Bundled Loyalty Discounts in Healthcare: Evidence from Physician-Administered Vaccines*

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May 2026

Abstract

Multi-product sellers often offer bundled loyalty discounts: lower prices to buyers who do not purchase competing products from rivals. These contracts can expand sales but may also foreclose rivals, including those with better products. I quantify this trade-off in the U.S. market for pediatric and adolescent vaccines, which physicians buy from manufacturers and administer to their patients. I obtain the discount rules from antitrust litigation records and combine them with all-payer claims data from Colorado (2012–2019) that track each medical practice's vaccine purchases and utilization across all of its patients and payers. I develop and estimate a model in which —on the demand side— practices choose a basket of vaccine brands, trading off patient benefits, expected insurer reimbursement, and purchase prices, and —on the supply side— manufacturers set vaccine prices under Bertrand competition. The model separately identifies the size of the unobserved discounts and practices' preference for buying from few suppliers. Estimated discounts range from 7% to 23% of list prices, in line with figures disclosed in litigation. Banning bundled discounts, with manufacturers re-optimizing prices, leads practices to stock fewer vaccine types and older brands: the share of eligible patients immunized falls by 6 to 14 percentage points for "optional" vaccines, i.e., those not required for school entry. Provider and patient surplus falls by about 9%, with modest savings for insurers. Manufacturers whose portfolios are concentrated in optional vaccines lose the most. In this market, the market-expansion effect of bundled discounts dominates their foreclosure effect.

*I am deeply grateful to my advisors Michael J. Dickstein, Chris Conlon, and Luís Cabral for their advice and constant encouragement. I thank Giulia Brancaccio, Tommaso Denti, Emma Dean, Sunita Desai, Mario Leccese, Luca Maini (discussant), Felix Montag, Julie H. Mortimer, Anh Nguyen, Alex Olssen (discussant), Ellie Prager, Tiziano Rotesi, Maher Said, Paul Scott, Dan Waldinger, and Larry White for their thoughtful feedback, as well as participants at the NYU Stern IO seminar and research group, NYU applied micro lunch, ASHEcon 2024, IIOC 2025, and TSE 3rd Health Economics Conference for helpful comments. I also thank Robin Wurl at Stern and the staff at the Center for Improving Value in Health Care (CIVHC) for their patience in helping me store and navigate the data. I gratefully acknowledge financial support from Stern's Center for Global Economy and Business. All errors are my own.

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1 Introduction

Bundled loyalty rebates have recently been at the forefront of many policy debates due to their frequent use in contractual arrangements across various industries. A multi-product seller may offer discounted prices to buyers who purchase from the seller's portfolio while excluding competing products from rival sellers. The welfare implications of such arrangements are theoretically ambiguous, and their legal treatment is constantly evolving (Scott Morton and Abrahamson, 2016). On the one hand, these contracts can increase the quantities purchased, which generally tends to enhance welfare. On the other hand, the adoption of such discounts may foreclose competing sellers, including those offering superior products, which typically reduces welfare. As a result, bundled loyalty rebates have often been subject to antitrust scrutiny,[1] and careful empirical analysis is crucial for assessing the relative importance of these effects. However, empirical work is challenging due to limited data availability, as contracts between buyers and sellers are typically proprietary information.

In the context of pharmaceuticals, bundled loyalty discounts are of particular interest as they may directly affect the volume and type of drugs delivered to patients—and thus, ultimately, patients' health outcomes. Broadly speaking, pharmaceutical companies offer different but partially overlapping portfolios of drugs to medical providers (e.g. physicians). For the broad class of treatments administered in the office-setting, i.e. "physician-administered treatments",[2] providers purchase those treatments directly from manufacturers or through intermediaries, and then store and administer them to patients. Patients, in turn, are covered by insurers, who reimburse medical providers for the drugs and services provided to their insured patients. As a result of this purchasing system, providers play a crucial role in choosing which products to buy and from which manufacturer(s), by weighing clinical factors against their own financial interests. Providers' central role motivates pharmaceutical companies to strategically use bundled loyalty discounts as a tool to enhance purchases.

This paper develops a model of medical providers' demand and manufacturers' supply of physician-administered treatments in the presence of bundled loyalty contracts. I estimate the empirical version of this model, using detailed data on physicians' in-office treatment administrations over time across their entire pool of patients in Colorado. Using the estimated model, I illustrate the impact of banning bundled loyalty discounts on providers' treatment choices, patient health, insurer costs, and manufacturers' profits. I show that, in the absence of discounts, providers would purchase cheaper and fewer drugs. This change in purchasing could

[1] See Mortimer and Genchev (2017) for an extensive review of the main antitrust cases and judicial decisions. More recently, in the healthcare sector, see *FTC v. Amgen Inc. (2024)* in the context of treatments for thyroid eye disease, and *Regeneron v. Amgen Inc. (2022)* in the market for cholesterol-lowering treatments.

[2] These treatments include oncology drugs, injections for arthritis and osteoporosis, dialysis, and vaccines. They accounted for about $37 billion in healthcare spending in 2019 in Medicare alone (The Kaiser Family Foundation, 2021). They differ from prescription drugs because of their particular purchasing system, as described later.

pose risks to patient health if less expensive drugs are also older and less effective, and if the resulting equilibrium leads to treatment under-provision. In the short term, insurer costs would decrease, while the effect on manufacturers' profits would depend on their product portfolio and the forgone opportunity to leverage bundled discounts for customer base expansion. I then examine alternative policy measures, such as increasing insurance reimbursements to providers, to assess their potential in achieving comparable levels of treatment provision and drug selection as observed with bundled discounts. Finally, I explore the possibility that bundled loyalty contracts might exclude high-value treatments. Specifically, I ask: how high must a drug's quality be to avoid being foreclosed by these contracts? This question is critical, as it may ultimately influence the trajectory of pharmaceutical innovation over the long term.

I focus my analysis on the U.S. market for child and adolescent immunizations, a prime example of physician-administered treatments with several attractive features for my study. First, there is a well-documented under-provision of immunizations in both the U.S. and most Western countries, particularly for vaccines that are not strictly required for school entry (henceforth referred to as "optional" vaccines). Second, pharmaceutical companies differ in the portfolios of *vaccine types* they offer, with each vaccine type targeting a specific disease. For a given vaccine type, multiple manufacturers typically provide competing *brands* (i.e. a vaccine type - manufacturer combination) that vary in terms of novelty, injection method, and adverse effects. Third, and importantly, I can rely on documents disclosed in prior antitrust cases involving bundled loyalty contracts in the context of vaccines[3] to obtain detailed information on discount rules. Specifically, these documents provide insights into the exact vaccine purchasing requirements that providers must meet to qualify for discounts from a given company.[4] Finally, changes in market structure over time—such as mergers among pharmaceutical companies and the approval of new vaccines—have altered companies' portfolios, and thus the pool of vaccines that providers must purchase to obtain discounts.

To analyze the role of bundled discount contracts in providers' vaccine purchasing decisions, I first match providers to the medical practice(s) they belong to, in order to capture the centralized purchasing decision at the practice level. I then examine medical practices' purchasing patterns and recover some stylized facts. First, knowing pharmaceutical companies' vaccine portfolios and their discount requirements, I can determine which practices meet those requirements by observing their vaccine choices. For example, I find that, in 2014, around 80% of the primary care practices in my sample were eligible for discounts from one or more phar-

[3] *Castro M.D PA v. Sanofi Pasteur Inc.* (2011-2017); *SugarTown Pediatrics, LLC v. Merck & Co* (2018-2023).

[4] I am not the first one to rely on official documents from courts to learn about information that would have been otherwise inaccessible to researchers. For example, Starc and Wollmann (2023) use antitrust cases surrounding the largest price-fixing case in the U.S. industry, involving generic drug manufacturing, to learn about the products involved and the related time periods. The authors then build a structural model to quantify the effect of entry on cartel profitability.

maceutical companies.[5] Second, practices vary in their immunization needs, primarily due to differences in their patients' age distribution. A large pool of eligible patients for a particular disease translates into a high observed probability of meeting the discount requirements of a company offering immunizations against that disease. Practices also differ in their expected insurance reimbursements for the same vaccine brand, as different insurers reimburse the same brand at different rates, and each practice covers a different mix of insurers. As a result, even without any discounts, practices experience heterogeneous financial gains from similar vaccine purchasing behaviors, since these gains depend on the difference between the insurance reimbursement and the price paid to manufacturers. Third, changes in market structure over time have altered the breadth of pharmaceutical companies' portfolios, prompting many providers to adjust their vaccine purchasing patterns to remain eligible for bundled discounts. For example, in 2015, GSK acquired Novartis's vaccine division, including its meningitis vaccine brand. I observe that practices previously purchasing meningitis vaccines from competitors switched to GSK's new product—particularly when buying from a competitor would have compromised their eligibility for GSK's bundled discounts.

The multiplicity of levers driving physicians' decision making and the unobserved nature of the discounts call for an equilibrium model of the providers' choice problem and the manufacturers' price competition. The model allows me to simulate counterfactual choices *and* prices in the absence of bundled loyalty contracts, and thus to evaluate the impact of discounts on providers' surplus, patients' health outcomes, insurance costs and pharmaceutical profits.

Motivated by the empirical evidence, I develop a model of practices' demand and pharmaceutical companies' supply of vaccines. On the demand side, practices choose how to combine vaccine types into a vector of brands, namely a *basket*. Baskets vary in composition, as they can include brands produced by one or multiple manufacturers. They also differ in length, as baskets can cover a broader or narrower range of diseases. Practices face a discrete choice problem, as they choose their preferred basket among all the available combinations of brands.

When making their choice, medical practices weigh their own financial gain against other non-financial aspects, such as the novelty and quality of the brands for patients' health, as well as the storage mode. In particular, practices account for the fact that some of the available baskets of vaccines are discounted. This occurs when the way brands are combined in the basket respects the discount requirements from one or more pharmaceutical companies. Ultimately, to qualify for the discount, a basket must not include any rival brands *if* those brands can be substituted by a product offered by the discounting company.

To model the financial complementarity among brands produced by the same manufac-

[5]Given the observed purchasing choices, a practice can be eligible for discounts from two companies simultaneously if the two companies' portfolios are complementary, meaning that meeting the discount requirements for one manufacturer does not automatically violate the requirements of the other. In my context, Sanofi and Merck are the only pair of manufacturers with mutually compatible discount requirements.

turer, I draw upon tools from prior research (Gentzkow, 2007; Iaria and Wang, 2024) and allow for complementarities in the form of (unobservable) discounts off the purchasing prices of each brand. From estimating demand, I recover medical practices' preference parameters and the magnitude of manufacturer-specific discounts that rationalize their immunization purchases. The estimated discounts are sizable and fall within the ranges provided in recent antitrust cases, which is reassuring. Importantly, I am able to distinguish between discounts and practices' preference for "single-sourcing", a potential factor beyond discounts that might drive practices to limit the number of suppliers. The separate identification of the two terms relies on the following intuition: consider two different baskets, covering the same diseases and whose *discounted* brands fully overlap. They may still differ in the number of manufacturers supplying the residual *non-discounted* brands. In other words, a provider's tendency to buy from fewer suppliers, even when there is no discount-driven incentive to do so, indicates a preference for single-sourcing.

On the supply side, I take the product offerings as given and allow pharmaceutical companies to set prices and discounts for their vaccines under Nash-Bertrand competition.[6] Each manufacturer's profit maximization problem is similar to the standard multi-product Bertrand case, except that it accounts for the presence of bundled discounts. In other words, depending on the specific basket a brand belongs to, the actual price of the brand may or may not be discounted. Using the equilibrium first-order conditions, along with the observed list prices, aggregate quantities, and the estimated magnitudes of discounts from the demand side, I recover the marginal costs associated with each vaccine brand.

I use my estimates and the model to evaluate the consequences of banning bundled loyalty discounts—a policy that has recently gained attention in antitrust and policy debates.[7] In doing so, I allow pharmaceutical companies to reset their prices optimally and medical practices to reoptimize their choices. In the new equilibrium without discounts, practices are more likely to choose baskets of vaccines that, even in the baseline equilibrium, were not discounted. This suggests that bundled loyalty contracts, by affecting relative prices, make discounted baskets more appealing than they would be otherwise. Specifically, in the new equilibrium, practices tend to choose baskets with fewer brands, often at the expense of optional vaccines. They also lean toward lower-quality brands, which are generally less costly for both practices and insurers but come with slightly reduced effectiveness and increased adverse effects for patients. Assuming

[6]Since medical practices in Colorado are typically small (around 2.3 physicians per practice, on average), I assume there is no role for negotiating ad-hoc prices and discounts with vaccine manufacturers. This was also mentioned by manufacturers and their representatives during meetings held with CDC researchers about challenges and opportunities in the market for vaccines: "In the private market, no single entity has any significant buying power in negotiating price with vaccine suppliers" (Coleman et al., 2005).

