Merger efficiency and coordinated effects: nothing to sneeze at? Evidence from cough and cold medicines in the Philippines †

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Abstract

This paper examines the competitive effects of a merger in the cough and cold medicines segment between GlaxoSmithKline (GSK) and Pfizer. The merger was cleared by competition authorities based on expected cost efficiencies. Using product-level data from the Philippines, we estimate a structural demand model to assess both efficiency and pricing effects. We find evidence of merger-specific efficiency gains, but these effects are asymmetric: prices and marginal costs decline for Pfizer products, while GSK prices increase. Further, the price of a close competitor, Sanofi, also increased following the merger, likely due to increased coordination between the merging parties and the competitor.

Key words: mergers, efficiency, coordinated effects, pharmaceuticals

JEL Classification: C63, D22, G34, L11, L25, L65

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1. INTRODUCTION

One of the central policy concerns with horizontal mergers is that increased market power may lead to higher prices. Accordingly, merging parties often justify transactions by claiming efficiency gains, while competition authorities assess whether such efficiencies—if realized—are sufficient to offset the price-increasing incentives created by the merger. While a default expectation may exist that horizontal mergers raise prices, efficiencies can counteract these negative effects, as emphasized by Williamson (1968), Farrell and Shapiro (1990), and Nocke and Whinston (2022). Consistent with this view, modern merger guidelines explicitly recognize efficiencies as a central component of merger assessment. Indeed, some scholars argue that the burden of proof should be revised in a way that gives more presumptive legitimacy to efficiencies claims (see Hovenkamp, 2025), while others argue that efficiencies may be rare (see Rose and Sallet, 2025). A related concern—one that is considerably harder to assess ex ante—is that a merger may facilitate increased coordination among competitors. In this paper, we address both concerns.

We study the merger between consumer health brands of GlaxoSmithKline (GSK) and Pfizer, which was cleared by competition authorities worldwide. Using detailed product-level data on over-the-counter cough and cold medicines from the Philippines, we document three salient post-merger facts. First, we find evidence of merger-specific efficiency gains, with marginal costs declining for Pfizer products by 6% but not for GSK. Second, following the merger, prices for GSK products increased by about 7.5% while those of Pfizer declined by 4.5%. Third, prices of the two main competitors, Sanofi, an international firm like the two merging parties, and Unilab, a local firm with many cheaper products sold mostly in local markets, also rose in the post-merger period by about 10% and 2.5% respectively.

Do the price increases observed for Sanofi and Unilab simply reflect a Nash–Bertrand pricing equilibrium, arising from strategic complementarity in response to GSK's price increase, or do they reflect increased coordination? If the latter, which firms are coordinating more closely in the post-merger period? To be clear, when one of the merging parties raises its price, competitors may optimally respond by raising their own prices even in the absence of coordination. By contrast, when a merger reduces the number of independent decision-makers, coordinated outcomes may become easier to sustain. Thus, if Pfizer/GSK coordinate with Sanofi, an increase in their prices that diverts substantial demand toward Sanofi may be

privately beneficial, as it raises Sanofi's margins. Distinguishing between these mechanisms is critical for interpreting observed price changes and for evaluating the broader competitive consequences of the merger.

In principle, reduced-form difference-in-differences methods and/or event studies can identify whether price changes are merger-specific, although finding appropriate controls and price indices can be challenging (see Ashenfelter and Hosken, 2010). Even then, such approaches do not allow one to observe changes in marginal costs directly, as these are unobserved. More importantly, they do not permit disentangling changes in market conduct from changes in underlying costs. Similarly, using only pre-merger data and estimating a structural demand model, one can back out pre-merger marginal costs under an assumed competition model—typically Nash–Bertrand price competition—and then predict post-merger prices by changing the ownership matrix while holding marginal costs fixed or allowing them to decline slightly (see, for instance, Berry et al. (1995) and Nevo (2000)). In such models, coordination—captured by off-diagonal elements of the ownership matrix—is set to zero by assumption, mechanically attributing post-merger price changes to altered ownership and/or costs (though some exceptions exist, such as Bjornerstedt and Verboven (2016), who impose a higher fixed value of this parameter).

In this paper, we first use difference-in-differences methods on prices to examine changes in the prices of the merging parties and their competitors, using a series of control products. This analysis indicates that prices for one of the merging firms declined following the merger, while prices for the other merging firm and its competitors increased. However, this exercise does not directly inform us about changes in costs, nor whether any such changes are merger-specific or instead reflect longer-run trends. It also does not provide evidence on whether firms coordinated their pricing behavior in the post-merger period.

To address these questions, we next estimate demand-side parameters using a standard random-coefficients discrete choice model. Based on the estimated demand parameters, we then follow Miller and Weinberg (2017) to estimate a coordination parameter. This parameter is fixed at zero in the pre-merger period and constrained to lie between zero and one in the post-merger period. We estimate this parameter allowing for coordination between GSK/Pfizer and Sanofi, motivated by their multimarket contact and the fact that all three are international firms offering higher-end, higher-priced products. Using the estimated

coordination parameter, we then back out marginal costs. Finally, because our data span both the pre- and post-merger periods, we apply a difference-in-differences approach to marginal costs to assess whether observed cost changes are merger-specific or reflect pre-existing trends that may have motivated the merger.

The results for the coordination parameter are asymmetric. They indicate that the post-merger price increases observed for Unilab can be explained by standard Nash–Bertrand pricing behavior, arising from strategic complementarity in response to GSK's price increase. By contrast, the price increases observed for Sanofi are not consistent with Nash–Bertrand competition alone. The estimated coordination parameter for interactions between GSK/Pfizer and Sanofi is at its upper bound and statistically different from zero, indicating substantial post-merger coordination. In contrast, when we re-estimate the coordination parameter for interactions between GSK/Pfizer and Unilab–where we expect it to be zero–it is indeed equal to zero and statistically insignificant. We interpret these findings as evidence that the merger facilitated coordinated conduct with Sanofi, but not with Unilab. This asymmetry is consistent with Sanofi's extensive multimarket contact with GSK and Pfizer across countries, whereas Unilab's interactions with the merging parties are largely confined to the Philippine market.

Our paper is related to the prior literature in three primary areas. First, it feeds into the examination of efficiencies within merger assessment, an area with recent empirical contributions from Eizenberg and Zvuluni (2025) and Demirer and Karaduman (2024) supporting the finding of efficiencies, and contrasting with Affeldt et al. (2021)'s suggestion that merger efficiencies are broadly unachievable at levels needed to counteract expected margin changes from market power. The prior empirical efficiencies literature is particularly sparse for developing countries, yielding notable value from our focus on the Philippines. Second, there is a small but growing literature looking at coordination post-merger. This includes Nevo (2001), which backs out estimates based on those that are most consistent with the data, Bjornerstedt and Verboven (2016) that considers a few possible values of coordination parameters to suggest the best explanation, and Turner (2025) which calculates a collusive sustainability index and simulates post-merger coordination.

The three coordination studies most closely related to ours are Ciliberto and Williams (2014), Miller and Weinberg (2017), and Michel et al. (2024), all of which estimate departures from

Nash–Bertrand competition by allowing elements of the ownership or conduct matrix to vary. Ciliberto and Williams (2014) model conduct as a continuous function of multimarket contact and identify coordination from cross-market variation in multimarket overlap, using predetermined airport gate constraints as instruments. Michel et al. (2024) identify conduct using internal instruments constructed from rivals' promotional activity interacted with product proximity, exploiting variation in competitive pressure that shifts markups but is orthogonal to marginal costs. By contrast, Miller and Weinberg (2017) exploit a regime shift associated with the Miller–Coors joint venture to identify an overall post-merger conduct parameter by comparing observed post-merger prices to those implied by unilateral effects, relying on the assumption that the joint venture does not affect the marginal costs of non-merging rivals. In this sense, identification relies on relative post-merger price movements across firms, under maintained assumptions on the evolution of unobserved marginal costs, in a manner akin to a difference-in-differences design. We follow the same event-based identification strategy as Miller and Weinberg (2017) to identify a coordination parameter between the merging firms and one other international firm with whom they have repeated contact. Our novelty is applying the approach to the pharmaceutical sector and to a developing country. We provide evidence that coordination increased between the merging firms and Sanofi per our preferred model. However, this result is not robust to some changes to the model specification.

The rest of the paper is organized as follows. The next section provides background on the merger and the market in the Philippines, and describes the data sources. This is followed by reduced-form evidence on price changes due to the merger. Section four sets up the structural demand model and presents the results. Section five examines the supply side and the associated results. The final section provides a summary and a brief discussion.

2. The merger and Philippine context

2.1. **GSK/Pfizer Joint Venture.** The merger in question was structured as a joint venture in which GSK and Pfizer combined their consumer healthcare businesses. Initially, GSK acquired Pfizer's consumer healthcare operations in August 2019, after which the combined business was demerged from GSK in July 2022 to operate as an independent firm, Haleon

plc. Under the terms of the deal, GSK held a 68% stake, while Pfizer held the remaining 32%. Over time, both companies divested their holdings in the joint venture, and by 2026 (i.e., at the time of writing), neither company holds any stake in Haleon plc. The consumer healthcare business comprises pain relief medicines, vitamins and supplements, oral hygiene products, digestive healthcare products, and respiratory healthcare products, including treatments for coughs and colds.

The merger was assessed, and cleared, in a number of jurisdictions including in the Philippines, from where we draw our data on the cough and colds segment.[1] The merging parties reported an expectation of efficiencies of half a billion GBP, i.e., between 5 and 10% of revenues, within three years (see press release, GSK, 2018). In the Philippines the acquisition was evaluated in terms of overlapping over-the-counter (OTC) products in respiratory health, pain relief, and nutritive health. After undergoing Phase 1 and Phase 2 reviews, it was formally granted clearance on 27 June 2019. In the decision document, the Philippine Competition Commission (PCC) noted that in adult cough medicines the merged entity will have market power but will not have any additional incentives to increase prices.

