The Effects of Mergers and Acquisitions on Marketing Decisions and Effectiveness: Evidence from the Biopharma Industry

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ABSTRACT

Mergers and acquisitions (M&As) may trigger adjustments to firms' marketing decisions and their outcomes. Yet, prior literature provides little empirical insight regarding the nature of these adjustments. We address this gap in the context of the biopharma industry, analyzing data on sales, prices, and detailing spending for 375 branded drugs acquired in 73 M&A deals between 2007 and 2020. We find that, on average, acquiring firms (1) reduce detailing spending on target drugs, (2) increase target drug prices, and (3) achieve increases in detailing elasticity for target drugs after the M&A, compared to before. The younger the target drugs and the more experience the acquirer has in marketing drugs in the drugs' therapeutic category, (1) the more likely we are to see reductions in detailing and increases in prices, and (2) the greater the likelihood that acquirers experience larger increases in detailing elasticity and reductions in price elasticity. For our 375 target drugs, acquirers generated over $23 billion more in revenue in the two post-deal years while spending over $1 billion less on detailing compared to the two pre-deal years. The paper provides a framework for firms regarding commercial returns on M&As and informs the debate on regulatory responses to M&As.

Keywords: Mergers and acquisitions, marketing, detailing, pricing, biopharma, pharmaceutical marketing, price elasticity, promotion elasticity, drug marketing.

INTRODUCTION

The worldwide value of merger and acquisition (M&A) deals has increased from an annual value of $0.35 trillion U.S. dollars in 1985 to a peak value of $5.24 trillion U.S. dollars in 2021 (Statista 2024a). In 2023, the pharma, medical and biotech industry, the empirical context of the current research, accounted for 15% of the M&A value across all industries with a total deal value of $472 billion (Statista 2024b).

M&A deals can bring two main commercial benefits to the joint firm beyond R&D benefits. First, an M&A deal can generate efficiencies in the respective firms' commercial operations. For example, after a deal, the sales force of the acquiring firm can integrate the target firm's product portfolio in its ongoing sales activities. This way, the same sales force is utilized for a broader portfolio of products. Indeed, in the 1984 revision of the Merger Guidelines, U.S. antitrust agencies formally acknowledged that mergers could generate essential economic efficiencies (Ashenfelter, Hosken, and Weinberg 2014). Merging firms have argued that reductions in costs are likely to translate into lower consumer prices following the deal (Ashenfelter et al. 2014; Lazarus 2018).

Second, an M&A deal can enable the respective firms to build more market power, by bolstering their total market share—which, in turn, enables the joint firm to increase its prices or channel power. Antitrust authorities view this enhanced market power as a potential antitrust concern (Syverson 2019). In the pharmaceutical industry, recent M&As have led to controversial and widely publicized instances of significant drug price increases, negatively impacting consumer welfare (Henkel and Ross 2017). A notable example is the 2015 acquisition of Salix Pharmaceuticals Ltd. by Valeant (included in our empirical investigation; see below). Following this acquisition, Valeant dramatically increased the prices of several Salix drugs. The price of

Glumetza, a diabetes medication, rose by approximately 800%; Zegerid, an acid reflux treatment, saw a price hike of about 700%; and the prokinetic drug Metozolv quadrupled in price, among other price increases (Chen and Koons 2015; Morgenson 2016; Pollack and Tavernise 2015).

In sum, following M&A deals, firms may make significant adjustments to marketing decisions, such as pricing and promotional activities, and firms may experience changes in marketing effectiveness, such as price and promotional elasticity. Prior literature has studied the effect of M&As on pricing (Ashenfelter et al. 2014). However, the reported findings on this effect vary significantly depending on the empirical context and methodologies applied. Prior literature has not studied the effect of M&As on promotion, nor has it studied the effect of M&As on price elasticity and promotional elasticity. The present paper complements the literature on the effect of M&As on pricing and is the first to comprehensively examine the empirical effect of M&As on promotion and on marketing effectiveness. As moderators of these effects, we study characteristics of the acquirer[1] and the target drug.

We adopt an empirics-first approach (Golder et al. 2023) to analyze a large set of deals. Our sample consists of 375 branded target drugs acquired in 73 M&A deals occurring between 2007 and 2020 (the data span the period 2004–2022). We collaborate with the leading biopharma analytics and research firm IQVIA to generate a unique, custom-built dataset. For each target drug, we analyze a period starting two-and-a-half years before the date of deal execution and ending two-and-a-half years after that date. Our data cover monthly sales, prices, and spending on detailing (i.e., visits of sales representatives to prescribing physicians) for all drugs in our sample, both target drugs as well as all competing drugs in the same Anatomical Therapeutic Chemical

[1] In our analysis, we consider both mergers and acquisitions; in the case of a merger, our identification of an "acquirer" firm is based on the classification of the deal dataset provider (i.e., classified as a principal vs. partner company).

(ATC) level-1 categories in which the firms are active.[2]

We complement the literature on M&As, in fields such as strategy (e.g., Bai, Jin and Serfling 2022; Capron 1999), organizational behavior (e.g., Rogan 2014; Shaver and Mezias 2009), and finance and accounting (e.g., Bena and Li 2014; Duchin and Schmidt 2013), which have devoted much attention to the study of M&A deals and their business consequences (see Table A1 in Web Appendix A for a review of M&A studies in top academic journals outside the domain of marketing). We also complement the sparse marketing literature on the impact of M&As, which has primarily focused on financial rewards, consumer reactions, and firm innovation (see Table 1 below for a review of marketing studies on M&As).

We report the following new findings. First, on average, acquiring firms reduce detailing spending and increase the prices of branded target drugs after the deal. This strategy is the most common within our sample of drugs and leads to the highest increase in detailing returns following the deal (as compared with alternative strategies, i.e., different combinations of increasing versus decreasing detailing spending and/or prices). This strategy of decreasing detailing spending and increasing prices is also more likely the younger the target drugs are, and the more experience acquirers have in the therapeutic category of the target drug. Our raw dataset further shows that the acquiring firms generated over $23 billion more in total revenue for our sampled 375 drugs during the two post-deal years compared to the target firms' revenues in the two pre-deal years. Additionally, the acquiring firms collectively spent over $1 billion less on detailing during the post-deal period than the target firms did in the pre-deal timeframe.

Second, we find that, on average, the detailing elasticity of our target drugs after the deal is

[2] In our study, drug prices reflect the amounts paid by dispensing outlets, chains, and health care providers to manufacturers in U.S. dollars to manufacturers, and not patient out-of-pocket costs (for more details see subsection "Pharmaceutical Marketing-Mix Effects" below).

higher than before the deal. On average, price elasticity remains unchanged, but we find that there is substantial heterogeneity in this effect across drugs. For example, the younger the drugs are, the stronger the increases in detailing elasticities and the decreases (less negative) in price elasticity. Similarly, acquirers with more commercial experience in the therapeutic category of the target drug are more likely to see increases in detailing elasticity and decreases (less negative) in price elasticity. Such decreases in price elasticities could indicate higher market power for these target drugs following the deals than before the deals (Elzinga and Mills 2011).

The large set of deals and target drugs in our sample allows us to gain empirical generalizability across different market conditions in the biopharma industry. In biopharma, marketing managers facing a prospective M&A might build on our findings to assess their potential marketing-mix responses and their likely elasticity outcomes, as a function of characteristics of the acquirer and the target drugs they would be responsible for. Our insights are also relevant to competing firms anticipating market changes when their competitors are acquired. Moreover, the conceptual and methodological framework we offer may prove useful to managers and analysts of M&As in other industries.

Our findings have important implications for regulators and policymakers. First, drug prices for branded target drugs tend to increase following M&A deals. Major deals, such as Pfizer's $43 billion acquisition of Seagen and JNJ's $14.6 billion purchase of Intra Cellular Therapies, have been approved or are in advanced stages of regulatory review (Loftus and Jacob 2025; Mishra and Erman 2023). The wave of consolidation is occurring alongside legislative and executive efforts (e.g., the Inflation Reduction Act) aimed at curbing rising prices (White House 2025; Cooney 2023). Such reforms risk being undermined if mergers enable firms to exert greater pricing power. The situation highlights the need for more proactive merger review standards and stronger

pricing safeguards (Fierce Pharma 2021).

At the same time, we find evidence for reduced detailing spending. This reduced spending may align with payers' interests, as well as with the interests of regulators, who may be concerned about negative consumer welfare effects of excessive detailing. On the other hand, we find that the younger the drug, the higher the reduction in detailing. This is opposite to regulators' likely preference to prioritize reduction of detailing for mature (vs. younger) drugs, given that detailing offers less informational value for mature drugs (Narayanan, Manchanda, and Chintagunta 2005).

RELATED LITERATURE

This article builds on three prior literature streams: (1) the downstream effects of M&A deals; (2) the connection between cost efficiency, market power and market concentration; (3) the effects of pharmaceutical marketing-mix instruments.

Downstream Effects of Mergers and Acquisitions

Fields such as economics, health economics and management have focused primarily on downstream M&A effects associated with R&D and innovation (e.g., Aggarwal and Hsu 2014; Capron 1999), managerial approach and management turnover (e.g., Bai, Jin and Serfling 2022; Shaver and Mezias 2009) and client relationships (e.g., Farronato, Fong and Fradkin 2024). See Web Appendix A for a review.

Within the field of marketing, studies of the downstream effects of M&A deals have focused on deal outcomes such as stock price returns (e.g., Saboo, Sharma, Chakravarty and Kumar 2017; Sorescu, Chandy and Prabhu 2007), post-deal innovation (Prabhu, Chandy and Ellis 2005; Rao, Yu and Umashankar 2016) and consumer responses to the deal (Biraglia et al. 2023; Van Lin and Gijsbrechts 2014 & 2019). Another set of studies, based on managers' surveys, examines the perceptions of managers regarding marketing resource redeployment following

M&A deals; these studies have found, for example, that managers believe that marketing resources are transferred between the joining firms, and that resources are more likely to be transferred from the acquirer to the target than vice versa (e.g., Capron and Hulland 1999; Homburg and Bucerius 2005). See Table 1 for a summary of M&A-related studies in marketing.

Prior marketing studies on M&A activity, while valuable in many respects, do not provide insight on the effects of M&A deals on firms' marketing-mix decisions—including product promotion practices as well as pricing decisions—or on demand responses to marketing efforts. Indeed, to our knowledge, only two M&A studies address promotion practices and outcomes, both in an empirical context of just one M&A deal. Bommaraju et al. (2018) empirically measured the effect of an M&A deal on the extent to which salespeople of the acquiring firm identify with their organization, and on the salespeople's consequent performance. In their investigation, the authors focused on the effect of the M&A announcement. They compared their focal outcome measures before and after the announcement, yet did not analyze the post-integration period. Therefore, their analysis could not shed light on salespeople's responses to the integration itself. Van Lin and Gijsbrechts (2019), in turn, examined the impact of one M&A deal in the retailing industry on consumer choice of the target outlets; specifically, the authors explored the extent to which store advertising under a new (versus pre-acquisition) banner affected target outlet choice. However, the study did not compare advertising sensitivity before and after the conversion, and thus did not provide insights on post-deal changes in promotional effectiveness.

