\,d\beta_i.$$

Table 3.4: *Own and Cross-Advertising Semi-Elasticities (Main Products with Nonzero Advertising)*

	Ancef	*Claforan*	*Cubicin*	*Fortum*	*Maxipime*	*Rocephin*	*Synercid*	*Tygacil*	*Vancocin*	*Zinacef*	*Zyvox*
Ancef	**0.240**	-0.093	-0.092	-0.095	-0.096	-0.092	-0.092	-0.092	-0.104	-0.093	-0.094
Claforan	-0.096	**0.239**	-0.094	-0.097	-0.099	-0.094	-0.094	-0.095	-0.108	-0.095	-0.097
Cubicin	-0.078	-0.078	**0.088**	-0.079	-0.079	-0.079	-0.082	-0.086	-0.079	-0.078	**-0.150**
Fortum	-0.100	-0.100	-0.099	**0.234**	-0.105	-0.099	-0.099	-0.101	-0.117	-0.100	-0.107
Maxipime	-0.103	-0.103	-0.102	-0.105	**0.229**	-0.102	-0.102	-0.106	-0.123	-0.102	-0.118
Rocephin	-0.108	-0.108	-0.108	-0.111	-0.116	**0.233**	-0.108	-0.116	-0.131	-0.108	-0.145
Synercid	-0.113	-0.113	**-0.182**	-0.113	-0.114	-0.113	**0.228**	-0.127	-0.116	-0.113	**-0.238**
Tygacil	-0.108	-0.108	-0.113	-0.110	-0.114	-0.108	-0.108	**0.217**	-0.126	-0.108	**-0.192**
Vancocin	-0.099	-0.099	-0.098	-0.102	-0.106	-0.099	-0.098	-0.102	**0.215**	-0.099	-0.114
Zinacef	-0.099	-0.099	-0.098	-0.101	-0.103	-0.098	-0.097	-0.099	-0.114	**0.238**	-0.103
Zyvox	-0.086	-0.086	-0.098	-0.087	-0.091	-0.087	-0.087	-0.104	-0.101	-0.086	**0.125**

Notes: This table presents the semi-elasticities of the market shares of products (in rows) to the advertising levels (1M US$ stock of advertising) of products (in columns). It shows the immediate quarter change in market share when advertising spending increases by 1M US$. A 0.25 advertising semi-elasticity of a million means that market share increases by 2.5% with one hundred thousand US$ in additional spending. Own semi-elasticities and cross semi-elasticities below -0.15 are in bold.

3.3 Supply model and identification of margins

We now turn to the supply-side oligopoly model of competition in terms of pricing and advertising. Let us denote by π_{ft} the variable profit of multiproduct firm f in market t. A firm f selling all of the products in set F_{ft} chooses price p_{jt} and advertising spending e_{jt} to maximize an expected discounted sum from period t of per-period profits $\pi_{ft}(\mathbf{p}_t, \mathbf{a}_t)$ minus advertising expenses e_{jt}, where:

$$\pi_{ft}(\mathbf{p}_t, \mathbf{a}_t) = \sum\nolimits_{j \in F_{ft}} (p_{jt} - c_{jt})\, q_{jt}(\mathbf{p}_t, \mathbf{a}_t)$$

where c_{jt} is the constant marginal cost of product j, and $q_{jt}(\mathbf{p}_t, \mathbf{a}_t)$ is the quantity of drug j demanded given the vector $\mathbf{p}_t$ of all drug prices and that of advertising expenditure stocks $\mathbf{a}_t$ for all J products (remember that for drug j, $a_{jt} = \sum_{\tau<t} \delta^{t-\tau} e_{j\tau}$). The demanded quantity is related to market share with market size M_t ($q_{jt}(\mathbf{p}_t, \mathbf{a}_t) = s_{jt}(\mathbf{p}_t, \mathbf{a}_t) M_t$).

Advertising expenditures are strategic variables that dynamically affect the state variable of the advertising stock because advertising affects both current and future demand. Thus, pharmaceutical firms maximizing the discounted expected sums of profits compete in a dynamic game. Solving this game implies that we need to specify the firms' dynamic problem and the equilibrium concept. As

in Dubois et al. (2018), it is clear that we can identify the marginal costs of all products without estimating the full dynamic game and, instead, using only the necessary price optimality conditions. Indeed, once we condition on the observed advertising state variables and the market structure (accounting for its change over time due to mergers and acquisitions), the price optimality conditions of the dynamic game are identical to those of the static game. The dynamic game played by firms that involves not only other strategic decisions, such as advertising, but also entry, exit and merging with other companies can be very difficult to solve given the space of actions and states as well as the possible complex dynamic strategies. This game is typically solved using the Markov perfect equilibrium concept (Maskin and Tirole, 1988) and empirically applied with discretized actions and states using Ericson and Pakes (1995) and Pakes and McGuire (1994).

As prices affect only demand and, thus, profit in a static way once other states and other strategic choices are given, assumptions on firms' advertising choices are not necessary to identify marginal costs, given the observation of advertising data. Thus, we consider firms' profit-maximizing conditions in terms of prices that are identical to the pure-strategy Bertrand–Nash equilibrium in prices. The price of any product j sold by firm f must then satisfy the following first-order condition

$$q_{jt} + \sum\nolimits_{k \in F_{ft}} (p_{kt} - c_{kt}) \frac{\partial q_{kt}\left(\mathbf{p}_t, \mathbf{a}_t\right)}{\partial p_{jt}} = 0 \tag{3.3}$$

which leads to equilibrium prices $\mathbf{p}_t^*(\mathbf{a}_t)$.

Using the estimated demand model and first-order price conditions (3.3), we recover the marginal costs and margins of all products. Regarding generic drugs, as we aggregate the market shares of the same-molecule generics because there are sometimes many generic companies that produce the same molecule and occupy very small market shares, we cannot assume that the price setting of these products is performed as if all generic companies producing the same molecule choose the price jointly. Thus, we take this into account in the first-order condition that must be satisfied by generic prices, which can be simply stated as a unique first-order condition for a given molecule by imposing that they all choose the same price. These first-order conditions rely on the fact that consumers have the same preference for all generics of a given molecule (see details in Appendix Section A.7).

Figure 3.2: *Estimated Margins for the Merger's Products*

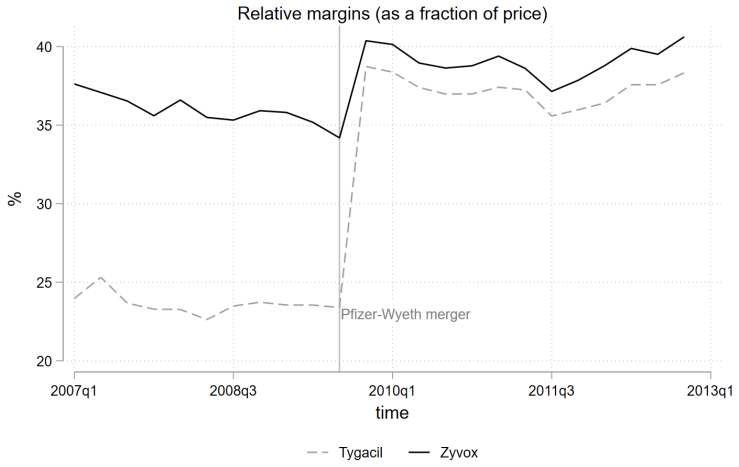


Figure 3.2 shows the estimated margins of Tygacil (Wyeth) and Zyvox (Pfizer) during the 2007-2013 period. For both drugs, the margins increased after the merger, although the margin increased less for Zyvox because the cross-price elasticity of Zyvox with respect to the Tygacil price is smaller and closer to zero. However, these estimates take as given the advertising expenditures on each brand. Thus, they cannot be interpreted as the effect of the merger on product margins because the advertising levels are different before and after the merger.

4 Counterfactuals

To evaluate the effects of the merger, we now use our structural model to perform counterfactual simulations and then develop additional welfare analysis that extrapolates the likely dynamic effects on innovation. Indeed, in the case of pharmaceutical markets, dynamic considerations, such as the effects on innovation, are as much of a concern as are the immediate price effects of mergers. Here, we are concerned with dynamic effects due to the changed incentives to innovate due to changes in profits when firms merge. We do not examine the merger effect on firms' R&D projects whose acquisitions can help firms select projects differently and eventually choose to shut down competing projects, as shown in (Cunningham et al., 2021). Here, we analyze the consequences of mergers on the trade-off between static and dynamic efficiency due to the merger effects on firms' profits, which is similar to the effect that price regulation involves (Acemoglu and Linn, 2004; Blume-Kohout and

Sood, 2013; Dubois et al., 2015) but that has not been studied.