[7]For example, see the CNBC article and the White House briefing available here and here for an overview of the Trump administration's proposal to ban drug companies' "backdoor" rebates, with the ultimate goal of reducing consumers' drug spending. The proposal was criticized for the potential unintended consequences for consumers and ultimately was not passed.

limited mobility of patients across primary care practices, the change in physician purchasing leads to reduced access to immunization for patients. In the short run, insurers benefit, as they cover costs for fewer, lower-priced shots. The impact on manufacturers varies, depending on their vaccine portfolios. In my context, for example, I find that GSK benefits in the presence of bundled loyalty contracts—primarily due to the market expansion effect on optional vaccines, which make up a significant portion of GSK's portfolio.

Related Literature. This paper contributes to several strands of the literature. First, my work builds on a large body of research in theoretical industrial organization and antitrust economics that examines the welfare effects of vertical contracts, such as bundling and loyalty rebates, employed by manufacturers to compete in various settings. Whinston (1990), Choi and Stefanadis (2001), and Nalebuff (2004) highlight how manufacturers can use these contracts to leverage their strong monopolistic position in one market to "monopolize" additional markets and exclude competitors. In oligopolistic settings, Ghosh and Balachander (2007) show that bundling strategies can be profitable and do not lead to a prisoner's dilemma, provided there is sufficient differentiation among the competing products. Similarly, Zhou (2021) finds that allowing for mixed bundling strategies in a duopoly has ambiguous consequences on prices, profits, and consumer surplus. Due to limited data availability on the specific contractual arrangements between sellers and buyers, very few papers investigate empirically the welfare consequences of bundling and loyalty rebates. Crawford and Yurukoglu (2012) estimate the welfare effects of bundling by modeling viewership, demand, pricing, and bargaining in the retail cable television market. Ho et al. (2012) analyze firms' use of vertical full-line forcing contracts using extensive data from the video-rental industry. Conlon and Mortimer (2021) study quantity-based vertical rebates in the snack food market and empirically quantify the extent to which these contracts can mitigate downstream moral hazard, as well as their foreclosure effects. Hristakeva (2022) examines the competitive implications of vendor allowances and their influence on product availability in the grocery sector. In my work, I leverage detailed claims data tracking medical providers' purchasing patterns, as well as information on the specifics of bundled loyalty discounts from prior antitrust cases, to provide a novel empirical investigation of the welfare effects of these contracts in the U.S. vaccine market. Specifically, I shed light on a new trade-off generated by these contracts—i.e., quantity increase vs. potential brand foreclosure—in the context of vaccine provision.

Second, I contribute to the recent empirical literature on rebates in pharmaceutical markets. Recent papers by Feng and Maini (2024), Ho and Lee (2024), and Conti et al. (2021) build models of negotiation between representative pharmacy benefit managers (PBMs), who typically act on behalf of insurers, and drug manufacturers. PBMs are willing to place drugs dispensed in retail pharmacies on "low-cost" tiers, which are more affordable for patients, in

exchange for manufacturers' rebates. The first two papers bring the model to data and highlight how prescription drug formularies[8] and patients' spending would change, absent those rebates. In a similar spirit, Olssen and Demirer (2023) infer bounds on the magnitude of those rebates in the market for statins, by exploiting insurer plans' observed formulary placement decisions. In line with these papers, I quantify the magnitude of bundled loyalty discounts offered by manufacturers to medical providers (as opposed to PBMs in their case). I infer the discount magnitudes from medical practices' observed purchases patterns, considering the requirements needed to access discounts and the manufacturers' brand portfolios. My findings align with aggregate discount data disclosed in prior antitrust cases related to vaccine procurement.

Moreover, while the referenced papers typically model single-product manufacturers and ignore the possibility of cross-product bundling, I account for *multi-product* manufacturers offering bundled loyalty contracts. In my context, medical providers must comply with a manufacturer's discount rule across all vaccine types they purchase, which requires modeling providers' joint purchasing behavior. As a result, methodologically, I draw upon tools that allow for demand estimation for consumers choosing "baskets" of goods (Hendel, 1999; Gentzkow, 2007; Iaria and Wang, 2020; Iaria and Wang, 2024). Closely related to my paper, Cao and Chatterjee (2022) study the equilibrium effects of fixed-dose combinations (FDCs), which "physically" bundle two drugs in a single pill, in the Alzheimer's drug market in India. The authors find that FDCs increase the utilization of valuable combination treatments among consumers and have sizable cost savings for firms. My work shows that the mere existence of contracts that "financially" link products of the same manufacturer together does have important welfare implications.

Finally, my work contributes to a broad discussion in health economics and health policy regarding the key drivers for enhancing preventive care provision in the U.S. and other Western countries. For example, several studies identify key factors to raise immunization rates, including appropriate counseling, targeted ads (Ho et al., 2023), low out-of-pocket costs for patients (Makhoul et al., 2023) and higher payments to medical providers (Cabral et al., 2023). Additionally, some research highlights the need for targeted interventions in disadvantaged areas, where healthcare facility penetration is limited, and trust in science is low (Alsan and Eichmeyer, 2024). Few papers focus on supply-side channels that could enhance preventive care. One exception is Li (2024), who highlights that insurer competition and patients' frequent reallocation across insurance plans disincentivize insurers from investing in preventive measures. My work further contributes to this area by illustrating how additional supply-side incentives, such as bundled loyalty discounts offered by pharmaceutical companies to medical providers, could boost immunization rates, particularly for optional vaccines. Since medical providers purchase and store doses in their offices, they act as *agents* between pharmaceutical

[8] Health insurers' formularies specify the list of drugs that an insurance plan covers and the associated cost-sharing rules for patients buying those drugs.

companies and patients. By increasing providers' profit margins, these discounts may partially align their financial incentives with patients' health benefits, thereby encouraging providers to expand their range of vaccine offerings. At the same time, I also highlight that such discounts may lead providers to limit their purchases to a few manufacturers, potentially compromising the quality of the chosen products.

Outline. The rest of the paper is organized as follows. Section 2 details the institutional background and the data, with a particular focus on how bundled loyalty contracts operate in the U.S. vaccine market. Section 3 presents the key descriptive patterns that motivate the model. Sections 4 and 5 introduce and estimate an empirical model of vaccine demand and supply in the presence of bundled loyalty discounts. Section 6 describes the simulated counterfactual scenarios. Section 7 concludes.

2 Background and Data

This section highlights what makes bundled loyalty discounts of particular interest in the context of the U.S. healthcare market. Specifically: (i) it describes the key role played by medical providers in buying physician-administered treatments for their patients, differently from standard prescription drugs; (ii) it presents the market for pediatric and adolescent vaccines in the U.S., where bundled loyalty discounts are in place; and (iii) it explains how pharmaceutical companies construct such contracts and discusses the associated welfare trade-offs.

2.1 Physician-administered treatments in the U.S.

Physician-administered treatments are infusions or injections administered by medical providers mainly within outpatient settings, such as doctors' offices or outpatient clinics. Examples of these treatments include oncology drugs, dialysis, medications for arthritis and osteoporosis, and vaccines. Together, these treatments accounted for about $37 billion in healthcare spending in 2019 in Medicare alone.[9]

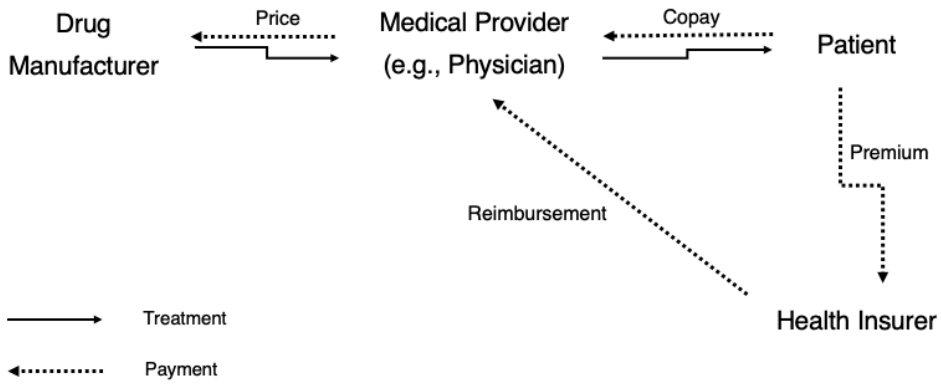
The case of physician-administered treatments differs substantially from the case of typical prescription drugs because of the central role played by providers. For prescription drugs, providers operate solely as prescribers, leaving to pharmacies the burden of purchasing and selling medical products to consumers. For physician-administered treatments, instead, the so-called "buy-and-bill" system is in place (see Figure 1). Medical providers purchase those treatments directly from manufacturers or via intermediaries,[10] and then store and administer

[9] Source: The Kaiser Family Foundation (2021) and Medicare Payment Advisory Commission (2022). Medicare accounts for about one-fourth of overall healthcare spending on drugs *and* services provided in outpatient settings (The Kaiser Family Foundation, 2023).

[10] Typically, hospitals purchase physician-administered treatments through large group purchasing organizations (GPOs). In contrast, physician practices often rely on physician buying groups (PBGs) for coordinating

them to patients. In turn, providers receive reimbursements from insurers and some payment in the form of cost-sharing (if any) from patients. As a result of this purchasing and distribution system, providers play a crucial role in deciding which treatments are delivered to patients by balancing clinical factors against their own financial interests. Additionally, most pharmaceutical companies are multi-product firms, and thus offer multiple drugs for various conditions to the same provider. The central role of providers, along with their potential multi-product relationships with drug manufacturers, drives pharmaceutical companies to strategically use bundled loyalty discounts as a tool to strengthen their customer base across their entire product line.

Figure 1: Purchasing and distribution system for physician-administered treatments.



Note: This figures illustrates the system of purchasing and distribution for physician-administered treatments. Medical providers purchase them from drug manufacturers in exchange for payment. Insurers reimburse the provider for the drug purchase and administration. Patients pay a cost-sharing (if any) to providers, and a premium to insurers.

2.2 The market for pediatric and adolescent vaccines

The U.S. market for vaccines is extremely concentrated, with the number of suppliers contracting over time. High entry costs and regulatory barriers partially explain the high concentration in the vaccine market. Being biologics, these products are extremely complex to produce and difficult to manage, store and duplicates. Moreover, since they are administered to a large and healthy population, authorities have set particularly stringent guidelines for testing and approval, leaving no pathway for generics - which do not exist in the U.S. vaccine market. Beyond entry costs and regulatory barriers, pharmaceutical companies' strategic pricing—such as bundled loyalty discounts—may further exacerbate market concentration and discourage entry.

As of 2014, Merck, GlaxoSmithKline (henceforth, GSK) and Sanofi Pasteur (henceforth,

vaccine and medical equipment purchases. PBGs are smaller than GPOs and primarily run by physicians.

Sanofi) dominate the market by offering several types of vaccines preventing a wide range of diseases, while Pfizer and Novartis have fewer products (see Table 1). Brands produced by competing companies and covering the same disease differ both horizontally and vertically. They might differ in terms of number of required doses, dosages and modes of injection (*horizontal differentiation*). They might also differ in terms of average efficacy and novelty, as measured by the number of years passed since their approval by the Food and Drug Administration authority (*vertical differentiation*).

Most pediatric vaccines are compulsory in the vast majority of U.S. states, including Colorado—which is my empirical setting of interest. This means that schools require all students to be immunized against certain diseases (e.g. measles, mumps and rubella), unless an exemption is filed.[11] A few other vaccines, instead, are suggested but not required (e.g. meningitis vaccine). In my discussion, I refer to the former group as the *"compulsory"* or *"required"* vaccines, and to the latter group as the *"optional"* vaccines.[12]

Table 1: Competition in the U.S. children and adolescent vaccine market, 2014

	Manufacturer				
Vaccine Type	**GSK**	**Merck**	**Novartis**	**Pfizer**	**Sanofi**
		Panel A: Required vaccines			
Diphtheria, Tetanus, Pertussis	●				●
Measles, Mumps, Rubella		●			
Hepatitis B	●	●			
Polio					●
Pneumococcal				●	
		Panel B: Optional vaccines			
Meningitis			●		●
Hepatitis A	●	●			
Haemophilus influenzae	●				●
Rotavirus	●	●			

Note: The table gives an overview of the main vaccines available to children and adolescents in the U.S. as of 2014. Each vaccine type protects against one or multiple diseases. Each dot represents a brand, i.e. a vaccine type - manufacturer combination. Panel A includes vaccine types required to access school in Colorado ("required" vaccines), while Panel B includes vaccines that are not required to this end, and thus "optional".