Regarding the effects of M&A deals on prices, to our knowledge, the work of Guler, Misra and Singh (2020) is the only marketing study related to the topic. They found that higher market concentration was associated with increased car rental prices for weekday travelers and decreased

prices for weekend travelers. However, the study did not directly measure changes in price sensitivity.

Studies outside marketing, mostly in the fields of law and economics, have investigated what happens to the prices consumers pay following M&A deals (see Ashenfelter et al. 2014 for a review). These studies mainly focused on the airline, banking, and hospital industries, and reported mixed results across different market conditions and industries. Some of these studies suggested that prices decrease after M&A deals (e.g., Sheen 2014), and others warned of a decrease in consumers' welfare due to potentially higher post-deal prices (e.g., Allen, Clark and Houde 2014).

Hüschelrath and Müller (2015), for example, examined how the merger of Delta and Northwest Airlines impacted ticket prices. They observed an initial increase in prices, which was moderated over time but still resulted in a net price increase for consumers. A more recent study, by Richman et al. (2016), focused on the pharmaceutical industry and concluded that the rise in blockbuster M&A deals did not trigger systematic increases in drug prices. However, the authors' conclusions might have been affected by aggregation bias: Specifically, Richman et al. (2016) did not analyze changes in the prices of merging firms' drugs. Instead, they examined the concentration level in the pharmaceutical market between 1998 and 2015 and suggested that the overall concentration was both low and relatively stable. They, therefore, concluded that a trend of drug price increases does not appear to emerge from increased market power due to M&As in the biopharma industry. Our evidence below contradicts the conclusions of this earlier work.

Table 1 – M&A-Focused Papers in Top Marketing Journals

M&A	Paper	Outcome Focus	Marketing-mix Outcomes	Sample type	Sample size
Firm performance	Capron and Hulland (1999)	Post-M&A resource transfer (acquirer to and from target), and 6 performance measures	-	Survey of managers	253 US and European firms
	Homburg and Bucerius (2005)	Post-M&A perceived difference in market share, cost savings, and returns on sales	-	Survey of managers	232 managers in European firms
Financial rewards	Sorescu, Chandy and Prabhu (2007)	Post M&A long-term financial rewards to the acquirer (stock returns)	-	Firm level panel data	238 acquisitions
	Swaminathan, Murshed and Hulland (2008)	Post-M&A stock returns of both firms (following the day of the announcement)	-	Firm level data	206 M&As
	Bahadir, Bharadwaj and Sriastava (2008)	Target brand value at deal (based on SEC fillings)	-	Firm level data	133 M&As of US public firms
	Wiles, Morgan and Rgo (2012)	Abnormal returns following brand acquisitions or disposals	-	Firm level data	322 firms acquiring/disposing brands
	Saboo, Sharma, Chakravarty and Kumar (2017)	Post-M&A abnormal returns	-	Firm level panel data	319 acquisitions
Consumer reactions	Van Lin and Gijsbrechts (2014)	Post-M&A consumer choice of supermarket stores	-	Store level panel data	300 Stores (917 households)
	Van Lin and Gijsbrechts (2019)	Post-M&A consumer response to store conversion over time	-	Store level panel data	100 Stores (1,500 households)
	Umashankar, Bahadir, and Bharadwaj (2022)	Post-M&A change in customer satisfaction	-	Firm level panel data	141 firms between 1995 - 2017
	Biraglia et al. (2023)	Consumer responses to brand acquisitions	-	Lab experiments	10 studies
Firm innovation	Prabhu, Chandy and Ellis (2005)	Post-M&A innovation output (yearly products in phase 1 trials)	-	Firm level panel data	35 US acquirers
	Rao, Yu and Umashankar (2016)	(1) Likelihood of two firms to merge; (2) Post-M&A innovation (number of patents)	-	Firm level panel data	1,979 international mergers
Marketing decisions and performance	Bommaraju et al. (2018)	Post M&A announcement (pre integration) change in acquirer salespeople performance	Promotion effectiveness	Survey + experiment	One M&A deal, 367 salespeople and 64 managers
	Guler, Misra and Singh (2020)	Post-M&A change in car rental prices	Price	Firm-airport level panel data	27 car rental firms
	Current paper	**Detailing spending, drug prices, detailing and price elasticities**	**Promotion, Price, Elasticities**	**Firm-product level panel data**	**375 target drugs, 73 M&As**

In this paper, we address the gaps discussed above by conducting a robust and expansive empirical evaluation of the effects of M&A deals on marketing-mix practices, as well as on demand responsiveness to these practices—based on a large set of M&A deals and branded target products.

Efficiency, Market Power, and Market Concentration

The relationship between efficiency, market power, and market concentration has been a central topic in industrial economics. On the one hand, increased market concentration could enhance market power for dominant firms, influencing pricing, investment in R&D, and advertising. For instance, Schmalensee (1987) proposes that higher market concentration can lead to collusive behavior among firms, thereby enhancing their market power and profitability. On the other hand, market concentration can arise from superior efficiency, where more efficient firms gain larger market shares and higher profitability without necessarily resorting to anti-competitive practices (Demsetz 1973). Clarke, Davies, and Waterson (1984) examined which of the two mechanisms, market power or efficiency, primarily drives the relationship between profitability and market concentration. They found that in some industries superior efficiency allows firms to achieve higher market concentration and profitability through better cost structures and innovation. In other industries, collusive behavior among dominant firms plays a more significant role in sustaining high profitability and market power.

Pharmaceutical Marketing-Mix Effects

Direct-to-physician promotion is a primary marketing channel for biopharma firms, prominently featuring detailing, where sales representatives visit physicians to promote drugs. Biopharma companies allocate significant marketing resources to detailing, making it the most studied marketing-mix instrument in biopharma (Kremer et al. 2008). Other direct-to-physician promotion tools include drug sampling and advertising in medical journals (Van den Bulte and Lilian 2001).

Early studies on detailing's impact used aggregate data (e.g., Lilien et al. 1981). Rizzo (1999), for example, found that detailing not only boosts sales but also reduces price elasticity. Similarly, research using physician-level data presents evidence that detailing visits increase prescriptions (e.g., Gönül et al. 2001; Kamakura, Kossar and Wedel 2004; Manchanda and Chintagunta 2004). A meta-analysis of 58 studies confirmed detailing as the most effective promotional tool in biopharma (Kremer et al. 2008), despite significant variability in effectiveness. Subsequent studies have explored factors affecting detailing elasticity, such as competitive entry (Kappe and Stremersch 2016), clinical trial publications (Sood, Kappe, and Stremersch 2014), and drug life cycle (Narayanan et al. 2005). To our knowledge, no study has examined M&A deals as events that affect detailing effectiveness.

Also relevant to our research are studies that explore the effects of drug prices on sales. Prior studies found low price elasticity in pharma drugs (Yeung et al. 2018). This low estimated elasticity can mainly be attributed to the products' high importance and the prescriber not being the payer.

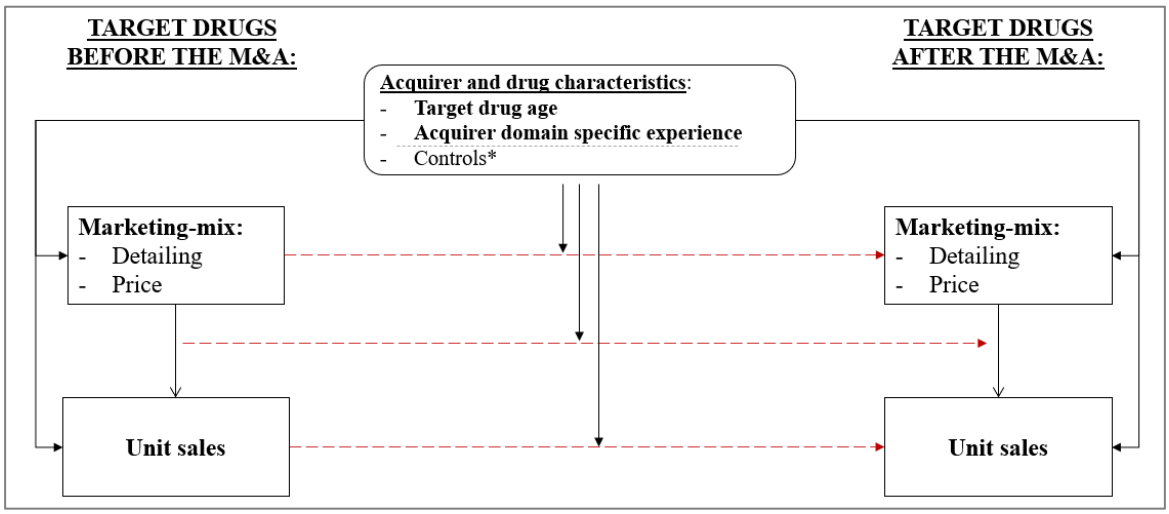
In our study, the price of a drug is calculated according to the net amount (in U.S. dollars) that the manufacturer receives for a unit of the drug; for a given patient, this amount comprises both the patient's out-of-pocket cost and their insurance payer's contribution. In the U.S., drug prices are primarily set through negotiations between drug manufacturers and insurers, including pharmacy benefit managers (PBMs). Manufacturers initially set high list prices, which are then negotiated down through rebates and discounts in exchange for favorable formulary placement, ensuring better market access and coverage for the drug. Prices are further determined by the drugs' competition level and their therapeutic benefits (Conti, Frank, and Gruber 2021). If pharmaceutical firms do not agree to lower prices, sales can be limited due to higher patient copayments and the drug's tier status within insurance plans, which may require patients to try cheaper alternatives first. This study

is the first to analyze the effect of M&A deals on drug price elasticity and to explore factors explaining the heterogeneity in this effect.

CONCEPTUAL FRAMEWORK

Figure 1 illustrates how detailing spending and price affect the unit sales of a target drug, and how an M&A deal affects both the joint firm's decisions with regard to these marketing instruments and the effectiveness of these instruments. We also examine the moderating roles of acquirer- and target drug characteristics in these relationships. As will be shown in what follows, M&As can trigger complex market dynamics that have competing effects on our variables of interest. As a result, though we can speculate on effects that might arise, it is not always possible to formulate clear hypotheses. Accordingly, we use an empirics-first approach in line with the rationale put forward by Golder et al. (2023). This approach prioritizes empirical observations and data analysis to characterize emerging phenomena rather than constructing hypotheses in advance. By grounding our research in real-world market dynamics and focusing on data-driven insights, we aim to provide a nuanced understanding of the effects of M&As.

Figure 1 – Conceptual Framework



* The control variables represent other factors, outside our main model variables, that may affect our focal outcome variables.

Underlying Conceptual Logics

We propose two possible logics that may underlie post-M&A changes in firms' marketing-mix decisions and effectiveness: (1) the cost-efficiency logic and (2) the market power logic.