> "... the merged entity will gain ability to exercise market power, but will not have enhanced incentive to increase prices in the market for ACMs (Adult Cough Medicines)..."

The pharmaceutical sector in the Philippines in 2020 was worth $4.5 billion of which OTC products represent 38% or $1.7 billion by value. Further, acute respiratory tract infections are among the top three causes of morbidity in the Philippines (Epidemiology Bureau, 2023). So while the merger affects several therapeutic areas, we focus on the OTC cough and cold medicines, which were worth about $160 million in 2020 with sales spread across 52 firms. However, the market is concentrated. Five of the firms and a third of the brands represent 94.4% of the market value, while the rest of the market is made up of 47 firms that capture the remaining 5.6%. Table 1 shows the market shares of the top five companies in 2018, as well as the respective counts of their products, the counts of their products by type, and the number of active substances. The largest firm, Unilab, represents two-thirds of the market,

[1] The transaction was assessed by the competition authorities in Australia, Austria, Brazil, Colombia, Chile, China, Costa Rica, the EC, Germany, India, Israel, Japan, Mexico, New Zealand, the Philippines, Serbia, South Africa, South Korea, Taiwan, Ukraine and the US. The EU required a divestment of a topical pain medicine of Pfizer, but no authority required divestment in the cough and cold segment.

TABLE 1. Shares, counts of products, active substances, and label types

Firm	Share	Products	Active Substances	Labels		
				Proprietary	Non-Proprietary	Private
Unilab	67.90	49	18	45	0	4
Pfizer	8.34	8	4	8	0	0
Sanofi	7.19	12	2	12	0	0
GSK	6.02	10	2	10	0	0
Pascual Lab	4.97	8	2	6	0	2
Others (47)	5.58	98	21	96	2	0
Total	100	185	49	177	2	6

Note: Shares are based on 2018 sales values. Products are defined as unique combinations of manufacturer, brand name or INN assigned by the firm, molecule (active substance), formulation (New Form Code, NFC), and target population (adult or pediatric).

owning far more brands, and using more active substances than other relatively large firms. Pfizer and GSK were second and fourth, respectively, overlapping in a narrower range of medications. Their combined shares put them second overall and result in a market share that is twice as large as the next firm, Sanofi.

The dataset contains 185 distinct products of which 87 are offered by five firms. These products contain 49 different active substances, and the majority are sold under proprietary brand names (often referred to as "branded-generics" as proprietary labels are attached to off-patent drugs), while a small minority are sold generically under International Nonproprietary Name (INN) or as private-label products through independent pharmacies. Importantly, the top five firms concentrate in different active substances. For instance, while Pfizer's overall share is 8.34%, it is distributed across four active substances, while GSK's 6.02% share is across two different active substances. For distribution across active ingredients used in drugs by Pfizer or GSK, see Table 2. Similarly, Sanofi overlaps with GSK in only one active substance (Ambroxol) and none with Pfizer.

2.2. **Data, products, and sample.** We use detailed product-level longitudinal sales data from IQVIA (formerly IMS Health and Quintiles). Our analysis draws on two datasets. The first is IQVIA's Philippine National Sales Audit (NSA), which provides subnational sales data from 2008Q1 to 2020Q4 and covers cough and cold medicines as well as pain and fever medicines. The second dataset is IQVIA's MIDAS World Review Pack, covering the period

TABLE 2. Market shares by active substance

		Active ingredient						
Firm	Share	(1)	(2)	(3)	(4)	(5)	(6)	Others
Unilab	67.90	18.52	2.33					47.05
Pfizer	8.34	0.92			3.89	3.29	0.24	
Sanofi	7.19		6.61					0.58
GSK	6.02		1.15	4.87				
Pascual Lab	4.97							4.97
Others (47)	5.58	80.56	89.91	95.13	96.11	96.71	99.76	47.40

Note: Active ingredients key: (1) Carbocisteine; (2) Ambroxol; (3) Butamirate; (4) Dextromethorphan + Guaifenesin; (5) Guaifenesin; (6) Brompheniramine + Phenylephrine

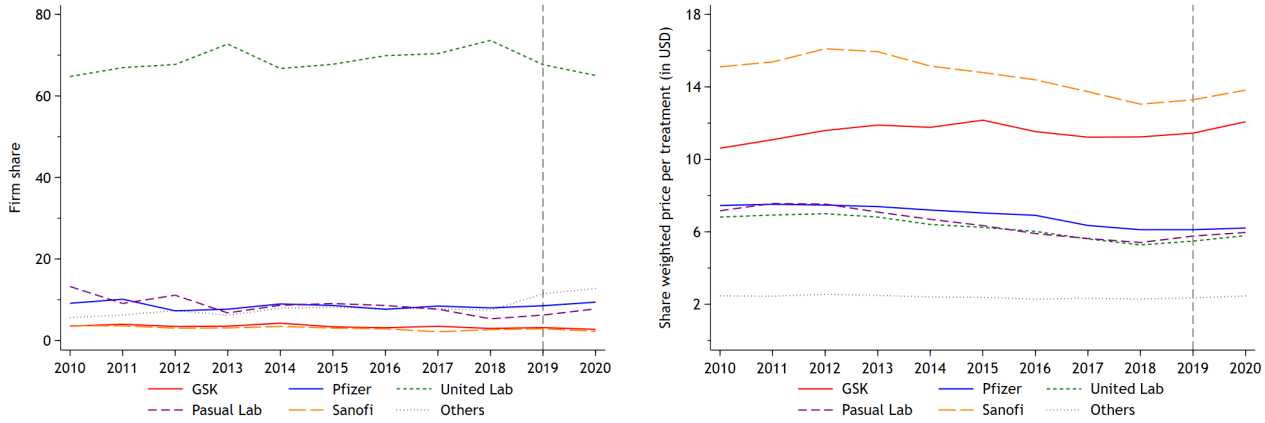
from 2009Q4 to 2021Q4, which provides national-level sales data across all therapeutic classes in the Philippines and in Indonesia, Malaysia, Thailand, and Singapore. From the MIDAS data, we extract sales information on cough and cold medicines for the other countries and on hypertension drugs for the Philippines. The revenues in both datasets are reported in nominal US dollars, which we convert to constant 2012 USD. The quantity measure is reported in dosage units and is defined by IQVIA as the smallest unit of the dosage form most commonly taken by the patient, such as one tablet or a 5mL teaspoon. We compute price per dosage as revenue divided by quantity. Our understanding from IQVIA is that revenues are constructed by multiplying volumes sold by national-level list prices; as a result, we recover national-level list prices rather than true subnational transaction prices. For this reason, we restrict our analysis to the national level.

For our analysis, we define a product as a unique combination of manufacturer, brand name or INN assigned by the firm, molecule (active ingredient), new form code (NFC), and target population (adult or pediatric). Under this definition, we identify 185 distinct products distributed across 52 firms; one drug appears in two flavors and is therefore treated as two separate products. This definition also aggregates data across pack varieties arising from differences in strength (e.g., 20 mg vs. 50 mg) or pack size (e.g., packs of 28 vs. 30 tablets).

Many products have negligible sales over the sample period. To focus on economically relevant products, we compute quarterly quantity shares for each product during 2009Q4–2020Q3 and then average these shares across quarters. After sorting products by average share in descending order, we retain those accounting for a cumulative 96% of total sales. This yields

a sample of 55 products corresponding to 11 firms. The individual average revenue shares for these 55 products and 11 firms are reported in Table A-1 and Table A-2 in Appendix A.

FIGURE 1. Shares and share-weighted prices by firms



(a) Aggregate quantity shares (b) Share weighted prices

Notes: Shares are computed as firm-level quantity sales divided by total market sales. Share-weighted prices are based on 2018 shares, and prices are expressed as price of treating a typical bout of illness.

Figure 1 shows the evolution of firm-level market shares and prices over time. For the purpose of reporting and graphing — but not for analysis — we convert price per dosage as price per bout or episode of illness defined as three dosages per day multiplied by 17.8 days, where the latter is the mean duration of cough reported in the meta-analysis of existing studies on acute cough illness (see Ebell et al., 2013). As can be seen from the graph, several prices, including those of products by GSK and Sanofi were already increasing before the 2019 merger, while the Pfizer prices were declining over time, but relatively flat in the period before the merger. In the next section we investigate the trend in individual product-level prices and if there was a change associated with the merger.

3. REDUCED FORM EVIDENCE ON PRICES

3.1. **Control groups and periods.** We provide reduced-form evidence based on a simple difference-in-differences comparison of prices before and after the merger. The key empirical challenge is the choice of an appropriate control group that satisfies the parallel trends assumption while remaining unaffected by the treatment. In the merger context, this choice is non-trivial. Products that exhibit similar pre-merger price trends—such as

drugs with comparable therapeutic uses or active substances—are also the most likely to be indirectly affected by the merger. In particular, if the merging firms adjust their prices post-merger, competing products may respond due to strategic complementarities in pricing. Such spillovers violate the Stable Unit Treatment Value Assumption (SUTVA) and complicate the interpretation of standard difference-in-differences estimates. Other issues include the choice between prices or log prices versus price indices (Laspeyres- or Paasche-style fixed weights), as well as the length of the event window, as discussed in Ashenfelter and Hosken (2010).

Following Ashenfelter and Hosken (2010), who use two main control groups—private-label products and other branded products—we also adopt these controls. In our setting, these correspond to private-label drugs in the cough-and-cold segment and proprietary products sold by competitors. In the Philippine context, this includes branded drugs produced by other foreign firms such as Sanofi, as well as proprietary local products marketed by Unilab and other domestic firms, often referred to as branded generics because they attach local proprietary labels to off-patent generic formulations.

