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Abstract

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JEL Classification: I10, L22, L41

Keywords: Innovation, Welfare, Advertising, Drugs, Merger

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October 2022†

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1 Introduction

Competition authorities frequently use ex ante simulations to predict counterfactual price changes and evaluate the anticompetitive effects of mergers that can result in higher prices or affect rates of innovation (European Commission, 2015). When firms with overlapping market activities merge, prices typically increase due to reduced competition, raising 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 it 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, leading to less advertising. The change in firms' profits, as well as welfare effects, may thus depend on advertising decisions. Moreover, concerning consumer welfare, two forces can be welfare improving. First, cost synergies can compensate for the negative effect of the increased market power of a merger, provided that marginal costs are not already very low. Second, higher industry profits might spur welfare-improving future innovation. Then, the tradeoff 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 prices indeed increase after a merger but that advertising spending decreases, which can be seen, in some cases, as a reduction in wasteful spending. Then, studying 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. We find that the merger effect on prices is smaller when we take into account 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 less than what would have been simulated ex ante with fixed advertising levels because the level of advertising was reduced after the merger. The standard substitution between competing products may lead to a reduction in advertising efforts and, as a consequence, downward pressure on price, thus counteracting the standard upward pressure effect of concentration. In the present case, although these factors are not enough to lead to a price reduction, they mitigate the price increase that would otherwise be observed if advertising were fixed.

This study draws attention to the promotional spending strategies in oligopoly competition that affect the price equilibrium and thus are important when considering the effect of market structure on prices, which 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 strategy. Our results can provide guidance regarding the 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 DG 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 tweaked to allow for advertising or quality as an additional strategic variable. In addition to this recommendation, such analysis has not been performed in the case of advertising in the pharmaceutical sector. Using pre- and postmerger data, we avoid complex simulations concerning the dynamic equilibrium changes to advertising that would need to be carried out for a purely ex ante evaluation but show that merger simulations should take into account 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. Then, we 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

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

be affected by market structure, as shown by Cunningham et al. (2021) but rather simply projects the effects of profitability on the future market entry of new products, which can be even larger if companies can be promised larger profits without changing the market structure.

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

Merger effects on aspects other than pricing strategies In addition to the standard literature on merger simulation and its 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 can also relocate products or change promotional strategies. Unless multiproduct firms sell complements (Song et al., 2017), the price effects of mergers usually raise 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 due to firms internalizing the situation of substitution between standalone products. Otherwise, some literature has 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, indeed, merger simulation ignoring product relocation can be misleading. Concerning advertising, the literature on its relationship with 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. There are, however, fewer studies on merger effects in pharmaceutical markets. Leheyda et al. (2011) is one of the few studies that investigating ex post the effects of a pharmaceutical merger, namely, that of Pfizer and Pharmacia in 2003 in the Swiss market. This situation confirms the predictions of the Swiss Competition Commission that the abovementioned 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.

Merger effects on innovation The literature has recently addressed the dynamic effects of mergers from a theoretical point of view. 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 the mergers of firms who 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 those efficiencies brought about by innovation can justify a more lenient policy toward innovation-intensive mergers. The above 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 merger. 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 the company is important for the late-stage development of pharmaceutical R&D projects and, hence, that mergers have a positive effect. European Commission (2020) analyze 149 merger and acquisition (M&A) cases (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. Comparing the approaches taken by the EU and the US in three recent major pharmaceutical mergers shows that the EU appears to place more explicit emphasis on effects in downstream markets than does the US, showing 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. The dynamic effects of mergers are thus a legitimate concern that should be taken into account when considering the benefits in terms of the future innovation of larger profits for 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 postmerger, Weinberg and Hosken (2013) compare the price effects obtained by simulation of the merger using pre- and postmerger data, showing that some discrepancies between observed and simulated price effects can come from the modeling of demand or conduct but establishing 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, showing how structural model simulation allows us to predict merging firms' price responses, showing that cost increases or partial collusion may explain the overestimation bias in predicting the price change of nonmerging firms.

Role of advertising The literature on advertising in pharmaceutical markets suggests its role in market expansion. Lakdawalla (2018) underlines that as advertising raises profitability, innovation and advertising become complements. Moreover, Lakdawalla et al. (2013) show that advertising levels are higher when 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 quality. Allowing consumers to differ in terms of brand loyalty, the above 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. Additionally, Castanheira et al. (2019) explain the fact that generic entry often leads to a drop in quantity while prices go down due to the reduction in promotional efforts on the market equilibrium. Anderson et al. (2013) find that ad information content is higher for higher-quality brands but lower for brands with a higher market share. Anderson et al. (2016) focus on comparative advertising; their analysis of the over-the-counter (OTC) analgesics market shows that comparative advertising negatively affects those competitors targeted in the ads more than they benefit the advertiser, generating excessive levels of advertising. Furthermore, 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, while physician advertising is more persuasive.

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 on a given drug market. Subsection 3.1 describes the market and advertising data. Then, Subsection 3.2 presents the demand model used for the market for antibiotic drugs on 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.

2.1 Data sources and construction

At the core of our analysis are data from IMS Health MIDAS (now called IQVIA), which provides data on the quarterly revenues and quantities sold for each drug in a country during the years 2002-2014. 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 service and nonfederal hospitals), disaggregated at the form (mode of administration) and strength levels. We aggregate over these two dimensions[2] to obtain a dataset where the unit of observation is a product-quarter.

Using only this dataset for merger analysis is impossible, as it retains only the ownership structure from the previous period in the sample, which implies that these data do not allow us to observe M&As among companies that market some drugs. To this end, we match the sales data with Citeline's Pharma Projects dataset from Informa, a comprehensive dataset of drug development projects, which also contains the ownership history for each entry, as well as with the MedTrack data from Informa, which records all deals in the biotech industry. The MedTrack data allow us to identify 144 M&As that concern companies that have drugs with some sales in the US over the period 2002-2014. 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 the molecule exists in both branded and generic forms, then we match only the branded entries in the sales data. As Pharma Projects tracks only those drugs released after the 1980s, we miss information on some older molecules (this is the case, for example, for the following molecules: cefazolin and its combinations, lincomycin, and spectinomycin, all developed in the 1960s).

Finally, we complement our dataset with advertising data from IMS Health Global Promotional Track. We have monthly data on 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 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 revenues and quantities of each drug that we use to compute average prices by quarter. However, several issues need to be taken into account for the careful measurement of 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 using a smoothed version over three

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

quarters of the price (see Appendix Section A.1 for details). 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 time period, average rebates were approximately 32% but varied widely between ATC4 classes and could even be as low as 7% 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 list prices and experience less of an increase in list prices over time, while food and drug stores usually have the highest prices. This pattern is quite common for all drugs. We thus use, for each drug, the ratio of the minimum price observed across all channels to the average 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 later test the robustness of our results to different measurement assumptions regarding 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], showing that the advertising spending is very small for some ATC classes but that for others, it can represent 5 to 8% of total revenue. Generic companies typically advertise their own products very little, 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 groups. 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	Total	Revenue Branded	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

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

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

We first use all the data on prices for all drug classes in the US for the years 2002-2014, advertising expenses for all drugs (available starting in 2005) and the 144 M&As that took place in this period to evaluate how mergers are correlated with prices and advertising. We define markets using the ATC level 4 classification. We observe, on average, 12 deals per year, 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 them, 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). However, our merger variable corresponds to the case where we observe both parties marketing competing products, which happens for only 14 deals (2 mergers, 8 100% acquisitions and 4 majority acquisitions) with 24 firms participating. 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).

Table A.1 in Appendix A.2 shows some descriptive statistics of the sample of products and time

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

	ATC4 classes with mergers	ATC4 classes without mergers
N products in the market	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)
Class sales ($1000s)	316,912.96	160,515.73
	(581,695.69)	(422,235.29)
Product price	27.88	22.43
	(214.17)	(235.11)

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

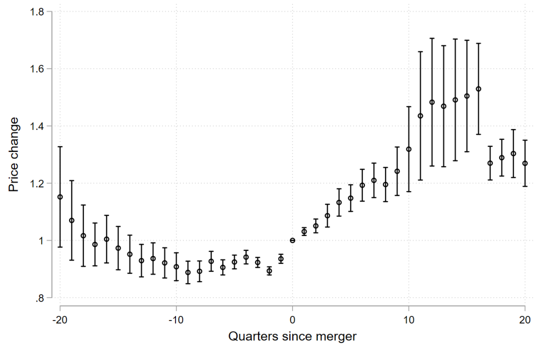
periods used in the reduced-form exercise, exhibiting that we have many markets (defined at the ATC4 level) in which firms who merge have overlapping products. Mergers of competitors affect 42 out of the 493 ATC4 markets. Table 2.2 shows how the classes with mergers compare to those markets that are unaffected. While the differences are not statistically significant, markets 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.

The descriptive statistics on prices and advertising of products of merging companies are informative. Figure 2.1 shows how the prices and advertising spending of the products of merging companies change around the time of the merger. By centering the time variable at the time of the merger, we can see a clear upward trend in prices and downward trend in advertising after the consolidation takes place. These changes appear persistent—the premerger levels are never attained again—and, in most cases, continue even 3 years after the merger.

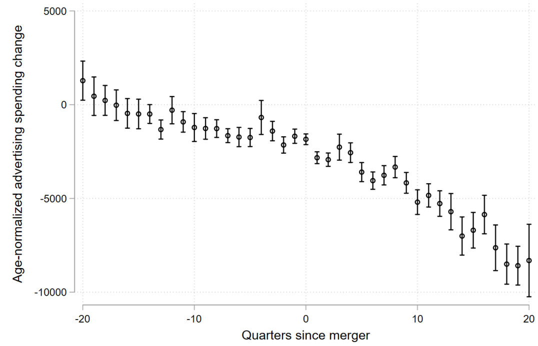
To quantify the changes in prices and advertising following a merger, we estimate a set of difference-in-differences regressions.

To estimate the merger effect on prices, we regress the log price, denoted as $\log(p_{jt})$ for drug j

Figure 2.1: *Changes in Prices and Advertising around the Time of the Merger*



Mean normalized price change (and standard deviation) defined as the ratio of the price at quarter t to that at the quarter of the merger. Only products of merging companies are considered.



Mean change (and standard deviation) in US$ advertising spending per quarter, net of the effect of product age on advertising (residuals from a regression of the effects of advertising spending, in dollars, on age dummies). Only products of those merging companies that advertise and have a known age are considered.

in quarter t, on a set of treatment dummies and controls:

$$\log(p_{jt}) = \underbrace{\beta_m T_j^m}_{\substack{\text{control for}\\ \text{being in a merger}\\ \text{in the past or future}}} + \underbrace{\gamma_m}_{\substack{\text{merger effect}\\ \text{on products}\\ \text{in a merger}}} \times \underbrace{D_{jt}^m}_{\substack{\text{being in a merger}\\ \text{after a merger}}} + \underbrace{\beta_c T_j^c}_{\substack{\text{control for being}\\ \text{a merger competitor}\\ \text{in the past or future}}} + \underbrace{\gamma_c}_{\substack{\text{merger effect}\\ \text{on the competing}\\ \text{products of merger}}} \times \underbrace{D_{jt}^c}_{\substack{\text{competing with}\\ \text{a merger}\\ \text{after a merger}}}$$
$$+ \underbrace{\lambda X_{jt}}_{\substack{\text{control}\\ \text{variables}}} + \underbrace{\alpha_{m(j)}}_{\substack{\text{molecule}\\ \text{fixed effects}}} + \underbrace{\delta_t}_{\substack{\text{quarter}\\ \text{fixed effects}}} + \underbrace{\eta_{c(j)}}_{\substack{\text{ATC4}\\ \text{fixed effects}}} + \varepsilon_{jt} \quad (2.1)$$

where T_j^m is a dummy variable equal to one for products j whose owners merged with firms marketing a product in the same ATC4 market any time during the sample time period, T_j^c is a dummy variable equal to one if product j belongs to an ATC4 market in which a merger implies that other firms are present in the sample time period and thus are competing with a product from the merger, D_{jt}^m 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_{jt}^c is a dummy variable equal to one if product j belongs to a firm that competes with some firm that merged with another firm before quarter t. Control variables X_{jt} are product characteristics, such as branded versus generic, drug age, time to patent expiration, number of firms present at time t in ATC4 class $c(j)$ of drug j, number of generics and branded products in ATC4 class $c(j)$ of drug j, δ_t are quarter fixed effects, η_c are ATC4-level fixed effects, and $\alpha_{m(j)}$ are molecule fixed effects with $m(j)$—the molecule of product j (some molecules are in different ATC4 classes).

The term $\beta_m T_j^m$ controls for the possible mean difference in the prices of products belonging to firms that intend to merge or have merged in some ATC4 markets, which is supposed to control for the selection of mergers correlated with unobserved fixed characteristics. The term $\beta_c T_j^c$ controls for the possible mean difference in the prices of products belonging to firms that are or will be competing with products that have merged in some ATC4 markets, which is supposed to control for the selection of not being in a merger that is correlated with unobserved fixed characteristics. Note that $T_j^m + T_j^c = 1$ if product j is in a market (ATC4 class) where some merger occurs at some point but provided this product j was or is still on market at the time of the merger. Thus, as product entries and exits occur in these markets, there is no perfect collinearity between dummies T_j^m and T_j^c and ATC4 fixed effects.

Finally, γ_m and γ_c are the effects of the merger on the outcome variable, which can be interpreted as causal if the assumption that time-varying unobservables are not correlated with the selection into merger is maintained. Given that we control for molecule fixed effects and many other observables that are time varying, the causal effect estimates are biased only if time-varying unobservables are correlated with price and the merger or if time-invariant unobservables that vary within a molecule and market and are not controlled by other observable product characteristics are correlated with prices and the merger event. Furthermore, we estimate a specification where we allow for postmerger effects γ_m and γ_c to be different postmerger during 3 years and after 3 years and another where we include product-level fixed effects.

Of course, although we have a rich set of fixed effects that can control for many unobservables that can potentially create an endogeneity bias in the merger, we can still have some unobserved news about product quality that happens to affect prices and advertising decisions and be correlated with the merger.

Table 2.3 shows the results of the estimation of (2.1) on prices, demonstrating that products affected by mergers are more expensive, on average, than are those that were not present in the market at the time of the merger and that those present at the time but not part of the merger are less expensive on average[4]. The coefficient estimate of γ_m (Postmerger in the table) shows a

[4]Table A.4 in Appendix Section A.3 shows the same regression on prices as that in Table 2.3, except that it uses

significant 11.2% increase after the merger and a significant 9.5% increase for competing products (γ_c for Postmerger and competitors in the Table) in the specification with product fixed effects. Then, the decomposition into the effect during the 3 years postmerger (short term) and after (long term) shows that the effect for the merging products is stronger in the short term but remains significant in the long term. These results are consistent with the findings of Bonaime and Wang (2019), 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.

However, caution should be taken in the causal interpretation of these effects. Indeed, a natural source of endogeneity bias in these price regressions is the other strategic variable chosen by firms, which we underline in the next regression analysis—advertising spending. Indeed, advertising varies over time and, in particular, with a change in ownership and is not controlled for in these price regressions, while it is likely to be correlated with prices. This situation calls for a more structural analysis of the effects of mergers on prices accounting for advertising, as advertising seems to also be affected by mergers.

To estimate the effect of a merger on advertising, we regress the log of per-product advertising expenditures $\log(e_{jt})$[5] on the same set of variables as that used in Equation (2.1) 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).

Table 2.4 shows the results of the estimation. Those products present in the market at the time of the merger had higher advertising spending than did those that were not, and the advertising spending of the products involved in the merger was much higher than that of their competitors. The coefficient estimates in columns (1) and (2) show a very large and significant decrease in advertising expenditure on the products involved in the merger postmerger but no significant effect for competing products. In columns (3) and (4), we introduce an additional interaction term to focus on products that were already advertised before the merger, and we can see that this subset drives the results. The decomposition of the effect between the short and long terms shows that the effect remains

nondiscounted gross prices that do not account for rebates. The results in the two tables are extremely similar.

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

Table 2.3: *Price Changes Postmerger*

VARIABLES	(1) $\log(p_{jt})$	(2) $\log(p_{jt})$	(3) $\log(p_{jt})$	(4) $\log(p_{jt})$
Treated (β_m)	0.207***		0.214***	
	(0.023)		(0.022)	
Treated, competitors (β_c)	-0.145***		-0.149***	
	(0.016)		(0.016)	
Postmerger (γ_m)	0.044	0.112***		
	(0.031)	(0.020)		
Postmerger, competitors (γ_c)	0.025	0.095***		
	(0.018)	(0.012)		
Postmerger, short term (γ_m^{short})			0.055	0.092***
			(0.032)	(0.019)
Postmerger, long term (γ_m^{long})			0.013	0.087***
			(0.033)	(0.019)
Postmerger, short term, competitors (γ_c^{short})			0.033*	0.041***
			(0.015)	(0.010)
Postmerger, long term, competitors (γ_c^{long})			0.027	0.098***
			(0.020)	(0.014)
Observations	467,028	466,692	467,028	466,692
R-squared	0.776	0.972	0.776	0.972
Controls	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
ATC4 FE	✓		✓	
Molecule FE	✓		✓	
Product FE		✓		✓

*Note: Product fixed effects encompass molecule and ATC4 fixed effects. Control variables are a branded/generic dummy, the age of the drug, dummy variables for each of the first quarters after entry, the time left to patent expiration, an off-patent dummy, the number of companies in the same ATC4 class, and the number of branded and generic 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* $p < 0.05$.

strong three years after the transaction.

Finally, we examine the merger effects on sales volumes, advertising units and prices. Table A.3 in Appendix A.2 shows a significant 31.7% decrease in the sales volume of products sold by merging firms and a significant 36.6% decrease for their competitors. The table also shows a significant 57.5% decrease in advertising units postmerger, suggesting that the decrease in advertising spending shown in Table 2.4 is not driven by lower advertising prices obtained by the merged firm. This finding is confirmed by the absence of effects on advertising price that do not change significantly postmerger.