The Cost-Efficiency Logic

The cost-efficiency logic suggests that acquiring firms achieve greater efficiency following M&A deals. The post-deal integration of supply, manufacturing, and distribution functions allows M&A firms to enhance efficiency and reduce costs (Eckbo 1983; Focarelli and Panetta 2003; Shahrur 2005; Stillman 1983). M&A deals can also lead to operational efficiency in marketing activities. Acquiring firms may be able to promote the newly acquired target drugs more cost-effectively than the original target firm. For example, economies of scale may allow the merged firm to allocate detailing calls more efficiently. Sales representatives of the combined firm can discuss both the acquirer's and the target's drugs in a single visit, whereas previously, two separate visits were needed for a given physician.

The impact of cost-efficiency improvements on prices depends on the market's competitive structure. When an M&A deal enhances cost efficiencies, firms facing competitive pressure may be strongly incentivized in their negotiations with insurers and other healthcare payers to reduce prices for better market access to gain or maintain a competitive edge, thereby passing the cost savings on to payers. In contrast, companies facing less competitive pressure are more likely to retain these savings and less likely to reduce prices. At the same time, these cost-efficiency improvements are not expected to affect the price elasticity of the target drugs. This is because such improvements are unlikely to impact demand-side entities other than through their potential effect on prices.

For detailing spending levels, the expected effect of increased cost efficiency is unclear a priori. The newly merged firm may choose to focus on cost saving by reducing detailing spending or, alternatively, capitalize on savings in other operational areas to increase detailing spending,

depending on its objectives. At the same time, we expect the enhanced efficiency in promoting the newly acquired target drugs and the potential cost savings in sales-calls to lead to higher detailing elasticity compared to the pre-deal levels achieved by the target firms. As a result, firms opting for cost saving by decreasing detailing spending could maintain similar revenues at lower costs. Alternatively, firms that choose to increase spending on the newly acquired drugs may further benefit from the anticipated positive impact of the M&A deal on detailing elasticity, leading to higher returns on detailing after the deal.

The Market Power Logic

The expected effects of increased market power on prices are generally positive. For example, a newly merged firm that controls drug therapies for a particular condition, previously held by two competing firms, could achieve near-monopoly status, thereby having the opportunity to raise prices. Additionally, even when acquirers were not active in the target drugs' therapeutic category before the deal, they may still be able to raise prices by adding pricing and reimbursement capabilities, such as negotiation skills with healthcare payers.

The expected effect of increased market power on price elasticity is negative. Specifically, we anticipate that price elasticity will decrease (become less negative) following an M&A deal compared to its level before the deal. Academic studies, both within and outside the context of M&A effects, including those focused on the pharmaceutical industry, regard the Lerner index as a tool to assess changes in market power. This is done either directly or indirectly by calculating the change in estimated own-price elasticities, with decreases in elasticity indicating increased market power (e.g., Dalen, Strom, and Haabeth 2006; Elzinga and Mills 2011; Kupcik 2022; Lopez and You 1993; Webster 2002).[3] In this paper, we adopt this approach, treating changes in price

[3] Closest to our context are the papers by Elzinga and Mills (2011) and Kupcik (2022). Elzinga and Mills (2011) offer a comprehensive overview of the Lerner Index, detailing its theoretical origins and practical applications in economic analysis and

elasticity following M&A deals as indicative of changes in market power. Specifically, we anticipate that target drugs will become less price-elastic (i.e., have less negative price elasticities) after M&A deals than before the deals due to increased market power.

Conversely, the effect of increased market power on detailing spending is expected to be negative. Firms with heightened market power may choose to exploit this advantage by cutting back on promotional expenditures. However, we do not have any a-priori expectations regarding the effect of increased market power on detailing elasticity.

Rows two and three in Table 2 summarize our expectations regarding the main effects of M&A deals on detailing spending, price levels, detailing elasticities and price elasticities of target drugs based on the two logics. NA refers to effects for which we do not have a priori expectations. Given competing logics, we seek to achieve two main objectives: (1) examine empirically on a large sample which main outcome generally manifests, for marketing-mix decisions and responsiveness, and (2) examine potential moderators that may further influence these effects.

Table 2 – Expected Main and Moderating Effects

		Detailing spending	Drug Prices	Detailing elasticity	Price elasticity*
Main effect	Market power logic	-	+	NA	-
	Cost efficiency logic	+/-	-	+	NA
Moderating effects	*Acquirer domain specific commercial experience*	I -	II +	III +	IV -
	Target drug age	V +	VI -	VII -	VIII +

Notes: The "+" and "-" signs indicate our expectations regarding the direction of the focal effect. NA means there is no a priori expectation regarding the direction of the effect. Price elasticity is negative. Therefore, an expectation for a decrease in price elasticity (as seen in Table 2) implies an expected positive interaction term in the estimation results. Roman numerals label cell numbers corresponding to expected moderating effects for easier referencing in the text.

Moderators

policy. While they emphasize the significance of the Lerner Index in measuring market power, their paper does not provide empirical evidence on the effects of M&As on price elasticity. Similarly, Kupcik (2022) examines the role of a firm's own price elasticity of demand in assessing market dominance. This paper also focuses on theoretical and methodological aspects rather than providing empirical evidence on M&As.

We focus on two key moderators in our study: acquirer domain-specific commercial experience and the age of the target drug. These moderators were chosen based on theoretical insights from prior literature and their relevance to our research context. Domain-specific commercial experience captures the degree of market or industry relatedness between the acquirer and the target. Prior research highlights that industry and market relatedness may facilitate the acquirer's ability to absorb, integrate, and exploit inter-organizational learning (Lane and Lubatkin 1998). This absorptive capacity is critical in generating post-acquisition value by enabling smooth post-merger integration and effective deployment of combined firm capabilities (Singh and Montgomery 1987).

The age of the target drug relates to product life cycle stages that influence the merger's impact on the marketing of the target drug. Prior literature has consistently demonstrated that the choice and effectiveness of marketing actions vary across different stages of the product life cycle (e.g., Parsons 1975; Saboo, Kumar, and Park 2016). Specifically, in the pharmaceutical industry, detailing has more of an informative role for younger drugs and more of a persuasive role for mature drugs (Narayanan et al. 2005).

In this section, we elaborate on the theoretical expectations for each moderator and its anticipated influence on our variables of interest (for a summary see Table 2).

Acquirer Domain-Specific Commercial Experience

To provide a comprehensive view on acquirer domain-specific commercial experience, we use two dimensions. First, we consider the acquirer's detailing spending in the target drug category before the deal. Second, we consider the number of branded drugs the acquirer introduced in the target drug's therapeutic category during the 9–14 years preceding the M&A deal (following Danzon, Epstein, and Sean 2007). This timeframe ensures that: (1) the acquirer has a minimum number of years of experience in the category (i.e., at least 9 years), and (2) the acquirer experience still concerns a drug under patent protection (i.e., at most 14 years on the market).

Acquirers with extensive domain-specific commercial experience will likely have developed critical assets such as industry know-how, marketing expertise, an established sales force, and strong relationships with key physicians, positioning them to market the target drug better than less-experienced acquirers (see cell III in Table 2). In addition, more-experienced acquirers, to a greater extent than less-experienced acquirers, can use economies of scale at the level of the category, enabling them to spend less on detailing. For instance, they can use the same sales force they are already operating, and this sales force will need limited (re)training. Therefore, we expect more-experienced acquirers to lower detailing spending post-deal to a greater extent compared with less-experienced acquirers (see cell I in Table 2).

Furthermore, acquirers that marketed drugs in the therapeutic category of the target drug before the M&A deal are expected to undergo greater increases in market power after the deal compared to those without such experience. This is because such acquirers are more likely to consolidate control over drug therapies for specific conditions that were previously held by two competing firms. Moreover, these acquirers are likely to possess domain-specific negotiation skills, enhancing their bargaining capabilities for the newly acquired drugs. Assuming that increases in market power are reflected in decreased price elasticity (Elzinga and Mills 2011), we expect higher experience in the category to be associated with lower post-deal price elasticity compared to lower experience in the category (see cell IV in Table 2).

While increased cost efficiencies could theoretically lead to price reductions under competitive pressure, the enhanced market power associated with higher experience tends to weaken such pressure. Consequently, all else being equal, we expect acquirers with more experience in the therapeutic category of the target drug to be more likely to increase prices following the deal compared to those with less experience (see cell II in Table 2).

Target Drug Age

As noted above, following a deal, an acquirer could enhance market power by introducing additional price negotiation and/or health economics capabilities, enabling them to negotiate better prices for a target drug. We suggest that acquiring firms may leverage these advantages more effectively the younger the target drugs are, as it is more difficult to introduce new scientific information or explain existing evidence in a novel way to demonstrate superior value for mature drugs (Sood, Kappe, and Stremersch 2014; Vakratsas and Wang 2024). Therefore, the more mature the target drugs are, the less likely the M&A deals are to enhance the market power for these drugs, reducing the likelihood of higher prices and lower (less negative) price elasticities (see cells VI and VIII in Table 2).

For detailing spending levels, as noted above, following M&A deals, acquirers may cut spending on detailing to save costs (Fee and Shawn 2004). However, prior literature has identified biases in firms' marketing spending, where firms tend to overspend on mature products (where spending is less necessary and less effective) and underspend on younger ones (Albers et al. 2010). Typically, the logic is that firms do not want to put large cash flows at risk. Often, mature branded drugs present larger cash flows than the same drugs at a younger age. Therefore, we expect that acquirers are less likely to cut detailing the more mature the target drugs are (see cell V in Table 2).

Regarding detailing elasticity, similarly to the case of price elasticity, we propose that following M&A deals, acquiring firms can more effectively utilize their scientific and sales force know-how and enhance the persuasiveness of detailing visits the younger the target drugs. For instance, new scientific information is easier to produce convincingly for younger drugs than more mature ones. Therefore, we expect that acquirers are more likely to achieve higher detailing elasticity following the deal the younger the target drugs are (see cell VII in Table 2).

METHODOLOGY

Data and Sample

We collected data from MarketLine and Clarivate on all M&A deals between 2007 and 2020 involving biopharmaceutical target firms that marketed at least one drug in the U.S. before the deal. Of an initial 107 deals, we kept 73 deals involving 375 target drugs that were promoted using detailing at least one month in the pre-deal or post-deal period. Our final sample of 73 deals involved 59 unique acquirers and 72 unique target firms (see Web Appendix B for more details).