We therefore begin by comparing post-merger changes in log prices for the merging parties relative to private-label products and, separately, relative to other proprietary labels. Because these controls are susceptible to violations of SUTVA, and because private-label products account for an extremely small share of the market (recall that there are only five private-label drugs), we also use prices from the OTC analgesics market as an alternative control. Analgesics are plausibly more comparable in that they are also often sold OTC, may be consumed jointly with cough-and-cold medications when symptoms include fever, headache, muscle and body aches, or sore throat, and share some overlap in active ingredients with cough-and-cold drugs. Although analgesics constitute a different therapeutic segment, both Pfizer and GSK are active in this market, so we exclude their products and use only prices of products from non-merging firms as controls.

Nonetheless, spillovers from the merger may still be present. As a final check, we therefore use hypertension drugs as a fourth comparison group. This segment was unaffected by the merger, does not share active ingredients with cough-and-cold products, and consists almost entirely of prescription drugs. While hypertension drugs are thus unlikely to be affected by the merger, they may not satisfy the parallel trends assumption. Although this assumption

cannot be tested directly, we complement our analysis with event-study specifications to look for deviations from parallel trends in the pre-merger data. For the main difference-in-differences analysis, we also conduct robustness checks with respect to the length of the event window. In the primary analysis, we use the full sample period, i.e., 2009Q4–2020Q3. The appendix reports results using a shorter window consisting of eight quarters before and five quarters after the merger, i.e., 2017Q1–2020Q3, with the quarter immediately preceding the merger used as the reference period.

3.2. **Event study analysis.** Starting with the event study, we estimate

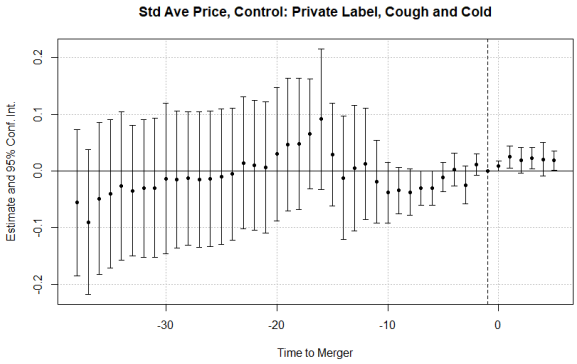
$$\ln p_{jt} = \alpha_j + \gamma_t + \beta_y \left(M_{jt} \times \sum_{\substack{y=-38 \\ y \neq -1}}^{5} I\left(t - t^* = y\right) \right) + \varepsilon_{jt}, \tag{1}$$

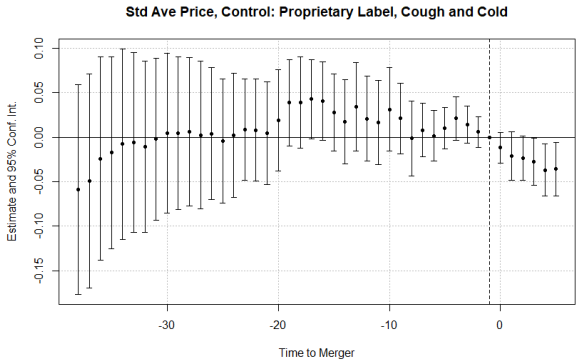
where p_{jt} is the price of the j-th product in market t, and α_j is a product fixed effect. Our primary interest is in the coefficients β_y on the interaction terms between the indicator variable M_{jt} and $I(t - t^* = y)$, where M_{jt} equals one if the product belongs to one of the merging parties and $I(t - t^* = y)$ denotes the event-time indicators. The reference period is the quarter before the merger. We also use an F-test for joint significance to see if β_y coefficients during periods before the merger are jointly statistically different from zero. Failure to reject the null hypothesis, ($H_0 : \beta_y = 0 \quad \forall \quad I\left(t - t^* = y\right)$ where $y < 0$), implies that the treatment and control groups are statistically the same before the merger and provide some confidence in the parallel trends assumption.

Figure 2 plots the interaction coefficients over time for the four control groups described above. Across all specifications, the pre-merger interaction coefficients are close to zero and statistically insignificant, providing support for parallel trends. A joint F-test of the pre-merger coefficients, reported below the figure, likewise fails to reject the null that these coefficients are jointly equal to zero in three of the four cases; the exception is the specification using private-label products as the control group. In the post-merger period, however, the estimated effect on the prices of the merging parties differs across control groups: relative to private-label products (top-left panel), prices increase slightly, whereas relative to the other three control groups, prices either decrease slightly (proprietary cough and cold or branded analgesics shown in the top-right and bottom-left panels, respectively) or decrease and then recover when compared to hypertension drugs (bottom-right panel). Some of the 95% confidence intervals include zero, but most point estimates indicate a slight price

FIGURE 2. Event study with alternative control groups

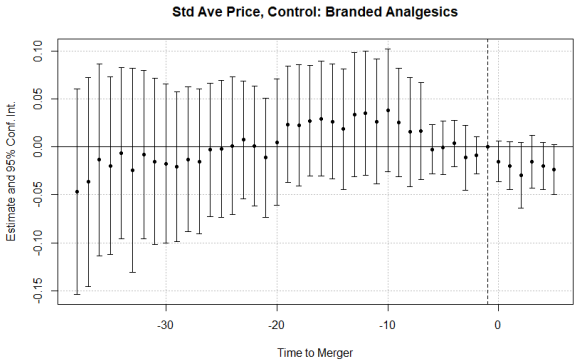
Philippine Cough and Cold Remedies

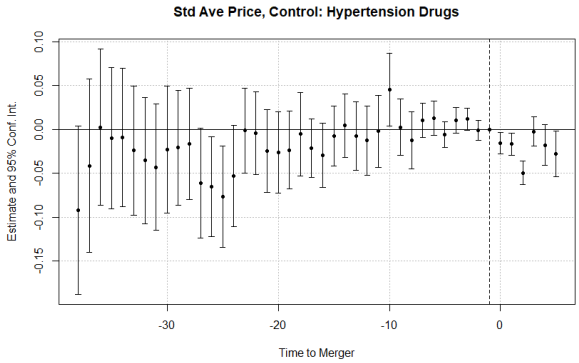




Private-labels, $F_{37,548} = 1.688, p = 0.008$ Proprietary labels, $F_{37,1521} = 0.663, p = 0.941$

Philippine Analgesics and Hypertension Remedies





Analgesics, $F_{37,2031} = 0.540, p = 0.990$ Hypertension drugs, $F_{37,5380} = 1.210, p = 0.179$

reduction. The most prominent price reduction for the merging parties occurs when prices are compared to other proprietary labels, as shown in the top-right panel.

3.3. **Difference-in-Differences.** To examine the effects more closely, we next estimate two difference-in-differences (DD) specifications. The first estimates the combined average effect for the merging parties,

$$\ln p_{jt} = \alpha_j + \gamma_t + \beta^M \left(M_{jt} \times \text{Post}_{jt} \right) + \varepsilon_{jt}, \tag{2}$$

and the second estimates the individual effects for each merging party,

$$\ln p_{jt} = \alpha_j + \gamma_t + \beta^G \left(\text{GSK}_{jt} \times Post_{jt} \right) + \beta^{Pf} \left(\text{Pfizer}_{jt} \times \text{Post}_{jt} \right) + \varepsilon_{jt}. \tag{3}$$

In both specifications, Post_{jt} is an indicator equal to one after the acquisition, and our interest lies in the parameters β^M, β^G, and β^{Pf}, which capture the combined and individual price effects. Since the merger occurred in 2019Q2, we drop observations from the quarter before, the quarter of, and the quarter after the merger, but otherwise use all quarters from 2009Q4–2020Q3 for estimation. Table 3 summarizes the estimated coefficients. The first four columns in the top panel report estimates from Equation 2, while the first four columns in the lower panel report the interaction coefficients from Equation 3. We discuss the final column later. Standard errors are clustered by product. The number of comparison products—and hence the number of observations used in the estimation—varies across columns.

For the combined effects, aside from the specification using other proprietary drugs as the control group (column (2)), none of the first four columns show a statistically significant decline in prices. These results are consistent with the event-study evidence presented above, where the proprietary-drugs comparison group exhibited the most pronounced price decline for the merging parties.

Turning to the individual effects, the first four columns show diverging price responses: GSK prices increase, while Pfizer prices decrease. Focusing on column (4), where the comparison group is hypertension drugs and thus least likely to be subject to spillover effects, the estimates imply a 7.5% increase in GSK prices and a 4.5% decline in Pfizer prices. These patterns are also in line with the raw price trends shown in Figure 1, but now they provide merger-specific effects. Interestingly, while the merger may have generated some efficiency gains—particularly for Pfizer products—it is unclear whether similar gains existed for GSK products; if they did, they did not translate into lower prices for GSK drugs.

As a robustness check, Table B-1 in Appendix B reports estimates using a shorter window around the merger, where we restrict the sample to data from 2017Q1 onward and again omit the quarter of the merger, as well as the quarters immediately before and after the merger. The results differ somewhat. Focusing on column (4), Pfizer prices decline by 3.8% instead of 4.5%, while the change in GSK prices is positive but not statistically different from zero. The combined effect on GSK and Pfizer prices is a 2.4% reduction and is statistically significant.