This reduced-form exercise suggests that the effect of a merger is denoted by an increase in prices and a decrease in advertising. The endogeneity of mergers in these cross-pharmaceutical classes is,

Table 2.4: *Advertising Spending Changes Postmerger*

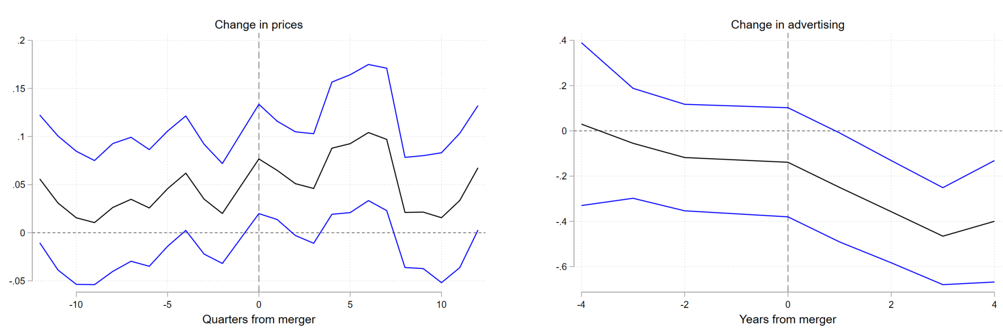
VARIABLES	(1) log (e_{jt})	(2) $\log(e_{jt})$	(3) log (e_{jt})	(4) $\log(e_{jt})$	(5) log (e_{jt})	(6) $\log(e_{jt})$
Merging: (β_m)	2.212***		1.735**		1.666**	
	(0.280)		(0.529)		(0.517)	
Competitors of merging (β_c)	0.531		0.509		0.608*	
	(0.297)		(0.301)		(0.280)	
Postmerger (γ_m)	-0.891***	-0.543***	-0.720*	-0.084		
	(0.140)	(0.109)	(0.308)	(0.163)		
Postmerger × Advertised premerger (γ_m^a)			-0.165	-0.672***		
			(0.325)	(0.193)		
Postmerger, competitors (γ_c)	-0.073	0.104	-0.082	0.101		
	(0.176)	(0.145)	(0.175)	(0.145)		
Postmerger, short term: (γ_m^{short})					-0.351	0.003
					(0.265)	(0.141)
Postmerger, short term × Advertised pre-merger $(\gamma_m^{a,short})$					-0.266	-0.411*
					(0.286)	(0.181)
Postmerger, long term (γ_m^{long})					-0.798*	-0.134
					(0.335)	(0.183)
Postmerger, long term × Advertised pre-merger $(\gamma_m^{a,long})$					0.030	-0.675**
					(0.370)	(0.241)
Postmerger, short term, competitors (γ_c^{short})					-0.133	-0.044
					(0.163)	(0.099)
Postmerger, long term, competitors(γ_c^{long})					-0.207	0.074
					(0.175)	(0.127)
Observations	47,663	47,649	47,663	47,649	47,663	47,649
Controls	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
ATC4 FE	✓		✓		✓	
Molecule FE	✓		✓		✓	
Product FE		✓		✓		✓

*Note: The lagged advertising stock coefficient is among the controls and is positively significant. Product fixed effects encompass molecule and ATC4 fixed effects. Control variables are a branded/generic dummy, the age of the drug, dummy variables for each of the first quarters after entry, the time left to patent expiration, an off-patent dummy, the number of companies in the same ATC4 class, and the number of branded and generic 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 $p < 0.05$. The number of observations is lower than that in the case of the price regression because advertising is available only starting in 2005.*

however, still possible, but otherwise, it seems to suggest that although the classical price increase effect of reduced competition appears, mergers also affect advertising decisions. This evidence on advertising across all drug classes in the US during the years 2005-2014 is quite new and suggests that mergers allow firms to reduce their advertising spending because of lower competition between substitute products within an ATC4 class market. Moreover, this evidence shows that competition authorities should probably account for merger effects on promotional spending, which affect not only demand shape and consumer welfare but also equilibrium prices and firm profits through the changes in both advertising spending and variable revenue. As we know, the tradeoff faced by competition policy in the pharmaceutical industry is between allowing higher firm profits to stimulate innovation and reducing health care spending, and the effect of a merger on advertising together with prices is important to take into account.

As the mergers happened at different times over the sample time period, our results thus far rely on the assumption that the treatment effects are homogeneous. We can account for the heterogeneity of these treatment effects due to the staggered nature of the treatment using the technique proposed by Sun and Abraham (2021). Figure 2.2 represents the event study estimates obtained for changes in prices and advertising spending relative to the premerger period $(t-1)$. Confidence intervals are quite wide but confirm some significant effects for some quarters postmerger. For prices, the increase starts from the quarter of the merger and remains significant for two years following the transaction. The magnitudes in the event study are slightly smaller than the baseline results reported in Table 2.3. For advertising spending, given a much lower number of treated observations, we assume that the quarterly effects are homogeneous within a year and use yearly effects in the event study. The results show a significant decrease in advertising spending for the merging products starting from the first year after the merger. Figure A.3 in Appendix A.2 shows a similar behavior for advertising for products that were already advertised premerger. The figure also shows that prices seem to decrease from the postmerger higher level after two years as advertising simultaneously becomes lower. These results call for structural model estimation since one cannot assume that the advertising effects are not correlated with the unobservables of the price equation and that price effects are not correlated with the unobservables of the advertising equation.

Figure 2.2: *Event Study Estimates of the Merger Effect on Prices (left) and Advertising Spending (right)*



Notes: Point estimates and 95% confidence intervals follow Sun and Abraham (2021).

3 Structural model on a market with a merger

We now develop a model of supply and demand for a market of antibiotics in which a merger occurred in late 2009, taking into account 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 where Pfizer and Wyeth had potentially competing products (e.g., treatments for renal cell carcinoma and Alzheimer's disease, antidepressants, and antibiotics), finally concluding that the transaction did not raise anticompetitive concerns in human health product markets.

However, in Appendix A.5, we show how we finally define the relevant market concerning methicillin-resistant Staphylococcus aureus (MRSA) infections following the medical literature (Choo and Chambers, 2016; Welte and Pletz, 2010) and for which there is substantial overlap with the Pfizer molecule linezolid, under the brand name Zyvox, and the Wyeth tigecycline molecule, under the brand name Tygacil.

3.1 Descriptive statistics

Table 3.1 presents some summary statistics on the set of products belonging to the market considered. On average, there are 18.58 molecules marketed per quarter, with 17.29 being generic and 11.94 being branded. During the time 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 substitution patterns or 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 and vancomycin, and their resistance to other products in our sample has not been systematically tracked. Recent medical literature, mostly carried out after the time period of our analysis, has found instances of resistance of MRSA infections to antibiotics in the sample, but they 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

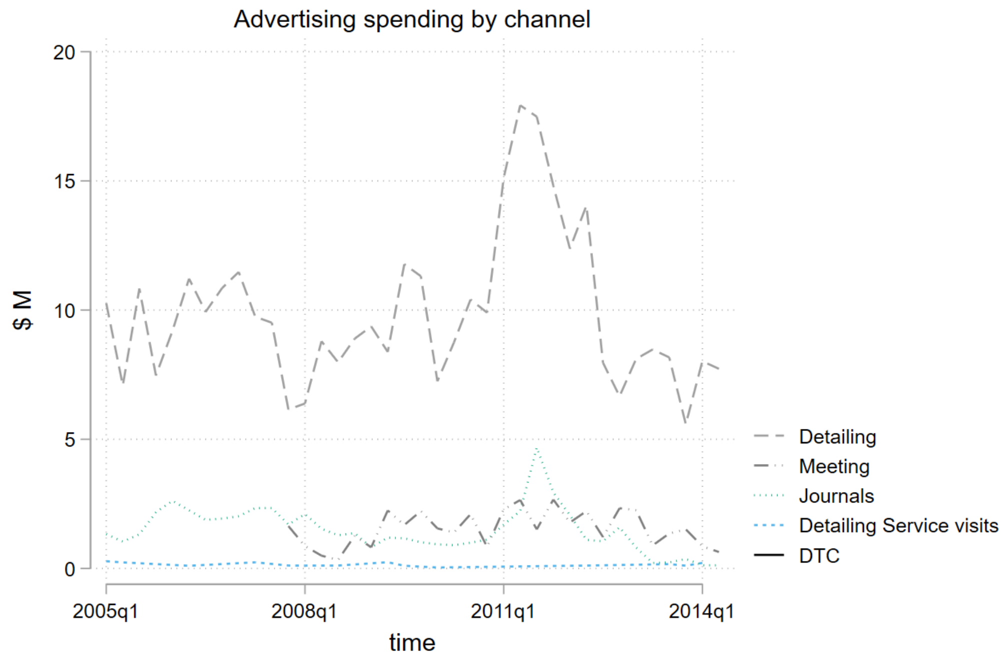
Note: Sales values and advertising spending per quarter are expressed in 1,000s of US$, and sales volumes per quarter is expressed in standard units.

Pharmaceutical companies have a particular interest in advertising antibiotics to physicians, as for many infections, the standard of care is to follow *empiric therapy*. This approach consists of the physician making an educated guess and prescribing an initial course of an antibiotic while waiting for the results of lab 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.

At the level of individual molecules, the same pattern holds (Figure A.5 in Appendix A.4)—the bulk of advertising expenditures is used on 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, instead of current advertising spending, in demand estimation, we use an advertising stock (following Erdem et al. (2008), Dubois et al.

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



(2018)) [6], defined for drug j at quarter t as the discounted sum of past flow spending $e_{j\tau}$:

$$a_{jt} = \sum\nolimits_{\tau \leq t} \delta^{t-\tau} e_{j\tau}$$

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, avoiding the initial value problem (as $0.5^4 = 0.0625$, 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 use a random coefficient logit model for the demand model for this market. Following Berry (1994); Berry et al. (1995); Nevo (2001), we specify the random utility for each drug $j \in \{1, .., J_t\}$ of

[6] Dubois et al. (2018) use an increasing concave transformation of the stock variable in the demand specification. An alternative functional form uses the stock of log advertising flows $a_{jt} = \sum_{i \leq t} \delta^{t-i} \log\left(e_{jt} + \sqrt{e_{jt}^2 + 1}\right)$ as in Dubé et al. (2005) and Shapiro (2018).

ATC4 class c for patient i in period t as

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

where $\delta_{m(j)}$ is a molecule fixed effect, p_{jt} is the price of the drug, $\mathbf{x}_{jt}$ is a vector of its characteristics, ζ_{ct} are class-period-specific effects, ξ_{jt} is an unobserved demand shock for product j at t, ε_{ijt} is consumer i's deviation from the mean utility of taking drug j in period t, and a_{jt} is the advertising stock for product j at quarter t.

Note that we test and reject a specification where advertising expenses of other products also affect the own product value in the decision model (see Table A.9 in Appendix A.7 and Appendix A.9 for the full results if we were to prefer the model with spillovers), which implies that the outside good market share is a decreasing function of any of the product advertising variables a_{jt} if $\gamma > 0$, meaning that advertising has a market expansion effect and a business stealing effect from other competing products. Other robustness checks concerning the demand specification are in Appendix A.7.

The model is completed by the inclusion of an outside good with normalized indirect utility $u_{i0t} = \varepsilon_{i0t}$. Indirect utility can then be redefined with mean utility $\delta_{jt} = \delta_{m(j)} - \beta p_{jt} + \gamma a_{jt} + \alpha \mathbf{x}_{jt} + \zeta_{ct} + \xi_{jt}$ and deviation $\mu_{ijt} = (\beta - \beta_i)\, p_{jt}$, where $\beta = E(\beta_i)$. Under the assumption that ε_{ijt} is i.i.d. extreme value type I distributed, the choice probability of alternative j by consumer i is as follows:

$$s_{ijt}(\mathbf{a}_t, \mathbf{p}_t) = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_k \exp(\delta_{kt} + \mu_{ikt})}$$

and the aggregate market share of product j, s_{jt}, is given by

$$s_{jt}(\mathbf{a}_t, \mathbf{p}_t) = \int s_{ijt}(\mathbf{a}_t, \mathbf{p}_t)\, \varphi(\beta_i)\, d\beta_i$$

, where the pdf of β_i is assumed to be the normal distribution $\mathcal{N}(\beta, \sigma)$. Then, own- and cross-price elasticities follow the classical formulas in a random coefficient logit model. We also specify the aggregate market size, which is set such that the average outside good market share is 15%, and then, we perform robustness checks.

We then follow the standard Berry et al. (1995) and Nevo (2001) approach for the identification and estimation of 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 instrumental variables.

Our instrumental variables also follow standard methods combining Hausman- and BLP-style instruments. Hausman-style instruments use the prices of the same products in other countries (Australia, France, Canada, India, Turkey, and the UK), while BLP-style instruments use the number of generics in the ATC4 class interacted with year dummies. Finally, we also construct a price for advertising since both price and advertising are endogenous. The instruments for prices can also be assumed to instrument for advertising expenses since their benefit also clearly depends on the margins and marginal costs that affect prices. However, as in Dubois and Lasio (2018), we add an instrument that should affect advertising independently of drug costs. As our promotional data report not only detailing spending but also "units" of detailing measured at the brand level and defined as direct contacts in promotional activity by the pharmaceutical company with a physician, we compute a detailing unit price that corresponds to how much it costs for a sales representative to visit a physician. 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).

Table 3.2 shows the main parameter estimates of our preferred demand model[7] As we have many generic companies for some molecules and thus strong competition across generics for these molecules, we do not account for the generic name differentiation and aggregate generic products of the same molecule within a single generic-molecule product (see the details in Appendix Section A.11). We control for molecule fixed effects as well as ATC4-specific year fixed effects, which are not shown in the table but precisely estimated. The results show a price coefficient that is significantly negative with a variance parameter that is also precisely estimated. Moreover, we allow the price coefficient

[7]See Table A.8 for a robustness check with respect to market size, the stock parameter in Table A.7, the rebates in Table A.10 and the ad spillovers in Table A.9 in the Appendix).

Table 3.2: *Demand Model Estimates*

		Coefficients	Standard errors
Price	β	-0.36723	0.04057
	σ	0.14754	0.02047
Advertising stock	γ	0.00074	0.00019
log(Age) × Price		0.00780	0.00471
Patent dummy		2.90998	0.80583
Age		-0.06233	0.01931
Age max dummy		-1.61238	0.58560
Time since patent expiration		0.34197	0.06390
Time to patent expiration		-0.30754	0.06083
Patent information dummy		1.14374	0.56939
q1 after entry		-1.86213	0.53675
q2 after entry		-1.51415	0.51721
q3 after entry		-0.21326	0.50483
q4 after entry		-0.24639	0.50048
ATC4 × year FE		✓	
Molecule FE		✓	
N		994	

Note: 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 other Australia, France, Canada, India, Turkey, and the UK), and the price of a unit of advertising.

to vary with the log of age of the drug. The coefficient is positive, implying that the price sensitivity of demand tends to decrease over time, even if the effect is not strongly significant. The advertising effect is positive and significant, as is the dummy variable for the product being on patent. The age effect is negative but imprecisely estimated, while the dummy variable for the age being higher than the maximum observed age (because our measure of age is censored for drugs already present in 2002 and for which we do not observe the entry date) is negative and significant. Finally, we introduce some dummy variables for the drug being in the first, second, third or fourth quarter of entry, showing a negatively significant effect compared to the reference of later periods and an effect that decreases in absolute value with time. This finding is consistent with the fact that the diffusion of drugs after market entry is not immediate but rather seems to stabilize after a year.

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

	Cefazolin(gen)	Cefepime(gen)	Cefoxitin(gen)	Ceftriaxone(gen)	Cubicin	Maxipime	Tygacil	Vancocin	Vancomycin(gen)	Zyvox
Cefazolin(gen)	-0.76885	0.00827	0.00879	0.18915	0.00000	0.01408	0.00095	0.04038	0.14637	0.00204
Cefepime(gen)	0.57440	-5.40820	0.23023	0.83061	0.00109	0.25518	0.17462	0.72070	1.07197	0.57648
Cefoxitin(gen)	0.73619	0.28061	-5.14754	0.88495	0.00029	0.20986	0.09175	0.59441	1.03977	0.27492
Ceftriaxone(gen)	0.70340	0.04323	0.03841	-2.21352	0.00000	0.05540	0.00699	0.15821	0.44480	0.01652
Cubicin	0.00019	0.01251	0.00240	0.00083	-1.46725	0.00154	0.10636	0.00426	0.00197	1.27971
Maxipime	0.79295	0.20881	0.14115	0.85496	0.00013	-4.69073	0.05895	0.49384	0.95044	0.16765
Tygacil	0.22095	0.58400	0.24961	0.45871	0.02687	0.23920	-6.00426	0.67151	0.71422	2.20271
Vancocin	0.79486	0.20606	0.13970	0.85308	0.00012	0.17256	0.05782	-4.35533	0.94613	0.16409
Vancomycin(gen)	0.81794	0.08668	0.06938	0.67523	0.00002	0.09428	0.01735	0.26860	-2.98393	0.04400
Zyvox	0.11844	0.48129	0.18600	0.27368	0.07334	0.16936	0.54837	0.47445	0.45176	-3.20365

Note: The elasticities of products are in rows, and the prices of products are in columns.