[11] As of 2019, the compliance rate with vaccine requirements was around 95% in Colorado. Among vaccination exemptions, 88% were motivated by personal belief, 7.5% were religious exemptions and 4.5% were medical exemptions (Colorado Department of Public Health, 2024a).

[12] For extensive information on vaccine requirements by state, see Pew Research Center (2021). For Colorado, see Immunize Colorado (2024), Colorado Department of Public Health (2024b), and here.

Over the time-span of interest for this paper (2012-2019), the market evolved in two notable ways. First, new vaccines have been approved after 2015, such as GSK's and Pfizer's vaccines for meningitis (type B)[13]. Second, in March 2015 GSK acquired Novartis's vaccine division,[14] thus being able to add the Novartis's meningitis vaccine (type ACWY) to its product line. In Table **??** in appendix, I display companies' vaccine portfolios as of 2016, after the introduction of new products and after GSK acquisition.

As for most pharmaceutical products, vaccines are sold separately to the private sector and to the public sector.[15] Within the private sector—which is the main focus of this work—medical providers purchase vaccines directly from manufacturers or intermediaries at a price set by the manufacturers, and then administer them to their patients. Patients' insurers reimburse providers for their vaccine purchase and administration. After the Affordable Care Act (ACA), most employer-sponsored health plans and individually purchased insurance from and off the marketplaces are subject to specific vaccine coverage requirements and *must* provide coverage to patients without cost-sharing.[16]

Overall, vaccinations pose significant financial challenges for private practices. For instance, Coleman et al. (2009) find that the costs of private-stock pediatric vaccines can be one of the largest expenses for practices after staff salaries, and that it is not adequately compensated for by insurers. The study also highlights that most private practices incur losses as a result of the time and resource investments required to vaccinate their patients.

The remaining portion of vaccine purchases in the U.S. is supplied by the public sector. Specifically, the Department of Health and Human Services negotiates public vaccine prices with manufacturers under the Vaccines For Children program (VFC). As a result, public prices are usually between 30% and 50% percent lower than private list prices. Vaccines are then distributed at no charge to physicians' offices and public health clinics registered as VFC providers. Vaccine procured under the VFC can be administered exclusively to Medicaid-eligible, uninsured, or American Indian or Alaska Native patients under the age of 18. Children do not face any cost-sharing. In my empirical analysis, I focus exclusively on vaccine procurement through the private sector: since in the public sector medical providers receive vaccines for free, financial incentives in the form of bundled loyalty discounts are less likely to play a role.

[13] GSK's and Pfizer's vaccines for meningitis B were approved in 2015 and 2014, respectively.

[14] In March 2015, Novartis completed a global portfolio transformation which included the divestiture of its non-influenza vaccine division to GSK, in exchange for the acquisition of new oncology products from GSK.

[15] See The Kaiser Family Foundation (2020).

[16] Patients above 65—which are *not* the focus of this work—have their immunizations covered under Medicare Parts B and D. For those patients, influenza, pneumococcal vaccines and hepatitis B vaccines are covered by Part B, and are reimbursed 95% of their Average Wholesale Price (differently from other Part B drugs, which are reimbursed 106% of the Average Sales Price). The remaining vaccines are covered by Part D plans, that can choose which reimbursement to set.

2.3 Bundled loyalty contracts

Previous research documents the extensive use of sophisticated pricing contracts between sellers and buyers known as "conditional pricing practices". These pricing strategies allow the actual price paid by the buyer to the seller to vary, based on whether the buyer meets a set of conditions that the seller specifies. The conditions may require the buyer to meet a minimum quantity or share, to purchase multiple products, or even to deal exclusively with one seller. From the prospective of the seller, these contracts help develop a loyal base of customers, increase quantities sold and foreclose rivals. Examples of such arrangements include loyalty discounts or all units discounts (see Conlon and Mortimer, 2021 in the snack food industry), full-line forcing (see Ho et al., 2012 in the market for DVDs), vertical bundling (see Crawford and Yurukoglu, 2012 for the cable television sector), and bundled loyalty discounts (the focus of this paper). Across all industries, a significant challenge for researchers is that the exact terms of these arrangements are proprietary information of the sellers and, thus, unobserved.

Vaccines are an example of physician-administered treatments where bundled loyalty discounts are in place. How do bundled loyalty contracts in the market for vaccines work, in practice? Broadly speaking, a pharmaceutical company selling multiple vaccine types offers discounted prices to practices who purchase their vaccine needs exclusively from the manufacturer's portfolio and not from rivals, *unless* some vaccine types are not produced at all by the discounting manufacturer. Some observations are in order. First, if a certain pharmaceutical company does not produce any brand against a certain disease, providers can purchase it from a competitor and still qualify for the company's discount on its own vaccines. Second, the discount rule does not require providers to buy every brand a company is producing, *as long as* they don't buy it from competitors.[17] For example, a pediatrician can still qualify for discounts from a company that sells both pediatric and adult vaccines, even without buying adult vaccines at all. Similarly, a pediatrician can opt out from optional vaccines and still obtain a discount on the ones purchased.

The use of this type of contract in the vaccine market is motivated by several specific characteristics of the industry. First, the market is concentrated, with a few large companies selling multiple and (partially) overlapping vaccines types. Second, medical providers' financial gain from vaccine injections—as measured by the difference between insurance reimbursement and vaccine purchasing price—is relatively small, thus motivating the attractiveness of purchasing doses at discounted prices.

Similarly to other industries, also in the market for vaccines the terms of these arrangements are proprietary information. However, two antitrust cases dealt with those contracts in

[17] Drug manufacturers can easily verify providers' compliance with the discount rule. From conversations with providers, I learnt that pharmaceutical companies can access publicly available files storing information on providers' purchases from each manufacturer.

2011 (*Castro M.D. PA v. Sanofi Pasteur Inc.*) and 2018 (*Sugartown Pediatrics, LLC v. Merck & Co*), respectively.[18] From reading the official documents released for the cases, I recovered the exact purchasing requirements that medical practices must meet in order to qualify for discounts, as well as discount averages.[19] I compared this information with details obtained during recent conversations with healthcare providers. They all confirmed the existence of these types of contracts and their specific details, which is reassuring given that the antitrust cases may have lead companies to stop using them or to modify requirements.[20]

A stylized example. I present a simple example to further clarify how bundled loyalty discounts work in the vaccine market. Table 2 shows a simplified setting where three companies (i.e. 1, 2, 3) offer up to three vaccine types (i.e. A, B, C). Brands differ in terms of quality, as suggested by the heterogeneous list prices (i.e. before discounts) offered by each company.

Table 2: A stylized example of how bundled loyalty contracts work.

Available options:

	Manufacturer		
Vaccine Type	**1**	**2**	**3**
A	●	●	
B	●		●
C		●	●

List price/dose (before discount):

	Manufacturer		
Vaccine Type	**1**	**2**	**3**
A	$10	$8	
B	$10		$8
C		$10	$8

Note: Illustration of a simplified scenario, where a practice can choose among different manufacturers (1,2,3) offering several vaccine types (A,B,C). List prices before discounts are displayed on the right. Given this hypothetical scenario, practices can select different combinations of vaccines, and only some of them will provide access to a bundled loyalty discount. See the main text for more details.

Suppose a medical provider is willing to buy vaccine types A and B for its patients (for example, suppose the provider is a pediatrician and does not need any adult vaccine C). The

[18] *Castro M.D. PA v. Sanofi Pasteur Inc.*: The case was initially filed in December 2011. In October 2017, Sanofi agreed to pay $61.5 million to settle the dispute, without admission of guilt. *Sugartown Pediatrics, LLC v. Merck & Co*: The plaintiffs sued Merck in 2018. Merck moved to compel arbitration. While the district court initially dismissed that argument in 2020, the Third Circuit reversed that decision in 2022.

[19] According to the information released, contracts are pretty standard, namely discount sizes and rules are not individualized based on providers' features. This is why, in the model, I allow each company to set its own discount percentage, without differentiating among practices.

[20] As the large pharmaceutical companies I am considering produce several drugs in addition to vaccines, one may wonder whether firms could condition their discount not only on vaccine purchases, but also on other drugs' purchases. However, vaccine purchasing and distribution is usually separated from other drugs, as it goes mainly through intermediaries called Physicians' Buying Groups. Moreover, prior antitrust cases detailing the vaccine procurement system exclude this possibility. As a result, I can reasonably restrict discount boundaries to vaccines. This is among the reasons why I chose to focus my study on vaccines rather than other drug categories in the first place.

provider can choose among multiple purchasing alternatives, including the following:

- the provider may decide to buy 100% of the doses needed for A and B from company 1, thus securing a discount from company 1 on both vaccine types. As a result, the purchasing cost for the provider is: $\$(1-\delta_1)10 \cdot doses_A + \$(1-\delta_1)10 \cdot doses_B$
- the provider may decide to buy 100% of the doses needed for A from company 2, and 100% of the doses of B from company 1. In this way, company 2 will offer a discount on A, as company 2 produces exclusively A and C (that the provider is not buying at all). On the contrary, company 1 will not offer any discount, as company 1 is producing both A and B but the provider is buying A from the competing firm. As a result, the purchasing cost for the provider is: $\$(1-\delta_2)8 \cdot doses_A + \$10 \cdot doses_B$
- the provider may decide to buy 100% of the doses needed for A from company 2, and 100% of the doses of B from company 3. Similarly to the previous case, company 2 will offer a discount on A. At the same time, company 3 will offer a discount on B, as company 3 produces exclusively B and C (that the provider is not buying at all). As a result, the purchasing cost for the provider is: $\$(1-\delta_2)8 \cdot doses_A + \$(1-\delta_3)8 \cdot doses_B$

The final choice of the provider will depend ultimately on the size of discounts and list prices, on the amount of doses needed, and on how much the provider weighs its own financial gain from each dose against the products' attributes - including quality. These drivers will be key in my empirical model.

Welfare implications. How does the presence of bundled loyalty discount contracts affect providers' choices? In turn, how does this translate into aggregate welfare? I present some intuition informing the empirical model that will follow.

Firms compete on prices for selling their heterogeneous vaccines. Providers choose which and how many vaccine types to buy, by weighing the benefit for patients against their own financial gain (i.e. insurance reimbursement minus purchasing cost). The presence of bundled loyalty contracts reduces purchasing costs and, thus, increases providers' financial gain on the discounted doses. As a result, I expect two effects on providers' aggregate choices. First, providers might be more likely to buy several vaccine types from a single company, conditional on buying them (*leverage effect*). In other words, I expect less 'mix-and-match' across manufacturers, which could be positive or negative for patients. For example, it is negative if, by purchasing from a single manufacturer, practices do not select the best product for patients—as there may not exist a single firm producing the best products across all vaccine types. Instead, it is positive if these contracts encourage providers to choose high-quality products, that are usually expensive to buy without discounts. Second, providers might be willing to purchase

and store in their office more vaccine types in the first place (*coverage effect*). If this is the case, I expect a higher immunization uptake among patients, which is generally considered welfare improving given the well-known under-provision of vaccines and their externality. This is especially true for optional vaccines, that providers may choose not to store in the absence of discounts given the lower expected financial gains.

Furthermore, in the presence of bundled loyalty discount contracts, pharmaceutical companies may set list prices differently than in a standard scenario without discounts. On the one hand, firms may want to increase list prices to enhance the attractiveness of discounts; on the other hand, firms may want to decrease list prices to compete against rivals' discounted brands. The prevailing outcome will ultimately depend on the values of the key parameters (Zhou, 2021; Ghosh and Balachander, 2007).

2.4 Data

For my empirical analyses, I rely mainly on claims data from the Colorado All Payer Claims Database (CO APCD) and I complement them with auxiliary datasets. I describe each data source below.

Claims data. The CO APCD is a comprehensive collection of medical claims of Coloradans between 2012 and 2019. The dataset contains a rich set of variables at the claim-level, including visit-specific information (date of service, place of service, ICD codes for diagnoses, and CPT/HCPCS codes for procedures), type of insurance and health plan, payments to provider (e.g. patient cost-sharing, insurance reimbursement), patient-level and physician-level information (e.g. pre-conditions, specialty).