We now turn to the results in column (5). In this specification, we again use hypertension drugs as the control group, but we additionally include competing products from the

TABLE 3. Merger effects on prices

(in log)	Cough & Cold† Private (1)	Cough & Cold† Proprietary (2)	Analgesics Proprietary (3)	Parties (4)	Hypertension Competitors (5)
β^M (M×Post)	0.029	-0.038^a	-0.023	-0.005	-0.008
	(0.019)	(0.014)	(0.015)	(0.013)	(0.013)
β^G (GSK×Post)	0.109^a	0.042^c	0.057^b	0.075^a	0.072^a
	(0.026)	(0.022)	(0.023)	(0.023)	(0.022)
β^{Pf} (Pfizer×Post)	-0.012	-0.079^a	-0.064^a	-0.045^a	-0.049^a
	(0.016)	(0.011)	(0.011)	(0.009)	(0.009)
β^S (Sanofi×Post)					0.101^a
					(0.014)
β^U (UniLab×Post)					0.024^b
					(0.010)
Product FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Observations	677	1,736	2,333	6,283	8,035
No. of Qtrs	41	41	41	41	41
No. of Products	19	49	91	337	387
Treatment	12	12	12	12	73
Control	7	37	79	501	501

Note: Columns (1) and (2) include cough and cold products with the same active substance as GSK and Pfizer products. Column (3) is a proprietary label from the analgesics market. Columns (4) and (5) use hypertension drugs as controls. Column (5) contains additional post-merger dummies for Sanofi and Unilab. The top panel (first row) combines GSK and Pfizer, while the lower panel (rows 2–5) treats them separately. Quarters $t-1$, $t=0$, and $t=1$ are excluded, where $t=0$ is the quarter of the merger (2019Q2). Standard errors are clustered by product and reported in parentheses. Superscripts a, b, c denote statistical significance at the 1%, 5%, and 10% levels, respectively. Period used 2009Q4-2020Q3. For the shorter period see Table B-1.

cough-and-cold segment—such as drugs sold by Sanofi, Unilab, and other firms—that were not included in the specification for column (4). We also augment Equation 3 by adding interaction terms between the post-merger indicator and firm dummies for these competitors, specifically $\beta^S\left(\text{Sanofi}_{jt} \times \text{Post}_{jt}\right)$ and $\beta^U\left(\text{UniLab}_{jt} \times \text{Post}_{jt}\right)$, to test whether competitor prices increased following the merger. None of the previously estimated coefficients for the combined effect or the individual effects on GSK or Pfizer prices change meaningfully relative to the results in column (4). Importantly, however, we find that the prices of the main competitors—Sanofi and Unilab—increase by about 10% and 2.4%, respectively, and both

effects are statistically significant (in the robustness check with limited periods, the effects on Sanofi and Unilab prices both remain positive and significant, but the estimated increases are 2.1% and 1.2%, respectively). The increase in competitor prices could reflect a response to rising GSK prices, for example through Nash–Bertrand pricing behavior, or could instead be driven by an increase in coordinated effects.

We investigate these possibilities further in the next sections, beginning with the estimation of a structural demand model for cough-and-cold medicines.

4. Demand estimation

4.1. **Random coefficients logit model.** We use a standard discrete choice demand framework with random-coefficients for estimating model parameters. There are $t = 1, \ldots, T$ markets (quarters), each having a mass M_t of the population that can experience acute respiratory conditions—such as the common cold, influenza-like illness, or other upper respiratory tract infections—and can choose among the available cough and cold medicines or the outside option of no drug therapy. The decision maker i in market t faces the choice of $j = 1, \ldots, J_t + 1$ drugs, where $+1$ denotes the outside option of no drug, and by choosing drug j derives the utility

$$u_{ijt} = x_{jt}\beta_i + \xi_{jt} + \epsilon_{ijt}. \tag{4}$$

In the equation above, x_{jt} is a $1 \times k$ vector of observed drug characteristics including price, count of pack varieties, number of active ingredients (i.e., molecules), whether it is a foreign or local brand, whether it is in solid or other form, whether it is flavored or not, and whether it is marketed for adult or pediatric use. Other than prices and the number of pack varieties, drug characteristics are invariant over markets. The scalar ξ_{jt} captures characteristics not observed by the econometrician, such as availability, promotion, or prominent location within the store, all of which could influence choice. It is common across consumers within a market and is observed by both consumers and firms.

The β_i are $k \times 1$ vectors of random-coefficients and are specified as the sum of a mean vector, β, and individual-level dispersion around these means. This dispersion is captured by a $k \times 1$ vector of unobservable individual heterogeneity, v_i, which is assumed to be drawn from a multivariate standard normal distribution. As a result, $\beta_i = \beta + \Sigma v_i$ follows a multivariate normal distribution. The matrix Σ is diagonal, with the vector of standard deviations σ

along its diagonal and zeros elsewhere. In the empirical analysis, the standard deviations are allowed to differ from zero only for the constant, price, the foreign/local brand indicator, and the solid-versus-other formulation indicator. Thus, four coefficients are treated as random and enter the non-linear part of the model, capturing heterogeneity in consumer tastes.

If we define $\delta_{jt} = x_{jt}\beta + \xi_{jt}$ as the mean utility of drug j in market t and the individual-specific deviation as $\mu_{ijt} = x_{jt}(\beta_i - \beta) = x_{jt}\Sigma v_i$, then we can rewrite the utility as

$$\begin{aligned} u_{ijt} &= x_{jt}(\beta + \Sigma v_i) + \xi_{jt} + \epsilon_{ijt} \\ &= \underbrace{x_{jt}\beta + \xi_{jt}}_{\delta_{jt}} + \underbrace{x_{jt}\Sigma v_i}_{\mu_{ijt}} + \epsilon_{ijt} \\ &= \delta_{jt} + \mu_{ijt} + \epsilon_{ijt} \end{aligned} \tag{5}$$

If the idiosyncratic error term ϵ_{ijt} is assumed to be distributed as Type 1 extreme value, then standard integration over ϵ gives the individual choice probability as

$$P_{ijt} = \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{J_t} \exp(\delta_{kt} + \mu_{ikt})} \tag{6}$$

and the market share is the average of these probabilities over patients given by

$$s_{jt} = \int \frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{J_t} \exp(\delta_{kt} + \mu_{ikt})} \, dF(v_i) \tag{7}$$

and $F(\cdot)$ is the distribution of v_i. The simple logit model is obtained as a special case of the random-coefficients model where the distribution $F(\cdot)$ is degenerate so that $v_i = 0$ for all i. In that case $\mu_{ijt} = 0$, and we can get a closed-form expression, $\ln(s_{jt}) - \ln(s_{0t}) = \delta_{jt} = x_{jt}\beta + \xi_{jt}$ as shown by Berry (1994). In the random-coefficients case, we take draws of v_i from $F(\cdot)$, and for a given value of the heterogeneity parameters Σ, mean utilities are recovered by inverting the market share equations. The model parameters (β, Σ) are estimated via GMM using instruments for endogenous prices. As in the simple logit model, identification relies on the presence of an outside option, which pins down market size and scales mean utility levels. We therefore next discuss the definition of the outside option and the construction of instruments used for estimation.

4.2. **Outside share.** To construct the share of the outside option, we first define the potential market as the product of the population share experiencing relevant symptoms, the average duration of illness, and the recommended daily dosage. For the population share with

symptoms, we use 27.8%, based on evidence from Lee et al. (2019), who report the fraction of individuals classified as symptom positive in a tuberculosis-oriented active case-finding program conducted among households experiencing extreme poverty in the Philippines. While this figure does not represent population-wide incidence of acute respiratory illness, it provides a benchmark for the prevalence of respiratory symptoms in a high-risk setting. We take the average duration of acute cough to be 17.8 days, based on a meta-analysis of existing studies by Ebell et al. (2013), and assume a treatment frequency of three doses per day, which is the commonly recommended regimen for antitussives (e.g., dextromethorphan, butamirate) and expectorants (e.g., carbocisteine, ambroxol). The total potential market in each period is therefore given by the Philippine population multiplied by 27.8%, 17.8 days, and three dosage units per day. Product-level market shares are defined relative to this potential market as $s_{jt} = q_{jt}/M_t$, where q_{jt} denotes quantity measured in dosage units, and the outside option share is given by $s_{0t} = 1 - \sum_j s_{jt}$.

4.3. **Instruments.** We use two sets of instruments. The first is the standard BLP-style instruments constructed from linear combinations of product characteristics. Here we use the full set of products, i.e., 185, to exploit relevant variation across products and markets rather than restrict to just the $J = 55$ products used in the main model estimation. Specifically, we construct instruments based on the total number of competing products and the total number of active ingredients (molecules) offered by rival firms. In addition, we classify products by intended use (adult versus pediatric) and, within each group, construct instruments capturing the number of labels, pack varieties, and active ingredients offered by the same firm as the reference product. The second set consists of a Hausman-style instrument constructed from the price of the same drug in the other ASEAN countries (see Hausman et al., 1994, Hausman, 1996). The logic is that the same product in other geographic markets shares common cost shocks and hence has prices that are correlated across geographic areas but are uncorrelated with the market-specific product valuation. We use pricing data from neighboring ASEAN countries (Indonesia, Malaysia, Thailand, and Singapore) to compute the mean price for each drug in other countries. Since not all drugs are available in all countries, we match drugs using a matching criterion described in more detail in Appendix (A.2). Lastly, we use optimal instruments for the estimation as described by Reynaert and Verboven (2014), but postpone that discussion until the next section.

4.4. **Sources of variation, identification, and estimation.** Given that we restrict the analysis to the top 55 drugs with a cumulative average share of 96%, there is relatively little entry and exit over time. For example, as shown in Table 4, among the 55 drugs used in the full estimation sample, there are on average 52.5 drugs available in any given quarter, while an individual drug is observed in 42 of the 44 quarters used in estimation. While this entry and exit certainly contribute to sources of variation, the product group is largely stable, so identification in the demand model primarily comes from variation in prices, shares, and product characteristics across products and over time.

TABLE 4. Entry and exit of drugs

Variable	Obs	Mean	Std. Dev.	Min	Max
Number of drugs in a market	44	52.5	1.1	49	55
Number of markets a drug is on sale	55	42.0	5.5	21	44

Table 5 provides summary statistics for all variables used in the estimation of the demand model. The mean share of an individual drug is 0.003 and ranges from zero to 0.007. This, of course, is based on the definition of the outside good, which itself has a mean value of 0.828 and varies from 0.763 to 0.903. The mean price per dose is \$0.137, ranging from \$0.008 to \$0.792. While both shares and prices exhibit variation over time and across products, most of the variation is cross-sectional, i.e., across products, as *between variance* is typically larger than *within variance*. For instance, for shares, variance between products is 2.45 times larger than variance over time, whereas for prices it is 6.07 times larger.