Table 3.3 shows the own and cross-price mean elasticities of the main products, showing that Zyvox's own price elasticity is around -3.2, while that of Tygacil is -6.0 and also that these two products have the largest cross-price elasticities in this market with Tygacil having a larger cross-price elasticity than that of Zyvox, which can be rationalized by the fact that Zyvox (Linezolid) has 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 compared to the advertising of all products that advertise, showing own semi-elasticities of one million US$, between 32.2% and 73.3%, respectively. Thus, one million US$ in additional spending in advertising increases market share (or quantity sales) by 67.3% 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 33.6% one quarter later, 16.8% two quarters later and 8.4% three quarters later.

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	0.728	-0.005	-0.000	-0.009	-0.010	-0.000	-0.000	-0.001	-0.029	-0.003	-0.002
Claforan	-0.006	0.731	-0.000	-0.010	-0.013	-0.000	-0.000	-0.002	-0.038	-0.003	-0.004
Cubicin	-0.000	-0.000	0.231	-0.000	-0.000	-0.000	-0.012	-0.016	-0.001	-0.000	-0.199
Fortum	-0.004	-0.004	-0.000	0.723	-0.022	-0.001	-0.000	-0.006	-0.064	-0.003	-0.017
Maxipime	-0.002	-0.003	-0.000	-0.013	0.707	-0.002	-0.000	-0.014	-0.082	-0.003	-0.044
Rocephin	-0.001	-0.002	-0.001	-0.011	-0.032	0.733	-0.000	-0.034	-0.090	-0.002	-0.126
Synercid	-0.000	-0.000	-0.254	-0.000	-0.001	-0.000	0.720	-0.038	-0.002	-0.000	-0.414
Tygacil	-0.000	-0.001	-0.013	-0.006	-0.022	-0.003	-0.001	0.673	-0.062	-0.001	-0.320
Vancocin	-0.002	-0.003	-0.000	-0.013	-0.029	-0.002	-0.000	-0.014	0.654	-0.003	-0.043
Zinacef	-0.005	-0.004	-0.000	-0.012	-0.019	-0.001	-0.000	-0.004	-0.054	0.733	-0.010
Zyvox	-0.000	-0.000	-0.034	-0.003	-0.014	-0.002	-0.003	-0.067	-0.040	-0.000	0.322

Note: The semi-elasticities of products are in rows, and the advertising levels of products are in column. Immediate quarter change in market share when advertising increased spending by 1M US$. A 0.5 advertising semi-elasticity means that market share increases by 50% with one million US$ in additional spending.

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. As fixed costs and other R&D costs do not affect pricing and advertising decisions, 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 to the future of per-period profits π_{ft}:

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

where p_{jt} is the price of drug j and a_{jt} is the advertising expense stock. For drug j ($a_{jt} = \sum_{\tau \leq t} \delta^{t-\tau} e_{j\tau}$), 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 expenditures stocks $\mathbf{a}_t$ for all J products. 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 affect the state variable of advertising stock dynamically because advertising affects both current and future demand. Thus, pharmaceutical firms maximizing discounted expected sums of profits compete in a dynamic game. Solving this game implies that we need to specify 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 rather estimating only price optimality conditions. Indeed, price optimality conditions are static once we condition on the observed advertising state variables and market structure (including M&As). 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 and the possible complex dynamic strategies. This game is typically played using the Markov perfect equilibrium concept (Maskin and Tirole, 1988) and empirically applied with discretized actions and states using Ericson and Pakes (1995).

As prices affect demand and thus profit only 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 once they are observed. We thus consider firms' profit-maximizing conditions in terms of prices. Assuming that a pure-strategy Bertrand-Nash equilibrium in prices exists, the price of any product j sold by firm f must satisfy the first-order condition

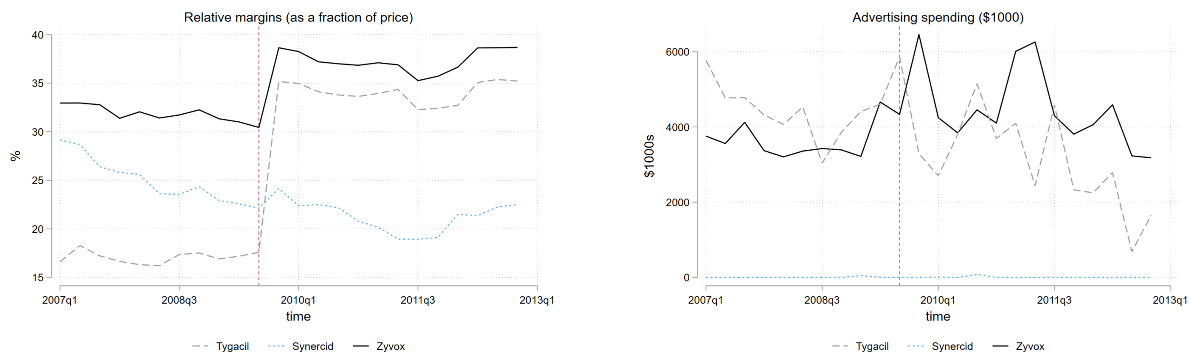
$$q_{jt} + \sum\nolimits_{k \in F_{ft}} (p_{kt} - c_{kt}) \frac{\partial q_{kt}\left(\mathbf{p}_t, \mathbf{a}_t\right)}{\partial p_{jt}} = 0 \tag{3.3}$$

which obtains 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. Concerning generic drugs, as we aggregate the market shares of the same molecule generics because there are sometimes many generic companies producing the same molecule and selling very small market shares, we cannot assume that the price setting of these products is done as if all generic companies producing the same molecule would choose the price jointly. We thus 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 and are detailed in Appendix Section A.11.

Table A.6 in Appendix A.6 shows the mean of estimated marginal costs per standard unit of each product. Figure 3.2 shows the estimated margins of Tygacil (Wyeth) and Zyvox (Pfizer) during 2007-2013 as well as the advertising spending on these two products during the same time period. This figure shows that both Tygacil and Zyvox increased in terms of margins postmerger, while the advertising level of these two products decreased within one year postmerger.

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



4 Counterfactuals

To evaluate the effects of the merger, we now use our structural model to perform some counterfactual simulations and then develop some additional welfare analysis extrapolating to 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.

4.1 Short-term merger effects

Immediately 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. We thus 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. As we observe the pre- and postmerger advertising stocks, we simulate the counterfactual price equilibrium with both cases of market structure and pre- or postmerger advertising, as well as the observed levels of advertising. In doing so, we avoid the difficulty of simulating the counterfactual advertising choices of firms that would require discretizing actions and state spaces in a dynamic Markov game (Pakes and McGuire, 1994; Ericson and Pakes, 1995). Although this approach prevents us from pinpointing the effect of the merger on advertising strategies, with the assumption that advertising levels would be either those observed postmerger or those observed premerger, we can obtain some realistic counterfactual simulations of short-term effects on prices.

Effects with pre- and postmerger advertising Denoting the product ownership without merger as $\tilde{F}_{ft}$, instead of F_{ft} with the merger, the price equilibrium must satisfy any product j sold by firm f according to the following first-order condition:

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

which gives $\tilde{\mathbf{p}}_t(\mathbf{a}_t)$ the equilibrium price vector function of advertising levels.

Then, for any advertising vector $\mathbf{a}_t$, we can compute demands $q_{kt}(\tilde{\mathbf{p}}_t, \mathbf{a}_t)$, profits $\tilde{\pi}_{ft} = \sum_{k \in \tilde{F}_{ft}} (\tilde{p}_{kt} - c_{kt}) q_{kt}(\tilde{\mathbf{p}}_t, \mathbf{a}_t) - a_{kt}$ and consumer surplus $\tilde{CS}_t(\mathbf{a}_t, \tilde{\mathbf{p}}_t)$ and compare them with merger equilibrium prices $\mathbf{p}_t(\mathbf{a}_t)$ and corresponding outcomes.

Figure 4.1: *Counterfactual Advertising Scenarios*

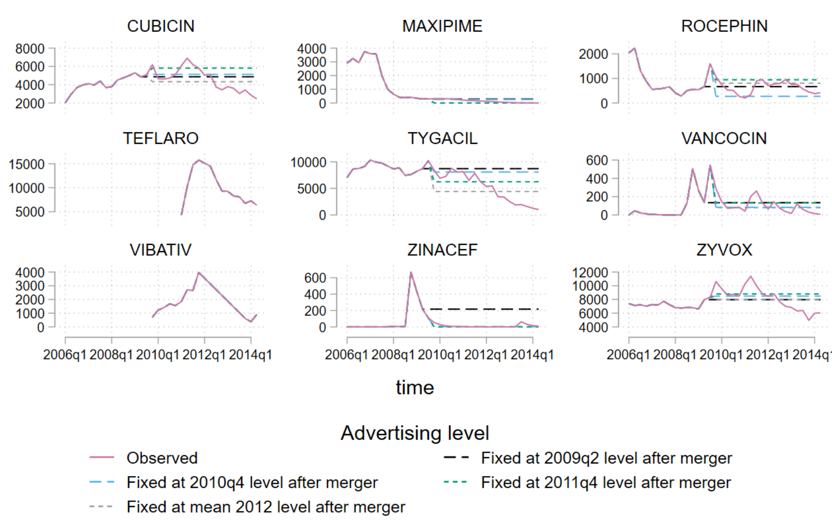
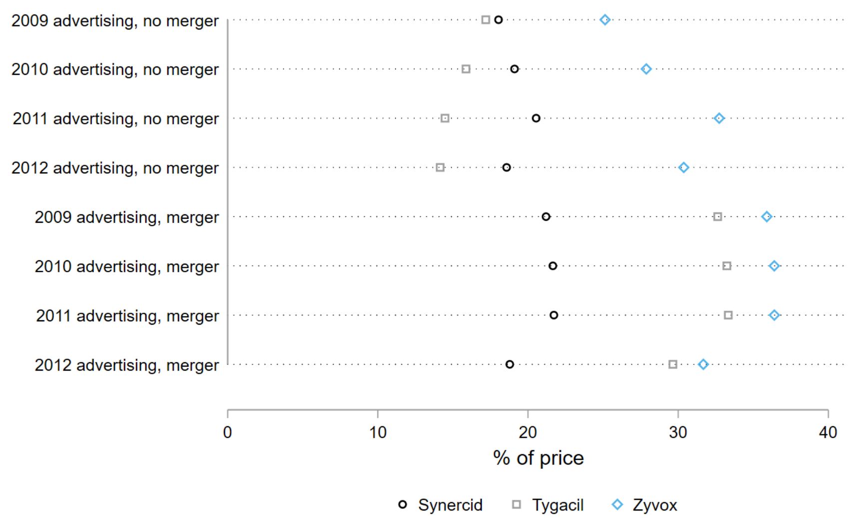


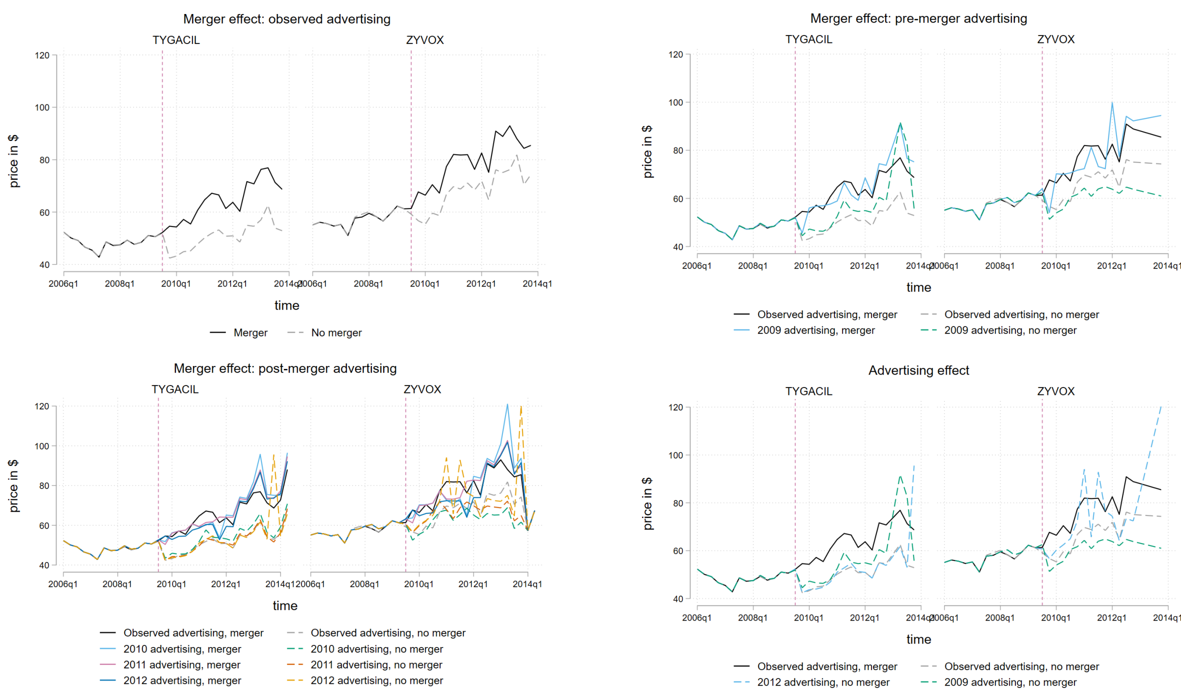
Figure 4.2: *Counterfactual Margins with/without Merger, with/without Advertising*



Note: Margins are relative to price $\frac{p_j - c_j}{p_j}$ *for the main products.*

Empirical results We estimate the price equilibrium under merger or no merger with different advertising scenarios, using either the observed advertising or some pre- or postmerger advertising levels. Figure 4.1 shows the different advertising levels for different products and the levels of advertising we use for those different counterfactuals. The margins estimated for the main products in this market under various counterfactual scenarios (merger or no merger) and various advertising levels are shown in Figure 4.2 as a percentage of price and in US$ in Figure A.11 in Appendix A.13, which includes the same figures adding the important but more expensive product Cubicin. The comparison of prices after the merger with or without advertising shows that the prices of most products go down when advertising for Zyvox and Tygacil, but not Vancocin, decreases to zero. The results show that Zyvox (Pfizer) and Tygacil (Wyeth), which are the main products resulting from the merger, would have been less expensive in the case of no merger given any level of advertising. Moreover, Synercid, a low-sales Pfizer product, would have been much less expensive and raised its price because of the higher equilibrium prices of Zyvox and Tygacil. The different counterfactual simulations also show that the magnitude of the merger effect depends on advertising levels. As advertising tends to decrease postmerger, although it first increased for Zyvox (Linezolid) before decreasing later and dropped immediately after the merger (occurring in October 2009) for Tygacil, the price increase due to the merger is first larger but then smaller when the advertising levels of both main products decrease. We can also observe that Zyvox, which has an advertising level that first goes up and then goes down, is the product that exhibits first a larger price increase than in the case with the premerger advertising level and then a smaller price increase. Figure 4.3 shows the dynamics of the prices in these different counterfactuals for the two products resulting from the merger.

Figure 4.3: *Counterfactual Prices of Tygacil and Zyvox under Different Scenarios*



Then, Table 4.1 shows the merger evaluation results for 2010 for average prices, firms' profits and total spending. Column 1 shows the effects on prices and profits changes with the observed advertising of 2010 and averaging over the four quarters of 2010, column 2 shows the same effects but using the advertising levels of premerger quarter 2 of 2009, column 3 shows the same effects but using the advertising levels of postmerger quarter 4 of 2010, and column 4 shows the effect of advertising as quarter 4 of 2010, instead of quarter 4 of 2009, when we keep the market structure as that without a merger.

The results show that mean prices on the market increase by \$2.52 per standard unit with the observed 2010 advertising level, meaning that if that advertising level observed in 2010 had been

Table 4.1: *Counterfactual Merger Evaluations (2010)*

	Merger effect			**Advertising effect**
	Observed advertising	Premerger advertising	Postmerger advertising	
	1.	2.	3.	4.
	A. Prices (mean across products)			
All	2.52	1.53	0.96	1.53
	[9.70]	[5.53]	[3.28]	[5.51]
Merger products	12.33	10.11	9.93	1.76
	[15.21]	[12.23]	[11.75]	[2.13]
Advertised products	5.61	3.34	2.01	3.50
	[11.95]	[6.55]	[3.69]	[6.87]
	B. Net profits $\Delta\Pi$			
Total	131,037	122,489	113,457	43,040
	[16.34]	[14.75]	[12.99]	[5.18]
Merger products	59,738	50,798	47,419	21,414
	[28.29]	[24.69]	[20.88]	[10.41]
Advertised products	107,117	97,843	88,905	39,202
	[19.11]	[16.54]	[14.10]	[6.63]
	C. Total spending			
	-185,315	-188,189	-184,936	308
	[-7.48]	[-7.57]	[-7.44]	[0.01]
	D. Consumer surplus ΔCS			
	-214,493	-198,324	-181,206	-38,889
	[-5.95]	[-5.58]	[-5.16]	[-1.09]

Note: The simulation is for 2010. Percentage changes are in brackets. For prices, we report mean changes across products in US$, while we report total changes for 2010 for profits, spending and consumer surplus in 1,000 US$.

identical to that without the merger, prices would have been lower, on average, by $2.52. However, the price increase is much larger for the products of the merged company than for other products and for products that are advertised. Columns 2 and 3 of the table show that the effect is smaller when advertising is at the 2009 level (premerger) or later after the merger (postmerger advertising of the last quarter of 2010).

The effects on profits show that a merger can lead to a profit increase for pharmaceutical firms in this market, for both merging and other companies. However, similar to the price effects, the profit increase is smaller with postmerger advertising levels than with premerger levels or with the observed levels of 2010 and even negative with those levels at the end of 2010. However, this situation does not mean that the pharmaceutical companies did not gain from the merger, as the net total effect depends on the sum of profits over the different years postmerger.

Overall and not surprisingly, prices and firm profits increase with this merger. The effect is approximately 15% for profit increase but slightly less when the level of postmerger advertising is going down. We now turn to the evaluation of the welfare effect of this merger.