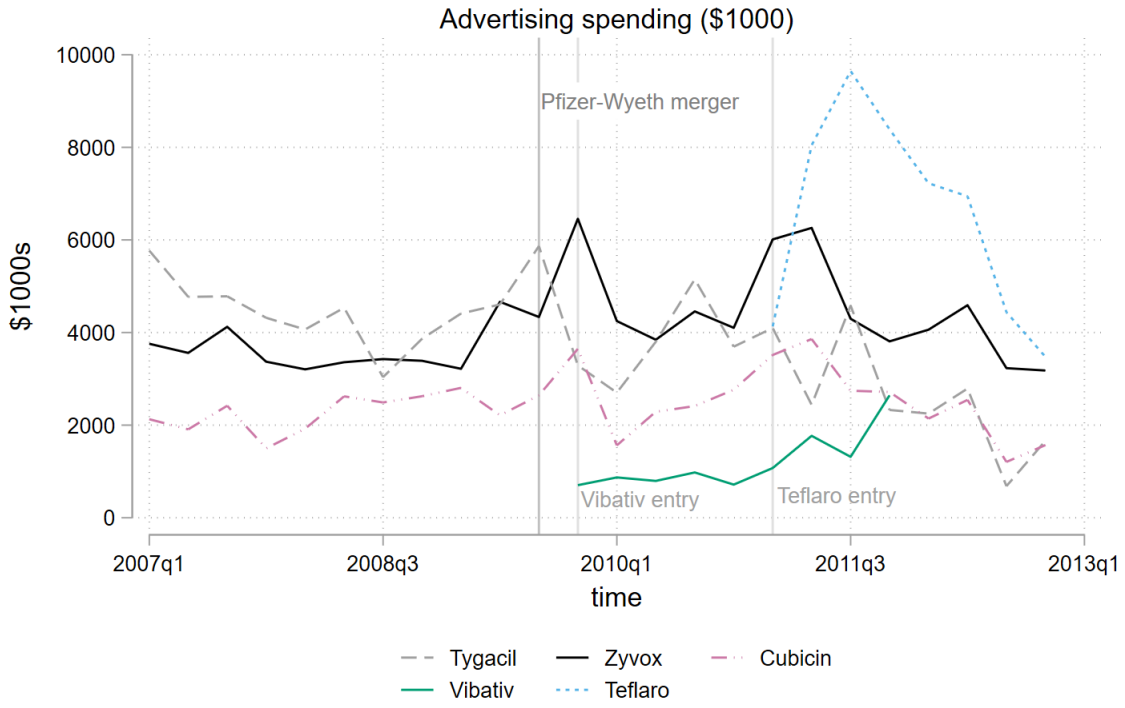
4.1 Short-term merger effects

After a merger between two pharmaceutical companies, the merged entity can internalize the cross-substitution effects of prices between products that were in competition before, typically leading to a price equilibrium change. Thus, we compare the price equilibrium in the absence of the merger to that in the presence of the merger, which can be obtained using first-order conditions of a pure-strategy Bertrand–Nash equilibrium in prices. However, we have shown that advertising strategies are also important for the price equilibrium and can be affected by the merger. Simulating the counterfactual advertising choices of firms is difficult, as it requires discretizing actions and state spaces in a dynamic Markov game (Pakes and McGuire, 1994; Ericson and Pakes, 1995). Given the difficulty of simulating MPE with firm decisions on both price and advertising, Shapiro (2018) simulates counterfactuals of a stylized model where advertising affects demand but holds the price equilibrium fixed. Here, given that we observe advertising before and after the merger, we use different advertising scenarios in the counterfactuals to simulate the corresponding price equilibrium with or without the merger.

More precisely, we use the observed premerger advertising stocks of advertising to simulate, for a given period, the effect of the merger, taking as given the marginal costs of products and using a post-merger advertising scenario. If the change in market structure post-merger is due solely to the merger, one could use the observed post-merger advertising for this counterfactual. However, if some drugs enter or exit the market at the same time as the merger, it is impossible to attribute the change in advertising to the merger. Figure 4.1, however, shows the entry of two drugs immediately after the merger (Vibativ and Teflaro), which are confounding factors with the merger effect on advertising and could explain why advertising of Zyvox increases after the merger, whereas the reduced-form regressions show that advertising usually decreases after a merger. Thus, it is very difficult to assume that the observed advertising level is the one that would have been observed in the case of the merger, holding all else equal. Instead, we simulate the effects with an alternative advertising level inferred from the reduced-form predictions.

Although this approach prevents us from pinpointing the effect of the merger on advertising strategies, we can simulate counterfactuals under various post-merger advertising levels to obtain

Figure 4.1: *Advertising Spending per Product (J1X+J1D2+J1F).*



Notes: Only products with advertising spending exceeding $ 1M.

plausible counterfactual simulations of short-term effects on prices. Although the long-term effects may differ, simulating advertising dynamics alongside prices for so many products and firms appears computationally intractable. However, patent life is limited, and advertising usually ceases once a drug becomes off-patent. Hence, long-term effects can be simulated with low or no advertising.

Effects with pre- and post-merger advertising Denoting product ownership with the merger as $\tilde{F}_{ft}$, instead of F_{ft} for the premerger observed product ownership, the merger price equilibrium implies that for any product j, the following first-order conditions must be satisfied ($f(j)$ being the firm of product j):

$$q_{jt} + \sum_{k \in \tilde{F}_{f(j)t}} (\tilde{p}_{kt} - c_{kt}) \frac{\partial q_{kt}\left(\tilde{\mathbf{p}}_t, \mathbf{a}_t\right)}{\partial p_{jt}} = 0$$

which gives $\tilde{\mathbf{p}}_t(\mathbf{a}_t)$ the merger equilibrium price vector function of advertising levels, whereas $\mathbf{p}_t(\mathbf{a}_t)$ denotes the equivalent mapping without the merger.

Then, for any advertising vector, we can compute demands, profits and consumer surplus with and without the merger.

Denoting $\mathbf{a}_t^0$, $\mathbf{a}_t^1$ the pre- and (hypothetical) post-merger advertising, given $\mathbf{p}_t()$ and $\tilde{\mathbf{p}}_t()$ the pre- and post-merger pricing equilibrium mapping between advertising and prices, we can decompose the change in prices into the effect of the change in ownership structure on the price equilibrium (*merger effect*) and the effect of the change in advertising levels, holding the ownership structure fixed (*advertising effect*).[14]

$$\tilde{\mathbf{p}}_t\left(\mathbf{a}_t^1\right) - \mathbf{p}_t\left(\mathbf{a}_t^0\right) = \underbrace{\left[\tilde{\mathbf{p}}_t\left(\mathbf{a}_t^0\right) - \mathbf{p}_t\left(\mathbf{a}_t^0\right)\right]}_{\text{merger effect}} + \underbrace{\left[\tilde{\mathbf{p}}_t\left(\mathbf{a}_t^1\right) - \tilde{\mathbf{p}}_t\left(\mathbf{a}_t^0\right)\right]}_{\text{advertising effect}} \tag{4.1}$$

We can also decompose the effect on profit that combines price and advertising effects as follows:

$$\begin{aligned}\pi_t\left(\mathbf{a}_t^1, \tilde{\mathbf{p}}_t\left(\mathbf{a}_t^1\right)\right) - \pi_t\left(\mathbf{a}_t^0, \mathbf{p}_t\left(\mathbf{a}_t^0\right)\right) =& \underbrace{\left[\pi_t\left(\mathbf{a}_t^0, \tilde{\mathbf{p}}_t\left(\mathbf{a}_t^0\right)\right) - \pi_t\left(\mathbf{a}_t^0, \mathbf{p}_t\left(\mathbf{a}_t^0\right)\right)\right]}_{\text{merger effect on prices}} \\ &+ \underbrace{\underbrace{\left[\pi_t\left(\mathbf{a}_t^1, \tilde{\mathbf{p}}_t\left(\mathbf{a}_t^0\right)\right) - \pi_t\left(\mathbf{a}_t^0, \tilde{\mathbf{p}}_t\left(\mathbf{a}_t^0\right)\right)\right]}_{\text{pure advertising effect}} + \underbrace{\left[\pi_t\left(\mathbf{a}_t^1, \tilde{\mathbf{p}}_t\left(\mathbf{a}_t^1\right)\right) - \pi_t\left(\mathbf{a}_t^1, \tilde{\mathbf{p}}_t\left(\mathbf{a}_t^0\right)\right)\right]}_{\text{advertising effect on prices}}}_{\text{total advertising effect}}\end{aligned} \tag{4.2}$$

where the *pure advertising effect* is the effect of advertising changes on profits, holding the price equilibrium constant. The decomposition of the static consumer surplus can be performed in the same way.

Empirical results We estimate the price equilibrium under merger or no merger with different advertising scenarios. For the premerger advertising $\mathbf{a}_t^0$, we use the value of the second quarter of 2009. Then, we compute a post-merger advertising level $\mathbf{a}_t^1$ using either a 45% drop in the advertising flow of the second quarter of 2009 (as predicted by the reduced-form effect of mergers on advertising), which translates to an approximately 20% reduction in the advertising stock for Pfizer products post-merger or a smaller reduction in advertising expenses of 10%.

Table 4.1 summarizes the merger evaluation results under the two scenarios. Overall, ignoring

[14] The change in advertising may be due to the merger and the total merger effect on prices should then be considered as the sum of the merger effect and the advertising effect defined in (4.1).

the advertising effect would lead to an overestimation of the effect on all the measures considered.

In Panel A, we show the disaggregation of the total merger effect on prices, as presented in Equation (4.1). We observe that without advertising changes, prices increase by 18.68% for products of the merger and increase by only 1.71% for other products. However, the decrease in advertising leads to a negative advertising effect on prices, mostly for products of the merged company. Thus, the total effect is that the prices of the merger company increase by 12.65% to 14.09%, depending on the advertising decrease being 45% or 10% of spending. For other products, prices are almost stable, with an increase of 0.39% to 0.70%.

In Panel B, we present the results for profits net of advertising spending, disaggregating the total effect according to Equation (4.2). Overall, the profits of Pfizer products either increase or decrease depending on the amount of the advertising change, whereas those of other products increase by 5.3% to 8.2%. The decomposition of the effects on profit shows that the pure price effect of the merger increases product profits, as expected, but the advertising reduction leads to a profit decrease, both because of its direct effect on demand and because it decreases the price equilibrium. Whether the total effect on profit is positive or negative depends on the amount of the advertising change. However, in both cases, the total industry profit increases, despite the reduction in advertising.

Finally, Panels C and D show the results for total spending and consumer surplus, respectively. Both effects are negative. Importantly, the negative effect on consumer surplus is due to the pure price increase effect of the merger and the pure advertising effect on demand, which are both not compensated for by the reduction in prices due to the reduction in advertising. The total consumer surplus change is 52 to 91 million $US for the quarter. This is an amount that we need to compare with the potential dynamic welfare effect of the industry profit increase.