There is also substantial variation in product characteristics, again mostly cross-sectional. Pack varieties per product range from one to 13, with a mean value of 1.848, and the number of molecules ranges from one to 11, with a mean value of 1.770. Of the remaining product characteristics that enter the utility function and are coded as 1/0 dummy variables, foreign/local and solid/other are slightly below the 50% even distribution, while only about 10% of products are flavored.

The model parameters are estimated using GMM, where we rely on orthogonality conditions between the instruments described above and the unobserved demand error term ξ_{jt}. In addition, we generate and use optimal instruments for estimation. Using Monte Carlo simulations, Reynaert and Verboven (2014) show that optimal instruments are more efficient than conventional instruments and help attenuate bias when there is limited product

TABLE 5. Descriptive statistics

Variable	Description	mean	min	max	s_O^2	s_B^2	s_W^2
Share variables							
s_j	Share of product j ($\times 100$)	0.327	7.85e-7	6.584	0.608	0.559	0.228
s_0	Share of outside good	0.828	0.763	0.903	0.034	0.002	0.034
$\ln(\frac{s_j}{s_0})$	Dependent variable (logit)	-6.525	-18.44	-2.455	1.705	1.340	1.123
Product characteristics							
p_j	Price (USD) per dose	0.137	8.21e-3	0.792	0.093	0.091	0.015
x_1	# of pack varieties	1.848	1	13	1.359	1.244	0.527
x_2	# of molecules	1.770	1	11	1.488	1.483	0
x_3	Foreign = 1; Local = 0	0.474	0	1	0.499	0.503	0
x_4	Solid = 1; Others = 0	0.418	0	1	0.493	0.501	0
x_5	Flavored = 1; No-Flavor = 0	0.095	0	1	0.293	0.290	0
x_6	pediatric only = 1; otherwise = 0	0.393	0	1	0.488	0.490	0
Instruments							
z_1	No. of products per group, same firm	6.451	0	19	6.344	6.485	0.748
z_2	No. of labels per group, same firm	3.654	0	13	4.072	4.099	0.851
z_3	Sum of packs per group, same firm	8.888	0	31	8.532	8.600	1.762
z_4	Sum of molecules per group, same firm	5.741	0	26	7.048	6.949	1.976
z_5	No. of products per group, competitors	33.42	12	57	9.654	8.798	4.167
z_6	No. of labels per group, competitors	25.06	11	42	6.227	5.072	3.725
z_7	Sum of packs per group, competitors	41.14	17	73	11.50	9.553	6.647
z_8	Sum of molecules per group, competitors	28.31	11	64	10.33	7.385	7.375
z_9	Price of j in ASEAN countries	0.121	1.94e-3	2.211	0.229	0.125	0.191
z_{10}	GSK/Pfizer/Sanofi $\times$ post-merger	0.049	0	1	0.217	0.066	0.206

characteristic variation across markets. Following Chamberlain (1987), we construct optimal instruments as the conditional expectation of the gradient of the structural error term with respect to the parameter vector. In the case of linear parameters and exogenous regressors, the gradient reduces to (minus) the covariates. In the case of nonlinear parameters, the optimal instruments are nonlinear functions of predicted variables. In our application, these instruments are constructed for price and for all elements of the σ vector.

4.5. **Estimated coefficients and substitution patterns.** Estimates of the demand parameters are reported in Table 6. Columns (1) and (2) present OLS and IV estimates from the simple logit model, which serve as a baseline for assessing the gains from moving to GMM estimation of the random-coefficients logit (RCL) model. The OLS estimate of the price coefficient is positive and statistically significant. Once price is instrumented (column (2)), the price coefficient becomes negative and statistically significant.

TABLE 6. Estimated demand parameters

	Logit			*RCL* (1)		*RCL* (2)	
	OLS-β (1)	IV-β (2)	FS (3)	β (4)	σ_β (5)	β (6)	σ_β (7)
Constant‡	-1.885^a	-2.008^a	2.059^a	-0.767	0.016	-0.831	1.256^c
	(0.638)	(0.628)	(0.546)	(0.982)	(1.702)	(1.183)	(0.705)
p:price	8.511^a	-19.809^b		-31.117^a	16.081^a	-29.991^a	15.282^a
	(1.771)	(9.543)		(10.923)	(5.956)	(10.982)	(5.930)
x_1:packs	0.568^a	0.554^a	-0.014	0.294^a	0.014	0.195^a	
	(0.055)	(0.058)	(0.061)	(0.074)	(0.145)	(0.058)	
$x_2^‡$:molecules	-0.013	-0.003		-0.308^b	0.003	0.003	
	(0.130)	(0.130)		(0.129)	(0.502)	(0.135)	
$x_3^‡$:foreign	-1.050^a	-0.968^a		-0.823	0.723	-0.932^a	
	(0.313)	(0.316)		(1.137)	(1.056)	(0.327)	
$x_4^‡$:solid	-0.447	-0.272		-0.122	1.848	-0.291	
	(0.401)	(0.395)		(2.536)	(1.829)	(0.385)	
$x_5^‡$:flavored	-0.563	-0.451		-7.844^b	0.021	-0.683	
	(0.498)	(0.490)		(3.738)	(1.527)	(0.479)	
$x_6^‡$:pediatric	-0.534	-0.379		-3.091^a	0.168	-0.453	
	(0.395)	(0.379)		(0.967)	(1.909)	(0.416)	
x_7:time	-0.010^a	-0.026^a	-0.078^a	-0.020^a		-0.021^a	
	(0.002)	(0.006)	(0.005)	(0.004)		(0.004)	
z_7:instrument			0.053^a				
			(0.011)				
z_9:instrument			0.702^a				
			(0.074)				
z_{10}:instrument			-0.448^c				
			(0.244)				
Observations	2,312	2,312	2,312	2,312		2,312	
R^2	0.625	0.574	0.979	0.767		0.802	
F-stat			37.99				
$(p-c)/p$		0.416		0.458		0.441	
Elasticity (own)		-2.882		-2.567		-2.524	
Elasticity (cross)		0.008		0.010		0.010	
Negative MC		6.5%		1.9%		1.9%	

Notes. All specifications include quarter dummies and product dummies. The β coefficients for variables marked with ‡ are backed out using Chamberlain's minimum-distance GLS approach. First-stage estimates are multiplied by 100 in column (3). Superscripts a, b, c indicate significance at 1, 5, and 10% respectively. Price-cost margin and elasticity are reported for cases where marginal cost is positive, and are computed only for the pre-merger period. RCL(1) uses all the instruments listed in Table 5 while RCL(2) uses z_7, z_9, and z_{10}.

Under the IV logit specification, the mean own-price elasticity is −2.88, while the mean cross-price elasticity is 0.008. We postpone a detailed discussion of implied markups and marginal costs to the next section. For the purpose of gauging model fit, we note here that marginal costs are recovered for the pre-merger period under the assumption of Nash–Bertrand pricing with no coordination effects across firms. Under the IV logit model, implied marginal costs are negative in 6.5% of observations, whereas under OLS they are negative in essentially all observations.

The corresponding first-stage coefficients are reported in column (3). The joint F-statistic for the excluded instruments in the first-stage regression is 37.99, although the chi-square test does not reject the null that the model is over-identified ($\chi^2_{(2)} = 13.39$, p-value $= 0.0012$).

All models include product fixed effects. Consequently, coefficients on time-invariant product characteristics are not identified directly in the logit specifications. Instead, these coefficients are recovered using a GLS projection of the estimated product fixed effects onto observable product characteristics.[2]

Columns (4) and (5) report estimates from the first random-coefficients model, RCL(1), which relaxes the restrictive substitution patterns implied by the independence of irrelevant alternatives (IIA) property of the simple logit. In this specification, we allow dispersion around the mean to be non-zero for all product characteristics, i.e., we attempt to estimate σ_β for all product characteristics. Column (4) reports the mean coefficients (β), while column (5) reports the corresponding standard deviations (σ_β).

Under the RCL(1) specification, the fraction of observations with negative implied marginal costs in the pre-merger period declines further to 1.9%. The mean price coefficient is −31.12 and is estimated with substantial heterogeneity: the estimated variance is 16.08 and is statistically significant, indicating considerable dispersion in the marginal utility of income across consumers. The implied mean own-price elasticity is −2.57. The signs of the mean coefficients on observable product characteristics are economically intuitive and broadly consistent with those obtained under the IV logit specification. However, with the exception of the σ_β coefficient for price, none of the others are statistically significant. In

[2]Product fixed effects are also included in the linear part of the RCL models. Mean utility coefficients (β) are recovered using Chamberlain's minimum-distance GLS approach, while all product characteristics enter the non-linear part of the model to identify the associated σ coefficients. For further details, see Chamberlain (1982), Nevo (2000), and Bokhari et al. (2024).

part, this may be driven by the lack of demographic draws from heterogeneous sub-national markets.

Accordingly, we switch to RCL(2), which does not attempt to estimate random-coefficients for all product characteristics. In this model, we retain the random coefficient for the constant term and the price coefficient, both of which are statistically significant. The pseudo R^2 is higher relative to RCL(1), but in all other ways remains comparable. We take the more parsimonious model as the preferred specification, as it does not induce predicted shares from statistically insignificant σ_β coefficients, and discuss other results mostly from this model, while also referring to RCL(1) where necessary for robustness checks.

Table 7 reports own- and cross-price elasticities implied by the RCL (2) model. The top panel summarizes the distribution of elasticities across all 55 products and over all periods. The mean elasticity (both the simple average and the weighted mean) is about -2.51, while the median is -2.64, with values ranging from almost -3 to unit elastic.