4.2 Welfare evaluation of mergers

Standard merger evaluation using simulation compares consumer surplus and firm profit changes to evaluate whether it is beneficial for society (Nevo, 2000). In the case of industries where innovation plays an important role in consumer welfare, such as in the case of pharmaceuticals and health care products, the usual static tradeoff 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 the R&D activities and project development of drugs in different phases, from phases I to III. As mentioned in the Introduction, there are mixed results on this effect, and they do not seem to be identical depending on the stage of project development of drugs. We abstract from these dynamic effects on project development but account for the effect of industry profits on future innovation outcomes.

As is well known (Acemoglu and Linn, 2004; Blume-Kohout and Sood, 2013; Dubois et al., 2015), the expected future profits of pharmaceutical firms affect their incentives to invest in R&D and thus increase the rate of innovation. 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 also relax current financial constraints on investment. We can thus evaluate the dynamic effects on welfare induced by a merger due to the identification of changes in profits. As advertising strategies also modify 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 but not when they also compete in advertising. Changes in advertising strategies can not only lead firms to compete less for patients and save promotional spending but also reduce their quantity sales.

We denote by p^m the postmerger equilibrium prices and p^c the premerger (competitive) prices.

The evaluation can be performed ex post by observing the postmerger advertising choice a^m given the premerger advertising level a^c or using some ex ante prediction of postmerger advertising level with different scenarios for postmerger advertising vector a^m. Then, the change ΔCS in static consumer surplus implied by a merger is as follows:

$$\Delta CS = CS\left(\mathbf{p}_t^m, \mathbf{a}_t^m\right) - CS\left(\mathbf{p}_t^c, \mathbf{a}_t^c\right) \tag{4.1}$$

As our demand model includes a price effect that depends on product age, we cannot compute the consumer surplus using the usual closed-form solution. Instead, we search for a transfer, w, that satisfies the following compensating variation:

$$\begin{aligned} &\int \ln\left(1+\sum\nolimits_j \exp\left(\delta_{m(j)} + (\beta_i^1 + \beta^2 logage_{jt})(p_{jt}^m + w) + \gamma a_{jt}^m + \alpha \mathbf{x}_{jt} + \zeta_{ct} + \xi_{jt}\right)\right)\ \varphi\left(\beta_i\right) d\beta_i \\ &= \int \ln\left(1+\sum\nolimits_j \exp\left(\delta_{m(j)} + (\beta_i^1 + \beta^2 logage_{jt}) p_{jt}^c + \gamma a_{jt}^c + \alpha \mathbf{x}_{jt} + \zeta_{ct} + \xi_{jt}\right)\right)\ \varphi\left(\beta_i\right) d\beta_i \end{aligned} \tag{4.2}$$

The change in consumer welfare is approximated by $\Delta CS = M_t w$.

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:

$$\Delta\Pi = \Pi\left(\mathbf{p}_t^m, \mathbf{a}_t^m\right) - \Pi\left(\mathbf{p}_t^c, \mathbf{a}_t^c\right) \tag{4.3}$$

with

$$\Pi(\mathbf{p}_t, \mathbf{a}_t) = \sum\nolimits_{j=1}^{J} \left(p_{jt} - c_{jt}\right) q_{jt}(\mathbf{p}_t, \mathbf{a}_t) - a_{jt}$$

We denote by W the dynamic consumer welfare that accounts not only for 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 for the whole duration of the patent life because of the merger, then we can consider that the expected discounted profit increase is 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 then[8] as follows:

$$\Delta W = \Delta CS + \underbrace{\frac{\partial CS}{\partial I}}_{\substack{\text{Sensitivity of}\\\text{consumer surplus}\\\text{to innovation}}} \times \underbrace{\epsilon_{\Pi}^{I}}_{\substack{\text{Elasticity}\\\text{of innovation}\\\text{to profit}}} \times \underbrace{I}_{\substack{\text{Expected number}\\\text{of innovations}\\\text{per year}}} \times \underbrace{\frac{1-\beta^{L}}{1-\beta}}_{\substack{\text{Sum over } L\\\text{patent years}\\\text{discounted by } \beta}} \times \frac{\Delta\Pi}{\Pi} \tag{4.4}$$

where ΔCS comes from equation (4.1), I is the expected number of new products per year, Π is the one-year industry profit, and $\Delta\Pi$ is the one-year increase from equation (4.3).

Concerning the sensitivity of consumer surplus to innovation ($\frac{\partial CS}{\partial I}$), we need to know the expected future additional consumer surplus brought about by a future innovative drug on the market. There are several possible measures of this future expected increase in consumer surplus depending on not only the quality of new drugs but also the expectation of future price equilibrium. Indeed, an innovation also involves an additional product on the market and lower prices because of increased competition. We can assume that induced 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 brought about by current products. If equal to the mean surplus, then $\frac{\partial CS}{\partial I}$ is defined as follows:

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

If equal to the maximum among existing drugs (and equivalently for the median), then $\frac{\partial CS}{\partial I}$ is defined as follows:

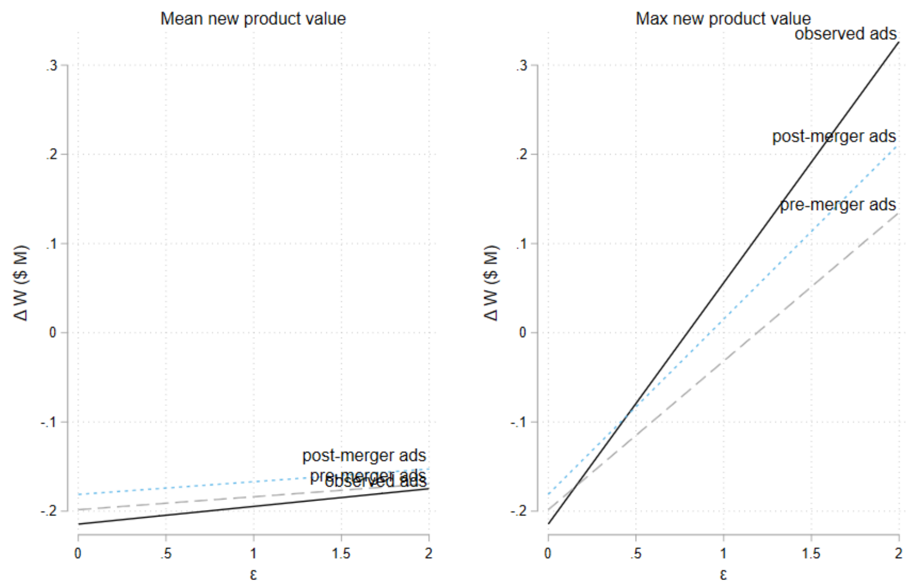
$$\frac{\partial CS}{\partial I} \equiv M_t \max_{j=1,..,J} \int \frac{1}{\beta_i}\left[\ln\left(1+\sum\nolimits_k \exp\left(\delta_{kt}+\mu_{ikt}\right)\right) - \ln\left(1+\sum\nolimits_{k\neq j}\exp\left(\delta_{kt}+\mu_{ikt}\right)\right)\right]\ \varphi\left(\beta_i\right) d\beta_i$$

Then, dynamic welfare depends on the sensitivity of innovation to industry profit. Figure 4.4 shows the dynamic welfare as a function of ϵ_{Π}^{I}, with I fixed to the observed rate of innovation in the antibiotic market (0.75; there are 8 entries of new products over the 12 years of the sample), under the different advertising levels and with the value of the new product $\frac{\partial CS}{\partial I}$ equal to either the mean (graph on the left) or the maximum (graph on the right) of the products in this market. If the innovation spurred by the higher postmerger profit

[8]Note that this formula can be used for any policy that affects the pharmaceutical drug price equilibrium, such as any change in regulation.

produces a product with a value close to the mean of the products observed, then ϵ_{Π}^{I} needs to be very high for dynamic welfare to be positive, much higher than the estimates from the literature: 0.28 (see 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 attainable 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.

Figure 4.4: *Dynamic Welfare as a Function of the Elasticity of Innovation to Profit ($I = 0.75$)*

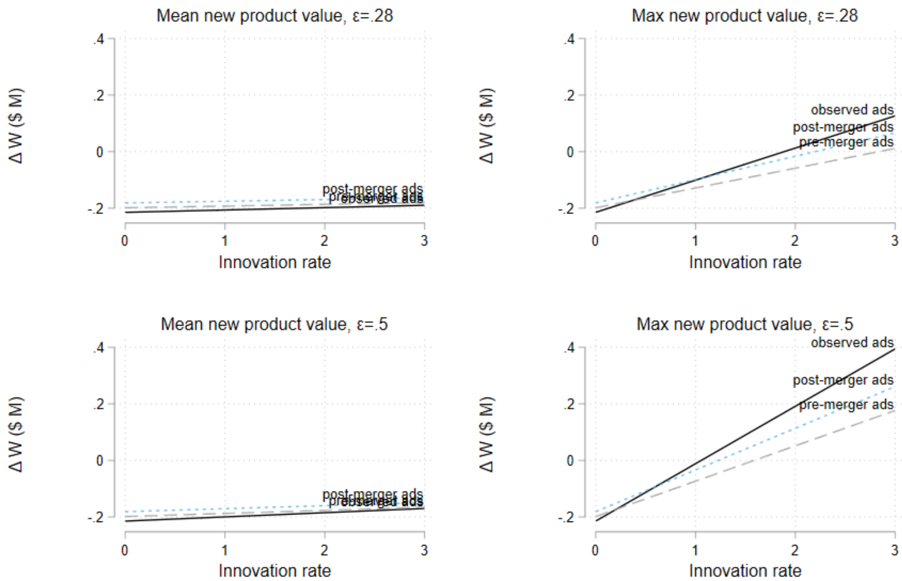


In Figure 4.5, we fix ϵ_{Π}^{I} to 0.28 and 0.5 and present ΔW as a function of the rate of innovation. At these values of the elasticity of innovation to profit, the deciding factor is still the value of the new product—at the mean value, the rate of innovation would have to be an order of magnitude higher for dynamic welfare to be positive.

Table A.11 in the Appendix shows some selected results of the dynamic welfare estimation: while the merger decreases static consumer surplus by slightly more than $200 million in 2010 and increase profits by $130 million if we keep advertising levels the same as those observed in 2010, then the dynamic welfare effect becomes weaker, namely, the consumer surplus decrease when we assume that the innovation value will be of a drug at least as good as the best one on the market during our time period. Indeed, even with a relatively small elasticity of 0.28, this effect reduces the consumer welfare cost from $212 to 126 million. With an elasticity of 0.68, in such a case, there would be no welfare cost for consumers. With the postmerger advertising level (column 3), we can see that the merger cost in terms of consumer welfare is slightly smaller, as it reduces to $119 million instead of 126.

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

Figure 4.5: *Dynamic Welfare as a Function of the Rate of Innovation*



5 Conclusions

In this study, we first show some reduced-form results across all classes of drugs of the effect of mergers on both prices and promotional spending. We show that prices indeed can increase but that advertising spending can also decrease, raising some alerts as to the validity of such evaluations based only on prices. Then, studying the case of the merger between Pfizer and Wyeth, who overlapped activities on 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. We find that the counterfactual simulation of the merger effect on prices is much smaller when we take into account the changes in the advertising decisions of firms. This finding calls for further research into the modeling of the dynamic decisions of firms that compete both in prices 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). A pure ex ante evaluation would have to be carried out to simulate all the possible postmerger advertising decisions. Finally, we perform some welfare evaluation, showing that advertising level reductions tend to diminish the negative impact in terms of consumer surplus. We also show how to evaluate the effects of the additional expected benefits on innovation that will be generated by increased industry profit.

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A Appendix

A.1 Price measurement

The IMS data allows us to observe quarterly 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 may affect the computed prices especially for products entering the market during the sample time period. Typically, at entry, when regular stocks are not yet built, sales can be large but quantities dispensed to patients 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, towards the end of our sample time period, average rebates were around 32% but varied widely between ATC4 classes and could be as low as 7% and as high as 64%, moreover, they change over time. As 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 on the current and two previous quarters). At the product entry we use a three quarters smoothed price using forward revenues and quantities instead of lagged values.

Concerning the rebates, the IMS data provide sales values and volumes for nine different channels: clinics, food-stores, long term care hospital, drugstores, HMO, Mail services, Federal facilities, home health care and non federal facilities. Figure A.1 shows the dynamics of list prices (after the smoothing described above) in different distribution channels for the example of two high-price drugs. We notice that in general, clinics and federal facilities both have lower list prices and experience less of an increase in list prices over time, while food stores and drug stores have usually the highest prices. This pattern is quite common to all drugs. We thus use for each drug 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 rebate that must be used if prices are equal to the net price in these two channels:

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

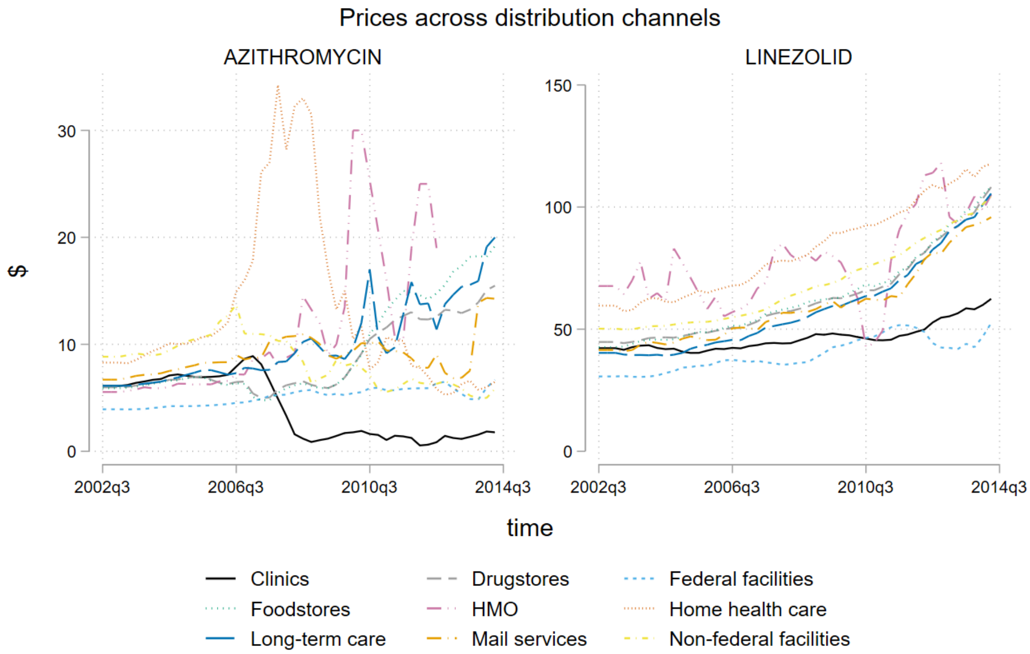


Figure A.1: *Variation of list prices across distribution channels and over time.*

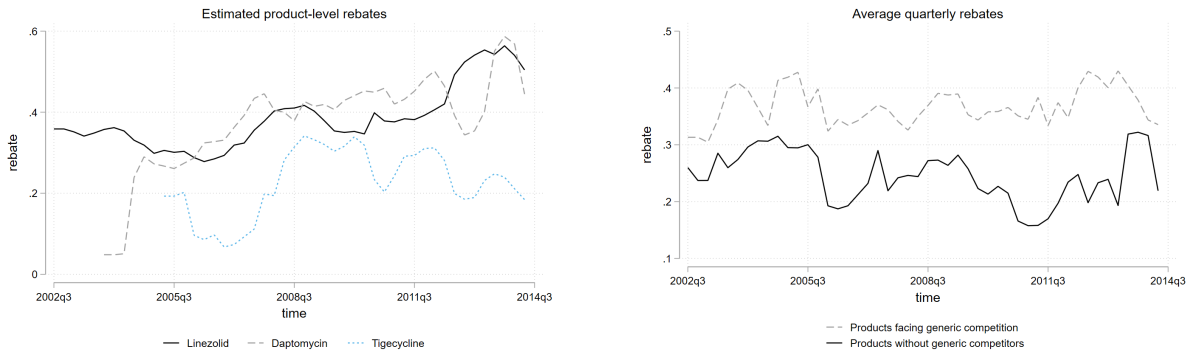
where y_{djt} is the revenue from channel d, q_{djt} the quantity sold through channel d, and J_t is the set of products marketed at time t.

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. Remark that rebates are relatively stable during that time period. Kakani et al. (2020) found growing rebates over time starting in 2012. Figure A.2b shows the estimated average rebate $1 - b_t$ for products facing generic competition and those who don't. 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.