Table 4.1: *Counterfactual Merger Effects with a Decrease in Advertising*

A. Prices			
	Merger Effect	**Advertising Effect**	**Total Effect**
Merger products	10.66	$[-4.38; -2.69]$	$[6.69; 8.18]$
	18.13%	$[-5.96\%, -3.64\%]$	$[11.75\%, 14.17\%]$
Other products	1.26	$[-0.72; -0.49]$	$[0.36; 0.60]$
	1.64%	$[-0.91\%, -1.10\%]$	$[0.53\%, 0.38\%]$
Total	2.19	$[-0.95; -0.64]$	$[0.99; 1.35]$
	3.27%	$[-1.23\%, -1.28\%]$	$[1.63\%, 1.74\%]$

	Pure Price Effect	**Pure Advertising Effect**	**Advertising Effect on Prices**	**Total Effect**
B. Net Profits $\Delta\Pi$				
Merger products	8,147	$[-9,909; -2,268]$	$[-4,030; -2,597]$	$[-5,792; 3,281]$
	12.29%	$[-13.31\%, -3.05\%]$	$[-6.24\%, -3.60\%]$	$[-8.73\%, 4.95\%]$
Other products	12,411	$[6,493; 1,449]$	$[-3,084; -2,700]$	$[15,819; 11,159]$
	5.75%	$[2.85\%, 0.64\%]$	$[-1.31\%, -1.18\%]$	$[7.33\%, 5.17\%]$
Total	20,558	$[-3,416; -819]$	$[-7,114; -5,298]$	$[10,027; 14,441]$
	7.29%	$[-1.13\%, -0.27\%]$	$[-2.38\%, -1.76\%]$	$[3.56\%, 5.12\%]$
C. Total spending				
	-19,077	$[-14,813; -3,429]$	$[3,271; 1,657]$	$[-30,620; -20,848]$
	-3.69%	$[-2.98\%, -0.69\%]$	$[0.68\%, [0.34\%]$	$[-5.93\%, -4.04\%]$
D. Consumer Surplus ΔCS	-63,175	$[-55,541; -12,601]$	$[34,677; 23,114]$	$[-84,040; -52,662]$
	-11.52%	$[-11.45\%, -2.60\%]$	$[8.07\%, 4.89\%]$	$[-15.33\%, -9.60\%]$

Notes: The simulation is for 2009q2. Percentage changes are below absolute changes. For prices, we report the mean changes across products in US$, weighted by the market share, while we report total changes for profits, spending and consumer surplus in 1,000 US$. Intervals in brackets are for advertising changes of a 10% to 45% decrease in advertising expenditures, with the first element in brackets for the largest advertising decrease.

4.2 Welfare evaluation of mergers

A standard merger evaluation using simulation compares consumer surplus and firm profit changes to evaluate whether a merger is beneficial for society (Nevo, 2000). In the case of industries where innovation plays an important role in consumer welfare, as is the case with pharmaceuticals and health care products, the usual static trade-off is modified by the consideration of future innovation induced by the change in market structure. A recent concern about the merger effect is the reorganization of R&D activities and project development of drugs in different phases, from phases I to III (Cunningham et al., 2021). As mentioned in the introduction, there are varied results on the effects of mergers and acquisitions on R&D, but overall, they seem to be negative. Here, we do not study the effects of mergers on ongoing R&D project development. Rather, we examine the potential

effects of industry profits on future innovation.

As is well known (Acemoglu and Linn, 2004; Blume-Kohout and Sood, 2013; Dubois et al., 2015), larger expected profits of pharmaceutical firms increase their incentives to invest in R&D and, thus, increase the rate of innovation. Moreover, as pharmaceutical R&D is self-financed because of the enormous uncertainty and moral hazard involved in long-term research projects in this area, larger profits relax current financial constraints on investment. However, the reason firms invest in R&D is not because of available liquidity due to increased profit but is because of larger future expected profits which are affected by the merger policy. Any regulation or policy change that affects revenue leads to changes in innovation. Assuming merger policies affect firms' profit expectations, mergers should affect innovation, like price regulations of pharmaceuticals do. Thus, we evaluate the effects on dynamic welfare induced by changes in profits due to a merger. As advertising strategies also modify the price equilibrium and quantity sales, we need to account for those in the evaluation. The merger effect on industry profits is unambiguously positive when firms compete only in price, not when they also compete in advertising. Changes in advertising strategies can lead firms to not only compete less for patients and save on promotional spending but also reduce their sales quantity.

Given $\tilde{\mathbf{p}}_t\left(\mathbf{a}_t^1\right)$ post-merger equilibrium prices, $\mathbf{p}_t\left(\mathbf{a}_t^0\right)$ premerger prices with post-merger advertising $\mathbf{a}_t^1$ and premerger advertising level $\mathbf{a}_t^0$, the change ΔCS in static consumer surplus implied by a merger is as follows:

$$\Delta CS \equiv CS_t\left(\mathbf{a}_t^1, \tilde{\mathbf{p}}_t\left(\mathbf{a}_t^1\right)\right) - CS_t\left(\mathbf{a}_t^0, \mathbf{p}_t\left(\mathbf{a}_t^0\right)\right) \tag{4.3}$$

The change in industry profit due to the merger, denoted by $\Delta\Pi$, including the change in variable profits and the change in advertising spending, is as follows (as in Equation (4.2)):

$$\Delta\Pi \equiv \pi_t\left(\mathbf{a}_t^1, \tilde{\mathbf{p}}_t\left(\mathbf{a}_t^1\right)\right) - \pi_t\left(\mathbf{a}_t^0, \mathbf{p}_t\left(\mathbf{a}_t^0\right)\right) \tag{4.4}$$

We now denote by W dynamic consumer welfare, accounting for not only the static surplus change due to the merger but also the dynamic effect on firms' profits and innovation. If industry profits increase by a given amount per year over the entire patent life due to the merger, then we can treat the expected discounted profit increase as equivalent to a one-year increase in the total

discounted amount during the patent life. Thus, with a discount factor of β and a patent life, L, the profit increase is equivalent to a one-year lump-sum increase of $\frac{1-\beta^L}{1-\beta}\Delta\Pi$.

Thus, the change in welfare, including dynamic effects for a representative period, is the sum of the static consumer surplus and the value of innovation, as revealed by consumer surplus:[15]

$$\Delta W = \Delta CS + \underbrace{\frac{\partial CS}{\partial I}}_{\substack{\text{Sensitivity of} \\ \text{consumer surplus} \\ \text{to innovation}}} \times \underbrace{\epsilon_{\Pi}^{I}}_{\substack{\text{Elasticity} \\ \text{of innovation} \\ \text{to profit}}} \times \underbrace{I}_{\substack{\text{Expected number} \\ \text{of innovations} \\ \text{per year}}} \times \underbrace{\frac{1-\beta^L}{1-\beta}}_{\substack{\text{Sum over } L \\ \text{patent years} \\ \text{discounted by } \beta}} \times \frac{\Delta\Pi}{\Pi} \tag{4.5}$$

where ΔCS comes from Equation (4.3), I is the expected number of new products per year, Π is the one-year industry profit, $\Delta\Pi$ is the one-year increase from Equation (4.4) and $\frac{\partial CS}{\partial I}$ represents the change in consumer surplus due to an innovation, as revealed by the demand in the market studied.

Regarding the sensitivity of consumer surplus to innovation ($\frac{\partial CS}{\partial I}$), we need to know the expected additional consumer surplus from an innovative drug entering the market. There are several possible measures of this future expected increase in consumer surplus that depend not only on the quality of new drugs but also on the expectation of the future price equilibrium. Indeed, an innovation also involves an additional product in the market and lower prices because of increased competition. We consider several scenarios that assume that future innovation has an expected surplus equal to the current mean surplus of drugs, the current median surplus across existing drugs, or the maximum surplus generated by current products.

Denoting $\frac{\partial CS_t}{\partial I_j}$ the consumer surplus gain of drug j for period t, we can define it according to revealed preference by:

$$\frac{\partial CS_t}{\partial I_j} \equiv M_t \int \frac{1}{\beta_i}\left[\ln\left(1+\sum\nolimits_k \exp\left(\delta_{kt}+\mu_{ikt}\right)\right) - \ln\left(1+\sum\nolimits_{k\neq j} \exp\left(\delta_{kt}+\mu_{ikt}\right)\right)\right] \varphi\left(\beta_i\right) d\beta_i$$

In the scenario where innovation results in a surplus equal to the current mean drug surplus for existing drugs, the gain in consumer surplus is $\frac{\partial CS_t}{\partial I} \equiv \frac{1}{J}\sum_{j=1}^{J} \frac{\partial CS_t}{\partial I_j}$. In the scenario where innovation brings the current maximum among existing drugs (and equivalently for the median), it is defined as $\frac{\partial CS_t}{\partial I} \equiv \max_{j=1,..,J}\{\frac{\partial CS_t}{\partial I_j}\}$.

[15] Note that this formula can be used for any policy that affects the pharmaceutical drug price equilibrium, such as

Table 4.2: *Counterfactual Merger Effects on Dynamic Welfare with a 10% Decrease in Advertising*

	Pure Price Effect	**Pure Advertising Effect**	**Advertising Effect on Prices**	**Total Effect**
D. Consumer Surplus ΔCS	-63,175	-12,601	23,114	-52,662
	-11.52%	-2.60%	4.89%	-9.60%
E. Net profits $\Delta\Pi$				
	20,558	-819	-5,298	14,441
	7.62%	-0.28%	-1.83%	5.35%
F. Dynamic Welfare				
Median $\frac{\partial CS}{\partial I}$				
$\epsilon = 0.28$	-63,025	-12,583	23,081	-52,527
$\epsilon = 0.5$	-62,906	-12,569	23,055	-52,420
$\epsilon = 4$	-61,024	-12,350	22,646	-50,728
Mean $\frac{\partial CS}{\partial I}$				
$\epsilon = 0.28$	-62,427	-12,513	22,951	-51,989
$\epsilon = 0.5$	-61,839	-12,445	22,823	-51,461
$\epsilon = 4$	-52,486	-11,353	20,788	-43,051
Max $\frac{\partial CS}{\partial I}$				
$\epsilon = 0.28$	-54,694	-11,611	21,269	-45,037
$\epsilon = 0.5$	-48,031	-10,833	19,819	-39,045
$\epsilon = 4$	57,983	1,542	-3,248	56,277

Notes: The simulation is for 2009q2 for a 10% advertising decrease of the merged company. Percentage changes are below absolute changes. We report total changes for profits, consumer surplus and dynamic welfare in 1,000 US$. Dynamic welfare ($\Delta W = \Delta CS + \frac{\partial CS}{\partial I} \times \epsilon_{\Pi}^{I} \times I \times \frac{1-\beta^L}{1-\beta} \times \frac{\Delta\Pi}{\Pi}$) using $I = 0.67$, as we observe in this market 8 new products in 12 years, $\beta = 0.99$, $L = 20$.