The middle panel reports mean elasticities (averaged over markets, i.e., quarters) by product type, classifying products as branded, branded generics, or generics. This classification is based on whether a product carries a proprietary label owned by an international firm (GSK, Pfizer, or Sanofi), a proprietary label owned by a domestic firm (Unilab, Pascual, or others), or a non-proprietary (generic) label. The elasticity at the group level is computed by aggregating the shares of individual drugs within the group and computing a share-weighted average price for the group within each market. Thus, for the group labelled "Branded," we sum the shares of the 25 individual drugs in that group and compute a share-weighted average price for branded drugs. These group-level shares and prices are then used in the elasticity formula corresponding to the random-coefficients model, and the table reports averages over markets. The same grouping procedure applies when groups are defined at the firm level, such as GSK or Pfizer, in the third panel discussed below. Notably, the own-price elasticities of branded drugs versus branded generics or generics (only one product) are quite comparable in the cough and cold segment, although branded drugs have the most elastic demand, at -2.9 compared to the other two groups.

The bottom panel reports mean elasticities, again averaged over markets, but now grouped at the firm level. The same grouping procedure as in the middle panel is used. The mean

TABLE 7. Mean own- and cross-price elasticities

Overall (55)	Average	Weighted Average	Median	Standard Deviation	Min	Max
Own	-2.512	-2.505	-2.642	0.413	-2.984	-1.002
Cross	0.010	0.036	0.004	0.017	1.07e-9	0.233

			Branded	Brand-Gen	Generic
Branded (25)			-2.937	0.137	0.143
Brand-Gen (29)			0.398	-2.281	0.480
Generic (1)			0.002	0.002	-2.543

	GSK	Pfizer	Sanofi	Unilab	Pascual	Others
GSK (4)	-2.798	0.026	0.027	0.025	0.025	0.022
Pfizer (8)	0.041	-2.787	0.041	0.053	0.054	0.053
Sanofi (7)	0.027	0.026	-3.250	0.025	0.025	0.022
Unilab (22)	0.274	0.373	0.276	-2.356	0.392	0.408
Pascual (5)	0.037	0.048	0.037	0.050	-2.702	0.051
Others (9)	0.019	0.028	0.019	0.031	0.030	-2.202

Notes. The middle and lower panels report average group-level elasticities, where the average is taken over all periods. The middle panel defines groups as branded, branded generics, and generics. The lower panel defines groups based on firm identity. The number of products in each group is listed in parentheses. Group-level elasticities are computed by defining a group share and a group price, given by the sum of individual shares and the share-weighted average price, respectively. Cell (j, k) reports the percentage change in the quantity of group j induced by a one-percent increase in the price of group k. Diagonal entries report average own-group elasticities. For example, in the lower panel, the GSK–GSK entry (-2.798) is the own-price elasticity for the GSK group, while the Pfizer–GSK entry (0.041) reports the change in Pfizer quantities induced by a one-percent increase in GSK prices.

own-price elasticities are always larger in magnitude than -2.2, and for the three more well-known and more expensive foreign brands—Sanofi, GSK, and Pfizer (see Figure 1)—demand is more elastic than for Unilab or the other less well-known and cheaper brands. In terms of cross-price elasticities, cell (j, k) gives the mean percentage change in the quantity of drugs in group j induced by a one-percent increase in the price of drugs in group k. The cross-price elasticity between GSK and Sanofi is 0.027, while the strongest substitution is toward Unilab's 22 products following a price increase in any of the other foreign or local brands (see the row labelled Unilab in Table 7). The magnitude of the cross-price elasticities in this row is about an order of magnitude larger than in any of the other rows.

5. SUPPLY SIDE

5.1. **Oligopoly pricing.** We next back out costs and markups using supply-side first-order conditions derived from a Nash–Bertrand pricing model. Following Miller and Weinberg (2017), we allow for partial coordination through a conduct parameter, κ, whereby a firm internalizes a fraction of its rivals' profits when setting prices. In the benchmark case of Nash–Bertrand competition without coordination, $\kappa = 0$, while $\kappa = 1$ corresponds to full joint profit maximization. We therefore set $\kappa = 0$ in the pre-merger period and estimate κ in the post-merger period.

Let c_{jt} denote the marginal cost of product j in market t. Firms are multiproduct, and firm $f = 1, \ldots, F$ chooses the vector of prices p_{ft} to maximize profits. Firm f's problem is

$$\max_{p_{ft}} \Pi_{ft}(p_{ft}) = \max_{p_{ft}} \sum_{l \in \mathcal{J}_{ft}} (p_{lt} - c_{lt})\, q_{lt}\big(\theta^D; p_t\big)\,, \tag{8}$$

where $\mathcal{J}_{ft}$ denotes the set of products owned by firm f in market t, and $q_{jt} = s_{jt} M_t$ denotes unit sales.

The first-order conditions give a system of J_t equations for each market t as

$$p_t = c_t + \underbrace{\Delta_t^{-1} s_t(p_t; \theta^D)}_{m_t}, \tag{9}$$

where m_t is the vector of markups, θ^D are the demand parameters, and Δ_t is the $J_t \times J_t$ Jacobian matrix with elements $\Delta_{t,jk} = -\partial s_{kt}/\partial p_{jt}$ if products j and k are owned by the same firm and zero otherwise.

Rewriting the pricing equation explicitly in terms of an ownership matrix gives

$$p_t = c_t - \Big[\Omega_t(\kappa) \odot \Big(\frac{\partial s_t(p_t; \theta^D)}{\partial p_t}\Big)^T\Big]^{-1} s_t(p_t; \theta^D) \tag{10}$$

where $\Omega_t(\kappa)$ captures ownership and coordination: under Nash–Bertrand pricing without coordination, Ω_t is block-diagonal with ones for products owned by the same firm and zeros otherwise. When firms partially internalize rivals' profits, off-diagonal elements take values between zero and one.

To illustrate, consider the simplified example given in Miller and Weinberg (2017) of four single-product firms, where the ownership matrix changes from Ω_{t1} in the pre-merger period

to Ω_{t2} in the post-merger period, where firms 1 and 2 merge but also coordinate with firm 3, but not with firm 4. This can be represented by the ownership matrices

$$\Omega_{t1} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad \Omega_{t2} = \begin{bmatrix} 1 & 1 & \kappa & 0 \\ 1 & 1 & \kappa & 0 \\ \kappa & \kappa & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{11}$$

where the pre-merger ownership matrix is diagonal, as there is no joint profit maximization, while in the post-merger case there is a one in the off-diagonal entries to indicate full joint profit maximization between the merging firms 1 and 2, and coordination with firm 3 is captured by the parameter κ.

We specify the marginal cost as

$$c_{jt} = w_{jt}\gamma + \lambda_j + \lambda_t + \eta_{jt}, \tag{12}$$

where w_{jt} includes the average price of the same drug from four ASEAN countries, the number of packs per drug, and an indicator for the Pfizer/GSK products in the post-merger period. The indicator captures any firm-specific efficiencies realized by the merging firms due to the merger, while λ_j and λ_t are the product and time fixed effects, and η_{jt} is the structural error term.

We estimate the supply-side parameters as follows. Let $\theta_0^S = (\kappa, \gamma, \lambda_j, \lambda_t)$ and let $\widetilde{\theta}^S$ be a candidate solution. Then, given the estimated demand parameters $\widehat{\theta}^D$, and the candidate solution, we can compute the structural error term as

$$\eta_{jt}^*(\widetilde{\theta}^S) = p_{jt} - w_{jt}\widetilde{\gamma} - \widetilde{\lambda}_j^S - \widetilde{\lambda}_t^S - \left[\Omega_t(\widetilde{\kappa}) \circ \left(\frac{\partial s_t(p_t; \widehat{\theta}^D)}{\partial p_t}\right)^T\right]^{-1} s_t(p_t; \widehat{\theta}^D). \tag{13}$$

Parameters can be estimated using the method-of-moments estimator

$$\widetilde{\theta}^S = \arg\min_{\theta^S} \eta(\widetilde{\theta}^S)' \, z' z \, \eta(\widetilde{\theta}^S), \tag{14}$$

where the vector z contains an excluded instrument orthogonal to the error term so that $E[z'\eta^*(\theta_0^S)] = 0$. To operationalize the estimation, we concentrate out the fixed effects and the marginal cost parameters and only search over κ in the non-linear search.[3] The

[3]To be clear, we use the estimated demand parameters and an initial guess for κ to compute the implied markups m_{jt}. We then regress prices net of markups $(p_{jt} - m_{jt})$ on cost shifters and fixed effects $(w_{jt}, \lambda_j, \lambda_t)$ to recover marginal cost parameters and construct the associated structural errors. We then form the GMM objective based on

excluded instrument is an indicator equal to one for Sanofi and GSK/Pfizer in the post-merger period, parallel to the construction and identification logic in Miller and Weinberg (2017). The instrument is valid if the unobserved costs of Sanofi are orthogonal to the instrument. This condition holds if changes in Sanofi's unobserved costs before versus after the merger are not systematically different from changes in the unobserved costs of other non-merging firms, such as Pascual or Unilab. With product and time fixed effects included in the marginal cost equation, level differences in costs are absorbed, and identification therefore follows a difference-in-differences logic based on relative changes in unobserved costs over time. In addition, the inclusion of a GSK/Pfizer post-merger indicator in the marginal cost specification allows merger-specific efficiency gains for the merging firms, thereby isolating the comparison between Sanofi and the non-merging firms. The relevance of the instrument follows from the results in column (5) of Table 3 which shows that Sanofi prices increased by about 10% relative to the controls.

5.2. **Coordination, markups, and marginal costs.** We begin with the estimates of the cost side and the coordination parameter reported in Table 8. The column labeled RCL(2) presents results based on the RCL(2) demand model, using the preferred and more parsimonious specification.

The γ coefficients indicate that marginal costs declined for GSK/Pfizer in the post-merger period, that marginal costs increased with prices in other ASEAN countries, and that drugs with a larger number of pack varieties have higher marginal costs. All of these effects appear reasonable, at least in terms of their direction.