Figure A.2: *Rebate estimates*



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

A.2 Additional Difference-in-Difference results

Table A.1: *Composition of the difference in difference 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.2: *Advertising Spending Changes after a Merger (only advertised products)*

VARIABLES	(1) log (a_{jt})	(2) log (a_{jt})	(3) log (a_{jt})	(4) log (a_{jt})	(5) log (a_{jt})	(6) log (a_{jt})
Treated (β_m)	-0.187		-0.228			
	(0.158)		(0.158)			
Treated, competitors (β_c)	0.248		0.266*			
	(0.127)		(0.128)			
Post merger (γ_m)	-0.054	0.164				
	(0.089)	(0.087)				
Post merger, competitors (γ_c)	0.046	0.141*				
	(0.056)	(0.056)				
Post-merger, short term (γ_m^{short})			0.065	0.148*		
			(0.079)	(0.073)		
Post merger, long term (γ_m^{long})			-0.045	0.213*		
			(0.098)	(0.096)		
Post merger, short term, competitors (γ_c^{short})			0.072	0.085		
			(0.050)	(0.050)		
Post merger, long term, competitors (γ_c^{long})			-0.015	0.110		
			(0.066)	(0.067)		
Branded × Treated ($\beta_m^{branded}$)					0.220	
					(0.197)	
Generic × Treated ($\beta_m^{generic}$)					-0.808***	
					(0.202)	
Branded × Treated, competitors ($\beta_c^{branded}$)					0.731***	
					(0.181)	
Generic × Treated, competitors ($\beta_c^{generic}$)					0.053	
					(0.145)	
Branded × Post merger ($\gamma_m^{branded}$)					0.127	0.389***
					(0.105)	(0.098)
Generic × Post merger ($\gamma_m^{generic}$)					-0.677***	-0.404*
					(0.157)	(0.162)
Branded × Post merger, competitors ($\gamma_c^{branded}$)					0.163**	0.212***
					(0.059)	(0.061)
Generic × Post merger, competitors ($\gamma_c^{generic}$)					-0.159	0.001
					(0.099)	(0.093)
Observations	60,214	60,199	60,214	60,199	60,214	60,199
R-squared	0.750	0.798	0.750	0.798	0.750	0.798
Controls	✓	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓	✓
ATC4 FE	✓		✓		✓	
Molecule FE	✓		✓		✓	
Product FE		✓		✓		✓

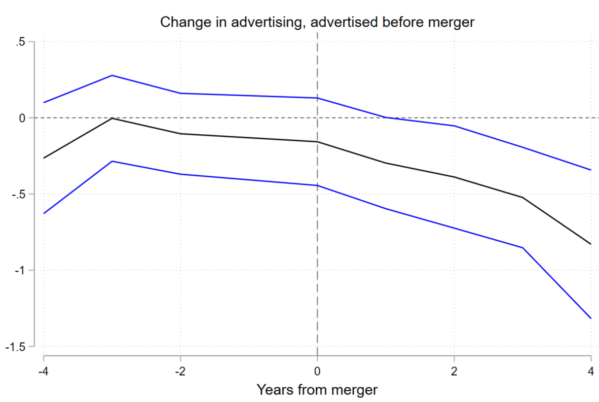
*Note: Control variables are a branded/generic dummy, the age of the drug, dummy variables for each of the first quarters after entry, the time left to patent expiration, an off patent dummy, the number of companies in the same ATC4 class, the number of branded and generic products in the same ATC4 class. Standard errors are clustered at the ATC3*quarter level. *** for* $p < 0.001$, *** for* $p < 0.01$, ** for* $p < 0.05$. *The number of observations is lower than in the case of the price regression because advertising is available only starting in 2005.*

Table A.3: *Changes in sales volumes, advertising volumes and advertising prices*

VARIABLES	(1) log (q_{jt})	(2) log (q_{jt})	(3) log (q^{ad}_{jt})	(4) log (q^{ad}_{jt})	(5) log (p^{ad}_{jt})
Treated (β_m)	1.030***		0.444***		0.008
	(0.059)		(0.070)		(0.010)
Treated, competitors (β_c)	1.146***		0.066**		0.004
	(0.042)		(0.024)		(0.007)
Post merger (γ_m)	-0.317***	-0.074	-0.575***	-0.044	0.012*
	(0.061)	(0.040)	(0.078)	(0.060)	(0.006)
Post merger, competitors (γ_c)	-0.366***	-0.052*	0.008	0.018	-0.004
	(0.023)	(0.020)	(0.018)	(0.015)	(0.004)
Observations	467,028	466,692	371,371	370,479	31,115
R-squared	0.436	0.886	0.644	0.862	0.310
Controls	✓	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓	✓
ATC4 FE	✓		✓		✓
Molecule FE	✓		✓		✓
Product FE		✓		✓	

*Note: q^{ad}_{jt} is advertising quantity and p^{ad}_{jt} is advertising price. Control variables are a branded/generic dummy, the age of the drug, dummy variables for each of the first quarters after entry, the time left to patent expiration, an off patent dummy, the number of companies in the same ATC4 class, the number of branded and generic products in the same ATC4 class. Standard errors are clustered at the ATC3*quarter level. *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.*

Figure A.3: *Event study estimates of the merger effect*



Note: Point estimates and 95% confidence intervals (Sun and Abraham, 2021)

A.3 Difference-in-difference results on gross prices

Table A.4 shows the same regression on prices as in Table 2.3 except that it uses non discounted gross prices that do not account for rebates.

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

VARIABLES	(1) $\log(p_{jt}^{norebate})$	(2) $\log(p_{jt}^{norebate})$	(3) $\log(p_{jt}^{norebate})$
Treated (β_m)	0.205***	0.212***	
	(0.023)	(0.022)	
Treated, competitors (β_c)	-0.146***	-0.150***	
	(0.016)	(0.016)	
Post merger (γ_m)	0.048		
	(0.031)		
Post merger, competitors (γ_c)	0.028		
	(0.018)		
Post-merger, short term (γ_m^{short})		0.054	
		(0.032)	
Post merger, long term (γ_m^{long})		0.020	
		(0.033)	
Post merger, short term, competitors (γ_c^{short})		0.034*	
		(0.015)	
Post merger, long term, competitors (γ_c^{long})		0.029	
		(0.020)	
Branded × Treated ($\beta_m^{branded}$)			0.025
			(0.032)
Generic × Treated ($\beta_m^{generic}$)			0.288***
			(0.032)
Branded × Treated, competitors ($\beta_c^{branded}$)			-0.157***
			(0.029)
Generic × Treated, competitors ($\beta_c^{generic}$)			-0.138***
			(0.018)
Branded × Post merger ($\gamma_m^{branded}$)			0.070*
			(0.029)
Generic × Post merger ($\gamma_m^{generic}$)			0.050
			(0.048)
Branded × Post merger, competitors ($\gamma_c^{branded}$)			0.248***
			(0.027)
Generic × Post merger, competitors ($\gamma_c^{generic}$)			-0.026
			(0.020)
Observations	467,028	467,028	467,028
R-squared	0.789	0.789	0.789
Controls	✓	✓	✓
Quarter FE	✓	✓	✓
ATC4 FE	✓	✓	✓
Molecule FE	✓	✓	✓

*Note: Control variables are a branded/generic dummy, the age of the drug, dummy variables for each of the first quarters after entry, the time left to patent expiration, an off patent dummy, the number of companies in the same ATC4 class, the number of branded and generic products in the same ATC4 class. Standard errors are clustered at the ATC3*quarter level. *** for* $p < 0.001$, *** for* $p < 0.01$, ** for* $p < 0.05$.

Table A.5: *Sales Volume Changes after a Merger*

VARIABLES	(1) $\log(q_{jt})$	(2) $\log(q_{jt})$	(3) $\log(q_{jt})$
Treated (β_m)	1.029***	1.000***	
	(0.060)	(0.059)	
Treated, competitors (β_c)	1.148***	1.080***	
	(0.042)	(0.043)	
Post merger (γ_m)	-0.330***		
	(0.061)		
Post merger, competitors (γ_c)	-0.367***		
	(0.023)		
Post-merger, short term (γ_m^{short})		-0.203**	
		(0.066)	
Post merger, long term (γ_m^{long})		-0.323***	
		(0.067)	
Post merger, short term, competitors (γ_c^{short})		-0.204***	
		(0.022)	
Post merger, long term, competitors (γ_c^{long})		-0.268***	
		(0.025)	
Branded × Treated ($\beta_m^{branded}$)			0.650***
			(0.054)
Generic × Treated ($\beta_m^{generic}$)			1.311***
			(0.070)
Branded × Treated, competitors ($\beta_c^{branded}$)			0.834***
			(0.051)
Generic × Treated, competitors ($\beta_c^{generic}$)			1.236***
			(0.043)
Branded × Post merger ($\gamma_m^{branded}$)			-0.297***
			(0.051)
Generic × Post merger ($\gamma_m^{generic}$)			-0.125
			(0.086)
Branded × Post merger, competitors ($\gamma_c^{branded}$)			-0.627***
			(0.037)
Generic × Post merger, competitors ($\gamma_c^{generic}$)			-0.315***
			(0.027)
Observations	467,028	467,028	467,028
R-squared	0.435	0.435	0.436
Controls	✓	✓	✓
Quarter FE	✓	✓	✓
ATC4 FE	✓	✓	✓
Molecule FE	✓	✓	✓

*Note: Control variables are a branded/generic dummy, the age of the drug, dummy variables for each of the first quarters after entry, the time left to patent expiration, an off patent dummy, the number of companies in the same ATC4 class, the number of branded and generic products in the same ATC4 class. Standard errors are clustered at the ATC3*quarter level. *** for* $p < 0.001$, ** *for* $p < 0.01$, * *for* $p < 0.05$.

A.4 Additional Descriptive Statistics

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

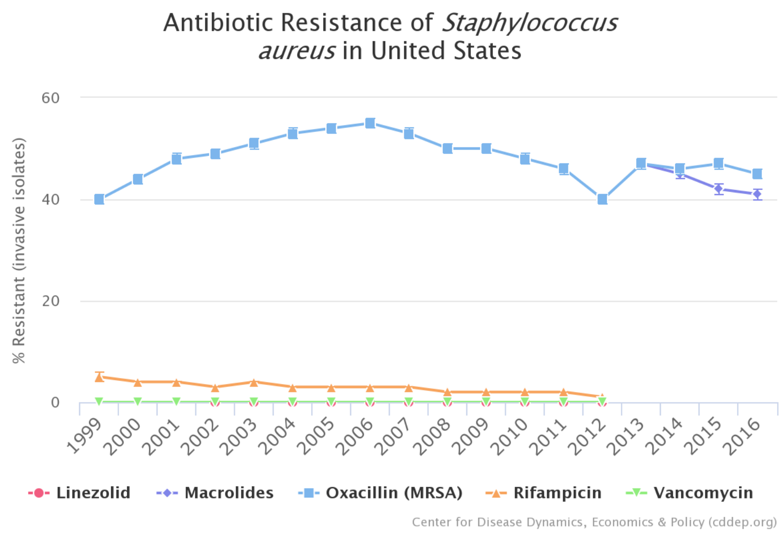


Figure A.5: *Advertising spending for molecules with the highest spending in 2010*

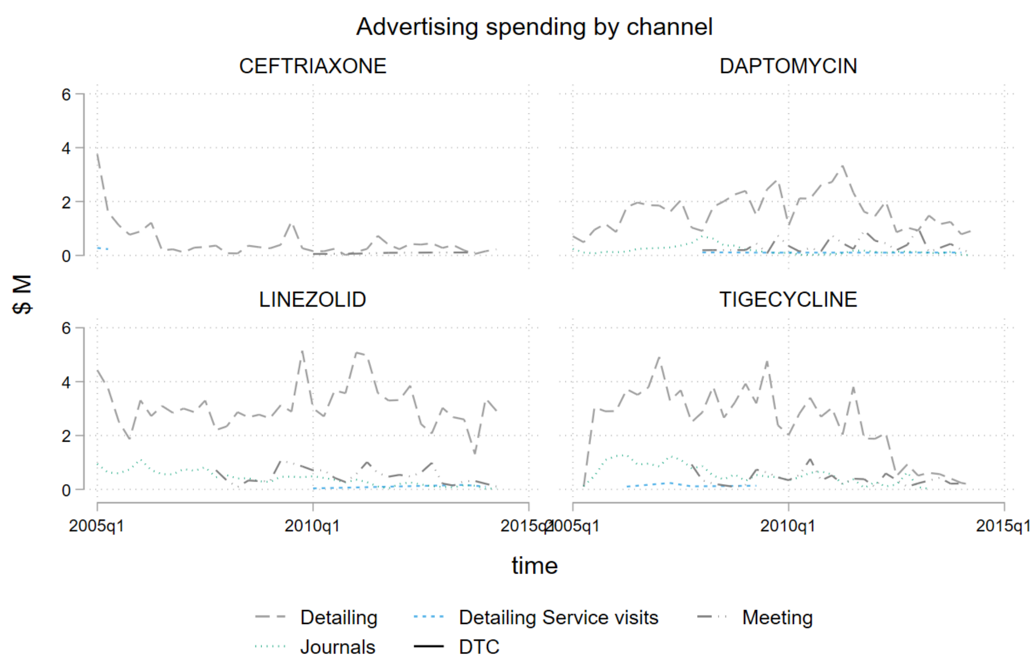
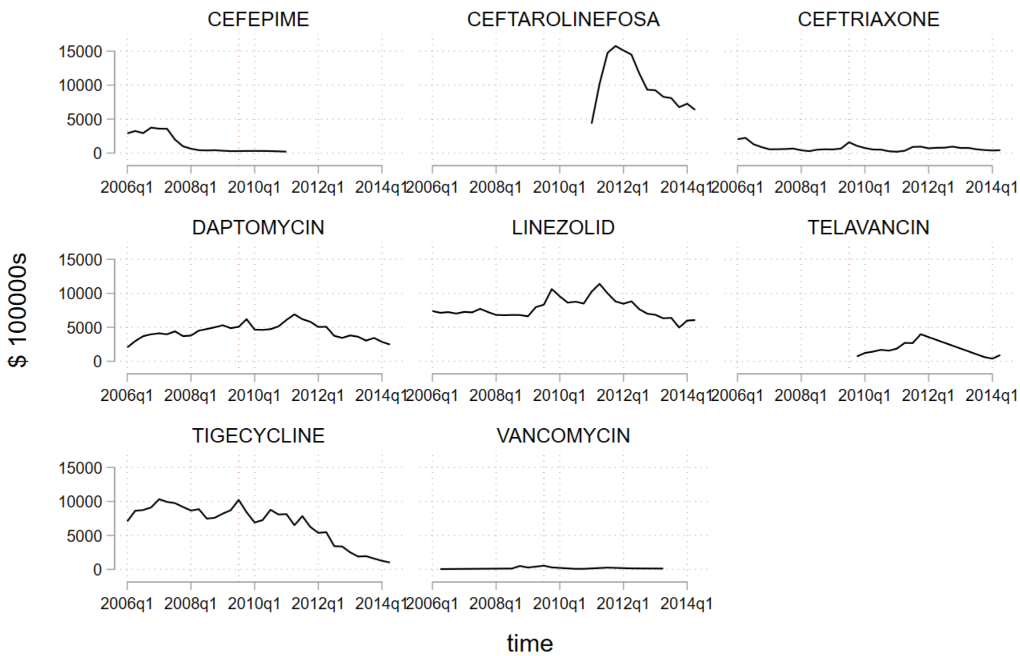


Figure A.6: *Advertising stocks by product (with quarterly discount $\delta = 0.5$)*



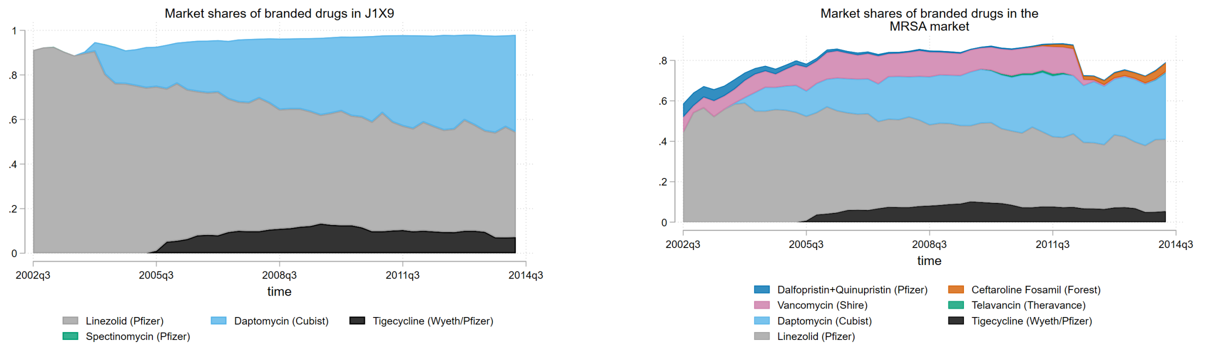
Note: Stocks use quarterly decay parameter $\delta = 0.5$. Tigecycline belongs to Wyeth until the merger and then Pfizer. Linezolid is the molecule of Zyvox.

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 this J1X9 class, Pfizer marketed its molecule Linezolid under the brand name Zyvox, and Wyeth marketed Tigecycline under the brand name Tygacil. Figure A.7 shows the evolution of market shares of branded drugs in J1X9. 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 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. Still, figure A.8 shows that there is an overlap in the approved indications of Tigecycline and Linezolid and other molecules in J1X9. Of these, both the FTC and European Commission considered Methicillin-Resistant Staphylococcus Aureus (MRSA) infections to be the most prominent one.