Importantly, unlike other datasets, the CO APCD allows me to track each provider over time and across its entire pool of patients, no matter their insurance company. As a result, I can recover the entire portfolio of drugs each provider uses over time and the manufacturers they buy from.

For my scope, I focus on claims containing at least one vaccine administration. My sample of interest includes around $1,000$ providers (mainly pediatricians and family medicine doctors who provide primary care) administering compulsory and optional vaccines to children and adolescent in Colorado, between 2012 and 2019. The average provider administers around 230 doses of compulsory vaccines per year, and 100 doses of optional vaccines per year.[21]

List prices. Despite its richness, the CO APCD doesn't contain information about the actual price paid by medical providers to purchase each vaccine. To this end, I turn to the Centers for

[21] I exclude flu vaccines from the sample, as their ad-hoc purchasing process and seasonal demand patterns are unique and different from those of most pediatric and adolescent vaccines.

Medicare & Medicaid Services (CMS)'s website to extract quarterly data on list prices for each vaccine brand and each manufacturer, before discounts. The website contains both the private prices, offered by pharmaceutical companies to the private sector, and the public prices, negotiated under the VFC program (see Section 2.2). As previously mentioned, I focus primarily on the private sector, where financial incentives from bundled loyalty contracts play a significant role. I can merge this pricing information to claims data using product specific NDC codes.

Private list prices for vaccines covering the same disease vary across manufacturers and over time. Moreover, insurer reimbursements (observed in CO APCD) vary across manufacturers, over time, and across different insurance plans (see Table **??** in appendix). As a result, a provider's financial gain from purchasing a certain brand will depend on the manufacturer producing it, as well as on the expected reimbursement given the insurance mix across patients (see Table **??** in appendix). This generates important heterogeneity among providers in terms of financial incentives, that may motivate different vaccine choices.

The exact magnitude of bundled loyalty discounts is part of the contractual arrangements between medical practices and pharmaceutical companies and, thus, *net prices* are not available to researchers. This paper estimates discount magnitudes from providers' purchasing patterns, and compares estimated values to average discount amounts from recent antitrust cases.

Provider-practice match. I expect medical providers operating within the same practice to make a centralized purchasing decision at the practice level. As a result, I employ the SK&A's survey to link providers, as identified by their own National Provider Identifier (NPI), to the practice they belong to. This survey, conducted over multiple yearly rounds since 2012, contains this type of information and can be merged with CO APCD using the NPIs. Moreover, I complement physician-level information available in CO APCD with the National Plan and Provider Enumeration System data (NPEES), which contains physicians' specialty, gender, education, and graduating institution. It can be merged with CO APCD using the NPIs.

3 Stylized Facts

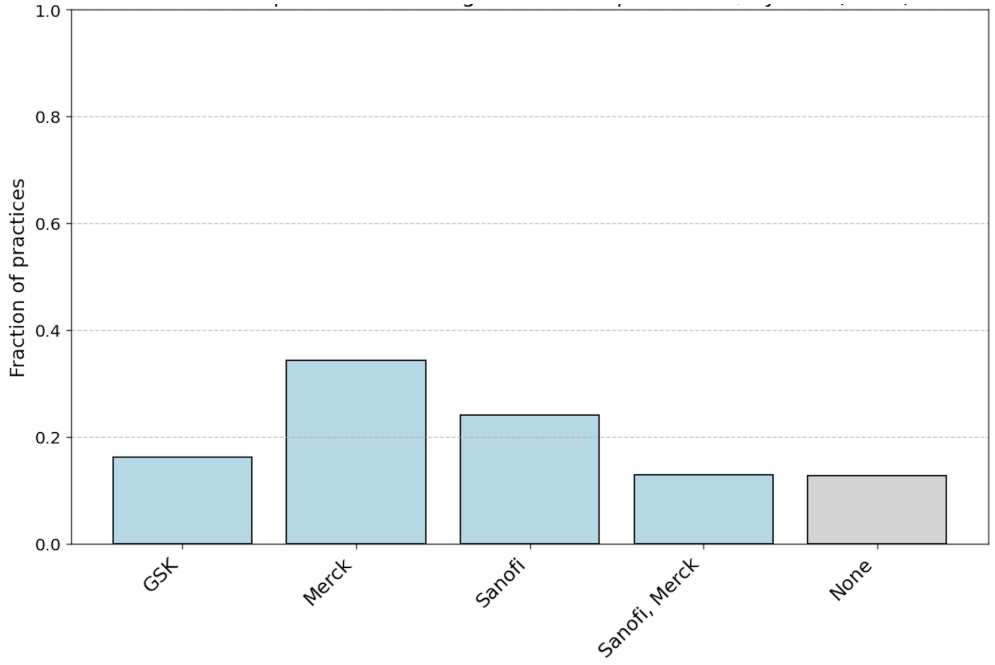
In this section, I document several empirical facts that motivate the modeling choices in the following section. I begin by showing that a large fraction of medical practices in my sample complies with the discount requirement rules for one or multiple pharmaceutical companies, as I can deduce from their purchasing patterns. Second, I show that practices differ in the financial gains they obtain from the same vaccine choice—which may lead some practices to perceive discounts as more attractive than others. Third, I estimate that having a large pool of eligible patients for a certain disease translates into a high observed probability of complying with the discount rules of a company offering immunization against that disease. Finally, I illustrate

that changes in market structure over time modify the breadth of pharmaceutical companies' portfolios, and prompt many providers to adjust their vaccine purchasing patterns to remain eligible for bundled discounts.

3.1 Medical practices comply with vaccine discount requirements

Practices decide how to *combine* vaccine types. This joint decision across vaccine types determines whether discount requirements set by pharmaceutical companies are met (see Section 2.3). Since I recover companies' discount requirement from previous antitrust cases, I know pharmaceutical companies' vaccine portfolios, and I observe medical practices' vaccine choices from the data, I can ultimately determine whether practices meet those requirements. As a result, I am able to infer which practices are likely to pay discounted prices on all their vaccine purchases, and from which manufacturer. Figure 2 shows the resulting scenario as of 2014: around 18% practices are eligible to receive discounts from GSK, 22% from Sanofi, 35% from Merck, 13% from Sanofi and Merck jointly (given their complementary portfolios), while 12% do not receive any discount. In the model, I allow for complementarities among brands produced by the same manufacturer in the form of discounts deduced from practices' purchasing prices.

Figure 2: Fraction of medical practices meeting discount requirements, by company.



Note: This figure displays the fraction of medical practices eligible for discounts from one or multiple manufacturers, as of 2014. Receiving discounts from both Sanofi and Merck is possible as they have a complementary vaccine portfolio, so obtaining discounts from one company does not automatically violate the discount requirements of the other. I can recover which practice is eligible for which discount since I know companies' portfolios, I observe providers' choices (from data), I extract the discount requirements (from prior antitrust cases).

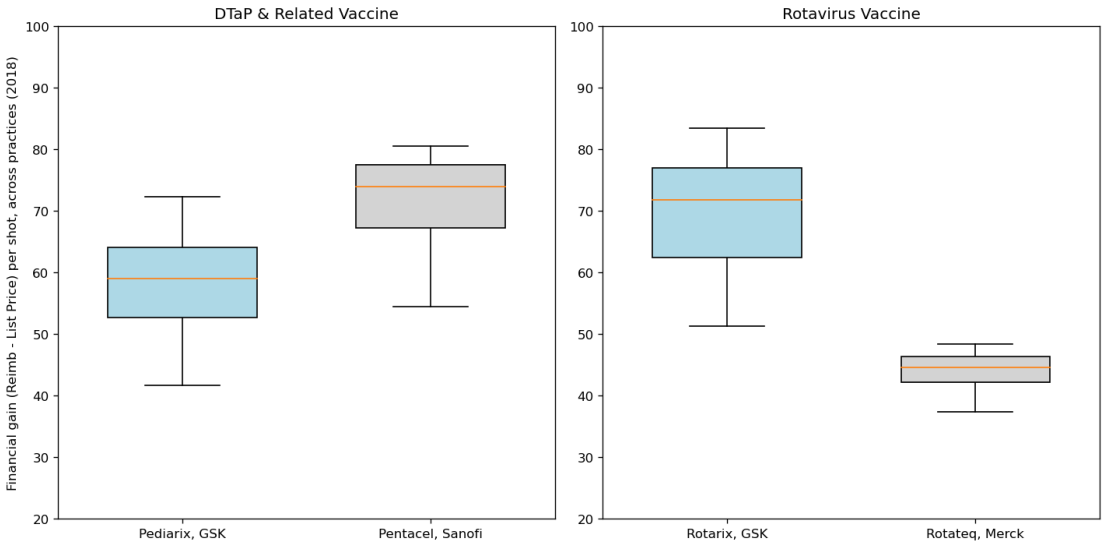
3.2 Practices differ in their financial gains from vaccine purchasing

Insurance companies reimburse practices for vaccine administration and for purchasing the vaccine brands administered to their patients. However, insurers differ in their reimbursement generosity for the same brand. Moreover, practices differ in their pool of patients and, thus, in the insurers they receive reimbursement from (*insurer mix*). As a result, different practices expect different reimbursements depending on the vaccine brand they purchase and on the insurers which typically cover their patients.

In addition, practices pay a price for purchasing vaccine brands from drug manufacturers. Competing pharmaceutical companies set different prices for their products, even when they protect against similar diseases, due to differences in injection mode, number of doses, novelty and expected efficacy. As a result, practices pay different list prices (even before accounting for discount) depending on the brand they purchase.

Ultimately, practices obtain a financial gain from each injection, equal to the difference between the insurance reimbursement and the purchasing price paid to the manufacturer. In Figure 3, I illustrate the case of vaccine brands protecting against diphtheria-tetanus-pertussis and rotavirus. The average financial gain differs among brands protecting against the same disease, but also among practices for the same brand.

Figure 3: Distribution of financial gains, across practices and vaccine brands.



Note: This figure shows the distribution (across practices) of the financial gains obtained from purchasing different brands. Financial gains are obtained as the difference between insurance reimbursement and list price. For example, the panel on the right displays the case of rotavirus, a vaccine type where two brands compete: Rotarix (produced by GSK) and Rotateq (produced by Merck). On average, choosing Rotarix generates higher gains for practices. However, I observe variation across practices, as they have different insurer mixes. Similarly, on the left I display Pediarix (produced by GSK) and Pentacel (produced by Sanofi), both protecting against diphtheria, tetanus and pertussis.

3.3 Practices' patient mix predicts their choice of discounted vaccines

To better understand the drivers of medical practices choices, I examine the relationship between a medical practice's patient mix and its vaccine procurement decisions. In the U.S., the Advisory Committee on Immunization Practices establishes rigid timelines for each vaccine type, prescribing specific administration windows tied to children's ages.[22] For instance, the diphtheria-tetanus-pertussis (DTaP) vaccine requires a first dose at 2 months, while the measles-mumps-rubella (MMR) vaccine is first administered at 12 months. Medical practices are heterogeneous in their patient populations. They differ not only in their total patient count but, crucially, in the age distribution of their patients. Some practices might serve a larger proportion of infants and toddlers, while others might have more school-age children. This variation in patient mix directly translates into different immunization needs across practices. In turn, these diverse immunization needs can influence a practice's choice of vaccine supplier and associated discounts. The connection arises from the fact that manufacturers differ in the portfolio of vaccines they produce and diseases they cover. When a practice has high demand for vaccines predominantly produced by specific manufacturers, the potential savings from those manufacturers' discount programs become more substantial. For example, if a practice serves many 12 month-old children requiring MMR vaccines (primarily produced by Merck), they might find greater value in Merck's discount program.