Importantly, the estimated value of the coordination parameter κ is equal to one and is statistically different from zero. This result provides some evidence that the large 10% post-merger increase in Sanofi prices is not driven solely by Nash–Bertrand pricing resulting from increased market power—reflected in the roughly 7.2% increase in GSK prices reported earlier in Table 3—but may instead reflect increased coordination among firms. As a falsification check, we also re-estimate the coordination parameter for interactions between GSK/Pfizer and Unilab using the RCL(2) specification and find it to be equal to zero and statistically insignificant (results not shown for brevity). That said, while the estimate is statistically

these structural errors and search over κ only. At each evaluation of κ, markups and marginal cost parameters are updated (the latter via OLS), and the procedure continues until the GMM objective is minimized.

TABLE 8. Supply side parameters

	Parameter	RCL (2)	RCL (1)
Coordination parameter	κ	1.000^b	0.000
		(0.509)	(0.732)
GSK/Pfizer × post dummy (×100)	γ_1	-0.797^a	-0.703^a
		(0.072)	(0.090)
ASEAN price (×100)	γ_2	0.471^a	0.283^a
		(0.058)	(0.039)
Pack (×100)	γ_3	0.068^b	0.029
		(0.029)	(0.028)
Constant (×100)	γ_0	0.438^a	0.546^a
		(0.123)	(0.132)
Product FE	λ_j	✓	✓
Time FE	λ_t	✓	✓

Notes: Standard errors are reported in parentheses. Superscripts a, b, c denote statistical significance at the 1%, 5%, and 10% levels, respectively. All coefficients except κ scaled by 100.

significant, it is not particularly robust to changes in the demand specification. The column labeled RCL(1), which is based on the RCL(1) demand model, yields an estimate of κ equal to zero. In this specification, most other estimated parameters are also smaller in magnitude, and the coefficient on the number of pack varieties loses statistical significance. Nonetheless, for the remainder of the analysis, we focus on the results from RCL(2).

Next, using the estimated κ value for the post-merger period, and keeping it at zero in the pre-merger period, we back out the estimated average markups $(p - c)/p$ across products at the firm level given in Table 9. Both GSK and Pfizer show a significant increase in the markups, and while other firms, including Sanofi also show an increase in the markups, none are statistically significant.

Finally, we use the backed-out marginal costs for all products and all periods (again using RCL(2) and the associated value of κ in the post-merger period). These are shown in Figure 3. Next, we apply the difference-in-differences framework of Equation 2 and Equation 3 to assess whether changes in marginal costs for the merging parties are merger-specific or instead part of a longer-run trend. As dependent variables, we consider both marginal costs

TABLE 9. Average markups before and after the merger

	Before	After	Mean change	p-value
GSK	40.07	43.66	3.59	0.048
Pfizer	38.65	40.31	1.66	0.009
Sanofi	47.26	48.33	1.07	0.784
Unilab	44.43	45.30	0.86	0.054
Pascual	42.13	40.73	-1.40	0.489

Notes: Markups are expressed in percentage, so $100 \times (p-c)/p$. "Before" and "After" refer to average markups in the pre- and post-merger periods using $\kappa = 0$ and $\kappa = 1$ respectively. Change is the simple difference between post- and pre-merger averages and p-value reports associated probability in a two-sided t-test on the mean difference. For results with shorter period (2017Q1-2020Q3), see Table B-2.

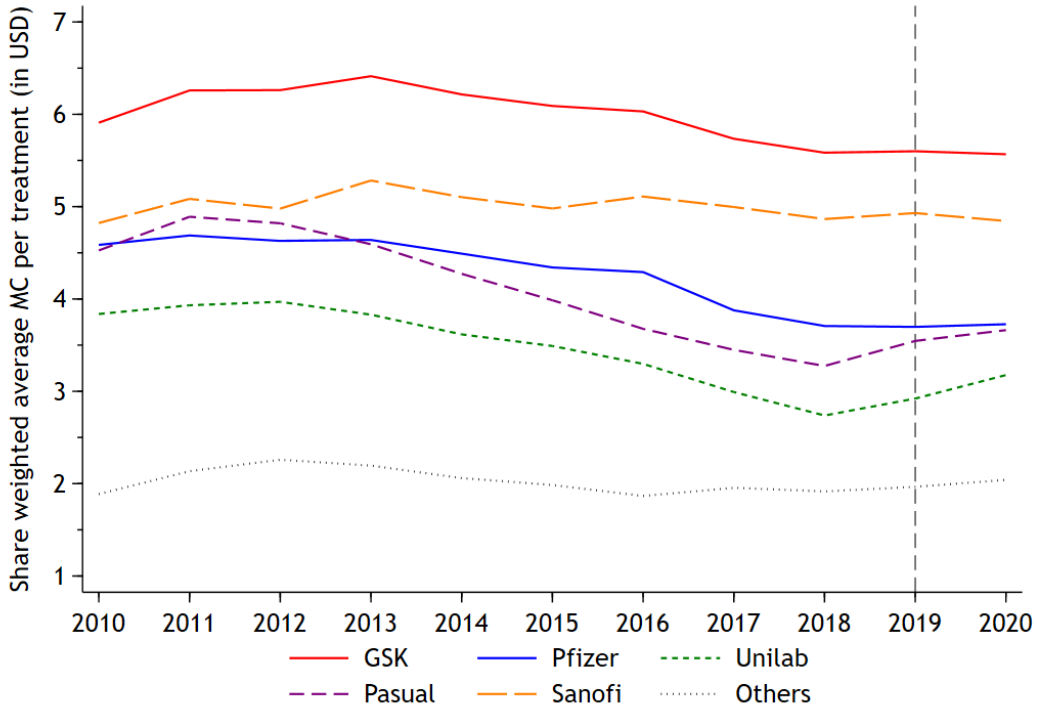
and the log of marginal costs. As controls, we use all other non-merging cough and control drugs, since there is no clear reason to expect merger-specific changes in their marginal costs. This assumption holds provided that the merger does not induce a sudden and substantial shift in demand for other drugs that would affect their costs, for example if marginal costs were increasing or decreasing in output.

The results are reported in Table 10. There is statistically weak and non-robust evidence that marginal costs for GSK decreased following the merger. This finding is, of course, consistent with the price increase reported for GSK products in Table 3, since estimated marginal costs are calibrated to rationalize observed prices and markups given the demand model. However, when we use a shorter period around the merger for the difference-in-differences estimation, even GSK's drop in costs becomes significant (see Table B-3). In contrast, for Pfizer there is much stronger and more robust evidence of a post-merger decrease in marginal costs, which appears distinct from any longer-run trend in marginal costs.

6. SUMMARY AND DISCUSSION

GSK and Pfizer applied for, and received, approval to merge in several jurisdictions. One of the main arguments advanced in support of the merger was that it would increase efficiency and, in the explicit judgment of at least one competition authority—presumably others as well—that while the merger might lead to an increase in market power, it would not generate enhanced incentives to raise prices.

FIGURE 3. Share-weighted marginal cost by firm



Our evidence shows that the markups of both parties increased following the merger (see Table 9). There was a gain in efficiency for Pfizer, but not necessarily for GSK, as the evidence for the latter is not robust (see Table 10 and Table B-3). Further, while the prices of Pfizer products declined by 4.5%, the prices of GSK products increased by 7.2%, resulting in no net increase in the combined prices of the two firms, primarily because Pfizer has a slightly larger market share than GSK.

Nonetheless, the prices of competitors also increased. Unilab, a regional local firm with a sales share of 67.9% in 2018 just prior to the merger, increased the mean price of its products by 2.4%, while Sanofi, an international firm and a close competitor, increased its prices by 10.1% (see Table 3). One important question we pursue is whether Sanofi's price increase reflects a strategic response—given that firms compete in prices and that an increase in Sanofi's prices would be a natural Nash–Bertrand response to GSK's price increase arising from greater market power—or whether it is due to (increased) price coordination among the three large international firms, given that the number of independent decision-makers declined as a result of the merger.

TABLE 10. Change in marginal cost pre-post GSK/Pfizer merger

	MC (1)	lnMC (2)
M × Post	-0.445^a	-0.080^a
	(0.107)	(0.024)
GSK × Post	-0.237^c	-0.038
	(0.141)	(0.031)
Pfizer × Post	-0.549^a	-0.101^a
	(0.098)	(0.022)
Product FE	✓	✓
Time FE	✓	✓
Observations	2,115	2,115
No. of Qtrs.	41	41
No. of Products	54	54
Treatment	12	12
Control	42	42

Note: Estimated marginal costs based on RCL(2). Products with estimated negative marginal costs (n = 46) are not included. Controls are all other cough and cold drugs. Column (1) reports DD estimates for marginal cost, while column (2) reports DD estimates for ln marginal cost. The top panel (first row) combines GSK and Pfizer, while the lower panel (rows 2–3) treats them separately. Quarters $t-1$, $t=0$, and $t=1$ are excluded, where $t=0$ is the quarter of the merger (2019Q2). Standard errors are clustered by product and reported in parentheses. Superscripts a, b, c denote statistical significance at the 1%, 5%, and 10% levels, respectively. Period used 2009Q4–2020Q3. For the shorter period, see Table B-3.

Our structural demand estimation, followed by estimation of the supply-side parameters, suggests coordination, as evidenced by a statistically significant estimate of the conduct parameter, with $\kappa = 1$ (see Table 8). Nonetheless, we urge caution in interpreting this result, as it is not very robust to alternative specifications of the demand system.

This paper's findings are valuable in two particular areas. The first is in exploring the post-merger achievement of efficiencies. While Pfizer and GSK are multinational firms, their cough and cold segment is relatively small in the Philippines. Even so, we find that one of the merging firms realized non-trivial efficiencies within two years of the merger, with prices for that firm's products declining accordingly. The magnitude of these efficiencies is broadly consistent with those predicted prior to merger approval, contributing to the small

but growing empirical literature documenting the realization of merger efficiencies. Notably, these efficiencies were achieved by a firm without a particularly large market share in the segment examined, suggesting that large market shares are not a prerequisite for realizing post-merger efficiencies.