Then, we define the market of antibiotics used for the treatment of MRSA following the medical literature (Choo and Chambers, 2016; Welte and Pletz, 2010), which gives us 7 molecules marketed in the US during

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



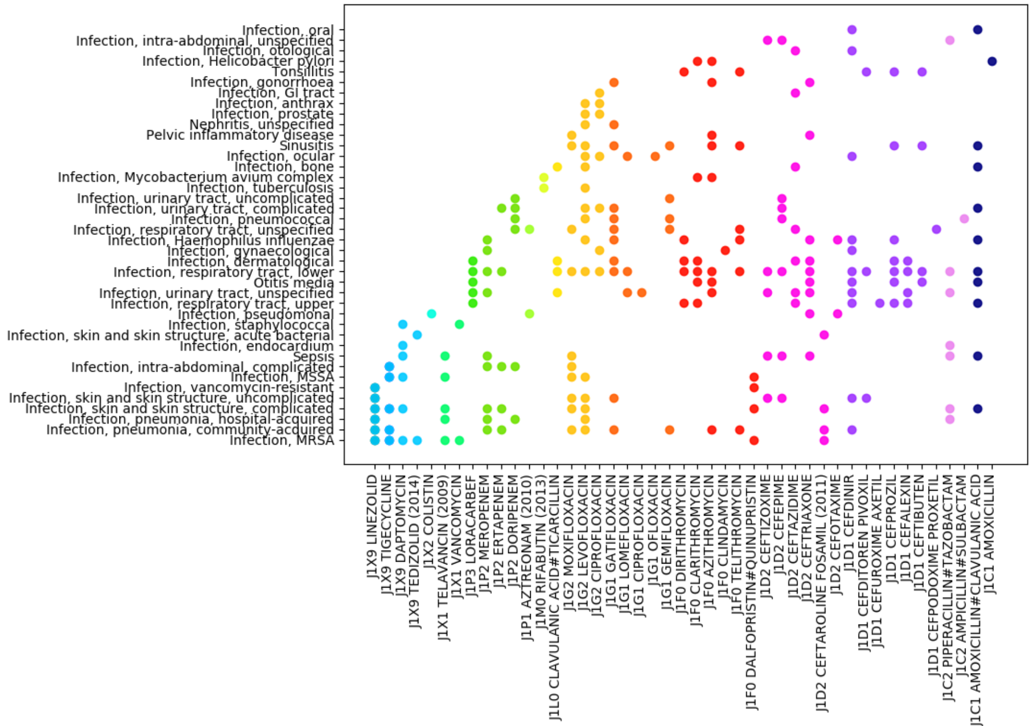
(a) *Market shares of branded drugs in J1X9 (shares of total revenue). Spectinomycin is only present in 2003 and 2004 and has very small shares. The missing area corresponds to the market share of generics of the molecule Bacitracin.*

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

our sample time period. Figure A.7b shows the evolution of market shares of the branded products in this market. We then also include the antibiotic classes of these molecules [9] and the whole J1X ATC3 class to account for competition in other disease indications. 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, Cefepime in 2007). Four of the branded drugs and all of the generics were never advertised.

[9] 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*



Note: Vertical list is for indications and 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 Marginal Costs Estimates

Table A.6: *Marginal cost estimates*

	Cost	Price	Market share
Cefazolin (generic)	0.004	2.237	19.80
Vancomycin (generic)	8.066	11.121	17.94
Ceftriaxone (generic)	2.977	5.642	16.87
Zyvox	46.210	72.310	6.44
Vancocin	15.596	19.843	5.18
Cefepime (generic)	7.790	11.014	4.72
Bacitracin (generic)	5.932	8.728	2.99
Maxipime	10.296	13.724	1.93
Cefoxitin (generic)	8.793	11.884	1.85
Tygacil	42.332	59.195	1.48
CefazolinGlucose (generic)	5.596	8.597	1.40
Cubicin	55.118	219.784	1.35
Tazicef	3.426	6.068	0.88
Fortum	6.117	8.942	0.78
PolymyxinB (generic)	7.583	10.535	0.77
Apatef	13.723	17.218	0.74
Teflaro	37.895	44.530	0.61
Colistin (generic)	16.641	20.550	0.54
Cefuroxime (generic)	3.426	5.948	0.54
Ceftazidime (generic)	9.420	12.813	0.54
Claforan	2.636	5.154	0.38
Cefotaxime (generic)	2.705	5.157	0.34
Cefazolin	0.172	2.419	0.33
Cefepime	8.864	12.233	0.32
Ceftriaxone	8.815	12.163	0.30
Cefotetan (generic)	14.472	18.527	0.28
Zinacef	4.131	6.752	0.21
Rocephin	27.485	32.345	0.14
Epocelin	9.202	12.187	0.08
Vibativ	102.641	171.800	0.05
Synercid	113.504	148.201	0.05
Colymycinm	20.472	24.731	0.04

Note: Not shown are two products for which we obtained negative costs: Ancef, the cheapest product in the market, with the mean price of 0.93, mean cost -1.27 and mean market share of 0.5% and Mefoxin, marketed only in the first quarter of 2006 with a market share of 0.01%.

A.7 Demand Estimation Robustness Checks

Table A.7: *Demand Estimates 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	-0.36723	-0.37600	-0.35306	-0.45603	-0.34380	-0.44655
		(0.04057)	(0.04217)	(0.03767)	(0.07701)	(0.03583)	(0.07930)
	σ	0.14754	0.15406	0.13982	0.17788	0.13491	0.17606
		(0.02047)	(0.02144)	(0.01895)	(0.03419)	(0.01823)	(0.03579)
a_{jt}^{κ}	γ	0.00074	0.00051	0.00013	0.10102	0.00000	0.07128
		(0.00019)	(0.00013)	(0.00005)	(0.03452)	(0.00000)	(0.02774)
log(Age) × price		0.00780	0.00672	0.01079	0.01354	0.00922	0.01233
		(0.00471)	(0.00477)	(0.00435)	(0.00474)	(0.00453)	(0.00467)

Note: Main parameters of BLP demand estimates under variants. Specification uses additive effect of advertising γa_{jt}^{κ} in mean utility equation3.1. 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 same products in France, Canada, India, Turkey, Italy), and the price of a unit of advertising.

Table A.8: *Demand Estimates Robustness Checks: Market size and outside good*

Market Size		rM	rM	M	M	My	My
Outside Good Share		15%	25%	15%	25%	15%	25%
Price	β	-0.36723	-0.37870	-0.36453	-0.37532	-0.37158	-0.37949
		(0.04057)	(0.04141)	(0.03965)	(0.04082)	(0.04064)	(0.04104)
	σ	0.14754	0.15277	0.14610	0.15089	0.15050	0.15314
		(0.02047)	(0.02100)	(0.01998)	(0.02071)	(0.02068)	(0.02071)
Advertising stock	γ	0.00074	0.00073	0.00073	0.00072	0.00072	0.00070
		(0.00019)	(0.00018)	(0.00019)	(0.00018)	(0.00019)	(0.00018)
log(Age) × price		0.00780	0.00655	0.00766	0.00657	0.00677	0.00631
		(0.00471)	(0.00479)	(0.00462)	(0.00474)	(0.00477)	(0.00472)

Note: Main parameters of BLP demand estimates under variants. M is the observed market size, My is the max market size observed within a (calendar) year, rM is the rolling mean of the market sizes of the last 4 quarters. Columns 1,3,5 assume 15% outside option size, columns 2,4,6 25%. 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 same products in France, Canada, India, Turkey, Italy), and the price of a unit of advertising.

Table A.9: *Demand Estimates Robustness Checks: Advertising spillovers*

		(1)	(2)	(3)
Price	β	-0.317171	-0.313850	-0.312024
		(0.031796)	(0.031331)	(0.031079)
	σ	0.117997	0.116008	0.115236
		(0.015297)	(0.015138)	(0.015086)
Own advertising stock	γ	0.000510	0.000513	0.000519
		(0.000146)	(0.000146)	(0.000146)
log(Age) $\times$ price		0.011437	0.011762	0.011712
		(0.004194)	(0.004192)	(0.004189)
Advertising stock of all others		-0.000016		-0.000042
		(0.000012)		(0.000019)
Advertising stock of others in ATC4			0.000005	0.000063
			(0.000023)	(0.000036)

Note: Main parameters of BLP demand estimates under variants. 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 same products in France, Canada, India, Turkey, Italy), and the price of a unit of advertising. The two variables accounting for competitors' advertising are lagged one period

Table A.10: *Demand Estimates Robustness Checks with or without rebate*

		No rebate	With rebate
Price	β	-0.28088	-0.36723
		(0.02807)	(0.04057)
	σ	0.12509	0.14754
		(0.01566)	(0.02047)
Advertising stock	γ	0.00072	0.00074
		(0.00018)	(0.00019)
log(Age) $\times$ price		-0.00040	0.00780
		(0.00340)	(0.00471)

Note: Main parameters of BLP demand estimates under variants. 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 same products in France, Canada, India, Turkey, Italy), and the price of a unit of advertising.

A.8 Additional counterfactual results

Table A.11: *Counterfactuals with Dynamic Welfare Evaluation Results (2010)*

	Merger effect			**Advertising effect**
	Observed advertising	Pre-merger advertising	Post-merger advertising	
	1.	2.	3.	4.
D. Consumer Surplus ΔCS				
	-214,493	-198,324	-181,206	-38,888
	[-5.95]	[-5.58]	[-5.16]	[-1.09]
E. Dynamic Welfare ΔW				
Mean value of new product				
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-208,029	-193,663	-177,281	-37,299
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-202,950	-190,000	-174,198	-36,049
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-207,441	-193,366	-177,221	-37,146
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-201,900	-189,471	-174,091	-35,778
Median value of new product				
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-213,391	-197,247	-180,300	-38,581
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-212,525	-196,400	-179,588	-38,339
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-213,527	-197,392	-180,434	-38,561
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-212,768	-196,660	-179,828	-38,304
Max value of new product				
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-126,373	-144,794	-119,029	-9,599
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-57,135	-102,735	-70,175	13,414
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-125,645	-134,077	-107,801	-16,313
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-55,836	-83,596	-50,126	1,425
F. ϵ solving $\Delta W = 0$				
Mean value of new product				
$\left(\frac{\partial CS}{\partial I}\right)^{merge}$	9.29	11.91	12.93	
$\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	8.52	11.20	12.73	
Median value of new product				
$\left(\frac{\partial CS}{\partial I}\right)^{merge}$	54.50	51.54	55.99	
$\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	62.16	59.57	65.78	
Max value of new product				
$\left(\frac{\partial CS}{\partial I}\right)^{merge}$	0.68	1.04	0.82	
$\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	0.68	0.86	0.69	

Note: Simulation for the year 2010. Percentage changes are in brackets. For prices, we report mean changes across products in US\$, while we report total changes for 2010 for profits, spending and consumer surplus in 1,000 US\$. Discount factor is set to $\beta = 0.99$ and expected patent duration to $L = 15$ years.

A.9 Results from a model with advertising spillover

In this section, we present results from our estimation procedure using the model in column (3) of table A.9 which includes the effects of lagged advertising stock of other products in the whole market and in the ATC4 class.

Figure A.9: *Estimated Margins for Merger's Products and Observed Advertising*

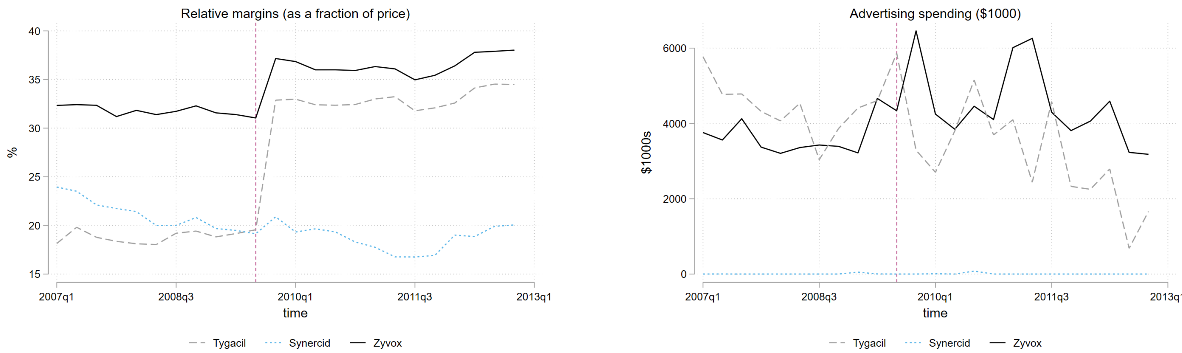


Table A.12: *Marginal cost estimates*

	Cost	Price	Market share
Cefazolin (generic)	-0.490	2.237	19.80
Vancomycin (generic)	7.723	11.121	17.94
Ceftriaxone (generic)	2.110	5.642	16.87
Zyvox	46.564	72.310	6.44
Vancocin	15.410	19.843	5.18
Cefepime (generic)	6.996	11.014	4.72
Bacitracin (generic)	5.394	8.728	2.99
Maxipime	9.867	13.724	1.93
Cefoxitin (generic)	8.329	11.884	1.85
Tygacil	42.072	59.195	1.48
CefazolinGlucose (generic)	5.224	8.597	1.40
Cubicin	87.248	219.784	1.35
Tazicef	2.896	6.068	0.88
Fortum	5.630	8.942	0.78
PolymyxinB (generic)	7.066	10.535	0.77
Apatef	12.219	17.218	0.74
Teflaro	37.950	44.530	0.61
Colistin (generic)	16.047	20.550	0.54
Cefuroxime (generic)	2.872	5.948	0.54
Ceftazidime (generic)	7.815	12.813	0.54
Ancef	-1.769	0.936	0.51
Claforan	2.153	5.154	0.38
Cefotaxime (generic)	2.064	5.157	0.34
Cefazolin	-0.329	2.419	0.33
Cefepime	8.415	12.233	0.32
Ceftriaxone	7.900	12.163	0.30
Cefotetan (generic)	13.960	18.527	0.28
Zinacef	3.631	6.752	0.21
Rocephin	27.486	32.345	0.14
Epocelin	8.998	12.187	0.08
Vibativ	166.767	171.800	0.05
Synercid	118.676	148.201	0.05
Colymycinm	19.789	24.731	0.04
Mefoxin		0.845	0.01

Note: In the last two quarters of 2014, Vibativ's estimated cost is larger than its price, and consequently the margin is set to 0.

Table A.13: *Static Counterfactuals 2010*

	Merger effect			**Advertising effect**
	Observed advertising	Pre-merger advertising	Post-merger advertising	
	1.	2.	3.	4.
		A. Prices (mean across products)		
All	0.83	1.32	1.31	-0.03
	[2.77]	[4.47]	[4.43]	[-0.11]
Pfizer	9.11	13.36	13.48	-0.03
	[10.59]	[15.93]	[16.07]	[-0.04]
Advertised products	1.74	2.90	2.87	-0.07
	[3.20]	[5.40]	[5.34]	[-0.14]
		B. Net profits $\Delta\Pi$		
Total	89,061	321,397	322,389	17,987
	[10.39]	[31.54]	[31.09]	[1.76]
Pfizer	33,569	180,536	182,445	14,286
	[13.82]	[36.56]	[35.91]	[2.89]
Advertised products	67,838	214,697	214,973	14,893
	[12.15]	[30.13]	[29.55]	[2.09]
		C. Total spending		
	-160,187	-531,392	-533,428	30,120
	[-6.57]	[-13.97]	[-13.92]	[0.79]

Postmerger advertising level is 2010q4 level

Table A.14: *Dynamic Counterfactuals 2010*

	Merger effect			Advertising effect
	Observed advertising	Pre-merger advertising	Post-merger advertising	
	1.	2.	3.	4.
D. Consumer Surplus ΔCS				
	-156,371	-607,992	-602,950	28,889,897
	[-0.45]	[-0.19]	[-0.17]	[8.97]
E. Dynamic Welfare ΔW				
Mean value of new product				
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-95,470	-303,949	-304,729	28,905,231
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-47,620	-65,059	-70,413	28,917,280
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-95,791	-331,417	-332,874	28,905,376
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-48,192	-114,109	-120,671	28,917,537
Median value of new product				
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-155,441	-607,992	-602,950	28,889,897
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-154,709	-607,992	-602,950	28,889,897
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-155,562	-607,992	-602,950	28,889,897
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-154,926	-607,992	-602,950	28,889,897
Max value of new product				
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	1,823,835	7,001,288	6,796,024	29,304,516
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	3,379,710	12,980,008	12,609,504	29,630,288
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	1,794,681	6,897,914	6,699,712	29,309,957
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	3,327,650	12,795,411	12,437,518	29,640,004
F. ϵ solving $\Delta W = 0$				
Mean value of new product				
$\left(\frac{\partial CS}{\partial I}\right)^{merge}$	0.72	0.56	0.57	
$\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	0.72	0.62	0.63	
Median value of new product				
$\left(\frac{\partial CS}{\partial I}\right)^{merge}$	47.05			
$\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	54.11			
Max value of new product				
$\left(\frac{\partial CS}{\partial I}\right)^{merge}$	0.02	0.02	0.02	
$\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	0.02	0.02	0.02	

Postmerger advertising level is 2010q4 level

A.10 Results from a model with generic collusion

In this section, we present results from our baseline model, estimated without applying the correction described in Section A.11, which accounts for the case of generic producers colluding.

Table A.15: *Marginal cost estimates*

	Cost	Price	Market share
Cefazolin (generic)	-0.870	2.237	19.80
Vancomycin (generic)	7.166	11.121	17.94
Ceftriaxone (generic)	2.326	5.642	16.87
Zyvox	46.210	72.310	6.44
Vancocin	15.596	19.843	5.18
Cefepime (generic)	7.627	11.014	4.72
Bacitracin (generic)	5.859	8.728	2.99
Maxipime	10.296	13.724	1.93
Cefoxitin (generic)	8.738	11.884	1.85
Tygacil	42.332	59.195	1.48
CefazolinGlucose (generic)	5.596	8.597	1.40
Cubicin	55.118	219.784	1.35
Tazicef	3.426	6.068	0.88
Fortum	6.117	8.942	0.78
PolymyxinB (generic)	7.566	10.535	0.77
Apatef	13.723	17.218	0.74
Teflaro	37.895	44.530	0.61
Colistin (generic)	16.606	20.550	0.54
Cefuroxime (generic)	3.412	5.948	0.54
Ceftazidime (generic)	9.401	12.813	0.54
Ancef	-1.268	0.936	0.51
Claforan	2.636	5.154	0.38
Cefotaxime (generic)	2.696	5.157	0.34
Cefazolin	0.172	2.419	0.33
Cefepime	8.864	12.233	0.32
Ceftriaxone	8.815	12.163	0.30
Cefotetan (generic)	14.462	18.527	0.28
Zinacef	4.131	6.752	0.21
Rocephin	27.485	32.345	0.14
Epocelin	9.202	12.187	0.08
Vibativ	102.641	171.800	0.05
Synercid	113.504	148.201	0.05
Colymycinm	20.472	24.731	0.04
Mefoxin	-1.184	0.845	0.01

Note: In the last two quarters of 2014, Vibativ's estimated cost is larger than its price, and consequently the margin is set to 0.