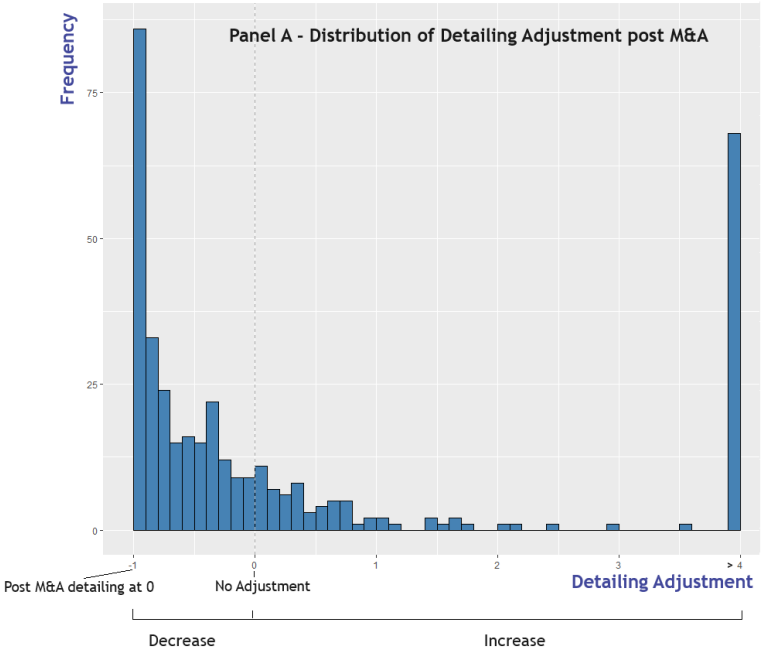
We obtained a unique, custom-built dataset from IQVIA on monthly drug sales, detailing spending and prices. Drug prices are calculated according to the amounts (in U.S. dollars) that manufacturers received in practice. The dataset tracks all brands of the firms involved in each M&A deal and all other drugs in those brands' ATC level 1 categories. As shifts in marketing-mix decisions and their effectiveness may already start before the deal's completion, and post-deal integration may require months (Sheen 2014), we do not analyze data from the six months before and after the month of M&A completion. For each deal, we focus on all months in the two years ending six months before the month of the deal's completion (we term this period the *pre-deal period*), and in the two years starting seven months after the month of the deal's completion (we term this period the *post-deal period*).

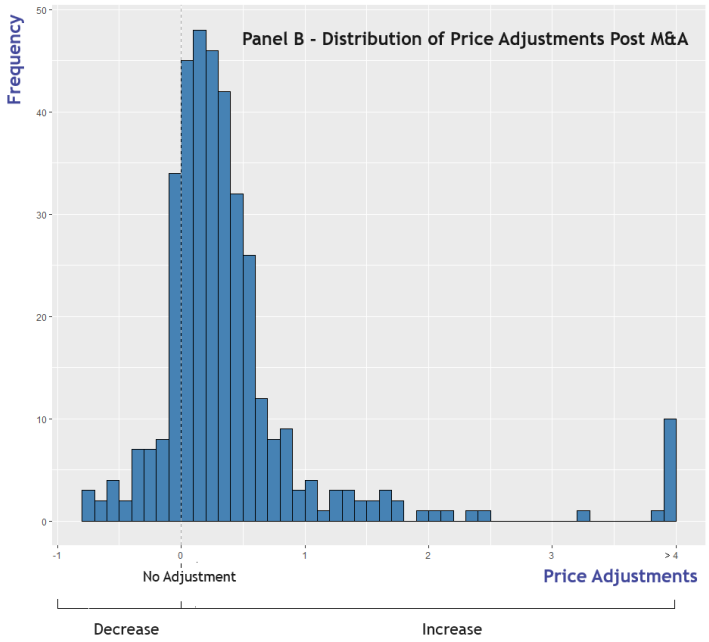
Figure 2 presents the distribution of percentage adjustment in detailing spending (Panel A) and in prices (Panel B) for the target drugs between the pre- and post-deal periods. Among the target drugs in our dataset, we observe a negative median percentage adjustment of -40.2% in detailing spending between the pre- and post-deal periods. On average this reduction in detailing amounts to $3.18 million per drug during the two-year post-deal period compared to the pre-deal period. Acquiring firms collectively reduced detailing expenditures for our sample of target drugs

by $1.19 billion during the post-deal period. This represents a decline from $3.23 billion spent by target firms in the pre-deal period to $2.04 billion spent by acquirers on the same drugs in the corresponding post-deal period.

The median percentage adjustment in prices between pre- and post-deal periods is an increase of 26.9%. After accounting for changes in unit sales, these price adjustments led to an average revenue increase of $61.34 million per drug during the two-year post-deal period compared to the pre-deal period. In total, acquiring firms generated an additional $23 billion in revenue across the 375 drugs in our sample during the post-deal period compared to the pre-deal period. This marks a rise from $107 billion in revenue for these drugs recorded by target firms during the pre-deal period to $130 billion achieved by acquirers in the corresponding post-deal period.

Figure 2 – Adjustments in Target Drug Detailing Spending and Prices: Pre- versus Post-M&A Deal

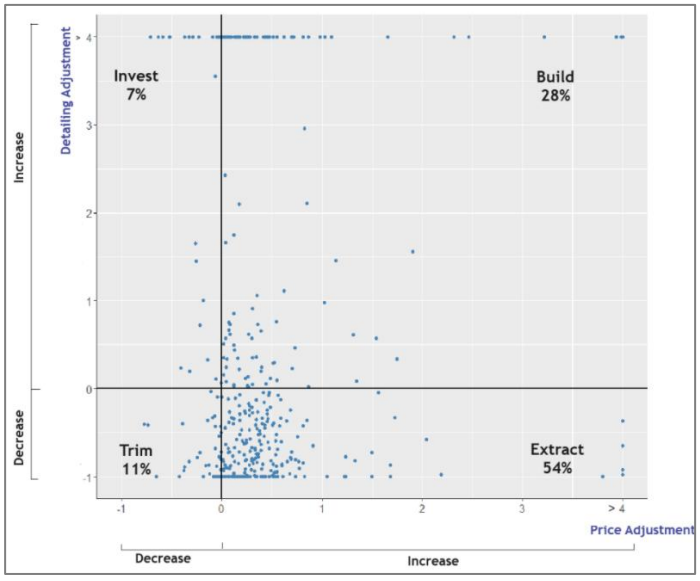




* Adjustments are calculated as post-deal mean monthly levels over a 24-month period, minus pre-deal mean levels over a 24-month period, divided by mean pre-deal levels, excluding the 6 months before and after the deal execution in our calculations.

Figure 3 presents a 2-by-2 plot divided into quadrants, onto which we map our observations according to whether their corresponding prices decreased or increased (X axis), and whether detailing spending decreased or increased (Y axis).

Figure 3 – Adjustments in Target Drug Prices and Detailing Spending



* For presentation purposes, all drugs with large positive adjustments are truncated at 4. In our sample, 68 target drugs have a positive change in detailing that is greater than 4. Of these, 55 (80%) are target drugs that were not promoted using detailing during the pre-deal period. The remaining 13 drugs had very low detailing spending in the pre-deal period (mean monthly spending of $12,696 compared to a monthly mean of $248,300 in the full sample; see Table 3 below). For 60 drugs in our sample, there was a positive level of detailing spending in the pre-deal period and no detailing spending in the post-deal period.

54% of observations fall in the bottom right quadrant, which we label *Extract* (cases with increased prices and decreased detailing of target drugs); 28% of observations fall in the top right quadrant, which we label *Build* (increased prices and increased detailing of target drugs); 11% of observations fall in the bottom left quadrant, which we label *Trim* (decreased prices and decreased detailing); and 7% of observations fall in the top left quadrant, which we label *Invest* (decreased prices and increased detailing). For example, in Valeant's acquisition of Salix in 2015 (mentioned in the introduction), the target drugs Glumetza, Zegerid, and Metozolv all experienced price increases; Glumetza and Zegerid saw a decrease in detailing spending after the deal, placing them in the Extract quadrant, whereas Metozolv saw an increase in post-deal detailing spending, placing it in the Build quadrant.

The distribution of drugs across the two dimensions provides preliminary evidence that acquiring firms tend to reduce their promotional efforts and increase prices of the target drugs after the M&A deal. Such evidence is preliminary because price and promotion decisions are influenced by several factors and may be endogenous to drug demand. Accordingly, our analysis of these variables must control for co-dependencies and other factors that may affect sales, detailing spending, and drug prices.

Accounting for Deal Endogeneity

Acquirers may select targets by assessing their potential to improve the market performance of the target firm's products. Thus, both post-deal marketing-mix decisions and sales responsiveness to these instruments may be endogenously determined. To address this potential endogeneity, we use a two-step control function approach and explicitly account for the acquirer's decision in selecting target drugs (Saboo, Sharma, Chakravarty, and Kumar 2017; Wang, Saboo, and Grewal 2015).

The control function approach involves deriving a proxy variable that represents the

variability of the endogenous variable correlated with the error terms in the second-stage model, thereby facilitating consistent estimation in the main model equations (Petrin and Train 2010; Wooldridge 2015). The first-stage regression (i.e., the control function) models the target drug's choice based on all the variables used in the second stage, along with excluded variables (Hausman 1978; Maddala 1983). These excluded variables are factors expected to influence the likelihood of M&A deals between two firms yet not to directly affect the monthly dynamics in commercial outcomes of each specific target drug (i.e., sales and marketing mix levels and elasticities) beyond their effect on the likelihood of the deal. Specifically, these variables are firm-level, time-invariant characteristics measured prior to the deal, while the second-stage model focuses on monthly, drug-level fluctuations in outcomes. This difference in level and timing helps ensure that the instruments capture strategic alignment factors relevant to deal formation, but are unlikely to track or influence short-term, post-deal variations in commercial behavior or performance. Moreover, because they do not vary at the month-drug level and are predetermined relative to the outcome window, they are less likely to be driven by unobserved shocks that affect second-stage residuals. The residuals from this stage are then introduced as second-stage regressors, with the assumption that the errors of the two stages follow a multivariate normal distribution (Luan and Sudhir 2010; Wooldridge 2010).

The binary dependent variable in the first-stage model, denoted as $Choice_{jTAd}$, indicates whether target firm T that markets drug j took part in deal d with acquirer A. Given the binary nature of $Choice_{jTAd}$, the control function is specified as a probit model (Wooldridge 2015). The selection set includes all target drugs acquired during the year of deal d. Consequently, $Choice_{jTAd}$ equals one if drug j of firm T was acquired in deal d by acquirer A, and zero if it was acquired in the same year but not as part of deal d. As excluded variables, we consider the depth, breadth, and similarity of commercial knowledge between acquirer and target firms (Rao, Yo, and Umashankar

2016), as well as the relative sizes of the two firms (Palepu 1986; Park 2013). These variables, defined based on aggregate characteristics of the target and acquirer firms before the deal, are unlikely to be correlated with the error terms in the second-stage equations, which are specified at the month-drug level before and after the deal, supporting the validity of the exclusion restrictions. See Web Appendix C for first-stage model specification, estimation, and results.