To systematically examine how patient mix influences practices' choices of discounted vaccine baskets, I employ a multinomial logit regression framework. This approach allows me to quantify the relationship between a practice's patient population characteristics and their likelihood of selecting particular manufacturer discount programs, while controlling for other relevant factors such as practice size and temporal variations. I define five mutually exclusive alternatives (i.e., discount-types) to indicate the types of vaccine baskets that medical practices can choose from: GSK discounted, Merck discounted, Sanofi discounted, Sanofi and Merck discounted, Not discounted. Each practice is endowed with a pool of patients eligible for immunization across different diseases. For practice i at t, I denote this pool as $\mathbf{x}_{it}$, i.e. a vector where each entry consists of the number of patients eligible for a given disease. The probability that a practice i chooses a vaccine basket belonging to discount-type $\bar{d}$ at t, given $\mathbf{x}_{it}$, is:

$$\mathscr{P}(d = \bar{d}|\mathbf{x}_{it}) = \frac{exp(\gamma_1^{(\bar{d})} + \boldsymbol{\gamma_2}^{(\bar{d})}\mathbf{x}_{it} + \mu_{it\bar{d}} + \psi_{t\bar{d}})}{\sum_d exp(\gamma_1^{(d)} + \boldsymbol{\gamma_2}^{(d)}\mathbf{x}_{it} + \mu_{itd} + \psi_{td})} \tag{1}$$

My object of interest is the vector $\boldsymbol{\gamma_2}$, which describes how patient mix influences practices' choices of discounted vaccine baskets. Table 3 presents the marginal effects of changing the number of patients eligible for immunization, for one disease at a time, on medical practices'

[22] See here for the full immunization calendar.

probability of choosing a basket belonging to a certain discount type. My specification additionally control for practice size and time fixed effects. In general, the resulting estimates show that having a large pool of eligible patients for a certain disease translates into a high observed probability of complying with the discount rules of a company offering immunization against that disease. For example, if we consider an average practice, increasing by 10 units (around 1 standard deviation) the number of patients eligible for Hepatitis A increases the practice's probability of choosing a GSK-discounted basket by 5.8 percentage points, and a Merck-discounted basket by 2.9 percentage points. Unsurprisingly, GSK and Merck are the only manufacturers producing Hepatitis A. In turn, having a large pool of Hepatitis A-eligible patients makes GSK's and Merck's discount programs more attractive, all else equal. Since the average rate at which practices choose GSK-discounted (Merck-discounted) baskets is 18% (35%) over my sample, the estimated effects are substantial.

Table 3: Multinomial logit examination of vaccine basket choices

Basket of vaccines discounted by...					
	GSK	Merck	Sanofi	Sanofi&Merck	None
Quantity of patients eligible for...					
Diphtheria, Tetanus, Pertussis	-0.062	0.064	0.031	-0.047	0.014
	(0.015)	(0.020)	(0.014)	(0.008)	(0.010)
Hepatitis A	0.058	0.029	-0.020	-0.023	-0.045
	(0.015)	(0.020)	(0.015)	(0.008)	(0.010)
Hepatitis B	-0.086	-0.096	0.140	0.039	0.004
	(0.016)	(0.022)	(0.018)	(0.010)	(0.012)
Haemophilus influenzae	-0.046	-0.018	0.074	0.009	-0.019
	(0.022)	(0.031)	(0.023)	(0.013)	(0.014)
Measles, Mumps, Rubella	-0.083	0.197	0.070	-0.055	-0.127
	(0.030)	(0.037)	(0.027)	(0.015)	(0.017)
Polio	-0.084	-0.006	0.234	-0.166	0.023
	(0.047)	(0.052)	(0.038)	(0.028)	(0.028)

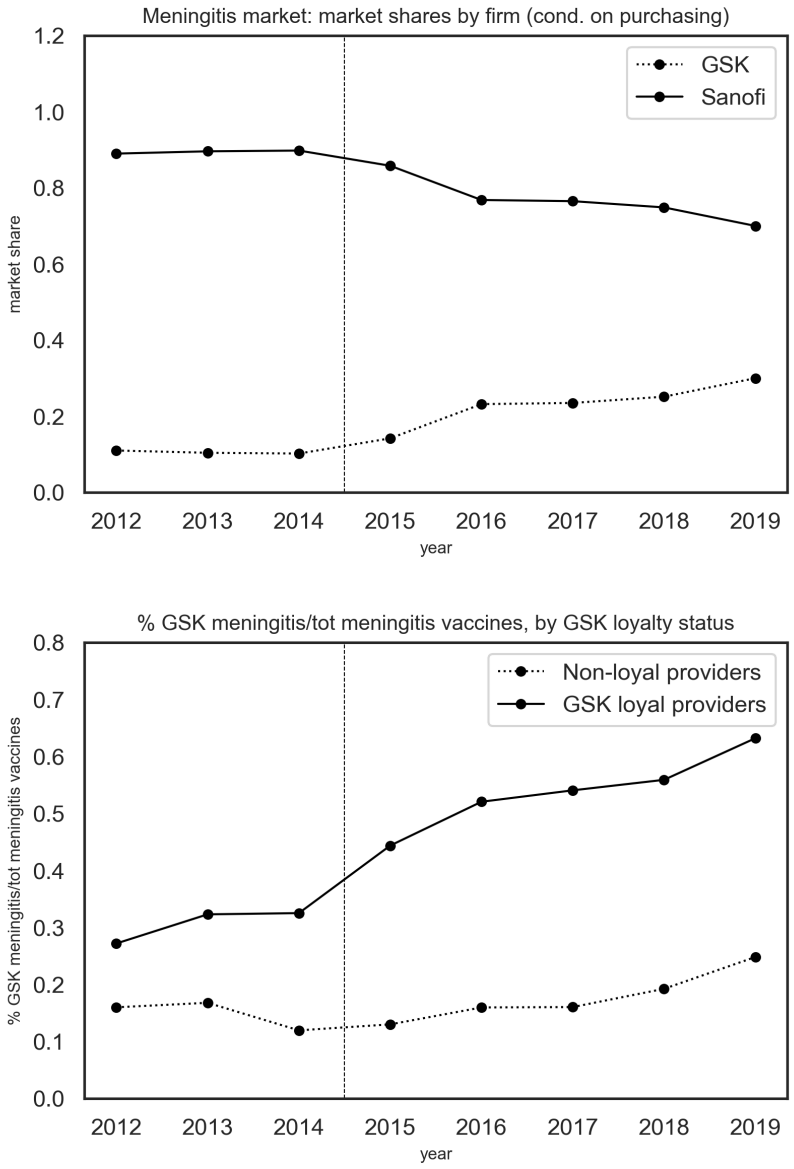
Note: This figure displays the marginal effect of changing the number of patients eligible for immunization, for one disease at a time, on medical practices' probability of choosing a certain type of vaccine basket. I group vaccine baskets into five mutually exclusive categories: GSK discounted, Merck discounted, Sanofi discounted, Sanofi and Merck discounted, Not discounted. Coefficients are obtained from a multinomial logit regression, where I also control for quarter fixed effects and practice size. I highlight cells in grey if the manufacturer in the corresponding column produces a brand covering the disease(s) in the associated row. The sample consists of all practices in all quarters. The number of eligible patients is divided by 10 for enhance interpretability. To recover the marginal effect, the remaining variables are set at their mean value. Standard errors in parenthesis are computed using the delta method.

3.4 Changes in manufacturers' vaccine portfolios affect practices' choices

I investigate whether changes in market structure over time induce a significant number of practices to modify their vaccine purchasing patterns in notable ways. Specifically, I focus on GSK's acquisition of Novartis's meningitis vaccine in 2015, as this acquisition directly affected the breath of GSK' vaccine portfolio. Before 2015, Novartis and Sanofi were the only producers of vaccines protecting against meningitis (type ACWY). While Novartis's vaccine portfolio was limited to the meningitis brand,[23] Sanofi offered a broader range of vaccines. In March 2015, Novartis completed a global portfolio transformation which included the divestiture of its meningitis vaccine to GSK. In Figure 4 (upper panel), I plot the evolution of market shares for the meningitis products before and after the acquisition. Following 2015, the former Novartis (now GSK)'s brand increased its market share at the expense of its competitor produced by Sanofi. In the bottom panel, I analyze how medical practices modified their purchasing patterns after the acquisition. To this end, I split practices into those who were complying with GSK discount requirements before the 2015 acquisition ("GSK loyal") and those who were not ("Non-loyal"). Importantly, before the acquisition, purchasing meningitis vaccines from Sanofi or Novartis (or not buying them at all) was not critical for being eligible for GSK discounts. After the acquisition, instead, practices purchasing meningitis vaccines were expected to buy the GSK meningitis brand to secure discounts on *all* GSK brands. As a result, unsurprisingly, I observe GSK-loyal practices switching to the GSK (formerly Novartis)'s brand to avoid compromising their eligibility for GSK's bundled discounts.

[23] This means that, within the category of children and adolescent vaccines, Novartis was selling exclusively the meningitis brand.

Figure 4: Market shares & purchasing patterns post-GSK's acquisition of Novartis's meningitis brand.



Note: The upper figure shows the evolution of the market shares for competing brands protecting against meningitis, before and after GSK's acquisition of Novartis's portfolio. I label the brand belonging to Novartis as "GSK" even before the 2015 acquisition, for consistency with the post-acquisition period. The bottom figure shows the evolution of practices' purchasing patterns. I split the practices into "GSK loyal" vs. "Non-loyal", where the GSK loyal ones are those complying with GSK discount requirements before the 2015 acquisition. I plot the number of GSK meningitis doses out of the total meningitis doses that each group purchases. After the acquisition, we observe GSK loyal practices preferring the GSK meningitis brand over the competitor's brand more frequently than before, and more often than non-loyal practices, in order to remain compliant with GSK discount rules.

4 Empirical Model

In this section, I present a model for medical practices' demand and pharmaceutical companies' supply of vaccines. On the demand side, practices' choice problem differs from the standard discrete choice framework, as obtaining bundled loyalty discounts from manufacturers is conditional on the *joint* purchases of multiple types of vaccines - if available - from a single producer. As a result, I require practices' utility function to include a complementarity term, which drives the additional utility gains from the joint purchase of some brands.[24] Moreover, my framework differs from most of the literature in industrial organization and health economics, where physicians prescribe their preferred drug at each patient encounter.[25] In my context, practices have to purchase treatments in advance and store them in their office, *before* meeting patients. As a result, practices make their treatment choices taking into account the expected returns from immunizations, which depends on the flow of eligible patients and the expected insurance reimbursement for each injected dose. On the supply side, manufacturers select prices and discounts for their vaccines, knowing that demand for their products is additionally influenced by the structure of bundled contracts.

4.1 Medical Practices' Demand for Vaccines

Environment and Product Space. I consider medical practices denoted by $i = 1, ..., I$ making child or adolescent immunization purchases in each quarter $t = 1, ..., T$. Practices are usually small (on average, 2.3 physicians are operating in a practice in my sample) and mainly composed of pediatricians and family medicine doctors together with nurses, supporting the health needs of newborns and young patients. In selecting vaccines to purchase, a practice chooses which diseases to cover and which manufacturer(s) to buy from. A *vaccine type* $v = 1, ..., V$ indicates the specific disease or group of diseases that a product helps prevent. For each vaccine type, there are usually multiple alternatives available, offered by competing manufacturers. For example, pediatric vaccines against hepatitis are offered by both GSK and Merck. A brand $j = 1, ...J_t$[26] indicates the specific vaccine type - manufacturer combination. For example, hepatitis - GSK is a brand. Brands differ in terms of year of approval and expected patients' efficacy, easiness of administration and storage, as well as acquisition cost and insurance reimbursement (as detailed later). Ultimately, each practice chooses how to combine brands together into a vector of brands, namely a *basket*, denoted by b. A basket is a combination of brands, with up to one

[24] The closest approach is Cao and Chatterjee (2022), studying fixed-dose combinations which "physically" bundle two drugs in a single pill in the Alzheimer's drug market. Differently from their approach, I allow for "financial" bundling in the form of discounts off the list price of vaccines, and I deal with a larger space of products that can potentially be combined together.

[25] See, for example, Dickstein (2017), Dickstein (2021) and seminal work by Pauly (1980) and Dranove (1988).

[26] The set of available brands is time-varying due to the introduction of new products over time.

brand for each vaccine type.[27] For example, a basket is the vector composed of: diphteria - GSK, measles - Merck, hepatitis B - GSK, polio - Sanofi, pneumococcal - Pfizer. Baskets of vaccines differ in terms of: (i) brands included and their related manufacturers; (ii) length, as they may include more or less vaccine types.

Bundled Loyalty Discounts. Absent discounts, the price that each practice faces in purchasing a basket of vaccines is the sum of the prices of the included brands. However, some baskets are discounted, which implies that practices are paying *less* than the sum of their brands' prices to procure them. Knowing the exact discount rules from the official documents released from prior antitrust cases on vaccines, I can determine *which* baskets are discounted and *by which* pharmaceutical company. Specifically, I assign to each basket an indicator function, $\mathbb{1}_{\{bft\}}$, which equals 1 if basket b is discounted by manufacturer f at t. This definition is time varying, as products change ownership over time due to changes in market structure. Also, I denote by $\delta^{(f)}$ the percentage discount offered by manufacturer f on its own products, when they are purchased within a discounted basket. Importantly, one of the purposes of my model is to estimate those discount terms, as they are unobserved. On a final note, I emphasize that not all brands within a discounted basket are actually discounted. For example, a basket discounted exclusively by GSK may contain undiscounted brands produced by Sanofi - provided GSK has no direct competitors in its portfolio. Moreover, if two manufacturers have no overlap in their portfolio of vaccines, the same basket might be discounted by both.[28] My model fully accounts for these possibilities.