Table 4.2 reports the consumer surplus and profit change in the case of a merger with a 10% decrease in advertising expenditures by the merger company (as reported in Table 4.1). It also adds the dynamic welfare change and its decomposition between the effect due to the price change implied by the merger (with fixed advertising), the effect due to the advertising change and the effect due to the price change implied by the advertising decrease. As the dynamic welfare effect depends on the elasticity of innovation to market size, we present the results with three different values of elasticity from the literature (Acemoglu and Linn, 2004; Dubois et al., 2015).

While the merger decreases static consumer surplus by approximately $53 million and increases profits by $14 million, the total effect on dynamic welfare (which includes the static consumer surplus change) is greater because the dynamic part of the welfare change is positive. It remains negative

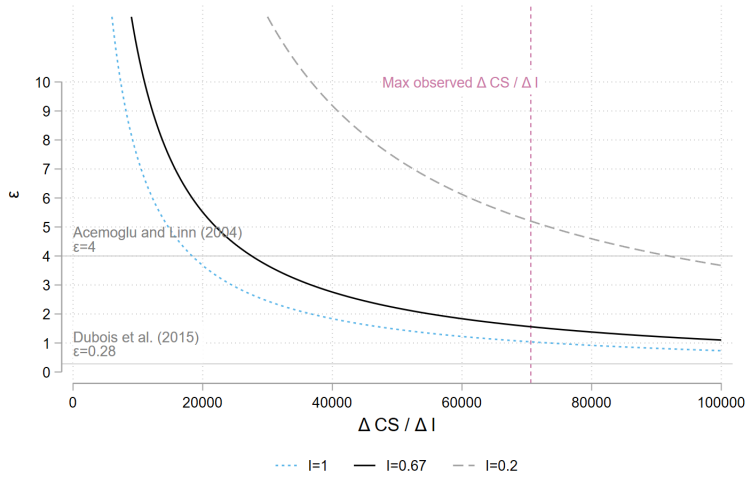
any change in regulation.

(but smaller in magnitude), except for the case of a large elasticity of innovation to market revenue and a large value of innovation ($\epsilon_{\Pi}^{I} = 4$ and using the maximum value of existing drugs for this market of $\frac{\partial CS}{\partial I}$). The decomposition of the dynamic welfare effect shows that when the elasticity and welfare benefits of innovation are such that the pure price effect on dynamic welfare remains negative like the effect on static consumer surplus, then the advertising reduction also decreases dynamic welfare. However, its impact on prices compensates with a positive effect on dynamic welfare. When the elasticity and consumer surplus increase because innovation is such that the dynamic welfare effect of the merger is positive, the advertising reduction has a negative effect that reduces the benefit from the increase in price and profit.

Figure 4.2 shows the dynamic welfare indifference curves in the space of ϵ_{Π}^{I} and the value of the new product $\frac{\partial CS}{\partial I}$ for different values of the average rate of innovation I. The indifference curves are such that the dynamic welfare effect is positive above or on the right of the curve and negative below or on the left. In the antibiotic market, the value is known to be small, and in our sample, it is equal to 0.67 because there are 8 entries of new products over the 12 years studied. We report on the graph on horizontal lines the values of the elasticity of innovation to market revenue found in the literature: 0.28 (for the anti-infective elasticity in Dubois et al. (2015)) and up to 4 in general, as in Acemoglu and Linn (2004). If the new product has a very high value, then positive values of ΔW are obtainable within this range of ϵ_{Π}^{I}. In both cases, the values of ΔW are much lower when advertising is at the high premerger level.

Although these simulations need to be interpreted with caution, they show that it may be important to account for not only the changes in advertising decisions implied by a merger but also the possibly positive dynamic effects of increased industry profit due to the expected innovative drugs that will be generated.

Figure 4.2: *Dynamic Welfare Indifference Curves in the* $(\epsilon_{\Pi}^{I}, \frac{\partial CS}{\partial I})$ *space*



Notes: The vertical dashed line reports the static consumer surplus value of an additional drug in the market studied $\frac{\partial CS}{\partial I}$.

5 Conclusions

In conclusion, by evaluating the effect of mergers on both prices and promotional spending, we first show that prices do indeed increase after a merger across all classes of drugs but that advertising spending decreases, suggesting some caution as to the validity of evaluations based only on prices. Then, studying the case of the merger between Pfizer and Wyeth, which overlapped activities in the market for antimicrobial drugs, we estimate a structural model of supply and demand with firms competing in terms of prices and advertising. We use the structural model to simulate the counterfactual price equilibrium without the merger for different scenarios of advertising decreases, as shown by the initial reduced-form analysis. We find that the counterfactual simulation of the merger effect on prices is much smaller when we account for changes in the advertising decisions of firms. This finding calls for further research on the modeling of the dynamic decisions of firms that compete both in price and advertising in the pharmaceutical industry, applying the methodologies of Ericson and Pakes (1995); Pakes and McGuire (1994), as was done for the simulation of price control effects on pharmaceutical R&D by Filson (2012). An ex ante merger evaluation would have to be conducted to simulate the possible post-merger advertising decisions that need to be accounted for simultaneously with price changes. Finally, we perform a welfare evaluation that compares the static

welfare effects and dynamic welfare effects of a merger when accounting for advertising changes in addition to prices. We show how to evaluate the dynamic effects using some externally set or estimated values of the innovation elasticity to market revenue in the pharmaceutical industry. On the one hand, the effects of price increases on static consumer surplus are attenuated by the reduction in advertising, which shows that one needs to account for this advertising reduction. On the other hand, the dynamic welfare effects of a merger due to the greater incentives for innovation when profits increase are also lower when accounting for advertising decreases.

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A Appendix

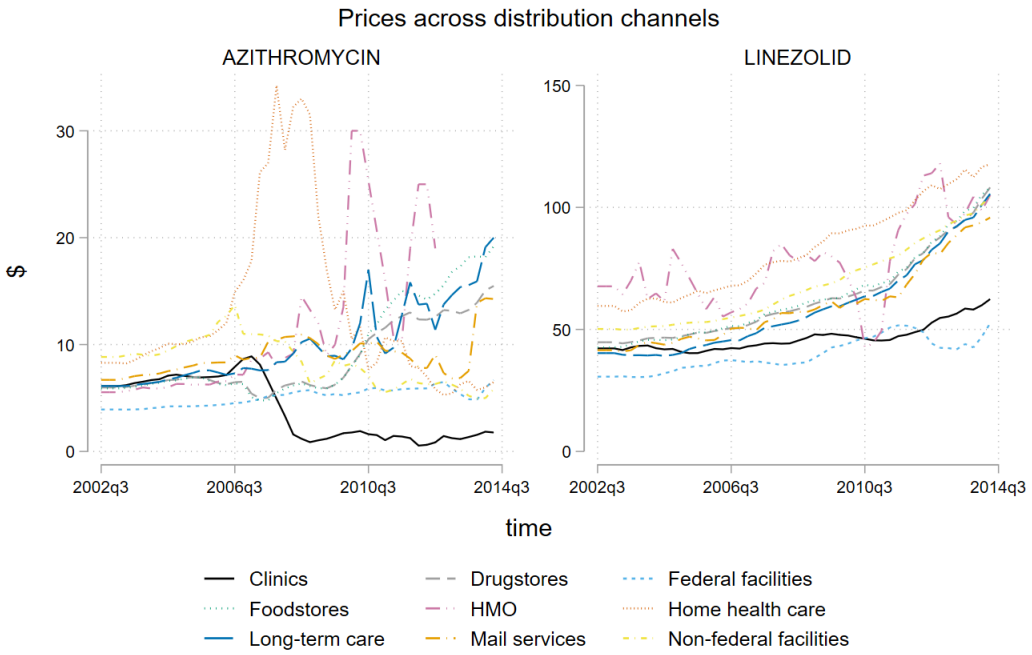
A.1 Price measurement

The IMS data allow us to observe quarterly the revenues and quantities of each drug that we use to compute average prices by quarter. However, revenues concern the products sold by the manufacturer in the given period, while the quantities are the units dispensed to patients in the same period (Kakani et al., 2020). Given that some establishments might hold stocks of medicines, this behavior may affect the computed prices, especially for products entering the market during the sample period. Typically, at entry, when regular stocks are not yet built, sales can be large, but quantities dispensed to patients are still low. Moreover, revenues are computed using list prices, but payers may negotiate rebates, which are confidential. Anecdotally, the rebates for high-price patent-protected products can be substantial. Kakani et al. (2020) show that, toward the end of our sample period, average rebates were approximately 32% but varied widely between ATC4 classes and could be as low as 7% and as high as 64%. Moreover, they change over time. Because abstracting from these issues could introduce a bias in our estimates and attenuate the price effects in demand estimation, we attempt to approximate the prices net of rebates.

To account for the discrepancy in the timing of recording revenues (y) and quantities (q), we compute an average price using a three-quarters smoothed price (equal to the ratio of total revenue y over total quantity q in the current and two previous quarters). At product entry, we use a three-quarters smoothed price with forward revenues and quantities instead of lagged values.