Second-Stage Model

For our second-stage model, we specify a log-log model for drug sales aimed at identifying heterogeneity in drug-specific marketing-mix effects before and after an M&A deal, focusing on understanding the sources of heterogeneity and accounting for the potential endogeneity in detailing spending and price setting. To achieve this, we employ a Hierarchical Bayesian model (e.g., Fok et al. 2006; Hariharan, Landsman, and Stremersch 2024; Schamp et al. 2024). The hierarchical structure of our model makes a Bayesian analysis more attractive than a frequentist approach, while remaining computationally efficient by leveraging iterative random draws from standard distributions. In particular, a Hierarchical Bayesian model offers several advantages in our setting. The first is its flexibility in capturing the response parameters' heterogeneity and the covariates explaining that heterogeneity, closely aligning with the core objectives of our study. In addition, a Hierarchical Bayesian estimation can accommodate missing or unbalanced data in complex model structures: By enabling information to be pooled across units, it effectively "borrows" strength from richer data segments to improve estimates for sparser ones (Allenby, Rossi, and McCulloch 2005; Fok et al. 2006; Manchanda, Rossi, and Chintagunta 2004). Accordingly, the second-stage model comprises two layers consistent with the Hierarchical Bayesian framework. The first layer is represented in Equations 1-3, and the second layer is represented in Equations 4-5 below.

In our model the log of unit sales for drug j in month t, $ln(sales_{jdt})$, is specified as follows:

$$
\begin{aligned}
(1)\ ln(sales_{jdt}) = {} & \beta^1_{0jd} + \beta^1_{1jd} Post_{dt} + \beta^1_{2jd}\, ln(Det_{jt} + 1) + \beta^1_{3jd}\, ln(Det_{jt} + 1) \times Post_{dt} \\
& + \beta^1_{4jd}\, ln(Price_{jt}) + \beta^1_{5jd}\, ln(Price_{jt}) \times Post_{dt} \\
& + \beta^1_{6jd}\, ln(CompSales_{jt} + 1) + \beta^1_{7jd} \hat{\gamma}_{jTAd} + \beta^1_{8jd} \hat{\gamma}_{jTAd} \times Post_{dt} \\
& + \beta^1_{9jd}\, ln(Sales_{jt-1} + 1) + \varepsilon^1_{jdt},
\end{aligned}
$$

where β^1_{0jd} is the brand-deal-specific fixed-effect for baseline sales that captures time-invariant differences in factors that affect the brand's sales. $Post_{dt}$ is a dummy variable set to 1 if month *t* is in the post-deal period of deal *d*. Det_{jt} is the level of detailing spending of drug *j* in month *t*. This cost represents the estimated dollar amount for physician detailing visits ("contacts") related to drug *j* in month *t*. $Price_{jt}$ is the price in dollars of drug *j* in month *t*. Prices and detailing spending in our estimation procedure are adjusted for inflation using January 2005 as a base period (around the starting time of our observation window). $CompSales_{jt}$ represents competitive sales, i.e., the unit sales of all other drugs in the ATC level 4 therapeutic category of drug *j* in month *t*. This variable captures two distinct phenomena leading to two opposing effects on target drug sales: a positive effect of category growth and a negative effect of switching between category competitors (Mizik and Jacobson 2004).[4] The estimated coefficient of $CompSales_{jt}$, β^1_{6jd}, will allow us to assess, on average, which effect dominates in our empirical setting. $\hat{\gamma}_{jTAd}$ are the "generalized residuals", corresponding to target drug *j* in deal *d* between target firm *T* and acquirer *A,* obtained from the first-stage control function (Wooldridge 2015). Our model specification adopts the approach outlined in Wooldridge (2015), which builds on Garen (1984) by adding the interaction term between $\hat{\gamma}_{jTAd}$ and the potentially endogenous variable. This selection-correction approach specifically accounts for the continuous nature of our selection variable and has been advocated in Hamilton and Nickerson (2003) and applied in other marketing studies (e.g., Ghosh, Dutta, and

[4] In Web Appendix D we illustrate the potential opposing effects captured by the competitive sales variable using simulations.

Stremersch 2006; Landsman and Stremersch 2011; Mooi and Ghosh 2010; Wetzel, Hammerschmidt, and Zablah 2014). We let β_{jd}^{1} be jointly distributed as $N(\bar{\beta}^{1}, V_{\beta}^{1})$. As we use a log-log specification, the parameters of the log-transformed variables in Equation 1 represent the elasticities of the respective variables. Specifically, β_{2jd}^{1} and β_{4jd}^{1} are the elasticities of detailing spending and price, respectively. Accordingly, β_{3jd}^{1} and β_{5jd}^{1} represent the changes in detailing and price elasticities following the deal, respectively.

As noted above, detailing spending and price in Equation 1 can be endogenous to sales, as unobserved factors can drive both the error term of the sales equation, ε_{jdt}^{1}, and the marketing variables. We resolve this potential endogeneity by utilizing instrumental variables to explain detailing spending and price (Chintagunta and Desiraju 2005; Narayanan, Desiraju, and Chintagunta 2004). For each endogenous marketing-mix variable, we employ two instrumental variables: one at the market-month level and one at the acquirer-month level. We further model all three variables (i.e., unit sales and our focal marketing-mix variables) as dependent variables in a system of equations and allow for a correlation structure between the error terms of all system equations (Rossi, Allenby, and McCulloch 2005)[5].

The instruments we use for detailing spending are the wage index of all employees in sales and office jobs, obtained from the Bureau of Labor Statistics ($wageidx_{t}$), and the acquirer's total monthly amount spent on detailing, excluding the ATC level 2 category[6] of the focal target drug

[5] The instrumental variable approach is implemented within the Bayesian hierarchical framework. Thus, what corresponds to the "first stage" regression in the frequentist two-stage least squares (2SLS) approach is incorporated into the first layer of the hierarchical model (Rossi et al. 2005). In this layer, the endogenous variables are modeled explicitly as functions of the proposed instruments, with uncertainty captured through the posterior distributions, estimated jointly with the full model estimation. The Bayesian approach provides flexibility in specifying complex model structures, which is especially valuable in our setting, as it involves multiple endogenous variables and instruments. This unified framework allows for coherent joint inference across all model parameters and is particularly advantageous in the presence of small samples or potentially weak instruments.

[6] The Anatomical Therapeutic Chemical (ATC) classification system is widely used for therapeutic drugs and consists of five classification levels. The broader ATC level 2 classes could be either pharmacological or therapeutic groups, while the ATC level 4 classes are more granularly defined chemical, pharmacological or therapeutic subgroups.

($AcqOtherDet_{jdt}$). The instrumental variables we employ for drug prices are the monthly producer price index for pharmaceutical manufacturing, obtained from the Federal Reserve ($pmppi_{\mathrm{t}}$) (Chintagunta and Desiraju 2005), and the acquirer's average monthly price across all drugs in its portfolio excluding the ATC level 2 category of the focal target drug ($AcqOtherMPrice_{jdt}$). We suggest that these variables adhere to the instrumental variable assumptions outlined by Grewal and Orhun (2024). In particular, for $wageidx_{\mathrm{t}}$ (our first instrument for detailing spending), we reason that sales and office job wage costs are directly related to operating a salesforce. They are therefore expected to influence biopharma firms' decisions regarding detailing expenditures, thereby satisfying the inclusion restriction assumption. Since this is a market-level variable, it remains consistent across all target drugs in a given month, which aligns with the stable unit treatment value assumption (SUTVA). Additionally, we do not anticipate these costs to have opposing effects on distinct target drugs or to directly impact drug sales except through their influence on detailing expenditures, thereby satisfying both the monotonicity and exclusion restriction assumptions. For $AcqOtherDet_{jdt}$ (our second instrument for detailing spending), we suggest that detailing expenditures for acquirer drugs outside the broader therapeutic category of the focal target drug are unlikely to influence the sales of the focal drug, as these drugs are unrelated to the focal drug aside from being marketed by the same firm post-acquisition. Thus, $AcqOtherDet_{jdt}$ adheres to the independence assumption. This instrument also complies with both the inclusion restriction assumption and the exclusion restriction assumptions because it captures two unique factors that may affect detailing expenditures for the focal target drug without directly impacting drug sales. First, it may reflect latent, time-varying elements influencing biopharma firms' detailing expenditure decisions, such as shifts in physicians' openness to detailing visits, as observed during the COVID-19 pandemic (Robinson 2020). Second, it may represent the acquirer's firm-level

strategic approach to detailing expenditures over time. The first effect may influence target drug spending even before acquisition, whereas the latter is more likely to occur post-deal. The acquirer's total monthly detailing expenditure, excluding the ATC level 2 category for a specific target drug each month, is not expected to spillover and influence the detailing spending for other target drugs in our sample in a way that is not captured by their respective levels of that instrument, thus supporting SUTVA. We also do not expect this instrument to have opposing effects on different target drugs thereby meeting the monotonicity assumption.

Using similar reasoning, we can likewise claim that our instruments for drug prices—$pmppi_{\mathrm{t}}$ and $AcqOtherMPrice_{jdt}$, which are similar in nature to $wageidx_{\mathrm{t}}$ and $AcqOtherDet_{jdt}$, respectively—satisfy the instrumental variable assumptions detailed by Grewal and Orhun (2024).

We specify the price and detailing spending equations as follows:

$$
\begin{aligned}
(2)\quad ln\big(Det_{jdt}+1\big) = {} & \beta^2_{0jd} + \beta^2_{1jd} Post_{dt} + \beta^2_{2jd} \ln\,(wageidx_t) + \beta^2_{3jd} \ln\big(AcqOtherDet_{jdt}\big) \\
& + \beta^2_{4jd} ln\big(price_{jt}\big) + \beta^2_{5jd} ln(CompDet_{t-1}+1) + \beta^2_{6jd}\hat{Y}_{jTAd} + \beta^2_{7jd}\hat{Y}_{jTAd} \times Post_{dt} \\
& + \beta^2_{8jd} \ln(Det_{jt-1}+1) + \varepsilon^2_{jdt},
\end{aligned}
$$

$$
\begin{aligned}
(3)\quad ln\big(Price_{jdt}\big) = {} & \beta^3_{0jd} + \beta^3_{1jd} Post_{dt} + \beta^3_{2jd} \ln(pmppi_t) + \beta^3_{3jd} \ln\big(AcqOtherMPrice_{jdt}\big) \\
& + \beta^3_{4jd} \ln\big(Det_{jt}+1\big) + \beta^3_{5jd} \ln\big(CompPrice_{jt-1}\big) + \beta^3_{6jd}\hat{Y}_{jTAd} + \beta^3_{7jd}\hat{Y}_{jTAd} \times Post_{dt} \\
& + \beta^3_{8jd} ln\,(Price_{jt-1}) + \varepsilon^3_{jdt},
\end{aligned}
$$

β^2_{0jd} and β^3_{0jd} are brand-deal-specific fixed effects that capture time-invariant effects of detailing spending and price, respectively. The error terms from Equations 1–3, ε^{1-3}_{jdt}, are jointly distributed, and $\beta^m_{jd}\ \forall\ m = 2, 3$ are distributed as $N\big(\bar{\beta}^m, V^m_\beta\big)$.