Preferences. Each medical practice faces a discrete choice problem in choosing one basket, among all the available ones. I denote by B_{it} the choice set that practice i faces at t, with the idea that the available baskets may change over time due to product entry and vaccine seasonality, and that different practices may face different choice sets depending, for example, on their specialty.[29] In each period, practices have an exogenous number of eligible patients demanding vaccination against certain diseases. I assume that this flow of eligible patients is predictable by practices, as it closely links to the age distribution of their pool of patients.[30] I denote the amount of eligible patients for practice i, vaccine type v and quarter t as w_{itv}. Furthermore,

[27] This is motivated by what I observe in the data: the vast majority of in-sample practices do purchase one brand per vaccine type, within a quarter. This pattern persists even for practices that do not purchase a discounted basket. My empirical specification models explicitly gains from single-sourcing.

[28] In my setting, this happens for Sanofi and Merck.

[29] In principle, I should allow the choice set to include all possible combinations of brands. This would pose a problem of dimensionality. As a result, I exploit several features of the data to reduce the choice set dimensionality, including: (i) brands' entry and exit; (ii) vaccine seasonality; (iii) physicians' specialty and their patients' age distribution (e.g., the choice set of a pediatric practice having exclusively newborns in its pool of patients will not include adolescent vaccines). By doing so, I obtain choice sets of (at most) 139 baskets. Future iterations of this paper will further elaborate on this approach.

[30] For example, children immunizations follow a rigid calendar based on a child's year and month after birth.

as detailed by the previous descriptive evidence section, practices also differ in the expected reimbursement from administering a given vaccine brand. This is due to the fact that practices have patients with heterogeneous insurance coverage in their pool, and that the patient mix is different across practices. As a result, each practice obtains its own specific financial gain from choosing a certain basket of vaccines, computed as the difference between the expected total reimbursement (which is practice-specific) and the total purchasing price of the basket.

More formally, practice i choosing basket $b \in B_{it}$ at t gets the following utility:

$$U_{ibt} = \sum_{j \in b} u_{ijt} w_{itv(j)} + \Gamma_{ibt} + \epsilon_{ibt} \tag{2}$$

In other words, the utility associated to basket b is equal to the sum of: (i) the utilities associated to each brand within the basket, weighted by the number of eligible patients immunized; (ii) a complementarity term, Γ_{ibt}; (iii) a type-I extreme value error term rationalizing the remaining variation in basket choices. I use one of the baskets in the choice set ($b = 1$) as my outside option, keeping it fixed across all times and practices. Other components of the utility equation are normalized relative to the outside option.[31]

The utility associated to each vaccine brand j takes the following simple form:

$$u_{ijt} = \underbrace{\beta_0^{(jt)} \mathbb{1}_{\{jt\}}}_{\text{non-financial motive}} + \underbrace{\alpha(reimb_{ijt} - p_{jt})}_{\text{financial motive (not yet discounted)}} \tag{3}$$

This specification highlights in a clear and transparent way the trade-off faced by practice i when considering which brand j to buy at t. On one hand, the practice weighs non-financial motives, such as the quality and efficacy of the brand for patients' health, the convenience of its injection and storage mode. I capture these features by introducing brand-by-quarter fixed effects, which allow these motives to change over time, for example due to shocks to information or advertisement. On the other hand, each practice takes into account the financial gain associated with purchasing a brand, i.e. the expected insurance reimbursement (which is practice-specific) minus the list price paid to manufacturers before discount.

I follow Gentzkow (2007) and Iaria and Wang (2024), and define the complementarity term Γ_{ibt} as the additional utility that some baskets provide to practices, beyond the simple sum of

[31] Since practices choosing not to buy any vaccine at all may be intrinsically very different from practices choosing to purchase vaccines, I prefer to avoid using the standard 'no purchase' option as the outside option in my model. Instead, I use one of the baskets in the choice set as my outside option. The outside option does not vary over time or across practices.

included brands. Formally:

$$\Gamma_{ibt} = \underbrace{\sum_{j \in b} w_{itv(j)} \sum_{f} \mathbb{1}_{\{bft\}} \mathbb{1}_{\{f(j)=f\}} \beta_1^{(f)} p_{jt}}_{\text{gain from bundled loyalty discount}} + \underbrace{\beta_2 X_{bt}}_{\text{loss from "multi-sourcing"}} + \underbrace{\beta_3^{(l)} \mathbb{1}_{\{length(b)=l\}}}_{\text{number of vaccine types included}} \tag{4}$$

Several remarks can be made on this specification. The first element composing the complementarity term is the foregone purchasing cost that practices do not pay, if basket b is discounted. In other words, if b is discounted from pharmaceutical company f at t - i.e., if $\mathbb{1}_{\{bft\}} = 1$ -, then all brands sold by f and included in b - i.e. $\mathbb{1}_{\{f(j)=f\}} = 1$ - will be purchased at a lower price. The total gain generated by discounts is clearly proportional to the number of eligible patients immunized with each discounted brand, thus I weigh it by $w_{itv(j)}$. Moreover, the magnitude of the gain depends on the percentage discount applied off the list price of each discounted brand. I express the percentage discount as $\delta^{(f)}$, where $\delta^{(f)} = \frac{\beta_1^{(f)}}{\alpha}$ to rescale utils in dollar terms.

The second element in the complementarity term captures additional motives for purchasing vaccines from a limited number of manufacturers, beyond those driven by the presence of bundled loyalty discount. Specifically, I construct X_{bt} as a continuous variable, representing the actual number of manufacturers producing the brands included in basket b, divided by the maximum number of manufacturers from which the same vaccine types covered in b could have been sourced. A high ratio X_{bt} implies that practices are "multi-sourcing", i.e. they are purchasing from several manufacturers rather than minimizing them. Even absent discounts, we expect practices to dislike "multi-sourcing", as this is likely to impose additional burden on them, such as coordinating multiple vaccine deliveries and handling various phone calls. I detail how I separately identify the discount magnitudes from the gains from "single-sourcing" in the estimation section.

Finally, the third element in the complementarity term captures additional costs from purchasing "longer" baskets, namely from offering multiple vaccine types. I model these costs with simple fixed effects for baskets' length, thus allowing costs to enter the utility function in a non-linear fashion.

Given the assumption on the errors ϵ_{ibt}, the probability that practice i at time t chooses a vaccine basket b (rather than selecting other baskets denoted by r in the choice set) can be expressed in closed form as:

$$\begin{aligned} s_{ibt} &= \frac{exp(V_{ibt})}{\sum_{r \in B_{it}} exp(V_{irt})} \\ &= \frac{exp((\sum_{j \in b} \beta_0^{(jt)} \mathbb{1}_{\{jt\}} w_{itv(j)} + \alpha(reimb_{ijt} - p_{jt}) w_{itv(j)}) + \Gamma_{ibt}(\beta_1, \beta_2, \beta_3))}{\sum_{r \in B_{it}} exp((\sum_{j \in r} \beta_0^{(jt)} \mathbb{1}_{\{jt\}} w_{itv(j)} + \alpha(reimb_{ijt} - p_{jt}) w_{itv(j)}) + \Gamma_{irt}(\beta_1, \beta_2, \beta_3))} \end{aligned} \tag{5}$$

where V_{ibt} is the observable part of basket b's utility for practice i at t.

4.2 Manufacturers' Supply of Vaccines

Profit Maximization. In each period t, multi-product pharmaceutical companies take product offering as given and choose pricing and discount strategies (if any) to maximize their profits under Nash-Bertrand competition.[32] Formally, I define $\mathscr{J}_f$ the set of brands within company f's vaccine portfolio, and $\mathscr{B}_j$ the set of baskets which contain brand j. The two subsets $\mathscr{B}^{\mathscr{D}}$ and $\mathscr{B}^{\mathscr{N}\mathscr{D}}$ further restrict $\mathscr{B}_j$ to the discounted and non-discounted (respectively) baskets containing brand j. Furthermore, q_{jb} is the quantity of brand j sold within basket b. Manufacturer f solves (I abstract from subscript t for clarity of exposition):

$$\arg \max_{p=\{p_j\}_{j\in\mathscr{J}_f},\delta_f} \pi_f(\mathbf{p}) = \sum_{j\in\mathscr{J}_f}\sum_{b\in\mathscr{B}_j}(\tilde{p}_{jb}-mc_j)q_{jb}(\mathbf{p},\boldsymbol{\delta})$$
$$= \sum_{j\in\mathscr{J}_f}[\sum_{b\in\mathscr{B}^{\mathscr{D}}{}_j}((1-\delta_f)p_j-mc_j)q_{jb}(\mathbf{p},\boldsymbol{\delta})+\sum_{b\in\mathscr{B}^{\mathscr{N}\mathscr{D}}{}_j}(p_j-mc_j)q_{jb}(\mathbf{p},\boldsymbol{\delta})]$$

The profit maximization problem extends the classic multi-product Bertrand game to allow for the presence of bundled loyalty contracts. In other words, when computing revenues and costs across all brands in the portfolio, each manufacturer accounts for the fact that brands in different baskets (discounted vs. not) have different prices.

To allow the profit function to depend explicitly on the closed form expression for shares derived from demand - and thus ultimately on demand parameters -, I can write the total quantity of brand j in basket b as the product of practices' individual probabilities of choosing basket b (derived in equation (5)), weighted by the number of their eligible patients for j, and summed over all practices. In short:

$$q_{jb}(\mathbf{p},\boldsymbol{\delta}) = \sum_i s_{ib}(\mathbf{p},\boldsymbol{\delta})w_{iv(j)} \tag{6}$$

After plugging this expression into the profit function, I can write manufacturer f's first-order optimality conditions with respect to prices (see appendix **??** for the full derivation):

$$FOC(p_j): [\sum_{b\in\mathscr{B}_j}\sum_i w_{iv(j)}s_{ib}(\mathbf{p},\boldsymbol{\delta})]+\sum_{k\in\mathscr{J}_f}\{(p_k-mc_k)\sum_{b\in\mathscr{B}_k}\sum_i w_{iv(k)}\frac{\partial s_{ib}(\mathbf{p},\boldsymbol{\delta})}{\partial p_j}\}+$$
$$-\delta_f[\sum_{b\in\mathscr{B}^{\mathscr{D}}{}_j}\sum_i w_{iv(j)}s_{ib}(\mathbf{p},\boldsymbol{\delta})]-\sum_{k\in\mathscr{J}_f}\delta_f p_k\sum_{b\in\mathscr{B}^{\mathscr{D}}{}_k}\sum_i w_{iv(k)}\frac{\partial s_{ib}(\mathbf{p},\boldsymbol{\delta})}{\partial p_j}=0 \tag{7}$$

[32] Medical practices in Colorado are typically small (around 2.3 physicians per practice, on average). As a result, I assume there is no role for negotiating ad-hoc prices and discounts with vaccine manufacturers in this context. This was also mentioned by manufacturers and their representatives during meetings hold with CDC researchers about challenges and opportunities in the market for vaccines: "In the private market, no single entity has any significant buying power in negotiating price with vaccine suppliers" (Coleman et al., 2005).

Several remarks are in order. First, differently from the standard multi-product Bertrand game, here the first-order conditions incorporate the discount terms. Second, the optimality conditions keep track of the impact of a change in brand j's price on the quantity of other brands within company f's portfolio, which are denoted by k, across all baskets containing k. Note that I do not derive first-order conditions with respect to the discounts, as they will be estimated from demand. In other words, estimated discounts rationalize practices' purchasing patterns and switches. After recovering discount terms with demand estimation, I can plug them directly into the first-order conditions with respect to prices derived above.