Figure A.10: *Estimated Margins for Merger's Products and Observed Advertising*

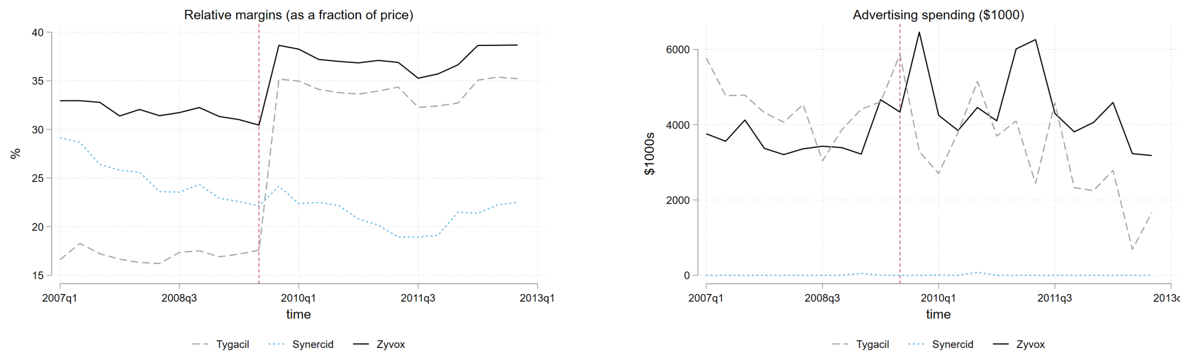


Table A.16: *Static Counterfactuals 2010*

	Merger effect			**Advertising effect**
	Observed advertising	Pre-merger advertising	Post-merger advertising	
	1.	2.	3.	4.
A. Prices (mean across products)				
All	0.84	1.54	0.96	1.53
	[2.87]	[5.55]	[3.29]	[5.51]
Pfizer	9.79	10.11	9.92	1.76
	[11.48]	[12.22]	[11.74]	[2.13]
Advertised products	1.72	3.33	2.01	3.50
	[3.17]	[6.54]	[3.68]	[6.87]
B. Net profits $\Delta\Pi$				
Total	113,271	127,525	118,494	43,885
	[12.42]	[14.43]	[12.78]	[4.97]
Pfizer	45,930	51,017	47,641	21,460
	[19.03]	[24.83]	[21.00]	[10.45]
Advertised products	84,841	98,217	89,291	39,275
	[13.83]	[16.62]	[14.17]	[6.65]
C. Total spending				
	-178,711	-186,980	-183,778	526
	[-7.27]	[-7.53]	[-7.40]	[0.02]
D. Consumer Surplus ΔCS				
	-174,834	-200,121	-183,050	-39,185
	[-4.99]	[-5.63]	[-5.21]	[-1.10]

Postmerger advertising level is 2010q4 level

Table A.17: *Dynamic Counterfactuals 2010*

	Merger effect			Advertising effect
	Observed advertising	Pre-merger advertising	Post-merger advertising	
	1.	2.	3.	4.
D. Consumer Surplus ΔCS				
	-174,834	-200,120	-183,050	-39,185
	[-4.99]	[-5.63]	[-5.21]	[-1.10]
E. Dynamic Welfare ΔW				
Mean value of new product				
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-170,498	-195,558	-179,189	-37,660
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-167,091	-191,973	-176,155	-36,462
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-170,509	-195,265	-179,127	-37,514
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-167,111	-191,449	-176,045	-36,201
Median value of new product				
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-173,980	-199,067	-182,159	-38,892
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-173,309	-198,239	-181,458	-38,661
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-174,099	-199,213	-182,295	-38,873
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-173,522	-198,499	-181,701	-38,627
Max value of new product				
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-100,641	-147,741	-121,882	-11,136
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{merge}$	-42,347	-106,586	-73,822	10,903
$\epsilon = 0.28$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-90,394	-137,310	-110,896	-17,570
$\epsilon = 0.5$, $\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	-24,047	-87,958	-54,205	-587
F. ϵ solving $\Delta W = 0$				
Mean value of new product				
$\left(\frac{\partial CS}{\partial I}\right)^{merge}$	11.29	12.28	13.27	
$\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	11.32	11.54	13.07	
Median value of new product				
$\left(\frac{\partial CS}{\partial I}\right)^{merge}$	57.30	53.19	57.51	
$\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	66.62	61.71	67.88	
Max value of new product				
$\left(\frac{\partial CS}{\partial I}\right)^{merge}$	0.66	1.07	0.84	
$\left(\frac{\partial CS}{\partial I}\right)^{nomerge}$	0.58	0.89	0.71	

Postmerger advertising level is 2010q4 level

A.11 Generics aggregation

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

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

With the random coefficient logit model, we have

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

because we assume generics are identical, consumers have identical preferences, and as they have the same price, they have equal market shares ($p_{jkt} = p_{jk't} = p_{jt}$, $s_{ijkt} = s_{ijk't} = \frac{1}{K(j)} s_{ijt}$). Then,

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

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

and for j' non generic

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

and for j' generic (with $K(j')$ generics of j')

$$\begin{aligned}
\frac{\partial s_{jkt}}{\partial p_{j'k't}} &= \int \alpha_i s_{ijkt} s_{ij'k't} dF\left(\alpha_i\right) = \frac{1}{K(j)K(j')} \int \alpha_i s_{ijt} s_{ij't} dF\left(\alpha_i\right) \\
\frac{\partial s_{jkt}}{\partial p_{j't}} &= \sum\nolimits_{k'=1}^{K(j')} \frac{\partial s_{jkt}}{\partial p_{j'k't}} \\
&= \sum\nolimits_{k'=1}^{K'} \int \alpha_i s_{ijkt} s_{ij'k't} dF\left(\alpha_i\right) = \frac{1}{K(j')} \sum\nolimits_{k'=1}^{K(j')} \frac{1}{K(j)} \int \alpha_i s_{ijt} s_{ij't} dF\left(\alpha_i\right) \\
&= \frac{1}{K(j)} \int \alpha_i s_{ijt} s_{ij't} dF\left(\alpha_i\right)
\end{aligned}$$

implying that for generics j

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

and

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

while for non generics j we have

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

and

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

As generic companies choose price to maximize their individual profit, then the first order conditions are:

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

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

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

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

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

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

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

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

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

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

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

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

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

A.12 Full Tables of Elasticities

Table A.18: *Own and Cross price Elasticities*

	Ancef	Bacitracin(gen)	Cefazolglucbaxt	Cefazolin(gen)	Cefepime(gen)	Cefotaxime(gen)	Cefotetan(gen)	Cefoxitin(gen)	Ceftazidime(gen)
Ancef	-0.40997	0.00858	0.00520	0.13560	0.00227	0.00269	0.00033	0.00259	0.00084
Bacitracin(gen)	0.02307	-3.59498	0.03098	0.82203	0.09189	0.02683	0.00635	0.07282	0.01896
Cefazolglucbaxt	0.01077	0.02386	-1.04017	0.32979	0.00758	0.00707	0.00097	0.00811	0.00254
Cefazolin(gen)	0.01133	0.02555	0.01331	-0.76885	0.00827	0.00752	0.00105	0.00879	0.00274
Cefepime(gen)	0.01320	0.19737	0.02125	0.57440	-5.40820	0.03150	0.01394	0.23023	0.04853
Cefotaxime(gen)	0.02165	0.08036	0.02749	0.72494	0.04382	-2.76003	0.00384	0.03895	0.01089
Cefotetan(gen)	0.02130	0.15061	0.03012	0.80340	0.15301	0.03045	-4.33381	0.10995	0.02695
Cefoxitin(gen)	0.01812	0.18959	0.02741	0.73619	0.28061	0.03386	0.01213	-5.14754	0.04009
Ceftazidime(gen)	0.01949	0.16125	0.02832	0.75752	0.18969	0.03103	0.00966	0.12967	-4.52440
Ceftriaxone(gen)	0.02094	0.07884	0.02666	0.70340	0.04323	0.01954	0.00378	0.03841	0.01072
Ceftriaxonebaxt	0.02181	0.12495	0.02977	0.79111	0.10337	0.02703	0.00675	0.07975	0.02042
Cefuroxime(gen)	0.02134	0.07692	0.02697	0.71096	0.04073	0.01933	0.00364	0.03657	0.01028
Claforan	0.02273	0.09817	0.02958	0.78218	0.06221	0.02324	0.00490	0.05252	0.01422
Claforan	0.01413	0.03490	0.01683	0.44078	0.01248	0.00996	0.00147	0.01282	0.00392
Colistin(gen)	0.01481	0.20405	0.02350	0.63419	0.39356	0.03341	0.01409	0.22639	0.04850
Colymycinm	0.00925	0.19727	0.01583	0.43046	0.58900	0.02812	0.01541	0.28977	0.05664
Cubicin	0.00000	0.00039	0.00001	0.00019	0.01251	0.00003	0.00005	0.00240	0.00028
Fortum	0.02308	0.11637	0.03082	0.81710	0.08574	0.02621	0.00607	0.06875	0.01803
Maxipime	0.02031	0.17232	0.02963	0.79295	0.20881	0.03288	0.01040	0.14115	0.03334
Polymyxinb(gen)	0.02229	0.14630	0.03112	0.82899	0.13885	0.03028	0.00822	0.10208	0.02538
Rocephin	0.01265	0.20665	0.02067	0.55950	0.47104	0.03206	0.01497	0.25542	0.05283
Synercid	0.00005	0.00386	0.00010	0.00272	0.07460	0.00034	0.00048	0.01734	0.00229
Tazicef	0.02280	0.10029	0.02977	0.78740	0.06468	0.02361	0.00503	0.05428	0.01464
Tygacil	0.00445	0.13411	0.00807	0.22095	0.58400	0.01709	0.01160	0.24961	0.04507
Vancocin	0.02039	0.17149	0.02971	0.79486	0.20606	0.03282	0.01032	0.13970	0.03306
Vancomycin(gen)	0.02308	0.11702	0.03085	0.81794	0.08668	0.02630	0.00611	0.06938	0.01818
Zinacef	0.02198	0.08470	0.02808	0.74117	0.04793	0.02082	0.00409	0.04206	0.01166
Zyvox	0.00230	0.08536	0.00431	0.11844	0.48129	0.01014	0.00789	0.18600	0.03181

Note: Elasticity of product in row with respect to price of product in column.

Table A.19: *Own and Cross price Elasticities*

	Ceftriaxone(gen)	Ceftriaxonebaxt	Cefuroxime(gen)	Claforan	Claforan	Colistin(gen)	Colymycinm	Cubicin	Fortum
Ancef	0.06725	0.00102	0.00291	0.00055	0.00314	0.00047	0.00001	0.00000	0.00455
Bacitracin(gen)	0.68922	0.01586	0.02821	0.00641	0.02088	0.01730	0.00036	0.00002	0.06165
Cefazolglucbaxt	0.17759	0.00288	0.00762	0.00149	0.00775	0.00153	0.00002	0.00000	0.01257
Cefazolin(gen)	0.18915	0.00309	0.00811	0.00159	0.00820	0.00167	0.00002	0.00000	0.01346
Cefepime(gen)	0.83061	0.02870	0.03216	0.00874	0.01611	0.07108	0.00229	0.00109	0.09759
Cefotaxime(gen)	0.50917	0.01023	0.02123	0.00455	0.01785	0.00848	0.00015	0.00000	0.04158
Cefotetan(gen)	0.78822	0.02040	0.03175	0.00760	0.02100	0.02813	0.00066	0.00005	0.07629
Cefoxitin(gen)	0.88495	0.02666	0.03492	0.00894	0.01997	0.04997	0.00139	0.00029	0.09483
Ceftazidime(gen)	0.80633	0.02217	0.03221	0.00792	0.02010	0.03445	0.00086	0.00008	0.08127
Ceftriaxone(gen)	-2.21352	0.01005	0.02074	0.00445	0.01734	0.00837	0.00015	0.00000	0.04078
Ceftriaxonebaxt	0.69588	-3.74120	0.02835	0.00655	0.02027	0.01934	0.00042	0.00002	0.06374
Cefuroxime(gen)	0.49179	0.00976	-2.67208	0.00438	0.01746	0.00790	0.00014	0.00000	0.03984
Claforan	0.59422	0.01269	0.02457	-3.20605	0.01952	0.01189	0.00023	0.00001	0.05054
Claforan	0.25093	0.00426	0.01070	0.00213	-1.44343	0.00250	0.00004	0.00000	0.01832
Colistin(gen)	0.87914	0.02945	0.03419	0.00917	0.01765	-5.84464	0.00214	0.00092	0.10115
Colymycinm	0.74802	0.02968	0.02842	0.00821	0.01249	0.09860	-6.82898	0.00669	0.09641
Cubicin	0.00083	0.00007	0.00003	0.00001	0.00001	0.00164	0.00025	-1.46725	0.00018
Fortum	0.67259	0.01527	0.02758	0.00623	0.02069	0.01619	0.00033	0.00002	-3.56461
Maxipime	0.85496	0.02375	0.03411	0.00842	0.02108	0.03782	0.00096	0.00013	0.08677
Polymyxinb(gen)	0.78241	0.01968	0.03164	0.00748	0.02152	0.02567	0.00059	0.00004	0.07429
Rocephin	0.84719	0.03031	0.03265	0.00901	0.01583	0.08080	0.00272	0.00194	0.10188
Synercid	0.00946	0.00068	0.00033	0.00012	0.00009	0.01025	0.00120	1.67716	0.00179
Tazicef	0.60377	0.01298	0.02494	0.00551	0.01969	0.01235	0.00024	0.00001	0.05160
Tygacil	0.45871	0.02088	0.01711	0.00524	0.00662	0.09432	0.00440	0.02687	0.06478
Vancocin	0.85308	0.02362	0.03405	0.00840	0.02112	0.03735	0.00095	0.00012	0.08638
Vancomycin(gen)	0.67523	0.01536	0.02768	0.00626	0.02072	0.01636	0.00034	0.00002	0.05992
Zinacef	0.53066	0.01082	0.02208	0.00476	0.01831	0.00925	0.00017	0.00000	0.04377
Zyvox	0.27368	0.01358	0.01010	0.00321	0.00362	0.07571	0.00409	0.07334	0.04093

Note: Elasticity of product in row with respect to price of product in column.

Table A.20: *Own and Cross price Elasticities*

	Maxipime	Polymyxinb(gen)	Rocephin	Synercid	Tazicef	Tygacil	Vancocin	Vancomycin(gen)	Zinacef	Zyvox
Ancef	0.00431	0.00202	0.00009	0.00000	0.00291	0.00023	0.01240	0.04941	0.00153	0.00047
Bacitracin(gen)	0.09840	0.03563	0.00393	0.00001	0.03438	0.01876	0.28025	0.67360	0.01580	0.04787
Cefazolglucbaxt	0.01303	0.00584	0.00030	0.00000	0.00786	0.00086	0.03739	0.13676	0.00403	0.00184
Cefazolin(gen)	0.01408	0.00628	0.00033	0.00000	0.00839	0.00095	0.04038	0.14637	0.00430	0.00204
Cefepime(gen)	0.25518	0.07251	0.01903	0.00029	0.04768	0.17462	0.72070	1.07197	0.01924	0.57648
Cefotaxime(gen)	0.05624	0.02209	0.00182	0.00000	0.02424	0.00714	0.16062	0.45353	0.01163	0.01696
Cefotetan(gen)	0.14039	0.04741	0.00669	0.00002	0.04095	0.03796	0.39888	0.83488	0.01812	0.10313
Cefoxitin(gen)	0.20986	0.06473	0.01264	0.00009	0.04844	0.09175	0.59441	1.03977	0.02043	0.27492
Ceftazidime(gen)	0.16085	0.05242	0.00838	0.00003	0.04277	0.05202	0.45644	0.89009	0.01857	0.14599
Ceftriaxone(gen)	0.05540	0.02172	0.00180	0.00000	0.02373	0.00699	0.15821	0.44480	0.01137	0.01652
Ceftriaxonebaxt	0.10605	0.03764	0.00444	0.00001	0.03514	0.02211	0.30184	0.69673	0.01596	0.05708
Cefuroxime(gen)	0.05311	0.02101	0.00169	0.00000	0.02331	0.00650	0.15172	0.43451	0.01123	0.01537
Claforan	0.07362	0.02788	0.00262	0.00000	0.02888	0.01120	0.21000	0.55169	0.01359	0.02748
Claforan	0.02012	0.00876	0.00050	0.00000	0.01128	0.00154	0.05768	0.19936	0.00571	0.00336
Colistin(gen)	0.25474	0.07374	0.01811	0.00024	0.04992	0.15784	0.71991	1.11068	0.02035	0.51058
Colymycinm	0.29917	0.07810	0.02815	0.00131	0.04503	0.34348	0.84244	1.06099	0.01739	1.29646
Cubicin	0.00154	0.00024	0.00076	0.05340	0.00006	0.10636	0.00426	0.00197	0.00002	1.27971
Fortum	0.09353	0.03415	0.00365	0.00001	0.03339	0.01710	0.26646	0.65111	0.01541	0.04331
Maxipime	-4.69073	0.05634	0.00926	0.00004	0.04551	0.05895	0.49384	0.95044	0.01969	0.16765
Polymyxinb(gen)	0.13211	-4.23063	0.00604	0.00002	0.04024	0.03296	0.37556	0.81266	0.01797	0.08837
Rocephin	0.27811	0.07736	-6.25326	0.00046	0.04922	0.21657	0.78488	1.11963	0.01964	0.73945
Synercid	0.01236	0.00214	0.00434	-6.35699	0.00069	0.39842	0.03429	0.01989	0.00022	4.08109
Tazicef	0.07582	0.02859	0.00273	0.00000	-3.23121	0.01179	0.21624	0.56329	0.01381	0.02902
Tygacil	0.23920	0.05724	0.02890	0.00448	0.02894	-6.00425	0.67151	0.71422	0.01070	2.20271
Vancocin	0.17256	0.05597	0.00913	0.00004	0.04536	0.05782	-4.35533	0.94613	0.01965	0.16409
Vancomycin(gen)	0.09428	0.03438	0.00370	0.00001	0.03354	0.01735	0.26860	-2.98393	0.01547	0.04400
Zinacef	0.06029	0.02347	0.00200	0.00000	0.02539	0.00800	0.17215	0.47751	-2.87615	0.01916
Zyvox	0.16936	0.03824	0.02444	0.01043	0.01778	0.54837	0.47445	0.45176	0.00640	-3.20365

Note: Elasticity of product in row with respect to price of product in column.