Modeling Moderation Effects

To model the effects of our moderators on changes in detailing spending, price, and the corresponding elasticities, we proceed to specify second-layer equations for the drug-deal-level parameters of interest in our hierarchical Bayesian model specified in Equations 1–3. The first-level

parameters are specified to depend on the characteristics of the acquirer and the drug as follows:

$$(4)\ \beta^1_{kjd} = \alpha^1_{k0j} + \alpha^1_{k1}AcqSpentCat_{jd} + \alpha^1_{k2}AcqMidCatBrnds_{jd} + \alpha^1_{k3}DrugAge_{jd} + \alpha^1_{k4}GenComp_{jd} + \alpha^1_{k5}BrandComp_{jd} + \alpha^1_{k6}AcqYngCatBrnds_{jd} + \alpha^1_{k7}AcqMatCatBrnds_{jd} + \alpha^1_{k8}AcqPortSize_d + \alpha^1_{k9}TarPortSize_d + \alpha^1_{k10}DrugPriceRatio_{jd} + \alpha^1_{k11}Merger_d + \omega^1_{kjd}\ ;\quad k=0\text{-}5$$

$$(5)\ \beta^\rho_{\pi jd} = \alpha^\rho_{\pi 0j} + \alpha^\rho_{\pi 1}AcqSpentCat_{jd} + \alpha^\rho_{\pi 2}AcqMidCatBrnds_{jd} + \alpha^\rho_{\pi 3}DrugAge_{jd} + \alpha^\rho_{\pi 4}GenComp_{jd} + \alpha^\rho_{\pi 5}BrandComp_{jd} + \alpha^\rho_{\pi 6}AcqYngCatBrnds_{jd} + \alpha^\rho_{\pi 7}AcqMatCatBrnds_{jd} + \alpha^\rho_{\pi 8}AcqPortSize_d + \alpha^\rho_{\pi 9}TarPortSize_d + \alpha^\rho_{\pi 10}DrugPriceRatio_{jd} + \alpha^\rho_{\pi 11}Merger_d + \omega^\rho_{\pi jd}\ ;\quad \pi=0,1,\ \rho = 2,3$$

where $AcqSpentCat_{jd}$ captures the detailing spending of the acquirer in the ATC level 4 therapeutic category of drug *j* during the pre-deal period; $AcqMidCatBrnds_{jd}$ represents the number of acquirer branded drugs in the ATC level 4 therapeutic category of target drug *j* that were introduced between 9 and 14 years before the time of the deal; and $DrugAge_{jd}$ represents the number of years since the introduction of drug *j* at the time of deal *d*.

In addition to including these moderating variables, in our second model layer we also control for the following variables: $GenComp_{jd}$ and $BrandComp_{jd}$ represent, respectively, the number of generic competitors and the number of branded competitors that were promoted using detailing in the ATC level 4 therapeutic category of target drug *j*. $AcqYngCatBrnds_{jd}$ and $AcqMatCatBrnds_{jd}$, respectively, represent the number of acquirer branded drugs in the ATC level 4 therapeutic category of target drug *j* that were introduced up to 8 years before the time of deal *d*, or at least 15 years before the deal and for which the patent has likely expired. $AcqPortSize_d$ and $TarPortSize_d$ represent the portfolio sizes of the target and acquirer firms in deal *d*, respectively. $DrugPriceRatio_{jd}$ is the ratio between the average price of drug *j* and that of other drugs in the ATC level 4 therapeutic category over the pre-deal period. $Merger_d$ is a dummy variable (i.e.,

merger vs. acquisition); its value is set to 1 if the deal is a merger and 0 otherwise.

RESULTS

Descriptive Statistics: First- and Second-Layer Variables

Table 3 presents the correlation matrix, means, medians and standard deviations of the first-layer variables in our empirical model. Table 4 presents the correlation matrix, means, and standard deviations of the second-layer variables in our empirical model.

Table 3 – Descriptive Statistics: First-Layer Variables

	Unit Sales	Detailing Spending	Post deal	Price	Competitive Unit Sales	Lag Unit Sales	Lag Detailing	Lag Price
Detailing Spending	0.16							
Post deal	-0.01	-0.09						
Price	-0.02	-0.02	0.04					
Competitive Unit Sales	0.65	0.01	-0.01	-0.03				
Lag Unit Sales	0.97	0.16	-0.01	-0.02	0.63			
Lag Detailing	0.16	0.95	-0.08	-0.02	0.01	0.16		
Lag Price	-0.02	-0.02	0.04	0.96	-0.03	-0.02	-0.02	
Mean	81,452	$248,300	0.5	$903	2,043,551	82,074	$249,643	$915
Median	10,695	-$	1	$168	785,822	10,775	-$	$167
Std.	392,621	787,107	0.5	8,947	4,160,166	398,247	792,192	9,458
N (drug-month combinations)	16,661	16,661	16,661	16,661	16,661	16,661	16,661	16,661

* Prices and detailing spending are inflation-adjusted

Estimation Results: First-Layer Estimates

We estimated our aggregate-level model using the Gibbs sampler algorithm. We let the sampler run for 100,000 iterations and discarded the first 90,000. We used 5,000 iterations of the posterior draws for inference. We graphically plotted the estimates and calculated the Geweke Diagnostic statistics to check for convergence (these statistics are available in Web Appendix E). Table 5 presents the estimation results for the first-layer parameters in Equations 1–3.

We start with our focal variables (shaded rows in Table 5). In the sales equation, detailing

elasticity is positive both before and after the deal (β^1_{2jd}=0.03), and is higher after the deal than before the deal (β^1_{3jd}=0.01). These levels of detailing elasticities are within the range reported by meta-analysis studies on detailing elasticities (Albers et al. 2010, Kremer et al. 2008).

As expected, price elasticity is negative ($\beta^1_{4jd} = -0.44$), consistent with prior findings (e.g., Ching 2010) that price elasticity for pharmaceutical drugs is typically between –1 and 0. Furthermore, we do not find evidence suggesting that price elasticity after the deal differs from that before the deal. According to the view that changes in price elasticities are indicative of changes in market power (Elzinga and Mills 2011), this result could indicate that, on average, target drugs do not experience a change in market power in post-deal periods compared to pre-deal periods. The absence of evidence for a shift in price elasticity after the deal is surprising, especially given the observed increase in drug prices both in the raw data and in our model estimation results (see below), which control for various other factors influencing price. Our second-layer estimates (presented in the subsequent section) uncover sources of heterogeneity in this effect, suggesting a potential resolution for this puzzle. Specifically, we notice that price increases are more pronounced for certain drugs, including target drugs that also tend to experience price elasticity decreases, such as younger drugs or drugs acquired by firms with prior category experience. If the price changes are disproportionately larger for these drugs, they could result in average price changes while average price elasticity remains unchanged.

In the detailing equation, the impact of a post-deal period is determined by the sum of the $Post_{dt}$ coefficient (β^2_{1jd}=0.82) and the interaction coefficient between $Post_{dt}$ and $\hat{\gamma}_{jTAd}$ ($\beta^2_{7jd} = -3.98$). The contrasting effect signs of β^2_{1jd} and β^2_{7jd} suggest that the higher the first stage residual—indicating a weaker explanation for the selection of drug *j* by acquirer *A* based on factors related to a potential market performance improvement due to the M&A—the greater the reduction

in detailing spending after the deal. Conversely, if the acquirer's choice to obtain the target drug can be perfectly predicted based on factors related to potential commercial improvements, that drug is more likely to see an increase in detailing spending post-M&A. In the price equation, we find that target drug prices are, on average, higher after the deal than before, and more so the larger the first-stage residual for the drug (β_{1jd}^{3}=0.04, β_{7jd}^{3}=0.66).

In sum, the estimated main effects of M&A deals on detailing spending and prices align more closely with the market power logic—showing reduced spending and increased prices (second row of Table 2). For detailing elasticity, where no specific expectation was derived from the market power logic, the results support the cost-efficiency logic, indicating increased elasticity (see the third row of Table 2). Regarding price elasticity, we do not find an indication for post-deal decreases, contrary to what would be expected based on the market power logic.

As for the other model variables, we find that competitive sales are positively associated with target drug sales (β_{6jd}^{1}=0.66). As noted above, the competitive sales variable may capture two opposing effects on sales. On the one hand, competitive sales capture the substitution effect of competing drugs (i.e., competing drugs may steal market share from focal drugs). On the other hand, competitive sales capture the growth (or decline) of the category (i.e., growing competing drugs may signal local category growth). The estimated positive effect implies that, on average, the effect of category growth is stronger than that of the substitution effect.

Table 4 – Descriptive Statistics: Second-Layer Variables

	Pre-Deal Acq. spent in category	*Drug age*	*Nr. generic competitors*	*Nr. branded competitors*	*Nr. acquirer young brands*	*Nr. acquirer mid-aged brands*	*Nr. acquirer mature brands*	*Acquirer portfolio size*	*Target portfolio size*	*Brand price ratio*	*Merger (vs. Acquisition)*
Drug age	-0.01										
Number of generic competitors in therapeutic category	0.05	0.20									
Number of branded competitors in therapeutic category	0.21	0.03	0.41								
Number of acquirer young brands (0-8 years)	0.22	-0.09	0.13	0.26							
Number of acquirer mid-aged brands (9-14 years)	0.16	-0.04	0.06	0.26	0.57						
Number of acquirer mature brands (15 years and older)	0.07	0.06	0.26	0.26	0.49	0.45					
Acquirer portfolio size	-0.12	0.20	0.12	-0.08	0.02	0.05	0.08				
Target portfolio size	-0.10	0.25	0.10	-0.07	-0.05	0.03	-0.02	0.77			
Brand price ratio	-0.02	-0.07	0.03	0.11	0.00	-0.01	-0.03	-0.10	-0.11		
Merger (vs. Acquisition)	-0.05	0.01	0.03	0.11	-0.10	-0.08	-0.06	-0.23	-0.08	0.03	
Mean	$1,937,063	11.90	34.09	16.37	0.33	0.18	0.59	136.79	52.36	8.82	0.08
Std.	$11,613,334	10.30	49.35	18.12	0.82	0.65	1.48	108.39	54.45	30.56	0.28
N (target drugs)	375	375	375	375	375	375	375	375	375	375	375