In a similar fashion, I derive first-order conditions for all brands and manufacturers in my setting. I stack the resulting equations in matrix form and represent the system of J equations in J unknowns (i.e., the marginal costs of each vaccine brand) for each t as follows:

$$\begin{aligned} q(\mathbf{p},\boldsymbol{\delta}) + \Delta(\mathbf{p},\boldsymbol{\delta}) \cdot (\mathbf{p} - \mathbf{mc}) &= \boldsymbol{\delta} \cdot q^D(\mathbf{p},\boldsymbol{\delta}) + \Delta^D(\mathbf{p},\boldsymbol{\delta}) \cdot \mathbf{p} \cdot \boldsymbol{\delta} \\ 0 = \Delta(\mathbf{p},\boldsymbol{\delta}) \cdot \mathbf{mc} - (q(\mathbf{p},\boldsymbol{\delta}) + \Delta(\mathbf{p},\boldsymbol{\delta}) \cdot \mathbf{p} - \boldsymbol{\delta} \cdot q^D(\mathbf{p},\boldsymbol{\delta}) - \Delta^D(\mathbf{p},\boldsymbol{\delta}) \cdot \mathbf{p} \cdot \boldsymbol{\delta}) \end{aligned} \tag{8}$$

The notation has the following meaning. $\mathbf{p}$ and $\boldsymbol{\delta}$ are the vectors of brands' prices and manufacturer-specific discounts. $q(\mathbf{p},\boldsymbol{\delta})$ and $q^D(\mathbf{p},\boldsymbol{\delta})$ are, respectively, the total and discounted-only quantities sold for each brand, with $q_j(\mathbf{p},\boldsymbol{\delta}) = \sum_{b\in\mathscr{B}_j}\sum_i s_{ib}(\mathbf{p},\boldsymbol{\delta})w_{iv(j)}$ and $q_j^D(\mathbf{p},\boldsymbol{\delta}) = \sum_{b\in\mathscr{B}^{\mathscr{D}}{}_j}\sum_i s_{ib}(\mathbf{p},\boldsymbol{\delta})w_{iv(j)}$. The derivatives are expressed in matrix form as:

$$\Delta_{(j,k)}(\mathbf{p},\boldsymbol{\delta}) = \begin{cases} \sum_{b\in\mathscr{B}_k}\sum_i w_{iv(k)}\frac{\partial s_{ib}(\mathbf{p},\boldsymbol{\delta})}{\partial p_j} & \text{for } j,k \in \mathscr{J}_f \\ 0 & \text{else} \end{cases}$$

$$\Delta^D_{(j,k)}(\mathbf{p},\boldsymbol{\delta}) = \begin{cases} \sum_{b\in\mathscr{B}^{\mathscr{D}}{}_k}\sum_i w_{iv(k)}\frac{\partial s_{ib}(\mathbf{p},\boldsymbol{\delta})}{\partial p_j} & \text{for } j,k \in \mathscr{J}_f \\ 0 & \text{else} \end{cases}$$

Derivatives and Elasticity. The relationship between brands' quantities and their prices is more convoluted than in standard multi-product supply problems. This is because, in a context where providers choose vaccine baskets, demand for a brand relates to demand for baskets containing that brand. Thus, when the price of brand j increases: (i) demand for basket b that contains j is negatively affected (*direct effect*). However, this effect is partially compensated by the fact that all baskets containing j - which are likely to be substitutes - are also negatively

affected (*indirect effect*); (ii) demand for basket b increases *if* it does *not* contain j. Formally:

$$\frac{\partial s_{ib}}{\partial p_j} = \begin{cases} s_{ib}\frac{\partial V_{ib}}{\partial p_j} - s_{ib}\sum_{r\in\mathscr{B}_j} s_{ir}\frac{\partial V_{ir}}{\partial p_j} & \text{if } j \in b \\ -s_{ib}\sum_{r\in\mathscr{B}_j} s_{ir}\frac{\partial V_{ir}}{\partial p_j} & \text{else} \end{cases}$$

$$\begin{cases} -s_{ib}w_{iv(j)}\alpha(1-\mathbb{1}_{\{bft\}}\mathbb{1}_{\{f(j)=f\}}\beta_1^{(f)} - \sum_{r\in\mathscr{B}_j} s_{ir}(1-\mathbb{1}_{\{rft\}}\mathbb{1}_{\{f(j)=f\}}\beta_1^{(f)})) & \text{if } j \in b \\ s_{ib}w_{iv(j)}\alpha(\sum_{r\in\mathscr{B}_j} s_{ir}(1-\mathbb{1}_{\{rft\}}\mathbb{1}_{\{f(j)=f\}}\beta_1^{(f)})) & \text{else} \end{cases} \tag{9}$$

where the second equality follows from the parametrization of demand. Note that the discount parameter, $\beta_1^{(f)}$, enters in the expression for the derivative. The full derivation is provided in appendix **??**.

After having defined how *basket* demand responds to a change in *brand* prices, I can now proceed describing how *brand* demand responds in turn:

$$\begin{aligned} \frac{\partial q_j}{\partial p_j} &= \frac{\partial(\sum_{b\in\mathscr{B}_j}\sum_i s_{ib} * w_{iv(j)})}{\partial p_j} \\ &= \sum_{b\in\mathscr{B}_j}\sum_i w_{iv(j)}\frac{\partial s_{ib}}{\partial p_j} \\ &= \sum_{b\in\mathscr{B}_j}\sum_i w_{iv(j)} * [\mathbb{1}_{\{j\in b\}} * (\frac{\partial s_{ib}}{\partial p_{j\in b}}) + (1-\mathbb{1}_{\{j\in b\}}) * (\frac{\partial s_{ib}}{\partial p_{j\notin b}})] \end{aligned} \tag{10}$$

where I can replace the expressions derived in (9) to fully characterize this derivative. In turn, elasticities are computed as:

$$\epsilon_{j,p_j} = \frac{\partial q_j}{\partial p_j} * \frac{p_j}{q_j} \tag{11}$$

Intuitively, I expect this elasticity to be relatively small (in absolute value) in the presence of bundled loyalty discounts, as the presence of discounts reduces the willingness to substitute across baskets (and thus brands) for small price variations.

5 Estimation Procedure and Results

Parameters of Interest. The purpose of estimation is to recover demand and supply parameters that can be used to inform counterfactual analysis. Demand parameters are denoted by $\boldsymbol{\theta}^D = \{\{\beta_0^{(jt)}\}_{jt}, \alpha, \{\beta_1^{(f)}\}_f, \beta_2, \{\beta_3^{(l)}\}_l\}$ and consist of, respectively: brand-by-quarter fixed effects, practices' sensitivity to financial gain, manufacturer-specific discount terms, the utility loss from multi-sourcing, and a basket length-specific utility loss. On the supply side, I am interested in recovering pharmaceutical companies' marginal costs of producing vaccines, which I denote by $\boldsymbol{\theta}^S = \{mc^{(jt)}\}_{jt}$.

Estimation and Identification. I exploit the richness of claims level data and estimate demand parameters via maximum likelihood. The likelihood of practices' basket choice can be written as:

$$L(\boldsymbol{\theta}^D) = \prod_{i=1}^{I} \prod_{b=1}^{B} \prod_{t=1}^{T} s_{ibt}^{d_{ibt}}(\boldsymbol{\theta}^D) \tag{12}$$

where s_{ibt} is the probability that practice i at time t chooses a basket b (whose closed form expression is shown in equation (5)) and d_{ibt} is an indicator equal to 1 if practice i *actually* chooses b at t, as observed from the data. Intuitively, the estimation procedure finds the value of the parameters $\hat{\boldsymbol{\theta}}^D$ that matches basket choices observed in the data to basket choice probabilities predicted by the model, i.e. $logL(\hat{\boldsymbol{\theta}}^D) = \arg\min_{\boldsymbol{\theta}^D} -logL(\boldsymbol{\theta}^D)$.

To recover supply parameters, I plug the analytical expression for basket choice probabilities derived in (5) into pharmaceutical companies' first-order conditions in (7). I write the system[33] of first-order conditions for each manufacturer and brand in my sample in matrix form (equation (8)) and back-out the values for brands' marginal costs holding in equilibrium using least-square methods (e.g. Levenberg-Marquardt).[34]

The intuition behind identification is as follows. Brand-by-quarter fixed effects are identified from average sales levels in each quarter, after normalizing for the outside option. The parameter capturing practices' sensitivity to financial gain is identified from variations in insurance reimbursement across practices and from practices' differing patient mixes. This generates heterogeneity in the total financial gain (i.e., reimbursement minus list price, weighted by immunization-eligible patients) that practices obtain from purchasing a given basket.

The identification of parameters within the complementarity term Γ_{ibt} leverages the observed demand for baskets of brands produced by a limited number of manufacturers. Specifically, manufacturer-specific discount terms rationalize purchases of discounted baskets over non-discounted ones. These discount terms are tightly linked to brand list prices, as I parameterize them as percentages of a manufacturer's brand list price *when* the basket is discounted by that manufacturer. Changes in company-specific discount requirements over time - such as those following GSK's acquisition of Novartis' vaccine division - induce useful variation in practices' choices.

The second object of interest, i.e. practices' utility loss from purchasing from multiple manufacturers (i.e., "multi-sourcing"), can be separately identified from the discount terms by

[33] The resulting system of equations is linear in marginal costs. When moving to the counterfactual scenario where I ban discounts instead, I need to solve a non-linear system in the new price levels, due to the logit expression for shares.

[34] Rather than solving the square system of J equations in J unknowns, I solve an overdetermined system of J equations in J-2 unknowns. This approach is due to a peculiarity of my empirical setting: Merck is selling two different MMR vaccines, without facing any competition from rivals. For this reason, solving the square system of equations yields unreliable values for the marginal costs of MMR vaccines. Therefore, I retain the optimality conditions for these products to account for their interdependence with Merck's other brands, while setting their two marginal costs to zero. I experiment with alternative values and find that the marginal cost estimates for all other brands remain largely consistent.

analyzing how baskets are constructed. Baskets may include products from multiple companies, even when discounted by only one. For instance, a Sanofi-discounted basket X might include Sanofi's brands A and B, alongside Merck's brands C and D, provided similar vaccine types are not offered by Sanofi. Consequently, two baskets—covering the same vaccine types and being discounted by the same company—may differ in the total number of companies involved. Returning to the example: a practice choosing basket X would purchase a Sanofi-discounted basket covering four vaccine types, owned by *two* manufacturers. Alternatively, the practice might select an otherwise identical basket Y, but substituting D with D' sold by GSK. This would result in a Sanofi-discounted basket covering four vaccine types but involving *three* manufacturers. Thus, conditional on discounts, I identify practices' utility loss from "multi-sourcing" by exploiting variations in the number of companies from which practices buy a basket, relative to the maximum possible number of manufacturers providing the same vaccine types.

Finally, I identify the parameters governing the utility loss associated with longer baskets (i.e., those containing more vaccine types) from average sales by basket size.

Results. Table 4 presents the main results from estimation. The profit sensitivity parameter can be translated in terms of elasticity of brand demand to its own price. Specifically, it maps to an average elasticity of -0.7, ranging from -0.3 to -1.7 depending on the brand. In the context of physician-administered treatments—but for medical procedures different from vaccines, and in the absence of bundled loyalty contracts—prior literature estimates an elasticity to physicians' reimbursement[35] between 0.5 and 1.5 (Xiang, Xiang; Clemens and Gottlieb, 2014). Intuitively, as anticipated in the section detailing the model, the presence of bundled loyalty contracts make practices less sensitive to tiny variations in their financial margin. Concerns about price endogeneity are mitigated by the presence of brand-by-quarter fixed effects, which capture potentially time-varying correlation between brand prices and brand unobserved quality. Estimated discounts, once expressed as percentages off brands' list prices, range from 7% (Merck) to 23% (Sanofi). These numbers are consistent with discount ranges discussed in prior antitrust cases concerning vaccines.[36] Moreover, there is an interesting relationship between these discount magnitudes and pharmaceutical companies' vaccine portfolios. For example, Merck is the only producer of vaccines against measles, rubella and mumps - a sizable class of vaccines required for school access. Unsurprisingly, Merck is able to leverage its favorable position in this market and offers a moderate (i.e., smaller than competitors) discount to practices purchasing its entire bundle of products. Practices also tend to dislike "multi-sourcing," as they are willing to forgo up to 8% of their financial gain on the average vaccine basket to purchase from one fewer pharmaceutical company. Turning to supply, I estimate marginal costs between

[35] Note that these studies measure physicians' sensitivity to reimbursement rather than to purchasing price, thus the sign is reversed.

[36] *Castro M.D PA v. Sanofi Pasteur Inc.* (2011-2017); *SugarTown Pediatrics, LLC v. Merck & Co* (2018-2023).

$0 and $2 per vaccine dose.