The second is in analyzing the extent to which coordination may have increased following a merger. Our results show that efficiency gains do not preclude adverse competitive effects. The results here, and in other papers, suggest that coordination fears can be real. We find that increased market power led to price increases for one of the merging firms and for competitors. In particular, a close competitor raised prices substantially following the merger. Our structural analysis provides evidence consistent with increased coordination, adding to a limited number of studies that examine coordinated effects in a structural framework. In this case, efficiencies at the merging firms largely offset their own price effects, but increased market power and coordinated effects among rivals appear to have contributed to higher prices elsewhere, underscoring the continued relevance of coordinated effects in merger assessment by competition authorities. We suggest that even more effort is worth devoting to understanding, measuring, and predicting increased coordinated effects that could arise after a merger.

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APPENDIX A. DATA CONSTRUCTION

A.1. **Product selection.** For the estimation, we select products whose average quantity share over the period 2009Q4–2020Q3 exceeds 0.2%. Equivalently, after sorting products by average quantity share in descending order, we retain those accounting for a cumulative 96% of the market. This selection results in a sample of 55 products (out of 185) and 11 firms (out of 52). The other 41 smaller firms collectively represent less than 4% of the market.

TABLE A-1. Product set average shares (2009Q4–2020Q3)

Count	ID	Share	CumSum	Count	ID	Share	CumSum	Count	ID	Share	CumSum
1	160	0.2043	0.2043	19	163	0.0143	0.7537	37	114	0.0045	0.9051
2	138	0.1126	0.3169	20	82	0.0142	0.7679	38	109	0.0045	0.9096
3	168	0.0774	0.3944	21	90	0.0130	0.7809	39	155	0.0044	0.9140
4	173	0.0355	0.4299	22	170	0.0121	0.7930	40	86	0.0041	0.9182
5	89	0.0305	0.4604	23	162	0.0116	0.8046	41	76	0.0040	0.9222
6	77	0.0298	0.4902	24	146	0.0107	0.8153	42	112	0.0037	0.9259
7	178	0.0269	0.5171	25	9	0.0101	0.8254	43	108	0.0037	0.9297
8	150	0.0249	0.5420	26	179	0.0092	0.8346	44	116	0.0037	0.9334
9	78	0.0246	0.5667	27	87	0.0090	0.8436	45	172	0.0033	0.9367
10	161	0.0241	0.5907	28	117	0.0087	0.8523	46	133	0.0033	0.9400
11	143	0.0229	0.6136	29	22	0.0074	0.8596	47	115	0.0032	0.9432
12	144	0.0221	0.6358	30	171	0.0073	0.8669	48	88	0.0030	0.9462
13	185	0.0204	0.6561	31	159	0.0072	0.8742	49	68	0.0030	0.9492
14	149	0.0177	0.6739	32	84	0.0067	0.8809	50	145	0.0026	0.9518
15	106	0.0172	0.6910	33	118	0.0053	0.8862	51	8	0.0023	0.9541
16	91	0.0168	0.7078	34	24	0.0049	0.8911	52	70	0.0022	0.9562
17	23	0.0167	0.7245	35	20	0.0049	0.8960	53	85	0.0021	0.9583
18	44	0.0148	0.7393	36	153	0.0047	0.9006	54	75	0.0021	0.9604
								55	113	0.0021	0.9624

TABLE A-2. Firm average shares (2009Q4-2020Q3)

Count	Firm	Share	CumSum
1	Unilab	0.6594	0.6594
2	Pfizer Inc	0.0852	0.7446
3	Pascual Lab	0.0808	0.8254
4	GlaxoSmithKline	0.0339	0.8593
5	Sanofi	0.0312	0.8905
6	Procter & Gamble	0.0172	0.9076
7	Johnson	0.0148	0.9225
8	Pediapharma	0.0142	0.9367
9	Bayer Philippines	0.0124	0.9491
10	Reckitt Benckiser	0.0082	0.9573
11	New Marketlink PH	0.0051	0.9624

A.2. **Hausman instruments.** We construct Hausman instruments using average prices of the same products in other ASEAN countries—specifically Indonesia, Malaysia, Singapore, and Thailand. Products in each country are defined using the same criteria as for the Philippines, except that we omit the adult or pediatric distinction, which is not available for the other countries. Accordingly, a product is defined as a unique combination of manufacturer, brand name or firm-assigned INN, molecule (active ingredient), and the drug's new form code (NFC).

We then search for the same product across countries (hereafter referred to as the level-1 search; see Table A-3). If the product is found in one or more countries, we compute the average price across those countries and use it as the Hausman instrument for the corresponding product and quarter. If no match is found in any of the four countries, we proceed to a level-2 search, which follows the same procedure but ignores the brand name or firm-assigned INN. In the level-2 search, we also exclude any products already used in level 1. If matches are found in multiple countries, we again compute the average price and use it to construct the instrument. If no match is found, we proceed to level 3, where we drop the NFC code and exclude products used in the previous levels. We continue this sequential procedure up to level 5. The fill rate at each level, as well as the cumulative fill rate, is reported in Table A-3.

There are two exceptions to this procedure. First, for drugs containing Butamirate or Vitex Negundo, we were unable to find any matches through the sequential search, even at level 5. However, matches were obtained by returning to level 3 without excluding products already used in level 2. Second, for four remaining drug–quarter observations, no matches could be found under any specification. In these cases, we use the one-period lagged price of the same drug as the instrument.

TABLE A-3. Product matching criteria

Levels	Description	Filling rate (%)	Cumulative (%)
level 1	Firm + Label + Molecule + NFC3	26.9	26.9
level 2	Firm + Molecule + NFC3	11.2	38.1
level 3	Firm + Molecule	8.10	46.2
level 4	Molecule + NFC3	37.4	83.6
level 5	Molecule	14.9	98.5

APPENDIX B. ADDITIONAL RESULTS

Table B-1 is similar to Table 3 in the main analysis. The main difference is that the DD here uses data from 2017Q1-2020Q3 instead of the full period 2009Q4-2020Q3. Similar to that main analysis, the DD here too does not use observations in the quarter of the merger or the one quarter immediately before and after the merger.

TABLE B-1. Merger effects on prices, restricted period

(in log)	Cough & Cold† Private (1)	Cough & Cold† Proprietary (2)	Analgesics Proprietary (3)	Hypertension Parties (4)	Hypertension Competitors (5)
β^M (M×Post)	0.022^a	-0.031^a	-0.032^a	-0.024^a	-0.024^a
	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)
β^G (GSK×Post)	0.049^a	-0.004	-0.005	0.003	0.003
	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)
β^{Pf} (Pfizer×Post)	0.009^c	-0.045^a	-0.046^a	-0.038^a	-0.038^a
	(0.005)	(0.005)	(0.008)	(0.006)	(0.006)
β^S (Sanofi×Post)					0.021^b
					(0.010)
β^U (UniLab×Post)					0.012^c
					(0.007)
Product FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Observations	197	494	701	2,143	2,696
No. of Qtrs	12	12	12	12	12
No. of Products	17	49	77	332	387
Treatment	12	12	12	12	67
Control	5	37	65	320	320

Note: Columns (1) and (2) include cough and cold products with the same active substance as GSK and Pfizer products. Column (3) is a proprietary label from the analgesics market. Columns (4) and (5) use hypertension drugs as controls. Column (5) contains additional post-merger dummies for Sanofi and Unilab. The top panel (first row) combines GSK and Pfizer, while the lower panel (rows 2–5) treats them separately. Quarters $t-1$, $t=0$, and $t=1$ are excluded, where $t=0$ is the quarter of the merger (2019Q2). Standard errors are clustered by product and reported in parentheses. Superscripts a, b, c denote statistical significance at the 1%, 5%, and 10% levels, respectively. Period used 2017Q1–2020Q3. For the full-period results, see Table 3.

Table B-2 is similar to Table 9 in the main analysis. The main difference is that the markups use data from 2017Q1-2020Q3 instead of the full period 2009Q4-2020Q3.

TABLE B-2. Average markups before and after the merger, restricted period

	Before	After	Mean change	p-value
GSK	41.75	43.66	1.91	0.419
Pfizer	39.64	40.31	0.67	0.125
Sanofi	47.44	48.33	0.89	0.832
Unilab	47.27	45.30	-1.98	0.002
Pascual	45.35	40.73	-4.62	0.058

Notes: Markups are expressed in percentage, so $100 \times (p - c)/p$."Before" and "After" refer to average markups in the pre- and post-merger periods using $\kappa = 0$ and $\kappa = 1$ respectively. Change is the simple difference between post- and pre-merger averages and p-value reports associated probability in a two-sided t-test on the mean difference. For the full period results, see Table 9.

Table B-3 is similar to Table 10 in the main analysis. The main difference is that the DD here uses data from 2017Q1-2020Q3 instead of the full period 2009Q4-2020Q3. Similar to the main analysis, the DD here to does not use observations in the quarter of the merger or the one quarter immediately before and after the merger.

TABLE B-3. Change in marginal cost pre-post GSK/Pfizer merger, restricted period

	MC (1)	lnMC (2)
M × Post	-0.295^a	-0.070^a
	(0.062)	(0.017)
GSK × Post	-0.248^b	-0.062^a
	(0.102)	(0.022)
Pfizer × Post	-0.319^a	-0.074^a
	(0.056)	(0.016)
Product FE	✓	✓
Time FE	✓	✓
Observations	621	621
No. of Qtrs.	12	12
No. of Products	54	54
Treatment	12	12
Control	42	42

Note: Estimated marginal costs based on RCL(2). Products with estimated negative marginal costs (n = 46) are not included. Controls are all other cough and cold drugs. Column (1) reports DD estimates for marginal cost, while column (2) reports DD estimates for ln marginal cost. The top panel (first row) combines GSK and Pfizer, while the lower panel (rows 2–3) treats them separately. Quarters $t-1$, $t=0$, and $t=1$ are excluded, where $t=0$ is the quarter of the merger (2019Q2). Standard errors are clustered by product and reported in parentheses. Superscripts a, b, c denote statistical significance at the 1%, 5%, and 10% levels, respectively. Period used 2017Q1–2020Q3. For the shorter period, see Table 10.