Table 5 – Estimation Results: Sales, Detailing and Price Equations

Equation		Variable	Parameter	Mean Estimate
Sales Equation		Post deal	β^1_{1jd}	**0.48**
		Detailing	β^1_{2jd}	**0.03**
		Price	β^1_{4jd}	**-0.44**
	M&A effects on elasticities	Post deal × detailing	β^1_{3jd}	**0.01**
		Post deal × price	β^1_{5jd}	-3.45E-03
		Competitive sales	β^1_{6jd}	**0.66**
		$\hat{\gamma}_{jTAd}$	β^1_{7jd}	**-2.52**
		$\hat{\gamma}_{jTAd}$ × Post	β^1_{8jd}	**-0.70**
		Lag sales	β^{13}_{9jd}	**0.51**
Detailing Equation	M&A effects on detailing levels	Post deal	β^2_{1jd}	**0.82**
		Post deal × $\hat{\gamma}_{jTAd}$	β^2_{7jd}	**-3.98**
		Wage index	β^2_{2jd}	**-0.07**
		Acquirer other detailing	β^2_{3jd}	4.32E-04
		Price	β^2_{4jd}	**4.16**
		Competitive detailing	β^2_{5jd}	-4.62E-07
		$\hat{\gamma}_{jTAd}$	β^2_{6jd}	**-16.89**
		Lag detailing	β^2_{8jd}	9.69E-05
Price Equation	M&A effects on price levels	Post deal	β^3_{1jd}	**0.04**
		Post deal × $\hat{\gamma}_{jTAd}$	β^3_{7jd}	**0.66**
		Producer price index	β^3_{2jd}	**0.01**
		Mean price other acquirer drugs	β^3_{3jd}	4.99E-04
		Detailing	β^3_{4jd}	**0.23**
		Competitive price	β^3_{5jd}	-4.32E-04
		$\hat{\gamma}_{jTAd}$	β^3_{6jd}	**4.29**
		Lag price	β^3_{8jd}	**2.02E-03**

*Bolded estimates indicate that 95% of posterior density excludes zero

Such a positive effect has also been found in other papers on pharmaceutical drug sales (e.g., Mizik and Jacobson 2004; Venkataraman and Stremersch 2007). The two terms $\hat{\gamma}_{jTAd}$ and $\hat{\gamma}_{jTAd} \times Post_{dt}$ are negative ($\beta^1_{7jd} = -2.52$, $\beta^1_{8jd} = -0.70$). The negative coefficient of $\hat{\gamma}_{jTAd} \times Post_{dt}$ provides evidence that the effect of a post-deal period depends on unobserved heterogeneity captured, in part, in the first-stage function. Finally, we find that lag sales have a positive effect on target drug sales (β^1_{9jd}=0.51). In the detailing equation, we find that detailing spending is positively associated with the price of the drug (β^2_{4jd}=4.16). Similarly, in the price

equation, we find that prices are also positively associated with detailing spending (β_{4jd}^{3}=0.23).

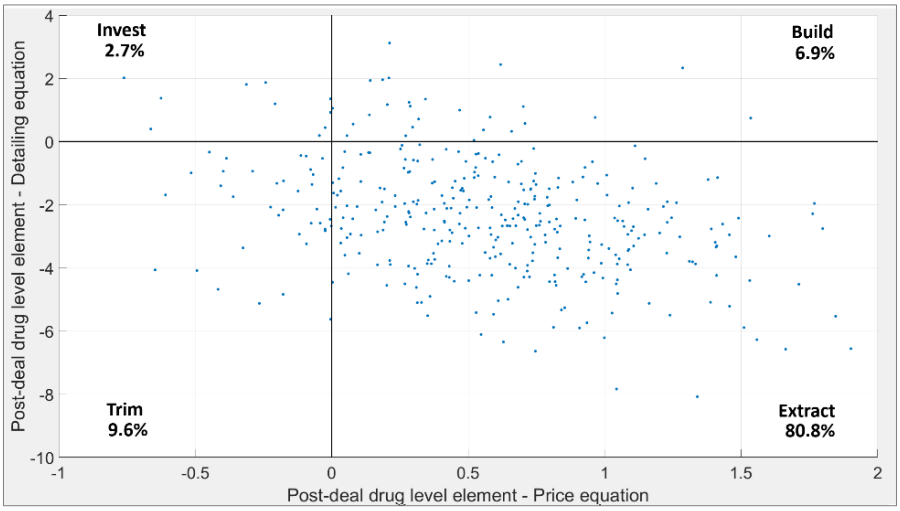
Based on the estimated drug-level coefficients associated with the post-deal dummy variables in the detailing and price equations (Equations 2 and 3), we assess the change in baseline detailing and baseline price during the post-deal period. For each drug, we compute:

$$(6)\ Detailing_{Post_{jd}} = \beta_{1jd}^{2} + \beta_{7jd}^{2}\hat{\gamma}_{jTAd}$$

$$(7)\ Price_{Post_{jd}} = \beta_{1jd}^{3} + \beta_{7jd}^{3}\hat{\gamma}_{jTAd}$$

These expressions capture the post-deal changes in baseline detailing and price, accounting for interactions with the first-stage residual. In Figure 4, we map these changes across the four strategic categories (of Figure 3) for different combinations of increase/decrease in detailing and price based on the estimated parameters. The results indicate that, once we account for model-based controls that address alternative explanations for shifts in price and detailing levels, the distribution of drugs across the four strategic categories shifts even more towards the Extract strategy (81%, up from 54%) and away from the other three categories.

Figure 4 – Estimated Change in Base Detailing and Base Price Across Target Drug



Estimation Results: Second-Layer Estimates

In the estimation results of the second-layer parameters (see Table 6) we focus on the two post-

deal marketing-mix effectiveness parameters (β^1_{3jd} for post-deal change in detailing elasticity, and β^1_{5jd} for post-deal change in price elasticity), and to the two post-deal parameters in the detailing and price equations (β^2_{1jd} and β^3_{1jd}).

Acquirer domain-specific commercial experience. We find that higher commercial experience of the acquirer in the therapeutic category of the target drug is associated with lower (less negative) post-deal price elasticity ($\alpha^1_{5,1jd} = 0.01$) and higher detailing elasticity ($\alpha^1_{3,2jd} = 0.02$), together with higher post-deal prices ($\alpha^3_{1,1jd} = 0.02$; $\alpha^3_{1,2jd} = 0.26$) and post-deal decreases in detailing spending ($\alpha^2_{1,2jd} = -1.60$).

Age of target drug. We find that the more mature the target drugs, the less likely acquirers are to experience increases in detailing elasticity or decreases (less negative) in price elasticity following the deal as compared to before the deal ($\alpha^1_{3,3jd} = -0.01, \alpha^1_{5,3jd} = -0.03$). Moreover, the more mature the drugs, the less likely acquirers are to decrease detailing spending or to increase post-deal prices ($\alpha^2_{1,3jd} = 1.00, \alpha^3_{1,3jd} = -0.09$).

To summarize, all second-layer estimates are in line with expectations (see Table 2).

Post-Deal Changes in Detailing Returns

We further employ the estimation results from our analysis to calculate the post-deal (vs. pre-deal) change in how an additional dollar spent on detailing affects firm revenues (Narayanan et al. 2004). For each drug, we use the draws from the estimated posterior distributions of our model parameters to simulate draws from the posterior distribution of the effect of a $1 U.S. dollar increase in detailing spending on drug revenues in the pre- and post-deal periods. We then calculate the posterior distribution of the difference between detailing return levels in the two periods and refer to it as the post-deal change in detailing returns.

Table 6 – Estimation Results: Second-Layer Parameters

*Variable**		*Sales Equation*						*Detailing Equation*		*Price Equation*	
		Intercept	***Detailing***	***Post deal***	***Price***	***Post X detailing***	***Post X price***	***Intercept***	***Post deal***	***Intercept***	***Post deal***
Intercept	α_{k0}^{τ}	1.01	0.01	0.22	-0.16	**0.04**	0.05	**0.45**	**2.40**	**0.56**	**-0.35**
Pre-Deal Acquirer spent in therapeutic category	α_{k1}^{τ}	**0.13**	**7.82E-04**	**-0.05**	**-0.03**	-1.69E-04	**0.01**	**-0.05**	2.14E-02	4.14E-03	**0.02**
Number of acquirer mid-aged brands (9-14 years)	α_{k2}^{τ}	0.11	**-0.02**	**-0.56**	0.16	**0.02**	0.04	**-0.14**	**-1.60**	0.09	**0.26**
Drug age	α_{k3}^{τ}	-0.28	1.24E-03	**0.15**	0.06	**-0.01**	**-0.03**	**-0.52**	**1.00**	**0.08**	**-0.09**
CONTROLS											
Number of generic competitors in therapeutic category	α_{k4}^{τ}	0.11	-1.87E-04	**-0.10**	**-0.08**	-2.00E-03	**0.02**	**-0.10**	**0.18**	**0.07**	**-0.05**
Number of branded competitors in therapeutic category	α_{k5}^{τ}	**-1.12**	-5.49E-04	0.05	**0.10**	6.26E-04	-0.01	**0.61**	**-0.64**	**-0.10**	**0.09**
Number of acquirer young brands (0-8 years)	α_{k6}^{τ}	-1.37	3.68E-03	**0.65**	0.22	-0.01	**-0.12**	**0.49**	**0.42**	0.03	**-0.14**
Number of acquirer mature brands (15 years and older)	α_{k7}^{τ}	-0.81	-3.79E-04	**0.41**	0.03	-4.18E-03	**-0.07**	**0.67**	0.04	**-0.15**	-0.12
Acquirer portfolio size	α_{k8}^{τ}	**0.63**	2.19E-03	-0.02	**-0.12**	8.78E-05	-0.01	**-0.23**	**-0.77**	**-0.12**	**0.07**
Target portfolio size	α_{k9}^{τ}	-0.31	-6.73E-04	0.08	0.03	-1.73E-03	-1.23E-03	**0.13**	**0.14**	0.02	-1.76E-03
Brand price ratio	α_{k10}^{τ}	-0.23	1.73E-03	**-0.10**	6.05E-04	-2.01E-03	**0.02**	**-0.51**	0.05	**-0.12**	**0.15**
Merger (vs. Acquisition)	α_{k11}^{τ}	**6.31**	-0.01	0.25	**-0.88**	0.01	-0.07	**-1.35**	**1.69**	-0.15	**-0.16**

* τ = 1,2,3; k=0-5

** Bolded estimates indicate that 95% of posterior density excludes zero

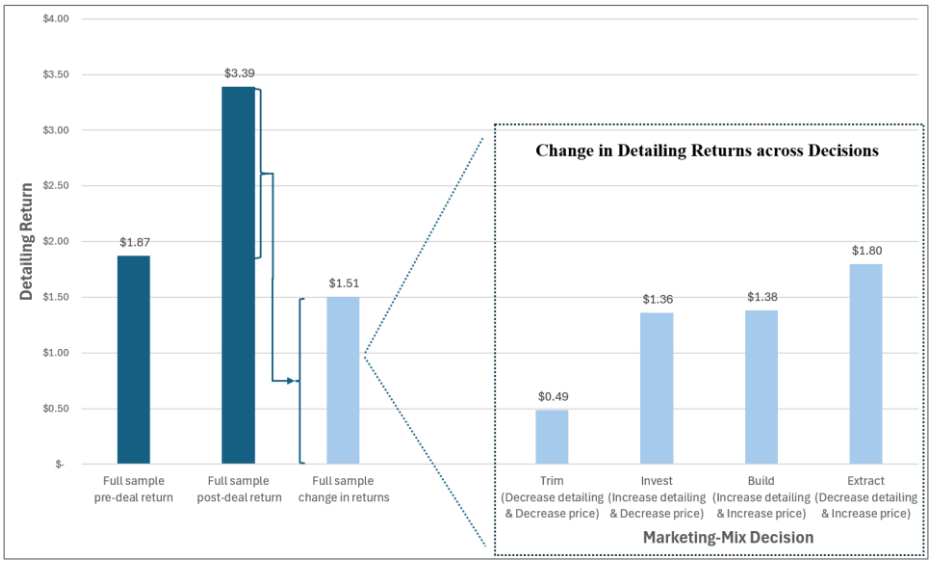
We obtain a positive mean change in detailing returns[7] of $1.5, corresponding to a shift from a mean pre-deal detailing return level of $1.9 to a mean post-deal detailing return of $3.4. These detailing return levels are comparable, in magnitude, to those obtained in prior literature. For example, Wittink (2002) reported mean detailing returns of $2.1 for brands with annual revenues of $100-$500 million and mean detailing returns of $11.6 for brands with more than $500 million in revenues between 1998 and 2000. Narayanan et al. (2004), who focused on large brands, reported current-period detailing return levels of $1.10-$3.73.