Table 4: Main Demand Estimates

Parameters		Est	S.E.
Sensitivity to Financial Gain	α	2.18	0.08
Discount Term, Sanofi	$\delta^{(Sanofi)}$	0.23	0.05
Discount Term, Merck	$\delta^{(Merck)}$	0.07	0.01
Discount Term, GSK	$\delta^{(GSK)}$	0.19	0.02
Loss from Multi-Sourcing	β_2	-2.14	0.10
Brand x Time FEs	$\beta_0^{(jt)}$	Yes	
Bundle Length FEs	$\beta_3^{(l)}$	Yes	

Note: The table reports point estimates and standard errors for the main demand parameters of interest. Prices are in hundreds of dollars, and discounts are expressed as percentages of list prices (i.e. $\delta^f = \frac{\beta_1^f}{\alpha}$). Standard errors are computed analytically using the "sandwich" estimator (Train, 2009).

6 Counterfactual Scenarios

Using the estimated model, I can simulate counterfactual scenarios to evaluate the welfare effects of bundled loyalty contracts in the context of vaccine provision. My aim is to evaluate the welfare implications for most of the agents involved, namely medical practices, patients, insurance companies and manufacturers. The absence of consensus among legal experts, judges, and academics on how bundled loyalty contracts (and similar contract types) should be assessed, along with the varied and sometimes conflicting outcomes in past litigated cases, highlights the unique and policy-relevant insights that empirical research can provide.

I begin by simulating an equilibrium in which bundled discounts are banned and pharmaceutical companies reset their prices optimally. I also evaluate asymmetric discounting scenarios, in which only *some* of the manufacturers are permitted to offer this type of contracts. This first exercise is motivated by recent policy discussions about the potential impact of banning rebates that drug companies pay to intermediaries or medical providers to consolidate market power. This discussion gained traction under the Trump administration, which urged Congress to pass a proposal banning drug companies' "backdoor" rebates, with the ultimate goal of reducing consumers' drug spending.[37] The proposal was criticized for the potential unintended

[37]See here and here for an overview of the Trump administration's proposals.

consequences for consumers and ultimately was not passed.

As a second exercise, I consider the potential of bundled loyalty contracts to foreclose specific brands. Specifically, I ask: how high must a drug's quality be to avoid being foreclosed by these contracts? This question is critical, as it may ultimately influence the trajectory of pharmaceutical innovation over the long term.

Finally, I evaluate alternative policies and assess their potential to achieve comparable levels of treatment provision and drug selection as observed with bundled discounts. For example, I consider an ad-hoc increase in insurance reimbursement to providers - a policy that has received large attention, especially following the COVID-19 pandemic, due to the well-documented financial vulnerability of primary care practices relative to other medical specialties.[38]

6.1 Banning discounts, and allowing manufacturers to reset their prices

Using the demand and supply models, I ban the possibility of offering bundled loyalty discounts for all pharmaceutical companies. I allow companies to reset new equilibrium prices for their vaccine brands. I then predict medical practices' choices of vaccines, in terms of types and volume.

Table 5 presents the resulting changes in practices' demand. In this new equilibrium without discounts, practices are more likely to choose baskets of vaccines that - even in the baseline equilibrium - were not discounted. This suggests that bundled loyalty contracts distort relative prices, making discounted baskets more appealing than they would be otherwise (Panel A). Specifically, in the new equilibrium, medical practices tend to opt for baskets with fewer brands, often at the expense of optional vaccines (Panel B). The average number of vaccine types per basket goes from 6.6 to 6.4, i.e. a 3% reduction. However, since five vaccine types are actually compulsory, and thus always included within baskets, the real induced change is a 12.5% reduction in average length. In turn, assuming limited mobility of patients across practices,[39] this finding translates into fewer eligible patients receiving immunization. For example, the share of eligible patients receiving hepatitis A falls from 73% to 67%. In the new equilibrium, practices also lean toward lower-quality brands, as proxied by the year of their FDA approval (Panel C). Those brands are usually cheaper for both practices and insurers, and thus more attractive to purchase in a setting where discounts are not offered. However, they come with slightly reduced effectiveness for patients.

[38] See Dafny and McWilliams (2020) for a discussion on the main challenges faced by primary care practices and potential remedies.

[39] Previous empirical studies highlight that distance from home, wait times, recommendations from family/friends are the key drivers guiding patients' choice of their primary care provider (Bornstein et al., 2000). As a result, patients' reallocation to primary care doctors following a change in their vaccine offering seems unlikely. Moreover, in my sample I observe very few patients multi-homing across practices to complete their vaccination cycle, both in the cross-section and over time. Future iterations of this work might consider relaxing this hypothesis.

Table 5: Change in Medical Providers' Demand, after Discount Ban & Manufs' Price Resetting

	Baseline	Ban Discounts & Reoptimize Prices	Diff (Ban - Baseline)
Panel A: Share of Baskets without Discounts (Under Baseline) ↑			
	0.22	0.27	5.0 p.p.
Panel B: Avg Number of Vaccine Types per Chosen Basket ↓			
	6.6 (1.6)	6.4 (1.4)	-3.0% (-12.5%)
Share of eligible patients receiving...			
Hepatitis A	0.73	0.67	-5.7 p.p.
Haemophilus influenzae	0.72	0.58	-14.0 p.p.
Panel C: Share of Patients receiving New High-Quality Brands ↓			
By vaccine type:			
Diphtheria, Tetanus, Pertussis	0.37	0.34	-2.7 p.p.
Hepatitis B	0.54	0.44	-9.2 p.p.
Measles, Mumps, Rubella	0.44	0.43	-1.1 p.p.

Note: The table shows the implications of banning discounts (and allowing companies to reoptimize prices) for practices' demand and, consequently, patients' uptake. Specifically, column "Baseline" reports the outcomes under the status-quo simulated equilibrium; column "Ban Discount and Reoptimize Prices" reports the outcomes after banning and optimal price setting; the last column reports the change (in percentage points, i.e. p.p., or percentages, i.e. %, depending on the outcome of interest) when moving from the status quo to the new equilibrium with the ban. Results are expressed as an average over months.

Overall, the changes induced by the discount ban (and price reoptimization) can be quantified in dollar terms. In Table 6 I report the welfare consequences for the various actors involved, in dollars per month. First, I compute total consumer surplus before and after the policy change. This object combines together the impact on medical practices and patients, since it is derived directly from the expression for practices' utility function, which takes into account also patients' health. Formally, I use the standard logit formula (Train, 2009) to compute total consumer (providers + patients) surplus, for each equilibrium:

$$CS_t = \sum_i \frac{1}{\alpha} log(\sum_{b \in B_{it}} exp(V_{ibt})) \tag{13}$$

where V_{ibt} is the observable part of basket b's utility for practice i at t, used to construct the expression for predicted probabilities in equation 5.

After the discount ban, providers and patients are worse off (Panel A). The former are worse off since, despite price re-optimization, they no longer benefit from discounts and they miss out on potential revenues due to a reduction in optional vaccine administrations. Patients are worse off because they receive fewer and lower-quality doses. On the contrary, insurers benefit in the short run in this scenario, as expressed by their lower total costs (Panel B).

This result is driven by the fact that they now have to cover fewer, lower-priced shots. The impact on pharmaceutical companies is slightly positive overall, as expressed by total industry profits.[40] However, it hides some interesting heterogeneity across manufacturers, depending on their vaccine portfolios (Panel C). In this context, I find that GSK benefits from bundled loyalty contracts - primarily due to the market expansion effect on optional vaccines, which constitute a significant portion of GSK's portfolio. On the contrary, Sanofi and Merck are worse off in the presence of discounts, but they optimally choose to offer them in equilibrium.[41]

Table 6: Welfare Effects, after Discount Ban & Manufs' Price Resetting

	Baseline	Ban Discounts & Reoptimize Prices	Diff (Ban - Baseline)
Panel A: Total Providers and Patients' Surplus (thousands of $)			
	755.1	687.3	-67.8
Panel B: Insurance Cost (thousands of $)			
	1400.1	1393.3	-6.8
Panel C: Pharmaceutical Companies' Profits (thousands of $)			
Total	849.7	857.8	8.1
By company:			
GSK	85.9	82.6	-3.9%
Merck	616.3	623.7	1.2%
Sanofi	147.4	151.5	2.8%

Note: The table shows the implications of banning discounts for providers' and patients' surplus, insurance costs, and pharmaceutical companies' profits. Amounts are expressed in thousands of $ per month. Specifically, column "Baseline" reports the amounts under the status-quo simulated equilibrium; column "Ban Discount and Reoptimize Prices" reports the amounts after banning and optimal price setting; the last column reports the change when moving from the status quo to the new equilibrium with the ban.

6.1.1 The case of asymmetric discounting

To further explore the implications of banning discounts for pharmaceutical companies' profits, I characterize also scenarios with asymmetric discounting. In other words, I ask: what if a *subset* of companies, rather than the totality, is forbidden to or is not willing to offer bundled

[40] As a sanity check, I compared the profit levels simulated here against the ones reported in official financial statements released by firms every year (e.g. 10-K), containing U.S. sales of vaccines. Magnitudes are comparable. For example, for Merck, see here.

[41] On a related note, previous theoretical literature characterizes conditions under which mixed bundling does or does not constitute a prisoner dilemma (Matutes and Regibeau, 1992; Ghosh and Balachander, 2007). Cao and Chatterjee (2022) provides an empirical quantification of firms' gains arising from mixed bundling in the context of Alzheimer's drugs: market expansion plays a key role in driving their results.

discounts? Operationally, I split the main actors into two groups, based on the different implications that bundled discounts seem to have on them as suggested by the analysis in the previous section. In the first exercise, I allow GSK to offer bundled discounts, while forbidding Sanofi and Merck from discounting. In the second exercise, I allow Sanofi and Merck to offer bundled discounts, while forbidding GSK to do so. All manufacturers reset their prices optimally, while discounts (if any) are fixed at the estimated values.[42] Pharmaceutical companies' profits under the different scenarios are displayed in Table 7, in dollars per month. The scenario (offer, offer) is the simulated status quo. The (not offer, not offer) scenario is the first counterfactual I computed in the previous section, where I ban discounts for all companies. As already mentioned, Sanofi and Merck would be better off if noone offers discounts, while GSK would be worse off. Here, I simulate also the two asymmetric cases. In the table, I highlight each manufacturer's best response to the rival(s). In my setting and given the estimated parameters, (offer, offer) is the unique equilibrium, as each manufacturer is best responding to its rivals. Moreover, offering bundled discounts is GSK's dominant strategy. Overall, the simulated game is not a prisoner's dilemma.

Table 7: Manufacturers' Profits, Under Alternative Bundling Scenarios

		Sanofi & Merck	
		Offer bundled discounts	**Do not offer bundled discounts**
GSK	**Offers bundled discounts**	85.9, 763.7	86.3, 748.3
	Does not offer bundled discounts	78.0, 768.3	82.6, 775.3

Note: The table reports companies' profits (in thousands of $, per month) under alternative discounting scenarios. Prices are reset optimally. Results are expressed as an average over month. I highlight each manufacturer's best response to the rival(s). In equilibrium, i.e. (offer, offer), each manufacturer is best responding to its rivals.

7 Conclusion

Bundled loyalty rebates have recently become a central topic in policy discussions due to their widespread use across industries and the theoretically ambiguous welfare implications they present. In the pharmaceutical sector—particularly in the case of physician-administered vaccines for children and adolescents—bundled loyalty discounts are of special interest because they can directly influence the volume and type of treatments delivered to patients.

[42] I recognize that discounts estimated when all companies are offering them (i.e. the current status quo equilibrium) could be different from the ones offered when only some companies do so. This is a simplifying assumption for tractability purposes, as solving for both discounts and prices is computationally challenging. The assumption holds in reality if companies take more time to adjust discounts than to adjust prices.

In this paper, I develop a model of medical practices' demand and drug manufacturers' supply of vaccines to assess the welfare consequences of banning these contracts for practices, patients, insurers, and pharmaceutical companies.

My analysis primarily focuses on the short-term effects of bundled loyalty discounts, without considering potential long-term consequences. For instance, such contracts may deter entry by manufacturers with limited drug portfolios, as they may struggle to compete without the ability to offer bundled discounts. This could lead these manufacturers to avoid investing in the development of new, high-quality drugs to rival existing treatments, potentially harming innovation and affecting patient health over time. I plan to address these issues in my future research agenda.

Additionally, I do not model insurers' decisions in equilibrium, so my counterfactual scenarios abstract from insurers' optimal responses. In other markets (e.g., Medicare Part B), insurer reimbursements are closely tied to purchasing prices, albeit with some time lag. Therefore, a potential avenue for future research is to investigate whether and how insurers would respond to the presence of bundled loyalty discounts, particularly in terms of reimbursement levels and premiums, given that these contracts may alter providers' financial incentives and affect patient uptake of preventive treatments.

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