Table A.21: *Own and Cross Ads Elasticities*

	Ancef	Bacitracin(gen)	Cefazolglucbaxt	Cefazolin(gen)	Cefepime(gen)	Cefotaxime(gen)	Cefotetan(gen)	Cefoxitin(gen)	Ceftazidime(gen)
Ancef	0.728	-0.017	-0.009	-0.224	-0.007	-0.005	-0.001	-0.007	-0.002
Bacitracin(gen)	-0.004	0.711	-0.005	-0.141	-0.025	-0.005	-0.001	-0.018	-0.004
Cefazolglucbaxt	-0.007	-0.019	0.728	-0.212	-0.008	-0.005	-0.001	-0.008	-0.002
Cefazolin(gen)	-0.007	-0.019	-0.008	0.525	-0.009	-0.005	-0.001	-0.008	-0.002
Cefepime(gen)	-0.001	-0.023	-0.002	-0.058	0.678	-0.003	-0.002	-0.030	-0.006
Cefotaxime(gen)	-0.005	-0.023	-0.006	-0.170	-0.017	0.730	-0.001	-0.014	-0.004
Cefotetan(gen)	-0.003	-0.026	-0.004	-0.115	-0.034	-0.005	0.734	-0.022	-0.005
Cefoxitin(gen)	-0.002	-0.025	-0.003	-0.084	-0.047	-0.004	-0.002	0.709	-0.006
Ceftazidime(gen)	-0.003	-0.026	-0.004	-0.101	-0.039	-0.005	-0.002	-0.024	0.730
Ceftriaxone(gen)	-0.005	-0.023	-0.006	-0.167	-0.018	-0.005	-0.001	-0.014	-0.004
Ceftriaxonebaxt	-0.003	-0.025	-0.005	-0.132	-0.028	-0.005	-0.001	-0.019	-0.005
Cefuroxime(gen)	-0.005	-0.023	-0.007	-0.172	-0.016	-0.005	-0.001	-0.013	-0.003
Claforan	-0.004	-0.024	-0.006	-0.157	-0.020	-0.005	-0.001	-0.015	-0.004
Claforan	-0.006	-0.020	-0.008	-0.203	-0.010	-0.005	-0.001	-0.009	-0.003
Colistin(gen)	-0.001	-0.024	-0.002	-0.064	-0.055	-0.004	-0.002	-0.030	-0.006
Colymycinm	-0.001	-0.018	-0.001	-0.036	-0.065	-0.003	-0.002	-0.030	-0.006
Cubicin	-0.000	-0.000	-0.000	-0.000	-0.002	-0.000	-0.000	-0.000	-0.000
Fortum	-0.004	-0.025	-0.005	-0.144	-0.024	-0.005	-0.001	-0.017	-0.004
Maxipime	-0.002	-0.026	-0.004	-0.100	-0.040	-0.005	-0.002	-0.025	-0.006
Polymyxinb(gen)	-0.003	-0.026	-0.005	-0.121	-0.032	-0.005	-0.002	-0.021	-0.005
Rocephin	-0.001	-0.022	-0.002	-0.053	-0.060	-0.003	-0.002	-0.030	-0.006
Synercid	-0.000	-0.000	-0.000	-0.000	-0.006	-0.000	-0.000	-0.001	-0.000
Tazicef	-0.004	-0.024	-0.006	-0.155	-0.021	-0.005	-0.001	-0.016	-0.004
Tygacil	-0.000	-0.012	-0.001	-0.017	-0.059	-0.001	-0.001	-0.024	-0.004
Vancocin	-0.002	-0.026	-0.004	-0.101	-0.039	-0.005	-0.002	-0.024	-0.005
Vancomycin(gen)	-0.004	-0.025	-0.005	-0.143	-0.024	-0.005	-0.001	-0.018	-0.004
Zinacef	-0.005	-0.023	-0.006	-0.167	-0.018	-0.005	-0.001	-0.014	-0.004
Zyvox	-0.000	-0.007	-0.000	-0.009	-0.045	-0.001	-0.001	-0.016	-0.003

Note: Elasticity of product in row with respect to advertising of product in column.

Table A.22: *Own and Cross Ads Elasticities*

	Ceftriaxone(gen)	Ceftriaxonebaxt	Cefuroxime(gen)	Claforan	Claforan	Colistin(gen)	Colymycinm	Cubicin	Fortum
Ancef	-0.125	-0.002	-0.005	-0.001	-0.005	-0.001	-0.000	-0.000	-0.009
Bacitracin(gen)	-0.133	-0.003	-0.005	-0.001	-0.004	-0.005	-0.000	-0.000	-0.013
Cefazolglucbaxt	-0.129	-0.002	-0.005	-0.001	-0.005	-0.002	-0.000	-0.000	-0.010
Cefazolin(gen)	-0.129	-0.002	-0.005	-0.001	-0.005	-0.002	-0.000	-0.000	-0.010
Cefepime(gen)	-0.091	-0.003	-0.004	-0.001	-0.002	-0.010	-0.000	-0.001	-0.011
Cefotaxime(gen)	-0.135	-0.003	-0.006	-0.001	-0.004	-0.003	-0.000	-0.000	-0.012
Cefotetan(gen)	-0.126	-0.004	-0.005	-0.001	-0.003	-0.006	-0.000	-0.000	-0.013
Cefoxitin(gen)	-0.111	-0.004	-0.004	-0.001	-0.002	-0.008	-0.000	-0.000	-0.013
Ceftazidime(gen)	-0.121	-0.004	-0.005	-0.001	-0.003	-0.007	-0.000	-0.000	-0.013
Ceftriaxone(gen)	0.601	-0.003	-0.006	-0.001	-0.004	-0.003	-0.000	-0.000	-0.012
Ceftriaxonebaxt	-0.131	0.732	-0.005	-0.001	-0.003	-0.005	-0.000	-0.000	-0.013
Cefuroxime(gen)	-0.135	-0.003	0.730	-0.001	-0.004	-0.003	-0.000	-0.000	-0.012
Claforan	-0.135	-0.003	-0.005	0.734	-0.004	-0.004	-0.000	-0.000	-0.012
Claforan	-0.131	-0.002	-0.006	-0.001	0.731	-0.002	-0.000	-0.000	-0.010
Colistin(gen)	-0.097	-0.003	-0.004	-0.001	-0.002	0.726	-0.000	-0.000	-0.012
Colymycinm	-0.067	-0.003	-0.003	-0.001	-0.001	-0.011	0.735	-0.003	-0.009
Cubicin	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.231	-0.000
Fortum	-0.133	-0.003	-0.005	-0.001	-0.004	-0.004	-0.000	-0.000	0.723
Maxipime	-0.120	-0.004	-0.005	-0.001	-0.003	-0.007	-0.000	-0.000	-0.013
Polymyxinb(gen)	-0.128	-0.004	-0.005	-0.001	-0.003	-0.006	-0.000	-0.000	-0.013
Rocephin	-0.086	-0.003	-0.003	-0.001	-0.002	-0.010	-0.000	-0.001	-0.011
Synercid	-0.001	-0.000	-0.000	-0.000	-0.000	-0.001	-0.000	-0.254	-0.000
Tazicef	-0.134	-0.003	-0.005	-0.001	-0.004	-0.004	-0.000	-0.000	-0.012
Tygacil	-0.038	-0.002	-0.001	-0.000	-0.001	-0.009	-0.000	-0.013	-0.006
Vancocin	-0.120	-0.004	-0.005	-0.001	-0.003	-0.007	-0.000	-0.000	-0.013
Vancomycin(gen)	-0.133	-0.003	-0.005	-0.001	-0.004	-0.004	-0.000	-0.000	-0.013
Zinacef	-0.135	-0.003	-0.006	-0.001	-0.004	-0.003	-0.000	-0.000	-0.012
Zyvox	-0.021	-0.001	-0.001	-0.000	-0.000	-0.007	-0.000	-0.034	-0.003

Note: Elasticity of product in row with respect to advertising of product in column.

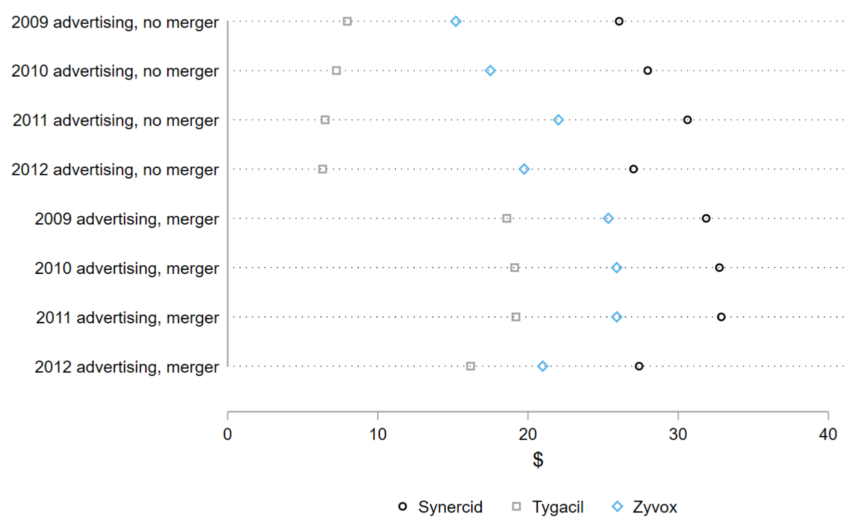
Table A.23: *Own and Cross Ads Elasticities*

	Maxipime	Polymyxinb(gen)	Rocephin	Synercid	Tazicef	Tygacil	Vancocin	Vancomycin(gen)	Zinacef	Zyvox
Ancef	-0.010	-0.004	-0.000	-0.000	-0.006	-0.001	-0.029	-0.099	-0.003	-0.002
Bacitracin(gen)	-0.023	-0.008	-0.001	-0.000	-0.007	-0.007	-0.065	-0.139	-0.003	-0.018
Cefazolglucbaxt	-0.012	-0.005	-0.000	-0.000	-0.006	-0.001	-0.034	-0.107	-0.003	-0.003
Cefazolin(gen)	-0.012	-0.005	-0.000	-0.000	-0.006	-0.001	-0.035	-0.108	-0.003	-0.003
Cefepime(gen)	-0.032	-0.009	-0.003	-0.000	-0.005	-0.030	-0.091	-0.124	-0.002	-0.111
Cefotaxime(gen)	-0.018	-0.007	-0.001	-0.000	-0.007	-0.004	-0.052	-0.129	-0.003	-0.009
Cefotetan(gen)	-0.027	-0.009	-0.002	-0.000	-0.007	-0.011	-0.076	-0.142	-0.003	-0.032
Cefoxitin(gen)	-0.031	-0.009	-0.002	-0.000	-0.006	-0.019	-0.087	-0.138	-0.003	-0.062
Ceftazidime(gen)	-0.029	-0.009	-0.002	-0.000	-0.007	-0.014	-0.081	-0.142	-0.003	-0.043
Ceftriaxone(gen)	-0.019	-0.007	-0.001	-0.000	-0.007	-0.004	-0.053	-0.130	-0.003	-0.010
Ceftriaxonebaxt	-0.024	-0.008	-0.001	-0.000	-0.007	-0.008	-0.069	-0.140	-0.003	-0.022
Cefuroxime(gen)	-0.018	-0.007	-0.001	-0.000	-0.007	-0.003	-0.051	-0.128	-0.003	-0.009
Claforan	-0.020	-0.007	-0.001	-0.000	-0.007	-0.005	-0.058	-0.134	-0.003	-0.013
Claforan	-0.013	-0.005	-0.000	-0.000	-0.006	-0.002	-0.038	-0.112	-0.003	-0.004
Colistin(gen)	-0.032	-0.009	-0.003	-0.000	-0.006	-0.027	-0.091	-0.128	-0.002	-0.096
Colymycinm	-0.030	-0.008	-0.003	-0.000	-0.004	-0.045	-0.084	-0.099	-0.002	-0.190
Cubicin	-0.000	-0.000	-0.000	-0.012	-0.000	-0.016	-0.001	-0.000	-0.000	-0.199
Fortum	-0.022	-0.008	-0.001	-0.000	-0.007	-0.006	-0.064	-0.138	-0.003	-0.017
Maxipime	0.707	-0.009	-0.002	-0.000	-0.007	-0.014	-0.082	-0.141	-0.003	-0.044
Polymyxinb(gen)	-0.026	0.727	-0.001	-0.000	-0.007	-0.009	-0.074	-0.142	-0.003	-0.028
Rocephin	-0.032	-0.009	0.733	-0.000	-0.005	-0.034	-0.090	-0.119	-0.002	-0.126
Synercid	-0.001	-0.000	-0.000	0.720	-0.000	-0.038	-0.002	-0.001	-0.000	-0.414
Tazicef	-0.021	-0.007	-0.001	-0.000	0.729	-0.005	-0.059	-0.134	-0.003	-0.013
Tygacil	-0.022	-0.005	-0.003	-0.001	-0.002	0.673	-0.062	-0.061	-0.001	-0.320
Vancocin	-0.029	-0.009	-0.002	-0.000	-0.007	-0.014	0.654	-0.141	-0.003	-0.043
Vancomycin(gen)	-0.023	-0.008	-0.001	-0.000	-0.007	-0.006	-0.064	0.598	-0.003	-0.017
Zinacef	-0.019	-0.007	-0.001	-0.000	-0.007	-0.004	-0.054	-0.130	0.733	-0.010
Zyvox	-0.014	-0.003	-0.002	-0.003	-0.001	-0.067	-0.040	-0.036	-0.000	0.322

Note: Elasticity of product in row with respect to advertising of product in column.

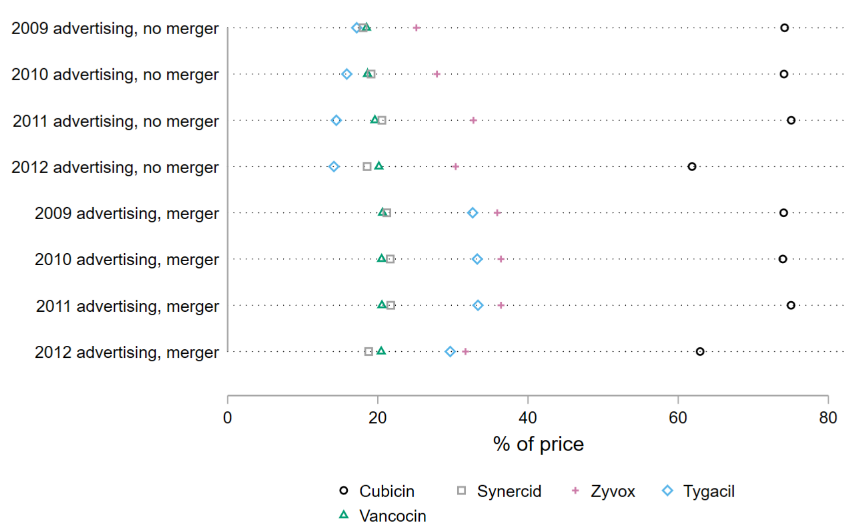
A.13 Additional Counterfactual Results

Figure A.11: *Counterfactual Margins with/without Merger, with/without advertising*



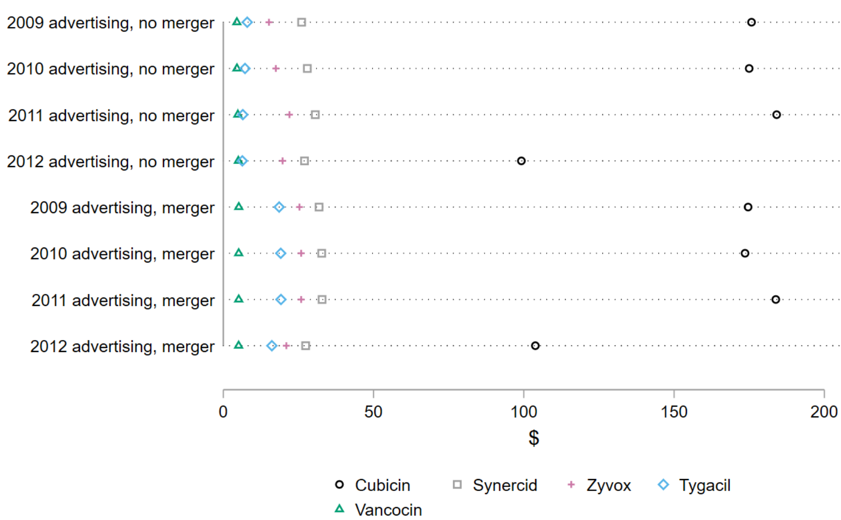
Note: Margins in US$ $(p_j - c_j)$ for the main products.

Figure A.12: *Counterfactual Margins with/without Merger, with/without advertising*



Note: Margins relative to price $\frac{p_j - c_j}{p_j}$ *for the main products.*

Figure A.13: *Counterfactual Margins with/without Merger, with/without advertising*



Note: Margins in US\$ $(p_j - c_j)$ *for the main products.*