Concerning the rebates, the IMS data provide the sales values and volumes for nine different channels: clinics, food stores, long-term care hospitals, drugstores, HMOs, mail services, federal facilities, home health care and nonfederal facilities. Figure A.1 shows the dynamics of list prices (after the smoothing described above) in different distribution channels for two high-price drugs used as an example. We notice that, in general, both clinics and federal facilities have lower list prices and experience less of an increase in list prices over time, whereas food stores and drugstores usually have the highest prices. This pattern is quite common for all drugs. Thus, for each drug, we use the ratio b_{jt} of the minimum price observed across all channels to the average price (smoothed over three quarters) across all channels except clinics and federal facilities as an approximation of the average

Figure A.1: *Variation in list prices across distribution channels and over time*



rebate that must be used if prices are equal to the net price in these two channels:

$$b_{jt} = \underbrace{\left(\frac{\sum_{i=0}^{2} \sum_{d \neq (\text{Clinics, Federal facilities})} y_{dj(t-i)}}{\sum_{i=0}^{2} \sum_{d \neq (\text{Clinics, Federal facilities})} q_{dj(t-i)}} \right)^{-1}}_{\substack{\text{Average price of } j \text{ in channels other} \\ \text{than clinics and federal facilities}}} \underbrace{\min_{d} \frac{\sum_{i=0}^{2} y_{dj(t-i)}}{\sum_{i=0}^{2} q_{dj(t-i)}}}_{\substack{\text{minimum price of } j \text{ at } t \\ \text{observed across channels}}}$$

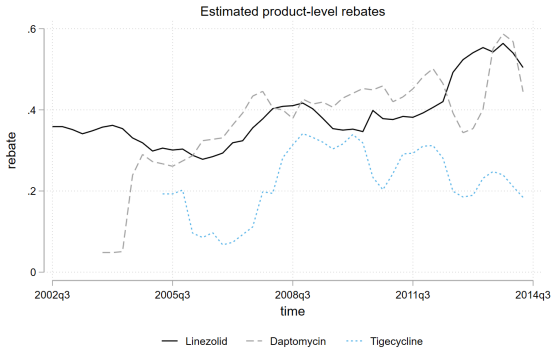
where y_{djt} is the revenue from channel d, q_{djt} is the quantity sold through channel d, and J_t is the set of products marketed at time t.

We then take the mean rebate across all drugs $1 - b_t = 1 - \frac{1}{J_t} \sum_{j=1}^{J_t} b_{jt}$ and define the net price of drug j for aggregate demand across channels $y_{jt} = \sum_d y_{djt}$ as:

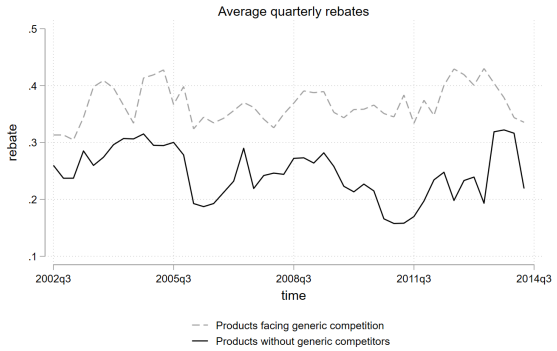
$$p_{jt} = \frac{\sum_{i=0}^{2} \sum_d y_{dj(t-i)}}{\sum_{i=0}^{2} \sum_d q_{dj(t-i)}} \times b_t$$

Figure A.2a shows estimates of product rebates $1 - b_{jt}$ for three molecules. Note that rebates are relatively stable during this time period. Kakani et al. (2020) reported growing rebates over time starting in 2012. Figure A.2b shows the estimated average rebate $1 - b_t$ for products facing

Figure A.2: *Rebate estimates*



(a) *Examples of product-level rebates* $(1 - b_{jt})$



(b) *Mean market-level rebates* $(1 - b_t)$

generic competition and those that do not. We use those rebates to obtain net prices. We find that rebates on products facing generic competition are, on average, larger than for those not facing generic competition.

A.2 Control Function approach

We want to identify the merger effect in the following product level price regression:

$$\log p_{jt} = \underbrace{\gamma_m}_{\substack{\text{merger effect} \\ \text{on merging} \\ \text{products}}} \times \underbrace{D^m_{jt}}_{\substack{\text{merging products} \\ \text{after a merger}}} + \underbrace{\gamma_r}_{\substack{\text{merger effect} \\ \text{on the rivals} \\ \text{of merging}}} \times \underbrace{D^r_{jt}}_{\substack{\text{rivals of merging} \\ \text{after a merger}}} + \lambda X_{jt} + \alpha_j + \delta_t + \varepsilon_{jt}$$

The problem is that the dummy variable indicating if product j belongs to a firm that merged with another one, $D^m_{jt} \in \{0, 1\}$, may be correlated with ε_{jt} such that $E\left(\varepsilon_{jt} | D^m_{jt}, D^r_{jt}, X_{jt}, \alpha_j, \delta_t\right) \neq 0$. One reason could be that the merger may coincide with a patent expiration or the anticipated introduction of new drugs in the market of drug j, that is unobservables affecting the pricing or advertising decision. Thus, we correct for this endogeneity problem using a control function approach where the decision of a firm to merge with another one is explained by its overall R&D pipeline that concerns other markets than the one of a particular drug.

Denoting $m_{ft} \in \{0, 1\}$ the dummy variable equal to 1 if the firm f is merging with another firm at period t and 0 otherwise, the post merger dummy for product j of firm $f(j)$ is then $D^m_{jt} =$

$\max_{\tau \leq t} \left\{ m_{f(j)\tau} \right\}$.

Assuming the merger decision at period t is given by:

$$m_{ft} = 1_{\left\{ Z_{ft}\beta + \delta_f + \delta_t + \omega_{ft} > 0 \right\}}$$

where δ_f is a firm fixed effect, Z_{ft} are firm level characteristics related to its R&D pipeline, and ω_{ft} is iid with a cumulative distribution function F, we obtain that

$$P(m_{ft} = 1) = 1 - F\left(-Z_{ft}\beta - \delta_f - \delta_t\right)$$

Using firm level data for all periods, we can identify this merger probability.

Then we can predict D^m_{jt} using the fact that

$$\begin{aligned} P(D^m_{jt} = 0) &= P(\max_{\tau \leq t} \left\{ m_{f(j)\tau} \right\} = 0) \\ &= \prod\nolimits_{\tau \leq t} P(m_{f(j)\tau} = 0) \quad \text{because all } \omega_{f\tau} \text{ are independent} \\ &= \prod\nolimits_{\tau \leq t} F\left(-Z_{f\tau}\beta - \delta_f - \delta_\tau\right) \end{aligned}$$

and thus we obtain that

$$P(D^m_{jt} = 1) = 1 - \prod\nolimits_{\tau \leq t} F\left(-Z_{f\tau}\beta - \delta_f - \delta_\tau\right)$$

We now assume that there exists a control function $h\left(.\right)$ such that

$$\begin{aligned} E\left(\varepsilon_{jt} | D^m_{jt}, D^r_{jt}, X_{jt}, \alpha_j, \delta_t\right) &= E\left(\varepsilon_{jt} | P(D^m_{jt} = 1 | f(j), \left\{ Z_{f(j)\tau} \right\}_{\tau \leq t}), D^m_{jt}, D^r_{jt}, X_{jt}, \alpha_j, \delta_t\right) \\ &= h\left(P(D^m_{jt} = 1 | f(j), \left\{ Z_{f(j)\tau} \right\}_{\tau \leq t})\right) \end{aligned}$$

meaning that the correlation of ε_{jt} with the post merger dummy D^m_{jt} can be completely explained by the post-merger probability. This implies that

$$\varepsilon_{jt} = h\left(P(D^m_{jt} = 1 | f(j), \left\{ Z_{f(j)\tau} \right\}_{\tau \leq t})\right) + \tilde{\varepsilon}_{jt}$$

where

$$E\left(\tilde{\varepsilon}_{jt}|P(D_{jt}^{m}=1|f(j),\left\{Z_{f(j)\tau}\right\}_{\tau\leq t},D_{jt}^{m},D_{jt}^{r},X_{jt},\alpha_{j},\delta_{t}\right)=0$$

In practice, we assume that ω_{ft} is uniform and estimate

$$\begin{aligned} P(m_{ft} &= 1) = 1 - F\left(-Z_{ft}\beta - \delta_f - \delta_t\right) \\ &= Z_{ft}\beta + \delta_f + \delta_t \end{aligned} \tag{A.1}$$

by linear regression. In Z_{ft} we include recent entries of competitors in the same ATC4 class, patent expirations, recent advancement or discontinuation of projects in late-stage development, the number of projects at each development stage, the mean and maximum product age, as well as firm and time fixed effects. Table A.1 presents the results of the estimation.

Table A.1: *Estimation of the control function*

	$P(m_{ft}=1)$	
	Estimate	SE
Competitor entry in ATC4 class	-0.00007*	(0.00003)
Patent expirations in past 12 months	0.00208***	(0.00042)
Discontinuations in Phase III or approval in past 12 months	0.00612***	(0.00069)
Successes in Phase III or approval in past 12 months	-0.00000	(0.00006)
Number of products on the market	-0.00002	(0.00003)
Mean age of products on the market	-0.00002	(0.00007)
Maximum age of products on the market	0.00006	(0.00004)
Number of projects in preclinical testing	0.00031***	(0.00008)
Number of projects in Phase I trials	-0.00233***	(0.00023)
Number of projects in Phase II trials	-0.00066***	(0.00017)
Number of projects in Phase III trials	0.00205***	(0.00031)
Number of projects in approval	-0.00186***	(0.00034)
Firm FE	✓	
Time FE	✓	
Observations	32,921	
R-squared	0.06	

We then predict

$$P(D_{jt}^{m}=1)=1-\prod\nolimits_{\tau\leq t}F\left(-Z_{f\tau}\beta-\delta_{f}-\delta_{\tau}\right)$$

adjusting the predicted values using the linear discriminant model and use them as a control in the price or advertising regression. On average, for non-merging firms we obtain $P(D_{jt}^m = 1)$ of 1.02% and for merging firms of 44.16%.