Next, we map the improvements in detailing returns on our four post-M&A marketing-mix decisions (see Figure 3). We find that the highest average increase (=$1.80) in return on detailing occurs for the Extract strategy (i.e., target drugs where there is a decrease in detailing but an increase in price after the deal). Next, for target drugs where firms implement a Build strategy (i.e., both detailing spending and price increase), the average increase in detailing return is $1.38, and for target drugs where firms employ an Invest strategy (i.e., detailing increases yet price decreases), the average increase in detailing return is $1.36. Finally, for target drugs where firms opt for a Trim strategy (i.e., decrease both price and detailing spending), the average increase in detailing return is $0.49.[8] Figure 5 presents the changes in average detailing returns. The first three bars present detailing return levels for the drugs in our sample in the pre- and post-deal periods as well as the average change in detailing returns, respectively. The last four bars present the average change in detailing returns for each of the four marketing-mix response strategies.

Figure 5 – Change in Detailing Returns between Pre- and Post-Deal Periods

[7] The detailing returns we calculate are inflation-adjusted. We exclude from this analysis drugs that had zero detailing spending in the full pre-deal period or in the full post-deal period and cap outlier detailing return levels at $70.

[8] Note that if pre-deal allocation rules for target drugs are highly suboptimal, the higher returns on detailing for drugs with decreases in spending may also result from diminishing returns on detailing spending.



* Detailing return is the effect of a $1 U.S. dollar increase in detailing spending on drug revenues

Robustness Analysis

We conducted two types of robustness analyses. First, to assess the sensitivity of our main results to our model specifications, we repeated our main analyses with the following modifications: (i) We estimated a model where we modified our sample period before and after the M&A deal to three instead of two years to see if our findings are sensitive to the definition of pre- and post-deal periods. Increasing the number of observations per deal-drug combination also allows us to examine the sensitivity of the estimates to a dynamic panel bias. (ii) We estimated a model in which we also controlled for other types of promotions (i.e., journal advertising, sampling) and their effects on our focal variables. (iii) We estimated a model where we did not include the lagged dependent variable and explicitly controlled for time (year). (iv) We estimated a model where we did not control for inflation. (v) To further examine the sensitivity of the estimates to a dynamic panel bias, we estimated Arellano-Bond corrections on a simpler fixed-effects model (without the endogeneity controls for detailing spending, prices and post-event). (vi) We estimated a one-stage model where we did not include the residual from a first-stage probit model. (vii) We estimated a model where we did not account for the potential endogeneity of detailing and price. Web Appendix F contains the results of these analyses. Our main findings were robust to alternative model

specifications.

Second, we analyzed difference-in-differences (DID) models for price and for detailing to examine whether the effects we see for target drugs go beyond general market trends. In other words, we sought to address the possibility that, for example, the higher drug prices we observed in post-deal periods as compared with pre-deal periods resulted from a general upward trend in prices in the pharmaceutical industry and were not an outcome of the M&A deals (Richman et al. 2016). We formulated a DID specification for pricing that focused only on the price dynamics of target drugs and compared them with the prices of control drugs (i.e., other drugs in the target drugs' broad, yet not immediate, therapeutic category, which were marketed by firms that were not involved in M&A activity). Similarly, we specified a DID to investigate the relative dynamics in detailing spending of our focal target drugs. Both the increase in drug prices and the decrease in detailing spending of target drugs were beyond those for the control drugs. For the specifications and estimation results of these models, see Web Appendix G.

DISCUSSION

This paper addresses a significant gap in the literature concerning the downstream effects of M&A deals. It is the first to provide a comprehensive empirical analysis of how firms adjust their marketing-mix decisions following M&A deals and to assess the post-deal changes in the effectiveness of these decisions. Focusing on the biopharma industry, we examined the pre- and post-M&A marketing-mix practices of firms involved in 73 M&A deals by analyzing changes in detailing spending and prices for 375 branded target drugs.

Our findings reveal that the most common post-M&A strategy is to reduce detailing spending on target drugs while increasing prices, results that align with the market power logic outlined in our conceptual framework. Additionally, the average return on detailing for target drugs generally increases post-M&A, in line with the cost-efficiency logic. Our

analysis also shows that specific drug characteristics (i.e., drug age) and acquirer characteristics (i.e., category-specific experience) influence the impact of M&A deals on marketing-mix decisions and the sales response elasticities of marketing-mix elements.

Implications

The insights from our study offer several benefits to firms. First, biopharma firms considering M&A deals can use our findings to evaluate potential synergies and assess marketing savings based on our benchmark information on potential savings (i.e., in detailing spending), changes in marketing effectiveness, and price increases. Specifically, firms can differentiate their expectations for prospective M&A deals based on the composition of the target firm's drug portfolio (see Web-Appendix H for a simulated illustration). Second, companies often mimic each other in setting prices and detailing spending (Kappe, Venkataraman, and Stremersch 2017). Moreover, drug payers, such as regulators and insurance companies, typically request that pharmaceutical firms support their ask prices with data regarding their drugs' competitive differential value and competitive prices of pharmaceutical drugs (e.g., Verniers, Stremersch, and Croux 2011). Our results give firms competitive information to anticipate market changes in case their competitors are acquired (e.g., they are likely to raise prices and lower detailing).

Our findings have significant public policy implications. While drug prices have generally increased over the years (Richman et al. 2016), our main model results, controlling for inflation, as well as our DID-based robustness analyses, show that post-M&A price increases exceed these trends. We find that branded target drugs experience greater price increases following M&A deals than they would absent the deals, suggesting that joint firms' pricing decisions are influenced by their gains in market power. While we do not find, on average, decreases in price elasticity for target drugs, which typically indicate increased market power, the increases in prices could be explained by the significantly lower post-deal

price elasticities for acquirers with more experience in the category and the younger the drugs.

As drug pricing reform gains momentum in the U.S., through measures like the Inflation Reduction Act, which enables Medicare to negotiate prices for select high-cost drugs, and more recent executive orders under the Trump administration expanding pricing transparency and introducing a most-favored-nation pricing model (Cooney 2023, White House 2025), it is equally important to address how M&As may undermine these efforts. Regulators and insurers should guard against the potential effects of M&A activity on the inflation of drug prices. For example, policies could mandate that for a specified period (e.g., 3 years) after the deal, acquirers cannot increase the prices of target drugs beyond the levels of control drugs. Such a policy could be implemented similarly to geographic reference pricing (Rémuzat et al. 2015), where a drug's price in one country cannot exceed the average price in specified other countries.

Moreover, in recent years, there have been calls to re-examine federal antitrust agencies' narrow market-by-market competitive analysis approach when assessing increases in concentration within specific drug markets in biopharma M&A evaluations (Danzon and Carrier 2022). This approach, aligned with the Horizontal Merger Guidelines (U.S. Department of Justice and Federal Trade Commission 2010) and the Hart-Scott-Rodino Antitrust Improvements Act, focuses on overlaps within the same therapeutic category. Our model shows that larger acquirers are more likely to increase target drug prices after M&A deals, even when controlling for domain-specific overlaps. These findings support critics arguing that the market-by-market competitive analysis is "… narrow, flawed, and ineffective" (Chopra 2020, p. 2).

Beyond firm strategy and regulatory considerations, our findings also have important implications for consumer welfare. The additional $23 billion in revenues for our sample of

drugs over the two-year post-deal is borne by insurers and ultimately also by individuals through higher premiums, out-of-pocket expenses, or taxes supporting public healthcare programs. While some of these expenditures may be justified by reinvestment in innovation, the persistent post-merger price increases raise concerns about diminished consumer welfare.

Regarding detailing, the dominant response we observe is to reduce detailing following an M&A deal. Thus, the interests of acquirers and healthcare payers seem to align, because payers routinely perceive detailing as a welfare loss. At the same time, we find that the more mature the target drugs, the lower the decreases in detailing spending. Public policy administrators might prefer the opposite (Feldman 2021), as detailing younger drugs is more informative and less likely to cause welfare loss compared with detailing older drugs (Narayanan et al. 2005).

In general, our results factually support calls for increased scrutiny of M&A activity in the biopharma industry (Feldman 2021; Kang 2022). Similarly, this need may exist in other concentrated sectors with high market power, such as energy, telecom and banking.

Limitations and Suggestions for Future Research

This study opens several directions for future research. First, post-deal higher prices may indicate that acquiring firms are not passing on efficiencies from M&A deals to consumers, raising public policy concerns. However, these savings might also be used to support innovation and R&D, benefiting society. The effect on innovation is a useful avenue for future investigation.

Second, our focus was on the effects of M&As on promotional efforts for target branded drugs, including only those promoted at least once before or after the deal. While our large sample of over 300 drugs encompasses diverse maturity and deal conditions, future research could explore commercial dynamics around non-promoted drugs, or discontinued target drugs. Additionally, the generic biopharma industry is experiencing substantial

consolidation, with over 50% of generic drugs produced by just four companies in 2017 (Feldman 2021). Investigating how generic firms respond in their commercial strategies to M&A activity and the consequent societal implications would be valuable.

Third, our study focuses on upstream pricing (i.e., manufacturer prices) and its potential relationship with price elasticity. However, we do not observe insurance coverage levels or patient-specific copayments, which likely vary across insurers and therapeutic areas (Chandra, Gruber, and McKnight 2010; Yeung et al. 2018). This limits our ability to make direct claims about individual-level responses to price. Pricing in the biopharma industry is institutionally complex, given that price and reimbursement outcomes are shaped by negotiations among manufacturers, insurers, pharmacy benefit managers, and other intermediaries. Integrating more granular data on pricing and insurance reimbursement in future research would be very valuable. Obtaining the appropriate data is difficult, which is why prior pharmaceutical marketing studies typically have also not integrated such data.

Fourth, we did not distinguish between mergers and acquisitions, though we controlled for the type of deal. Additionally, there are many other deal characteristics one could study, such as deal motivation or CEO compensation. These are all promising avenues for future research.

Fifth, our study focused on the context of a single industry. While such research is valuable and suitable in this case (Stremersch et al. 2023), similar studies in other sectors that test the generalizability of our findings would be very welcome.

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