A.3 Additional Difference-in-Difference results

Table A.2: *Composition of the difference-in-differences data set*

	Total	Branded	Generics
Full sample			
Number of ATC4 markets	493	362	436
All product-quarter observations	467,071	75,501	391,570
Merging firms			
Distinct ATC4 markets affected by a merger of competitors	42	40	34
Distinct product-quarter observations at the time of the merger	198	103	95
Product-quarter observations 3 years after merger	2,106	1,149	957
Competitors of merging firms			
Distinct product-quarter observations at the time of the merger	2,438	384	2,054
Product-quarter observations 3 years after merger	21,912	3,814	18,098

Table A.3: *Advertising Spending Changes by Advertising Channel*

	(1) DTC	(2) Detailing	(3) Detailing Service Visits	(4) Journals	(5) Meeting
Post merger (γ_m)	0.003	-0.812***	-0.415***	-0.313***	-0.021
	(0.039)	(0.098)	(0.057)	(0.065)	(0.070)
Post merger, rivals (γ_r)	0.116***	-0.228***	-0.098*	-0.169***	-0.035
	(0.025)	(0.065)	(0.038)	(0.040)	(0.035)
Advertising Stock $t-1$	0.000***	0.001***	0.002***	0.005***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	83,002	83,002	83,002	83,002	83,002

*Notes:All regressions include product and quarter fixed effects, the estimated probability of having merged, as well as control variables: dummies for the age of the drug, the time left to patent expiration, and the number of products in the same ATC4 class. Standard errors are clustered at the ATC3×quarter level. *** for $p < 0.001$, ** for $p < 0.01$, and * for $p < 0.05$.*

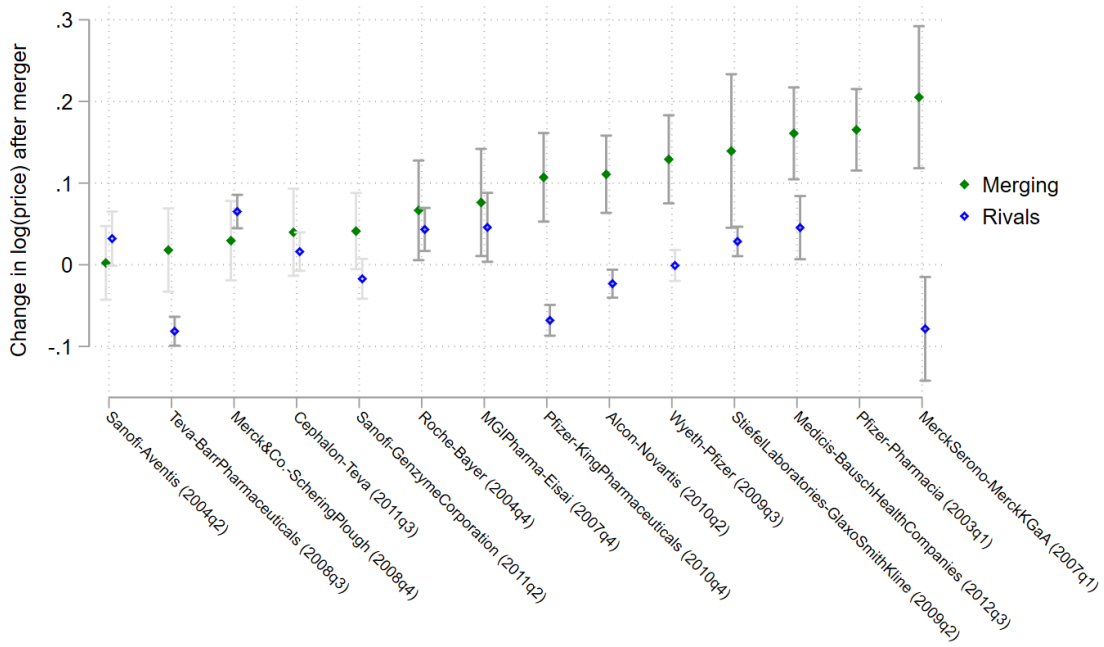
Table A.4 shows the same regression on prices as in Table 2.4, except that it uses nondiscounted gross prices that do not account for rebates.

Table A.4: *Gross Price Changes after a Merger*

	(1) $\log(p_{jt}^{\text{no rebate}})$	(2) $\log(p_{jt}^{\text{no rebate}})$
Post merger (γ_m)	0.114***	
	(0.020)	
Post merger, rivals (γ_r)	0.103***	
	(0.013)	
Post-merger, short term (γ_m^{short})		0.096***
		(0.019)
Post merger, long term (γ_m^{long})		0.092***
		(0.020)
Post merger, short term, rivals (γ_r^{short})		0.044***
		(0.010)
Post merger, long term, rivals (γ_r^{long})		0.097***
		(0.014)
Advertising Stock $t-1$	0.010***	0.010***
	(0.001)	(0.001)
Observations	399,849	399,849

Notes: All regressions include product and quarter fixed effects, the estimated probability of having merged, as well as control variables: dummies for the age of the drug, the time left to patent expiration, and the number of products in the same ATC4 class. Standard errors are clustered at the ATC3×quarter level. *** *for* $p < 0.001$, ** *for* $p < 0.01$, *and* * *for* $p < 0.05$.

Figure A.3: *Estimates from the merger by merger regressions: price changes*



Notes: Point estimates and 95% confidence intervals.

A.4 Additional Descriptive Statistics

Figure A.4: *Antibiotic resistance of Staphylococcus aureus in the US*

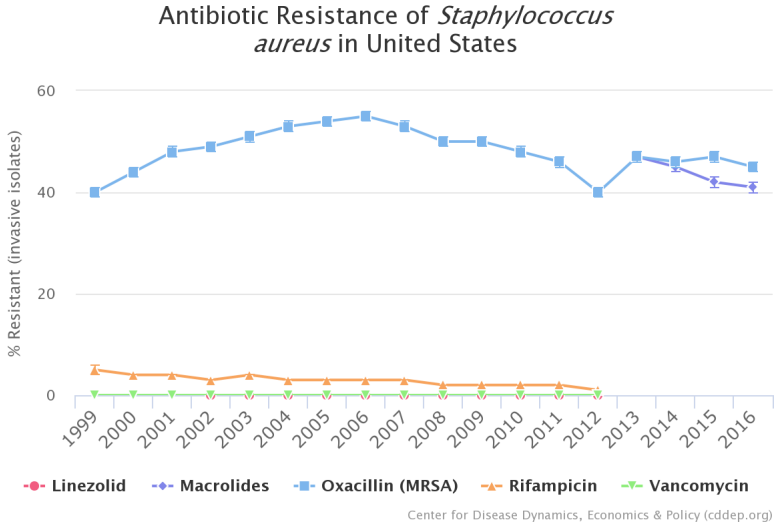


Figure A.5: *Advertising spending for molecules with the highest spending in 2010*

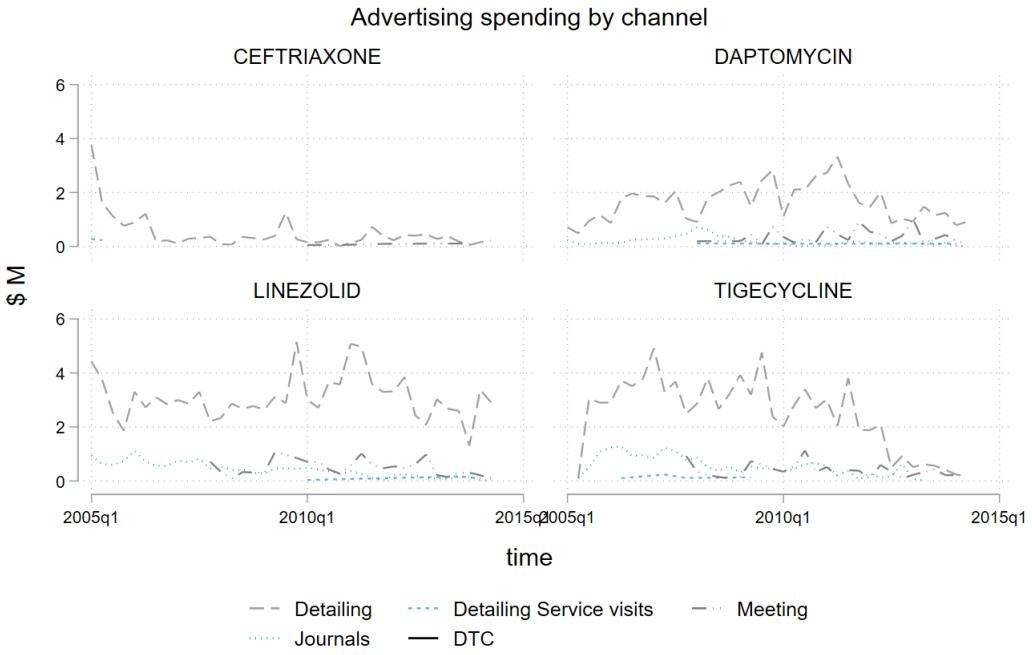
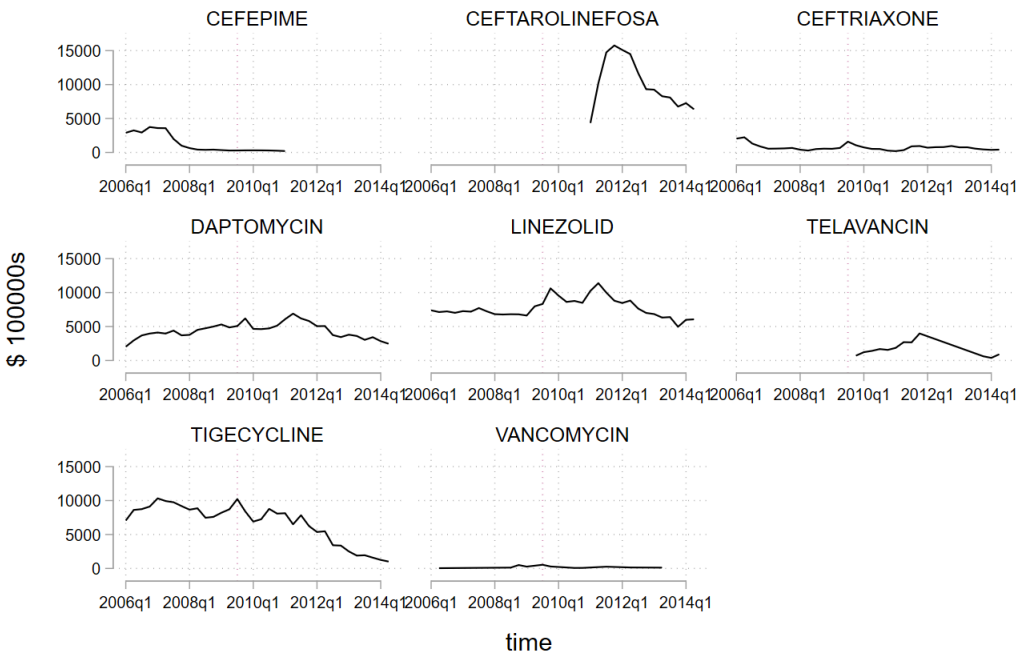


Figure A.6: *Advertising stocks by product (with quarterly discount $\delta = 0.5$)*



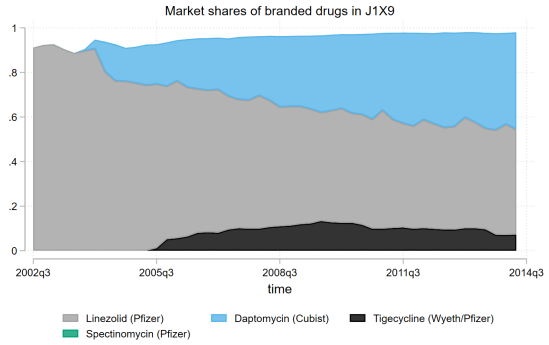
Notes: Stocks use quarterly decay parameter $\delta = 0.5$. Tigecycline belongs to Wyeth until the merger, after which it belongs to Pfizer. Linezolid is the molecule of Zyvox.

A.5 Market definition

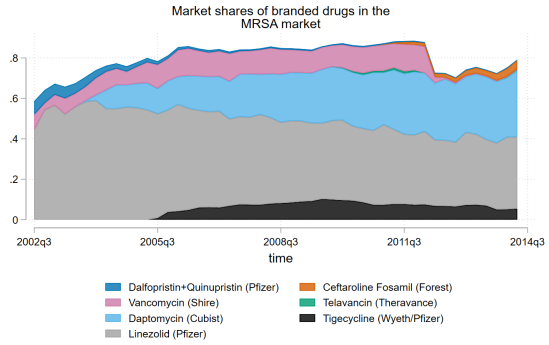
Concerned by the acquisition of Wyeth by Pfizer, competition authorities studied the markets of ATC4 class J1X9 labeled *all other antibacterials* in the European Pharmaceutical Marketing Research Association classification. In the J1X9 class, Pfizer marketed the molecule linezolid under the brand name Zyvox, and Wyeth marketed tigecycline under the brand name Tygacil. Figure A.7 shows the evolution of the market shares of branded drugs in the J1X9 class. At the time of the merger, in the third quarter of 2009, Pfizer's Zyvox generated almost half of the total revenue in this market in the US (48.24%), and Wyeth's Tygacil generated a further 12.73%. However, rather than products with similar characteristics, J1X9 groups antibacterials that do not fit into other ATC4 classes. The European Commission's merger case report calls it a "'catch-all' category comprising drugs with very different applications" and excludes the ATC4 classification as a meaningful definition of a market in this case. Nevertheless, Figure A.8 shows that there is an overlap in the approved indications of tigecycline, linezolid and other molecules in J1X9. Among them, both the FTC and the European

Commission consider methicillin-resistant Staphylococcus aureus (MRSA) infections to be the most prominent.

Figure A.7: *Market shares of selected products*



(a) *Market shares of branded drugs in J1X9 (shares of total revenue). Spectinomycin is present only in 2003 and 2004 and has very small shares. The missing area corresponds to the market share of generics of the molecule bacitracin.*

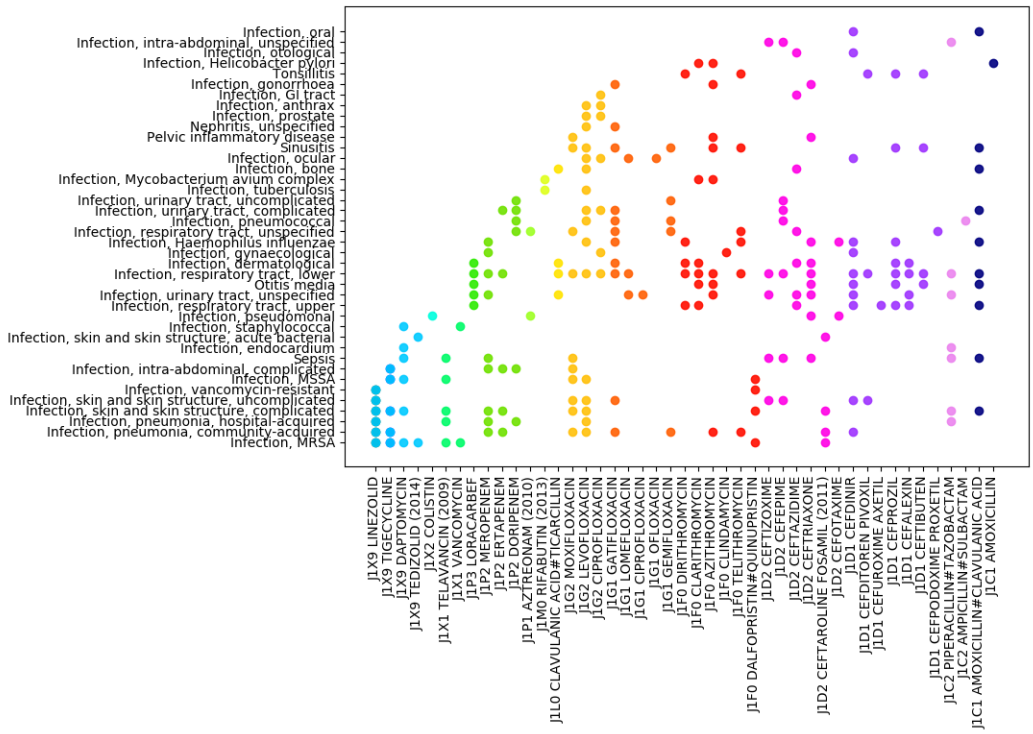


(b) *Market shares of MRSA drugs (shares of total revenue). The missing area corresponds to the market share of generics of the molecule vancomycin.*

We then define the market of antibiotics used for the treatment of MRSA according to the medical literature (Choo and Chambers, 2016; Welte and Pletz, 2010), which gives us 7 molecules marketed in the US during our sample period. Figure A.7b shows the evolution of the market shares of the branded products in this market. We also include the antibiotic classes of these molecules and the whole J1X ATC3 class to account for competition in other disease indications.[16] Table 3.1 presents some summary statistics of our estimation sample. On average, there are 18.58 molecules marketed per quarter, 17.29 generic products and 11.94 branded products. During the time period of our sample, 3 new molecules entered (tigecycline in 2005, telavancin in 2009 and ceftaroline fosamil in 2011), and 2 molecules lost patent protection and experienced generic entry (ceftriaxone in 2005 and cefepime in 2007). Four of the branded drugs and all of the generics were never advertised.

[16]For most of the MRSA molecules, their class is already included in the dataset (or other antibiotics of the class are not marketed in the US), with the exception of ceftaroline fosamil, which belongs to the class of cephalosporins.

Figure A.8: *Approved indications of J1 molecules*



Notes: The vertical list is for indications, and the horizontal list for molecules. Only indications for which 2 or more molecules are approved are listed. Molecules are identified by their ATC4 class, name, and launch year (if in 2009 or later).

A.6 Demand Estimation Robustness Checks

Table A.5: *Demand Estimate Robustness Checks: Ad stock parameters*

Power factor	κ	1	1	1	.5	1.5	.5
Decay factor	δ	.5	.7	.9	.5	.5	.7
Price	β	-0.23239	-0.22994	-0.22983	-0.23239	-0.23239	-0.22994
		(0.01797)	(0.01761)	(0.01752)	(0.01797)	(0.01797)	(0.01761)
	σ	0.10009	0.09963	0.10015	0.10009	0.10009	0.09963
		(0.00805)	(0.00795)	(0.00803)	(0.00805)	(0.00805)	(0.00795)
Advertising stock	γ	0.00029	0.00015	0.00003	0.00029	0.00029	0.00015
		(0.00011)	(0.00007)	(0.00004)	(0.00011)	(0.00011)	(0.00007)
Advertising spillover	Γ	0.00006	0.00005	0.00003	0.00006	0.00006	0.00005
		(0.00004)	(0.00003)	(0.00002)	(0.00004)	(0.00004)	(0.00003)

Notes: This table presents the main parameters of BLP demand estimates under variants. The specification uses the additive effect of advertising γa_{jt}^{κ} in mean utility equation3.1. The instrumental variables used are a set of BLP-style instruments (number of generics in the ATC4 class interacted with year dummies), Hausman-style instruments (prices of the same products in France, Canada, India, Turkey, and Italy), and the price of a unit of advertising.

Table A.6: *Demand Estimate Robustness Checks: Market size and outside goods*

Market Size		M_r	M_r	M	M	M_y	M_y
Outside Good Share		15%	25%	15%	25%	15%	25%
Price	β	-0.22994	-0.23342	-0.22994	-0.23448	-0.23064	-0.23600
		(0.01761)	(0.01825)	(0.01761)	(0.01802)	(0.01813)	(0.01844)
	σ	0.09963	0.09985	0.09963	0.10031	0.09953	0.10067
		(0.00795)	(0.00812)	(0.00795)	(0.00801)	(0.00815)	(0.00819)
Advertising stock	γ	0.00015	0.00014	0.00015	0.00014	0.00014	0.00013
		(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00008)	(0.00007)
Advertising spillover	Γ	0.00005	0.00004	0.00005	0.00005	0.00005	0.00005
		(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)

Notes: This table presents the main parameters of BLP demand estimates under variants. M is the observed market size, M_y is the max market size observed within a (calendar) year, and M_r is the rolling mean of the market sizes of the last 4 quarters. Columns 1, 3, and 5 assume a 15% outside option size, columns 2, 4, and 6 assume a 25% outside option size. The instrumental variables used are a set of BLP-style instruments (number of generics in the ATC4 class interacted with year dummies), Hausman-style instruments (prices of the same products in France, Canada, India, Turkey, and Italy), and the price of a unit of advertising.

Table A.7: *Demand Estimate Robustness Checks with or without rebate*

		No rebate	With rebate
Price	β	-0.16896	-0.23239
		(0.01142)	(0.01797)
	σ	0.07265	0.10009
		(0.00518)	(0.00805)
Advertising stock	γ	0.00008	0.00029
		(0.00007)	(0.00011)
Advertising spillover	Γ	0.00004	0.00006
		(0.00003)	(0.00004)

Notes: This table presents the main parameters of BLP demand estimates under variants. The instrumental variables used are a set of BLP-style instruments (number of generics in the ATC4 class interacted with year dummies), Hausman-style instruments (prices of the same products in France, Canada, India, Turkey, and Italy), and the price of a unit of advertising.

Table A.8: *Demand Estimate Robustness Checks: Advertising before and after the merger*

		Advertising pre- and post-
Price	β	-0.23103
		(0.01801)
	σ	0.09835
		(0.00814)
Advertising stock $t-1$	γ	0.00042
		(0.00015)
Advertising spillover $t-1$	Γ	0.00007
		(0.00006)
Advertising stock $t-1 \times$ Post merger	γ^{post}	-0.00013
		(0.00010)
Advertising spillover $t-1 \times$ Post merger	Γ^{post}	-0.00001
		(0.00003)

Notes: This table presents the main parameters of BLP demand estimates, adding an interaction of the advertissing effects with a post-merger dummy. The instrumental variables used are a set of BLP-style instruments (number of generics in the ATC4 class interacted with year dummies), Hausman-style instruments (prices of the same products in France, Canada, India, Turkey, and Italy), and the price of a unit of advertising.

A.7 Generics aggregation

We have J products, but demand is modeled using aggregate generics of a given molecule as a single product j. Here, we show how we account for this aggregation in the necessary first-order conditions that must be satisfied by the price equilibrium.

Denoting s_{jkt} as the market share of the generic firm k of the generic molecule aggregated in product j, we have the aggregate share s_{jt} of generics of product j with the same molecule as the sum of the market shares s_{jkt} of generics k of product j: $s_{jt} = \sum_{k=1}^{K(j)} s_{jkt}$ if there are $K(j)$ generics of molecule j.

Assuming that generics are identical, consumers have identical preferences for generics that have the same price, and all generics have equal market shares ($p_{jkt} = p_{jk't} = p_{jt}$, $s_{ijkt} = s_{ijk't} = \frac{1}{K(j)} s_{ijt}$); thus, with the random coefficient logit model, we have:

$$s_{jkt} = \int s_{ijkt} dF(\alpha_i) = \int \frac{1}{K(j)} s_{ijt} dF(\alpha_i) = \frac{1}{K(j)} s_{jt}$$

Then, for any generic drugs k and k' of molecule j:

$$\frac{\partial s_{jkt}}{\partial p_{jkt}} = -\int \alpha_i s_{ijkt} (1 - s_{ijkt}) dF(\alpha_i) = -\frac{1}{K(j)} \int \alpha_i s_{ijt} \left(1 - \frac{1}{K} s_{ijt}\right) dF(\alpha_i)$$

and

$$\frac{\partial s_{jkt}}{\partial p_{jk't}} = \int \alpha_i s_{ijkt} s_{ijk't} dF(\alpha_i)$$

If j' is not generic,

$$\frac{\partial s_{jkt}}{\partial p_{j\prime t}} = \int \alpha_i s_{ijkt} s_{ij\prime t} dF(\alpha_i) = \frac{1}{K(j)} \int \alpha_i s_{ijt} s_{ij't} dF(\alpha_i)$$

and if $j' \neq j$ is generic (with $K(j')$ generics of j'), we have:

$$\frac{\partial s_{jkt}}{\partial p_{j\prime k't}} = \int \alpha_i s_{ijkt} s_{ij\prime k't} dF(\alpha_i) = \frac{1}{K(j)K(j')} \int \alpha_i s_{ijt} s_{ij't} dF(\alpha_i)$$

and

$$\frac{\partial s_{jkt}}{\partial p_{j\prime t}} = \sum\nolimits_{k'=1}^{K(j')} \frac{\partial s_{jkt}}{\partial p_{j\prime k't}} = \sum\nolimits_{k'=1}^{K'} \int \alpha_i s_{ijkt} s_{ij\prime k't} dF(\alpha_i)$$
$$= \frac{1}{K(j')} \sum\nolimits_{k'=1}^{K(j')} \frac{1}{K(j)} \int \alpha_i s_{ijt} s_{ij't} dF(\alpha_i) = \frac{1}{K(j)} \int \alpha_i s_{ijt} s_{ij't} dF(\alpha_i)$$

implying that for generics j

$$\frac{\partial s_{jt}}{\partial p_{jt}} = \sum\nolimits_{k'=1}^{K(j')} \sum\nolimits_{k=1}^{K(j)} \frac{\partial s_{jkt}}{\partial p_{jk't}} = \sum\nolimits_{k'=1,k'\neq k}^{K(j')} \int \alpha_i s_{ijkt} s_{ijk't} dF(\alpha_i) - \int \alpha_i s_{ijkt} (1 - s_{ijkt}) dF(\alpha_i)$$
$$= \frac{K(j)-1}{K(j)^2} \int \alpha_i s_{ijt} s_{ijt} dF(\alpha_i) - \frac{1}{K(j)} \int \alpha_i s_{ijt} \left(1 - \frac{1}{K(j)} s_{ijt}\right) dF(\alpha_i)$$
$$= \int \alpha_i s_{ijt} \left[\frac{K(j)-1}{K(j)^2} s_{ijt} - \frac{1}{K(j)} \left(1 - \frac{1}{K(j)} s_{ijt}\right)\right] dF(\alpha_i)$$
$$= -\frac{1}{K(j)} \int \alpha_i s_{ijt} [1 - s_{ijt}] dF(\alpha_i)$$

and

$$\frac{\partial s_{jt}}{\partial p_{j't}} = \sum\nolimits_{k=1}^{K(j)} \frac{\partial s_{jkt}}{\partial p_{j'kt}} = \sum\nolimits_{k=1}^{K(j)} \frac{1}{K(j)} \int \alpha_i s_{ijt} s_{ij't} dF(\alpha_i) = \int \alpha_i s_{ijt} s_{ij't} dF(\alpha_i)$$

while for nongenerics, j we have

$$\frac{\partial s_{jt}}{\partial p_{jt}} = -\int \alpha_i s_{ijt} (1 - s_{ijt}) dF(\alpha_i)$$

and

$$\frac{\partial s_{jt}}{\partial p_{j't}} = \int \alpha_i s_{ijt} s_{ij't} dF(\alpha_i)$$

Because generic companies choose prices to maximize their individual profit, the first-order conditions are as follows:

$$s_{jkt} + (p_{jkt} - c_{jkt}) \frac{\partial s_{jkt}}{\partial p_{jkt}} = 0$$

if each generic company has only one product in the market.

As $p_{jkt} = p_{jt}$, $c_{jkt} = c_{jt}$, $s_{jkt} = \frac{1}{K(j)} s_{jt}$ and $\frac{\partial s_{jkt}}{\partial p_{jkt}} = -\frac{1}{K(j)} \int \alpha_i s_{ijt} \left(1 - \frac{1}{K} s_{ijt}\right) dF(\alpha_i)$, it implies that

$$\frac{1}{K(j)} s_{jt} + (p_{jt} - c_{jt}) \frac{\partial s_{jkt}}{\partial p_{jkt}} = 0$$

$$s_{jt} + (p_{jt} - c_{jt}) \frac{\partial s_{jkt}}{\partial p_{jkt}} K(j) = 0$$

$$\frac{1}{K(j)} s_{jt} - (p_{jt} - c_{jt}) \frac{1}{K(j)} \int \alpha_i s_{ijt} \left(1 - \frac{1}{K(j)} s_{ijt}\right) dF(\alpha_i) = 0$$

$$c_{jt} = p_{jt} - \frac{s_{jt}}{\int \alpha_i s_{ijt} \left(1 - \frac{1}{K(j)} s_{ijt}\right) dF(\alpha_i)}$$

If a firm has a generic of a molecule and other generics of other molecules, the first-order condition is as follows:

$$s_{jkt} + \sum_{j' \in F_f} (p_{j'k't} - c_{j'k't}) \frac{\partial s_{j'k't}}{\partial p_{jkt}} = 0$$

As $p_{jkt} = p_{jt}$, $c_{jkt} = c_{jt}$, $s_{jkt} = \frac{1}{K(j)} s_{jt}$, it Implies that

$$\frac{1}{K(j)} s_{jt} + \sum_{j' \in F_f} (p_{j't} - c_{j't}) \frac{\partial s_{j'k't}}{\partial p_{jkt}} = 0$$

$$s_{jt} + \sum_{j' \in F_f} (p_{j't} - c_{j't}) \frac{\partial s_{j'k't}}{\partial p_{jkt}} K(j) = 0$$

with

$$\frac{\partial s_{jkt}}{\partial p_{jkt}} K(j) = - \int \alpha_i s_{ijt} \left(1 - \frac{1}{K(j)} s_{ijt}\right) dF(\alpha_i)$$

and

$$\frac{\partial s_{j'k't}}{\partial p_{jkt}} K(j) = \frac{K(j)}{K(j')} \int \alpha_i s_{ijt} s_{ij't} dF(\alpha_i)$$

Thus, the first-order condition becomes

$$\begin{aligned}
\frac{s_{jt}}{K(j)} + \sum_{j' \in F_f, j' \neq j} \frac{p_{j't} - c_{j't}}{K(j)K(j')} \int \alpha_i s_{ijt} s_{ij't} dF(\alpha_i) - \frac{p_{jt} - c_{jt}}{K(j)} \int \alpha_i s_{ijt} \left(1 - \frac{s_{ijt}}{K(j)}\right) dF(\alpha_i) = & \quad 0 \\
s_{jt} + \sum_{j' \in F_f, j' \neq j} \frac{p_{j't} - c_{j't}}{K(j')} \int \alpha_i s_{ijt} s_{ij't} dF(\alpha_i) - (p_{jt} - c_{jt}) \int \alpha_i s_{ijt} \left(1 - \frac{s_{ijt}}{K(j)}\right) dF(\alpha_i) = & \quad 0 \\
s_{jt} + \sum_{j' \in F_f} (p_{j't} - c_{j't}) \int \alpha_i s_{ijt} \left[\frac{s_{ij't}}{K(j')} - 1_{\{j'=j\}} s_{ijt}\right] dF(\alpha_i) = & \quad 0
\end{aligned}$$

These are the first-order conditions that we use to identify the marginal costs of all drugs, including generics whose market shares are aggregated at the molecule level.